Social Conditioning of Police Officers: Exploring the interactive effects of driver demographics on traffic stop outcomes

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ABSTRACT
Officer decision-making has consistently been a focus of research throughout the past forty years. More recently, specific attention has been paid to understanding the impact of drivers’ race/ethnicity on traffic stops. The focus on traffic stop police-citizen encounters developed out of concerns that racial/ethnic disparities may exist in either the initial decision to stop a vehicle and/or in traffic stop outcomes. Studying the decision to initiate a traffic stop has been fraught with data and analytical limitations; thus, the focus of research is often directed toward traffic stop outcomes. Research findings have confirmed not only racial/ethnic disparities, but also gender and age disparities in these situations. Although measures of drivers’ gender and age are often included, these measures have received scant thorough attention. Moreover, exploration of driver demographic interaction effects has been virtually nonexistent. Finally, few research studies grounded their analyses in a theoretical frame to assist in directing and interpreting the results.

This dissertation aims to contribute to the existing literature on traffic stop outcomes by thoroughly reviewing the literature on traffic stop outcomes and exploring various theoretical explanations offered for the reported disparities. Substantively, this research examines if specific combinations of driver demographics (i.e., race/ethnicity, gender, and age) are related to traffic stop outcomes by using bilevel, multivariate modes to analyze officer-initiated traffic stops. The specific research hypotheses to be tested are grounded in a theory, the social conditioning model. The social conditioning model offers a theoretical framework for exploring and understanding disparities in traffic stop outcomes by suggesting that disparities are a product of unconscious stereotypes. These stereotypes link young, minority male drivers to criminal activity thereby affecting an officer’s decision-making. Based on the social conditioning model, it is expected that young, minority male drivers are more likely to be warned and arrested, and less likely to receive a citation. Results of the analyses and implications for the research hypotheses, the social conditioning model, and other research are discussed.
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CHAPTER 1: DRIVER DEMOGRAPHICS AND TRAFFIC STOP OUTCOMES

INTRODUCTION

Over the last several decades, researchers have explored various factors associated with decision-making by criminal justice personnel (Walker, 1993). Discretion has frequently been a central focus of this research due to the considerable freedom in action available to criminal justice actors when interacting with citizens. Thus, criminal justice actors possess considerable impact on the lives of citizens who come into contact with the criminal justice system (Bittner, 1970; Goldstein, 1969). In particular, police officers frequently use discretion when making decisions during police-citizen encounters (Gottfredson & Gottfredson, 1988).

Traffic stops, one example of a police-citizen encounter, are a situation in which discretion is available and used by police officers (Harris, 1997; Lundman, 1979; Ramirez, McDevitt, & Farrell, 2000; Wilson, 1968). Recent research has examined officers’ use of discretion in two separate, but related situations - the decision to initiate a traffic stop and the resolution of that traffic stop (i.e., the traffic stop outcome). This research is often rooted in a belief that citizen demographics should not be the sole factor in police decision-making (Harris, 2006; Ramirez et al., 2000), and underscores previous research examining if minorities (i.e., Black and/or Hispanic drivers) are stopped disproportionately compared to similarly situated White drivers, or if minority drivers receive a disproportionate number of more severe traffic stop outcomes (i.e., citations or arrests). Driver’s gender and age are
other factors often included in such research, but have not been a central focus of the analyses or discussions to date.

The current research continues the interest in identifying relationships between driver demographics (i.e., race/ethnicity, gender, and age) and traffic stops. In particular, this research narrows the focus exclusively to traffic stops outcomes, but also widens the examination of driver demographics by more thoroughly exploring the importance of drivers’ gender and age in traffic stop decision-making. Moreover, the research hypotheses are informed by a theoretical framework, the social conditioning model, thereby offering theoretically grounded analyses and conclusions. The current research explores if specific combinations of driver demographics are related to traffic stop outcomes. For example, this research addresses whether young, Black male drivers or young, Hispanic male drivers receive disparate traffic stop outcomes compared to other drivers. Answering these questions offers greater insight into police decision-making during a traffic stop and the identification of potential disparity for drivers related to their race/ethnicity, gender, and age.

This chapter explores the interest in traffic stop decision-making and the reasoning for analyzing such encounters. It also briefly introduces the theoretical framework, the characteristics of the data, and the specific research questions addressed in this research. The chapter concludes with an overview of the subsequent chapters.

**TRAFFIC STOPS**

Traffic stops are one form of police-citizen encounters that occur frequently (Skolnick, 1966). According to a recent survey, over half of all citizens aged 19 or older had contact with the police by way of a traffic stop (Durose, Smith, & Langan, 2007). Other research suggests that citizens’ experiences with the police inform their opinions regarding
law enforcement (Weitzer & Tuch, 2004; 2005). Thus, studying traffic stops assists in understanding citizen attitudes toward the police (Engel, 2005). Traffic stops also offer researchers an ability to examine decision-making in both discretionary and non-discretionary situations (Alpert, MacDonald, & Dunham, 2005; Meehan & Ponder, 2002; Novak, 2004). Traffic stops involve a variety of situations that offer the officer an ability to exercise their discretion. For example, in a traffic stop initiated for speeding, an officer has the opportunity to either write the driver a warning or a citation (depending on the jurisdiction and the agency’s policy on speeding). Examining these encounters assists in identifying and understanding an officer’s use of discretion and overall decision-making.

Beyond the interest in traffic stops as a decision-making point, traffic stops have also been a recent focus of research due to concerns about the inappropriate use of race/ethnicity in the decision to stop a vehicle and/or in the disposition of that traffic stop (Buerger & Farrell, 2002; GAO, 2000; Harris, 2002; 2006; Ramirez et al., 2000; Walker, 2001). Stemming from the war on drugs (Tonry, 1995), the use of race/ethnicity was actively promoted as a tool to identify and intercept criminal activity in the late 1980s and early 1990s (Harris, 1999). Awareness of this practice fueled an active response by social groups, legislators, politicians, and academics (Fridell, 2004; Harris, 2002; Novak, 2004; Ramirez et al., 2000). High profile legal challenges to this practice also brought attention to the issue (e.g., Wilkins v. Maryland State Police, 1993; State of New Jersey v. Soto, 1996). As a result of the mounting pressure to discontinue the use of race/ethnicity as a factor in decision-making, widespread data collection efforts were initiated to inform this issue (Engel & Calnon, 2004a; Ramirez et al., 2000).
These data collection efforts relied on a variety of data sources including official data, citizen surveys, and observational studies (Fridell, 2004; Lundman, 2004; Tomaskovic-Devey et al., 2006). Currently, the most common method for collecting and analyzing traffic stop information is official data (Barlow & Barlow, 2002; Birzer & Birzer, 2006; Kowalski & Lundman, 2007; Walker, 2001). This method requires the officer to record a variety of predetermined features of the traffic stop such as time of the day, location of the stop, driver characteristics, and stop disposition. This information is collated and analyzed by the agency or an independent researcher for patterns of disparity in initiating traffic stops and/or in the outcomes of a traffic stop.

Using official data, analysis is often split into an examination of the initial decision to stop a vehicle and the disposition of the traffic stop (Ramirez et al., 2000; Smith & Alpert, 2002). This research focuses exclusively on traffic stop outcomes (i.e., warnings, citations, and arrests) for three reasons. First, the impact for a citizen of being stopped by a law enforcement official is less serious compared to the effect of a warning, citation, or arrest (Ramirez et al., 2000). In other words, traffic stops are less severe, whereas the outcome of a traffic stop has the potential to be a greater intrusion on a citizen’s life. Second, if racial/ethnic, gender, or age disparities exist, they are more likely to manifest themselves during the disposition of a traffic stop when the driver’s demographics can be confirmed rather than in the initial decision to initiate a traffic stop (Ramirez et al., 2000). Finally, traffic stop outcome data enable researchers to employ more robust analytical techniques compared to those available to analyze traffic stops. Specifically, analyses of traffic stops are limited by benchmarking weaknesses (Engel & Calnon, 2004b; Smith & Alpert, 2002;
Walker, 2001); whereas, multivariate modeling is a more powerful analytic option to assess if disparities based on driver demographics exist in traffic stop outcomes.

In sum, traffic stops represent a frequent type of police-citizen encounter and influence the opinions of citizens towards the police. These encounters have generated numerous traffic stop studies in the past fifteen years. The large majority of these studies rely on official data to examine the relationship between driver demographics and traffic stops/traffic stop outcomes.

**CURRENT RESEARCH**

This research explores the relationship between driver demographics and traffic stop outcomes by relying on a theoretical framework to direct robust analyses of official data collected from a large traffic stop research project. The theoretical foundation, research hypotheses, and data used in the analyses are outlined below. Initially, a definition of biased policing is presented.

Several definitions describing the inappropriate use of race/ethnicity have developed over the past several years (Rojek, Rosenfeld, & Decker, 2004). These definitions can be generally grouped into two categories. A **broad** definition of biased policing suggests bias occurs when race/ethnicity is used *in combination with any other factor* during a police-citizen interaction or when minorities are targeted for unjustified traffic stops (Tomaskovic-Devey, Mason, & Zingraff, 2004). Alternatively, a **narrow** definition of biased policing in traffic stops reflects cases where race/ethnicity was the *only factor* used to influence a decision. This definition reduces the likelihood that law enforcement agencies or individuals are accused of biased policing because it is challenging to isolate one single factor (i.e., the driver’s race/ethnicity, gender, or age) as the cause of a decision (i.e., a traffic stop outcome).
Both definitions reflect a core concern that race/ethnicity is used inappropriately by the police when making traffic stop related decisions.

The most commonly accepted definition of biased policing is “any police-initiated action that relies upon the race, ethnicity, or national origin of an individual rather than the behavior of that individual or information that leads the police to a particular individual who has been identified as being engaged in or having been engaged in criminal activity” (Ramirez, et al., 2000:3). This definition encapsulates both the focus on driver’s race/ethnicity in recent policing research and applies to analyses of traffic stops and traffic stop outcomes. Thus, it is used as the foundation for determining disparity in this research’s analysis. In addition, any result indicating a statistical effect based on a driver’s gender and/or age would also be classified as evidence of disparity.

**Theory**

Similar to other social phenomenon, traffic stops outcomes are best understood by using a combination of theory and analyses. Theory offers an explanation of the processes that give rise to the outcome under study. As a result, theory may lead to specific research hypotheses to be tested, and also may provide explanations after analyses are complete. In either case, theory is an integral element to understanding social phenomenon such as traffic stop outcomes.

Criminal justice research has been criticized for its failure to develop and test theoretical explanations for decision-making (Hagan, 1989). More specifically, criticisms have been raised regarding the use of theory in understanding police behavior in traffic stops (Engel, Calnon, & Bernard, 2002), and in particular, the documented racial/ethnic, gender, and age disparities in traffic stops (e.g., Alpert Group, 2004; Alpert et al., 2006; Engel et al.,
More recently, theoretical explanations have been offered to explain such disparities (Tomaskovic-Devey et al., 2004; Warren et al., 2006). For example, expectancy theory (Mastrofski, Ritti, & Snipes, 1994), deployment practices (Novak, 2004; Parker et al., 2004; Warren et al., 2006), and focal concerns theory have applicability to understanding racial/ethnic disparities (Steffensmeier, Ulmer, & Kramer, 1998). Unfortunately, these and other theoretical approaches have limitations that restrict their effectiveness in explaining traffic stop outcomes.

This research adopts the social conditioning model as its framework for explaining driver demographic disparities in traffic stop outcomes. Bridging social psychological research and recent biased policing research, Smith & Alpert (2007) offer a model that describes the processes by which racial/ethnic disparities in traffic stop outcomes result from unconscious stereotypes. These profiles, commonly known as stereotypes (Fontaine & Emily, 1978), schemas (Good & Brophy, 1990), or scripts (Huesmann, 1988), are a form of cognitive shorthand to assist in decision-making (Katz & Braley, 1933). They are developed through personal and vicarious experiences and media exposure and are reinforced by social identity theory (Brewer, 1979; Hinton, 1993; Tajfel & Turner, 1979), the illusory correlation (Chapman, 1967), and the ecological fallacy (Robinson, 1950).

Through processes ranging from overt racism (Bobo, Kluegel, & Smith, 1997) to racial typification (Chiricos, Welch, & Gertz, 2004), minorities are often linked with criminal activity. As mentioned, vicarious experience and media exposure (Entman, 1992; 1990) reinforce these group differences. Citizens internalize this message, which leads to the formation of these psychological profiles. Police officers are also exposed to these beliefs.
and adopt unconscious profiles regarding specific demographic groups in society. For police, their experience further substantiates these profiles due to the increased exposure officers have to criminal activity. As a result, racial/ethnic differences in traffic stop outcomes result from the influence of these unconscious cognitive profiles. The social conditioning model is the primary theoretical foundation for this research and informs the development of several research hypotheses.

**Research Hypotheses**

Using the social conditioning model as a guide, this research addresses two sets of research questions. First, do driver demographics (i.e., race/ethnicity, gender, and age) exert an influence on the likelihood of receiving a warning, citation, or arrest, net of stop, officer, vehicle, and other driver characteristics? Answering this question will offer further evidence to support or reject the extant research’s findings that document racial/ethnic, gender, and age disparities in both traffic stops and traffic stop outcomes (e.g., Alpert Group, 2004; Alpert et al., 2006; Engel et al., 2007c; Farrell et al., 2004; Ingram, 2007; Lovrich et al., 2005; Ridgeway et al, 2006).

Second, do specific combinations of driver demographics exert an influence on the likelihood of receiving a traffic stop outcome, net of stop, officer, vehicle, and other driver characteristics? Sparse past research has examined the effect of an interaction between driver’s race/ethnicity, gender, and age and traffic stop outcomes (c.f., Moon & Cooley, 2007). Therefore, little is known about the impact of such demographic combinations on traffic stop outcomes. For example, what is the relationship between young, Black males or young, Hispanic males and traffic stop outcomes?

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1 In the data analyzed in this research, all cases result in one of these three outcomes.
Examining these driver demographic interactions is important for several reasons. This research’s hypotheses are grounded in a theoretical foundation and answer the call made by previous researchers for greater emphasis on theory in criminal justice research (Hagan, 1989; Engel et al., 2002). Examining driver demographic interaction terms is consistent with the processes described by the social conditioning model, and statistically significant relationships between these interaction terms and traffic stop outcomes would offer support for the accuracy of the social conditioning model. Importantly, the social conditioning model is not being directly tested in this research, as key measures required to accomplish such a task are not available.

Statistically significant interaction terms would also have policy implications. For example, law enforcement agencies may have to re-evaluate their training curricula to reflect the more nuanced relationship between driver demographics and traffic stop outcomes. Such a relationship would distinguish between whether driver’s race/ethnicity, gender, and age are independently or collectively related to the likelihood of being warned, cited, or arrested. Finally, previous research would have to be reassessed in light of these new findings to assess if those studies also possess finer distinctions in the relationship between driver demographics and traffic stop outcomes.

**Data**

Data for this research are drawn from an on-going, multi-year research project that collects a variety of information on all officer initiated\(^2\) traffic stops conducted by the agency. The participating law enforcement agency is a full service department within one state, although the majority of these data reflect a highway patrol function. The data \(^2\)These data do not include any collision encounters, encounters in which a motorist requested assistance, or if the officer was responding to a dispatch.
examined in this research represent traffic stops that occurred in 2006. These data were selected because they are considered to be an accurate record of all officer-initiated traffic stops within this year.

Data collected by the officers include stop characteristics (i.e., time and location of stop, and the reason for the stop), driver characteristics (i.e., age, gender, and race/ethnicity), vehicle characteristics (i.e., state of registration), and officer characteristics (i.e., age, gender, race/ethnicity, education, and experience). This rich data set allows an opportunity to examine if driver demographic combinations are related to traffic stop outcomes.

**OVERVIEW**

This document is organized into several chapters. Chapter 2 briefly addresses the reasons why the traffic stop is an important decision-point to study. Specifically, it outlines the methods of data collection and the distinction between traffic stops and traffic stop outcomes. The majority of the chapter is devoted to reviewing all traffic stop studies that examined official data with multivariate analyses. The emphasis of this review is to highlight any racial/ethnic, gender, or age disparities in traffic stop outcomes. This summary will also emphasize the lack of attention previous research has placed on the importance of examining interactions between driver demographics and their potential relationship with traffic stop outcomes.

In an attempt to understand the processes underlying the documented driver demographic disparities in traffic stop outcomes, Chapter 3 reviews several theories that offer explanations for these disparities. Most theories (i.e., racial bias, racial profiling, etc.) have direct application to these outcomes, while other theories (i.e., expectancy theory, focal concerns theory, and conflict theory) offer broader explanations for officer behavior but are
applicable to explaining disparities in traffic stop outcomes. The social conditioning model is the primary focus of Chapter 3, including its underlying assumptions and explanation for why and how demographic disparities develop in traffic stop outcomes.

Chapter 4 provides a thorough description of the research hypotheses, the data used in the analyses, and the analytical techniques employed in this research. Using evidence from previous research and the social conditioning model, specific research questions are presented in this chapter. The data are also described, including the method of collection, the measures in the data set, and their limitations. Finally, the research’s analytical techniques are outlined including bilevel, multivariate models.

Chapter 5 summarizes the results of the analyses in a step-by-step method. Zero-order analyses are initially reported to assess if there are statistically significant correlations between race/ethnicity, gender, and age, and the likelihood of a warning, citation, or arrest. Thereafter, a series of bilevel, multivariate analyses are computed for each traffic stop outcome (i.e., warnings, citations, and arrests) using non-mutually exclusive and mutually exclusive models.

Chapter 6 summarizes the results and their impact on the research hypotheses, the social conditioning model, and other research. In particular, all statistically independent variables are discussed with a specific focus on the relationship between driver demographics and traffic stop outcomes. The broader implications for future research are offered including the importance of theory, and the value of robust analytical techniques.
CHAPTER 2: PREVIOUS RESEARCH ON TRAFFIC STOP OUTCOMES

INTRODUCTION

Traffic stops are one situation in which law enforcement officers interact with citizens and make decisions regarding the treatment of those citizens. The resolution of the traffic stop, more commonly referred to as the traffic stop outcome, is a decision point at which racial/ethnic, gender, or age disparities may occur. Identifying such disparities in traffic stop outcomes is important due to the effect on citizens of more severe traffic stop outcomes (e.g., an arrest). Beyond the independent effect of these variables, these driver characteristics may coalesce and result in differential rates of traffic stop outcomes. For example, young, Black males or young, Hispanic males may receive disparate traffic stop outcomes compared to other combinations of driver demographics. Understanding these potential relationships may assist in developing agency-level policies regarding traffic stop outcomes.

This chapter reviews the past research on traffic stop outcomes by summarizing studies that used multivariate analysis to examine data collected by a law enforcement agency. Collectively, these studies offer a foundation of knowledge regarding traffic stop outcomes that assist in directing the research questions posed in this research. Initially, a brief discussion is offered on the merits of analyzing traffic stops.

THE TRAFFIC STOP AS A DECISION POINT

Police and citizens interact in a variety of situations. Such encounters occur when citizens make requests for assistance from the police (i.e., calls for service), during informal encounters in public places (i.e., on streets or in parks), and during traffic stops. Traffic stops are the specific focus of this research because they offer an opportunity to study frequently
occurring police-citizen interactions (Skolnick, 1966; Walker, 2001). In 2005, 19% of citizens 16 years of age and older had contact with law enforcement, and of those contacts, the majority (56%) occurred during a traffic stops, with the second most frequent reason – calling the police – occurring less than half as often (24%) (Durose et al., 2007).

If such encounters constitute the majority of exposure to law enforcement for citizens, traffic stops likely have a considerable impact on the development of citizen attitudes towards law enforcement. Research supports this postulate by suggesting that citizens form opinions regarding the police based on their experiences with the police (Brandl et al., 1994; Weitzer & Tuch, 2004; 2005). Further, it is plausible that the outcome of the traffic stop will have a significant impact on the citizen’s opinion. As a result, studying officer decision-making during a traffic stop, in particular, the stop disposition, can assist in understanding the development of citizen attitudes toward the police (Engel, 2005).

Traffic stops are initiated by officers for a multitude of reasons including policy requirements, the law, and based on discretion (Alpert et al., 2005; Meehan & Ponder, 2002). Analyzing traffic stops and their outcomes present an opportunity to examine decision-making in both situations. Traffic stops are one type of encounter that offers the officer considerable flexibility to proactively initiate contact with citizens (Novak, 2004). Using data collected during a traffic stop to study traffic stop outcomes enables a greater understanding of officer decision-making within such a discretionary context.

Data Collection

Studying traffic stops and their outcomes has become more common since the mid-1990s (Harris, 2002). Court cases in New Jersey (New Jersey v. Soto, 1996) and Maryland (Wilkins v. Maryland State Police, 1993) alleging racial profiling by law enforcement
agencies and officers attracted attention to this issue (Buerger & Farrell, 2002; GAO, 2000). These cases coincided with increasing pressure from the public, media, and politicians to address perceived racial/ethnic disparities in traffic stops and their outcomes (Barlow & Barlow, 2002; Novak, 2004; Walker, 2001). For example, an investigation by the New Jersey Attorney General found questionable patterns in the traffic stopping practices of the New Jersey State Police (Verniero & Zoubek, 1999). As a result, law enforcement agencies began collecting data on traffic stops and their outcomes (Harris, 2002; 2006). Law enforcement agencies had previously collected data on police-citizen interactions, but within this social climate, the focus now centered on all traffic stop encounters. These data collection efforts occurred regardless of the stop disposition and delivered data to examine for any patterns of racial/ethnic disparity.

Traffic stop data collection is most frequently conducted by the law enforcement agency (Barlow & Barlow, 2002; Engel & Calnon, 2004a; Lundman, 2004; Lundman & Kaufman, 2003). Referred to as official data, this type of data collection effort may be voluntarily initiated by the agency, as a result of a court settlement, or due to changes in the law (Engel, Cherkauskas, & Tillyer, 2007a). Official data offer insight into police behavior by offering a wealth of information regarding traffic stop encounters (Tomaskovic-Devey et al., 2006). For example, these data sets often include information on the stop (e.g., date, time, and location of the encounter), the driver (e.g., the race/ethnicity, gender, and age of the driver), the vehicle (e.g., the condition of the vehicle, its registration status), and in some cases, the officer initiating the stop (e.g., officer demographics, assignment, and education level (Alpert et al., 2006; Engel et al., 2007c; Farrell et al., 2004; Lovrich et al., 2005). Access to this range of information assists in identifying factors associated with officer
decision-making in traffic stop outcomes. Collecting a variety of potentially relevant variables also reduces the likelihood of misspecified models during analyses. Official data have made significant contributions to the current knowledge base regarding patterns of racial/ethnic disparities in traffic stops and traffic stop outcomes (Lundman, 2004; Tomaskovic-Devey, et al., 2006).

One obvious limitation of official data is the requirement of law enforcement cooperation (Tomaskovic-Devey et al., 2006). This may be more or less of a concern depending on the reason for initiating the data collection effort. Related, there is heavy reliance on law enforcement officials to collect data regarding traffic stops consistently and accurately (Berjarano, 2001; Lundman & Kaufman, 2003). Officers, aware of a focus on their behavior, may not be diligent in recording all traffic stops and their outcomes (Lundman, 2004; Walker, 2001); this concern has been documented in some jurisdictions (Donohue, 2000; Meeks, 2000; Verniero & Zoubek, 1999). Even more troubling is officer disengagement, in which officers change their traffic stopping behavior (Ramirez et al., 2000; Walker, 2001).

Data audits represent one method of addressing these concerns. Ideally conducted on a regular basis, data audits involve comparing the traffic stop data to other data sources such as a citation or arrest database to identify missing or incorrect information (Ramirez et al., 2000; Fridell, 2004). Errors in data collection can be identified and corrected quickly using this method to restore the validity of the data.

Citizen surveys offer a second source of data on traffic stops. These data are gathered by asking citizens to describe their experience(s) with law enforcement (Lundman, 2004; Tomaskovic-Devey et al., 2006). This approach offers a direct response from citizens
regarding this issue (Tomaskovic-Devey et al., 2006), and some suggest it is an improvement beyond official data (Lundman, 2004). Surveys can be used in conjunction with official data as a means to triangulate information regarding traffic stops. Additionally, citizen surveys circumvent the concern of officer error in accurately recording traffic stop information.

Despite the stated advantages, citizen surveys have limitations. For example, the respondents may forget incidents, they may not accurately report the specifics of the incident, or they may employ telescoping, which occurs when a respondent assigns the incident to the incorrect time period (Cantor & Lynch, 2000; Fisher & Cullen, 2000). Other weaknesses include: 1) failure to measure the impact of other variables such as the reason for the stop, officer behavior, and officer characteristics, etc., 2) concern that survey respondents often under-represent their involvement in illegal activity (Clark & Tifft, 1966; Tourangeau & McNeeley, 2002), and 3) the expense associated with conducting a citizen survey (Tomaskovic-Devey et al., 2006).

Various data collection efforts have used citizen surveys. For example, the Police-Public Contact Survey (PPCS), which is a supplement to the National Crime Victimization Survey (NCVS), offers national-level information on police-citizen encounters, including traffic stops (Durose et al., 2007; Schmitt, Langan, & Durose, 2002; Smith & Durose, 2006). A number of analyses have used these data to assess traffic stop outcomes (Engel & Calnon, 2004a; Lundman, 2004; also see Weitzer & Tuch, 2002 for a discussion of the public’s perception of racial profiling). Other analyses have been conducted using citizen surveys in North Carolina (Smith et al., 2003; Tomaskovic-Devey et al., 2006).

Observational studies offer a third method of data collection on police-citizen encounters (Lundman, 2004). This approach places an independent observer at the scene of
the encounter to document the specifics of the interaction (Engel & Silver, 2001; Mastrofski et al., 2000; Parks et al., 1999). Observational studies offer an independent report on the incident without the potential bias of either party involved (i.e., the officer or citizen). Independent recorders, however, may introduce their own bias (Mastrofski & Parks, 1990; Spano, 2005; 2006; Spano & Reisig, 2006). For example, the subjective nature of the observers may influence their characterization of the event. Moreover, this type of study is organizationally and fiscally demanding; thus, it has been used infrequently.

Official data, citizen surveys, and observational studies all provide information to assess racial/ethnic disparities in traffic stop encounters. As detailed below, the majority of traffic stop studies rely on official data most likely due to their availability, cost-effectiveness, and collection of relevant information. These analyses frequently make a distinction between the traffic stop and the traffic stop outcome.

**Traffic Stops & Traffic Stop Outcomes**

Analyses of official data on traffic stops are generally separated into two components: the traffic stop and the traffic stop outcome (Smith & Alpert, 2002; for an example, see Engel et al., 2004; Novak, 2004; Ramirez et al., 2000; Rojek et al., 2004). To identify potential racial/ethnic disparities in traffic stops, the percentage of drivers of a particular race/ethnicity stopped needs to be compared to the expected percentage of that same group at risk of being stopped. This comparison group (i.e., those at risk of being stopped) is more commonly referred to as a benchmark (Fridell, 2004; Gaines, 2006; McMahon et al., 2002; Rojek et al., 2004; Schafer et al., 2004; Smith & Alpert, 2002; Tillyer, Engel, & Wooldredge, 2008; Zingraff et al., 2000). If these two rates are equivalent, no disparity exists; however, if the stopping rate is higher than the benchmark, disparity is the result. The real difficulty
associated with benchmarking is the failure to have an accurate measure of the true driving population at risk.

To analyze traffic stops, proxies are often used as substitutes for the true driving population at risk (Walker, 2001). These benchmarks include the population rates for each race/ethnicity as reported by the Census Bureau (Engel et al., 2004), observational data gathered by researchers collecting the race/ethnicity of passing motorists (Lamberth, 1994; 1996; Meehan & Ponder, 2002), or not-at-fault accidents in which the racial/ethnic composition of these accidents represent the rate of drivers on the road and at risk of being stopped (Alpert Group, 2004; Alpert, Smith, & Dunham, 2004). There are a variety of other benchmarking techniques and all methods attempt to provide an accurate measure of the racial/ethnic composition of drivers and the likelihood of being stopped (Engel & Calnon, 2004b; Ramirez et al., 2000; Smith & Alpert, 2002). Unfortunately, several limitations accompany these benchmarking methods, including the inability to conduct more sophisticated analysis, the inexact measure of the driving population, and arguably most important, the failure to accurately measure the risk associated with being stopped (Engel & Calnon, 2004b; Engel et al., 2007a). As a result, studies of traffic stops produce conclusions that are at times inexact and at worse, potentially inaccurate.

Traffic stop outcome analyses use the same data sets but employ more robust and sophisticated techniques such as multivariate modeling. The goal is to identify any patterns of disparity for minority drivers in the likelihood of being warned, cited, arrested, searched, or in length of the stop (Fridell, 2004). Analyses of traffic stop outcomes do not require a benchmark because no comparison or base rate is required to determine if there are disparities in the traffic stop outcomes (Engel & Johnson, 2006). The ability to use
multivariate modeling is predicated on the fact that the whole population (i.e., all traffic stops) is known in traffic stop outcome analyses; whereas when traffic stops are analyzed, the whole population at risk of being stopped is measured using a proxy (i.e., a benchmark).

A multivariate statistical model considers a multitude of factors when attempting to explain a particular behavior (i.e., the likelihood of receiving a particular traffic stop outcome) (Weisburd & Britt, 2004). In other words, the individual impact of one variable on the outcome can be measured while considering all other variables simultaneously. This is an improvement over the inexact measure of the driving population at risk as measured by a benchmark.

In addition to the analytical differences between traffic stops and traffic stop outcomes, there are a practical differences. First, the outcome of a traffic stop has the potential to be a greater intrusion on a citizen’s life than simply being stopped by an officer. For example, traffic stops can result in a warning (verbal or written), citation, or arrest. When considering potential outcomes of the decision to initiate a traffic stop, the only options are to let the vehicle continue or to stop the vehicle. While being stopped is an inconvenience from the perspective of a citizen, receiving a citation or being arrested is more severe.

Second, racial/ethnic disparities are more likely to manifest themselves in the analyses of traffic stop outcomes rather than in analyses of traffic stopping patterns (Ramirez et al., 2000). If officers are using race/ethnicity as a factor in decision-making, it is more likely to become apparent after confirming the driver’s race/ethnicity during the encounter. Assessing the race/ethnicity of passing motorists is difficult and less likely to be accurate

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3 Importantly, traffic stops that result in a search of the vehicle or citizen(s) are not included in this continuum or this research. Search and seizure activity requires a review of different research, theoretical explanations, and analysis. Therefore, search and seizure activity is beyond the scope of this research.
when compared with a face-to-face encounter (Alpert et al., 2006). Thus, such disparities are more likely to occur in traffic stop outcomes compared to traffic stops.

In sum, traffic stops exemplify one officer decision-making point. The frequency of their occurrence, coupled with their impact on citizen attitudes toward the police, underscores the importance of studying such encounters. Moreover, traffic stops occur for discretionary and non-discretionary reasons, which enable analyses of both situations. Information on traffic stops is gathered most frequently by law enforcement agencies (i.e., official data), but may also be gathered through citizen surveys or observational research. Once collected, data are often categorized into traffic stops and traffic stop outcomes for analysis purposes. Benchmarking limitations threaten the confidence in traffic stop analysis, whereas analysis of traffic stop outcomes offer the option of a more robust analysis using multivariate models.

The remainder of this chapter details the recent research on traffic stop outcomes using official data. This review summarizes what is known regarding the relationship between driver’s race/ethnicity, gender, and age, and the occurrence of warnings, citations, and arrests. Additionally, this review also evidences the limited attention given to the relationship between driver demographic combinations (i.e., interactions among these characteristics) and traffic stop outcomes in previous research.

**TRAFFIC STOP OUTCOME LITERATURE**

This review does not summarize all studies of traffic stop outcomes; instead, various criteria were used to filter studies included in this review. First, only studies using official data are reviewed. Official data generally include important factors such as stop, citizen, vehicle, and officer characteristics all of which are important for conducting more robust analyses and developing valid conclusions regarding traffic stop outcomes. Only reviewing
studies of official data also enables an easier comparison of findings across studies since differences cannot be attributed to data collection methods. Moreover, much of the official data were collected over time (e.g., see discussion below on Pennsylvania, Washington State, and Los Angeles), which lessens concerns of missing data or officer disengagement.

A second criterion of this review was studies had to use some form of multivariate analyses. As previously described, multivariate models offer a robust analytic tool for identifying racial/ethnic, gender, and age disparities in traffic stop outcomes. This approach considers alternative factors that may be related to traffic stop outcomes. Other techniques, such as bivariate analysis, may report disparities in outcomes but do not consider the impact of other factors such as stop, vehicle, or officer characteristics. Propensity scores are an alternative method to assess traffic stop outcomes (Ridgeway, 2006); however, the validity of this approach has not been academically vetted and to date its use is limited (for an exception, see Ridgeway et al., 2006; 2006). The outcome test has also recently been applied to traffic stop outcomes (Knowles, Persico, & Todd, 2001), but its use is primarily for examining search and seizure activity, which is not the focus of this review. Thus, multivariate models offer an analytical tool widely accepted within the field to assess potential racial/ethnic, gender, and age disparities in traffic stop outcomes.

Collectively, studies using multivariate analyses of official data are commonplace in traffic stop research. Thus, a review of traffic stop outcome research based on these parameters offers a comprehensive overview of current knowledge regarding traffic stop outcomes. Discussion of each study includes the time period of data collection, the dependent and independent variables included in the model, and limitations of note. The relationship between the race/ethnicity, gender, and age of the driver and traffic stop
outcomes are the focus of this review. Studies are organized into state-level studies and local-level studies. This distinction assists in the organization of the review, but also because decision-making may be slightly different in these agencies depending on their law enforcement function. All studies are summarized in Table 2.1.

**State Agencies**

Since 2002, the Pennsylvania State Police (PSP) has collected data on all officer-initiated traffic stops. Three reports were produced from this official data set for the following years of data collection: 2002, 2003 and 2004-2005 (Engel et al., 2004; Engel et al., 2005; Engel, et al., 2007d). All reports contain multivariate and hierarchical analyses of warnings, citations, and arrests and include measures of driver, vehicle, stop, officer, and community characteristics for all officer-initiated traffic stops.

Data collected in 2002 and 2003 indicated that Hispanic and Other drivers were less likely to receive a warning compared to White drivers, while Black drivers were statistically indistinguishable from White drivers (Engel et al., 2004; Engel et al., 2005). During this same time period, male drivers were between 1.2 and 1.3 times less likely to be warned compared to female drivers, and older drivers more likely to be warned than younger drivers; however, this effect was statistically small. Traffic stops initiated as a result of speeding were also examined, and similar patterns emerged with respect to gender and age. Slight

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4 Driver characteristics included the race/ethnicity, gender, and age of the driver, and county and state of residency. Vehicle characteristics included registration information and the number of passengers in the vehicle. Stop characteristics included the time of day, day of the week, season, roadway type, the reason for the stop, the number of reasons for the stop, and if evidence was found during a search. Officer characteristics were collected by officer identification number recorded on the traffic stop form and include the race/ethnicity, gender, work experience, education level, and assignment of the officer. Community characteristics included population characteristics, percent males in driving-age population, percent Black and Hispanic residents in driving-age population, the average commute (in minutes), and factor scores of poverty, residential mobility, and traffic/travel patterns.

5 “Other” drivers included Asian/Pacific Islander, Middle Eastern, Native American, and unknown races/ethnicities.
variations developed with regard to race/ethnicity as Black drivers were actually more likely to receive a warning and Hispanic drivers fell out of statistical significance for speeding in both years when compared to White drivers. No race/ethnicity, gender, or age effect was reported in the 2004-05 data (Engel et al., 2007d).

Citations analyses produced results that were frequently the inverse of warnings, which is not surprising given the related nature of these outcomes (i.e., most frequently, one outcome is given to the driver at the expense of the other outcome) (Engel et al., 2004; Engel et al., 2005; Engel et al., 2007d). Hispanic drivers in 2002 and Other drivers in all four years were more likely to be cited compared to White drivers. There was no effect for Black drivers with the exception of a lower likelihood in 2005. Consistently, male drivers were more likely to receive a citation, while younger drivers were more likely to receive a citation compared to older drivers. For traffic stops initiated due to speeding in 2002 and 2003, male drivers and younger drivers were more likely to receive a citation. These patterns were consistent with all traffic stops for the driver’s race/ethnicity except Black drivers who were less likely to be cited compared to White drivers in 2002 and 2003, and Hispanic and “Other” drivers who were no longer statistically significant in 2002.

Examination of arrests in 2002 indicated that Black and Hispanic drivers were 1.5 and 1.8 times more likely to be arrested compared to similarly situated White drivers, respectively (Engel et al., 2004; Engel et al., 2005). No effect was reported for Other drivers in either year, and no effect was reported for any group in 2003. In both 2002 & 2003, male drivers were more likely to be arrested than female drivers, and in 2002, older drivers were more likely to be arrested. Analyses of traffic stops initiated due to speeding demonstrated
that Black drivers were *more* likely to be arrested in 2002 and 2003. The outcome patterns for gender and age were consistent with analysis of all traffic stops.

These reports offer a considerable amount of information on traffic stop outcomes; however, a couple of limitations are of note. One area of analyses not explored was the potential statistical significance of combinations of driver demographics. For example, the interactive effect of race/ethnicity, gender, and age was not analyzed. Further, the analyses do not measure all potentially related factors leading to questions of model misspecification. For example, these analyses do not include a measure of the driver’s behavior (Klinger, 1996; Worden & Shepard, 1996), vehicle condition (Engel et al., 2006), or the presence of bystanders (Engel, Sobol, & Worden, 2000). Each of these factors has been significant in other research. In fairness, the failure to measure all variables of interest is a criticism of all official data. Finally, the number of traffic stops could have an adverse effect on the results of the multivariate analysis, as higher numbers of cases increase the likelihood of reaching statistical significance.

The Department of Public Safety in Arizona has also been involved in collecting data on officer-initiated traffic stops. Using these data, Engel et al. (2007c) examined approximately 450,000 traffic stops conducted in 2006. Using logistic regression, the likelihood of being warned, cited, arrested, or receiving multiple citations was examined while controlling for driver, vehicle, stop, and legal variables. Black, Hispanic, and Other drivers were *less* likely to be warned, while Native American drivers were *more* likely to be warned compared to White drivers. Male drivers were 1.2 times *less* likely than female

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6 Driver characteristics included the race/ethnicity, gender, and age of the driver, and their state of residency. Vehicle characteristics included state of registration and type of vehicle. Stop characteristics included the time of day, day of the week, and season of the stop. Finally, legal variables included the reason for the stop and evidence found during a search.

7 This category was a collection of the remaining race/ethnicity groups.
drivers to be warned, and older drivers were more likely than younger drivers to receive a warning, although this effect was substantively small.

For citations, Hispanic, Black, and Other drivers were more likely to receive a citation, while Native American drivers were less likely to receive a citation. Male drivers were more likely than female drivers to be cited and younger drivers more likely than older drivers to be cited. Further analyses were conducted to examine traffic stops resulting in more than one citation issued to the driver. In these situations, the effects for gender and age were consistent with single citation stops; however, for race/ethnicity, the Hispanic effect was enhanced, the effect for Other drivers eliminated, and Native American drivers were more likely to receive multiple citations.

Finally, arrests were 1.7 times more likely to occur for Hispanic drivers, 2.2 times more likely for Native American drivers, and 1.6 times more likely for Black drivers. Similar to citations, male drivers and younger drivers were more likely to be arrested compared to female drivers and older drivers, respectively.

Unfortunately, this data collection effort did not employ a data auditing system raising a concern that the information analyzed may not accurately reflect all officer-initiated traffic stops. Model misspecification may also be a problem. Finally, no tests were conducted on the potential significance of interaction terms based on driver demographics.

The Washington State Patrol also collected data on traffic stops across multiple years, with findings summarized in two reports (Lovrich, et al., 2005; Lovrich, et al., 2003). Each report examined 40 autonomous patrol areas (APAs) and assessed the likelihood of a driver receiving a citation while considering the race/ethnicity, gender, and age of the driver, the number of violations associated with that stop, the seriousness of those violations, and
interaction terms for the effect of race/ethnicity and seriousness of violation. In the latter study (i.e., June 2002 to June 2004), the authors also included measures of geographic and temporal characteristics of the traffic stop.

Using logistic regression to examine the likelihood of receiving a citation\(^8\), the authors reported that between 2000 and 2002 only 3 of 40 APAs demonstrated an effect for Black drivers (i.e., 2 more likely; 1 less likely), 4 of 40 APAs showed an effect for Hispanic drivers (i.e., 1 more likely; 3 less likely), and 2 of 40 APAs had an effect for Native American drivers (i.e., less likely in 2 of 40) (Lovrich et al., 2003). Only Asian drivers demonstrated a modest pattern of disparity by being more likely to receive a citation in 10 of the 40 APAs. Analyses were also independently conducted on single citations and multiple citations with similar results - once controls were introduced, the effects of race/ethnicity were attenuated with the exception of Asian drivers.

Results from the data collected between 2002 and 2004 demonstrated a similar pattern (Lovrich et al., 2005); Black, Native American, and Hispanic drivers were not more likely to be cited in any of the 40 APAs, and were less likely in eight, one, and nine APAs, respectively. With regard to gender, male drivers were more likely to be cited in 30 of 40 APAs and 31 of 40 APAs in each of the two reporting periods. Even more pervasive was the effect of age; in both reports, younger drivers were more likely to be cited than older drivers in all APAs.

This study offered an analysis on citations at a lower level of analysis than other research (i.e., APAs); however, no overall results were offered at the state level regarding the impact of driver demographics. Other limitations of this study include the inability to measure several potentially important variables including driver demeanor, officer

\(^8\) This outcome measure included single and multiple citations issued in one traffic stop.
characteristics, and geographic factors (c.f., Lovrich et al., 2005). Inclusion of these variables would have strengthened these studies. Finally, as with the PA and AZ studies, no examination was offered on the interactive effects of driver demographics; however, these studies did explore the interaction between a driver’s race/ethnicity and the seriousness of the violation.

In North Carolina, a multi-year assessment of traffic stop outcomes has been conducted using a variety of methodologies (i.e., traffic stop data collection and citizen surveys). Smith and his colleagues (2003) examined data collected between 1997 and 2000 to assess the likelihood of a North Carolina driver receiving a citation. The authors developed a deployment model which included measures of individual officer’s geographic and temporal citation patterns (i.e., the proportion of citations by that officer issued to individuals’ under the age of 23 and issued to female drivers), and their individual characteristics (i.e., race/ethnicity, gender, age, and training background of the officer) in an attempt to predict the likelihood of citation for Black drivers. One of the most interesting results suggested that officers who attended training programs had a lower rate of Black citations. Thus, this study provides initial evidence that an officer’s previous training may influence traffic stop outcomes and suggests that the existence of disparities may be mitigated through policy and training modifications.

The approach undertaken in Smith et al’s study (2003) is a noticeable departure from other attempts to assess disparities in traffic stop outcomes and the authors admit they are approaching this issue with a unique methodology. One limitation of this approach is its failure to provide an overall assessment of whether or not there is a bias against minority motorists. They did suggest there is considerable variation in racial/ethnic disparities in
citations across different jurisdictions; however, they did not offer any multivariate analyses to detail these results. Finally, they did not explore the impact of driver demographic interaction terms.

**Local Agencies**

In addition to state-level analyses, several cities have gathered and analyzed data on traffic stop outcomes. Between July 2003 and June 2004, the city of Los Angeles commissioned a study of police-citizen encounters. Using these data, Alpert et al. (2006) conducted multivariate and hierarchical modeling to analyze the relationship between the race/ethnicity, gender, and age of the citizen and the likelihood of being cited or arrested.\(^9\) This analysis included both vehicle and pedestrian encounters and involved multiple variables of interest including citizen, encounter, officer, and geographic characteristics.\(^10\) The data were also separated into police-citizen encounters involving gang and non-gang officers and based on the reason for the stop.

For citations, Hispanic citizens were statistically *more* likely to receive this outcome in ten districts and in sixteen districts for Asian, American Indian, and Other races compared to similarly situated White citizens (Alpert et al., 2006). Conversely, Black citizens were *less* likely to receive a citation compared to similarly situated White citizens in ten districts. Importantly, the inclusion of control variables attenuated these effect sizes. This fact, in

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\(^9\) The study also analyzed requests to exit the vehicle, searches, and no action taken. These results are not reported here as they are beyond the scope of this study.

\(^10\) Citizen characteristics included the race/ethnicity, gender, and age of the driver. Encounter factors included the date and time of encounter, the initial reason for the stop, the number of suspects in encounter, and the type of suspect—driver, passenger, pedestrian. Officer characteristics included the race/ethnicity, gender, and age of the officer, their length of service, assignment, number of complaints received, and number of commendations received. Finally, geographic factors included the location of the encounter, the population characteristics of area, the calls for service in area, the crime rates in area, the amount of gang crime in area, the rate of abandoned buildings in area, the number of businesses in the area, and the number of shootings at officers in area.
combination with the statistical significance in some districts but not others, led the authors to suggest that contextual factors influence traffic stop outcomes.

Analysis of citizen’s gender indicated that males were less likely to receive a citation. The results also suggested that drivers between the ages of 18 and 25 and those over 46 years of age were more likely to receive a citation, whereas drivers between 36 and 45 years of age were less likely to receive a citation compared to drivers aged between 26 and 35 years of age. Citation analyses were also run on encounters in which the officer had more discretion\textsuperscript{11}. These results were similar to those for all citations in regard to the gender and age of the citizen, with one exception - drivers between the ages of 36 and 45 were no longer statistically significant. In higher discretion encounters, the Hispanic effect was reduced as some geographic areas became non-significant, whereas the Black effect became stronger (i.e., Black were even less likely to receive a citation).

The pattern of results was slightly different for arrests. Both Black and Hispanic citizens were more likely to be arrested in some districts, whereas Asians, American Indians, and Other races were less likely to be arrested. Male citizens were more likely to be arrested than females, and drivers between 18 and 25 years of age were less likely than those between the ages of 26 and 35. Drivers between the ages of 36 and 55 were more likely to be arrested. Similar to citations, arrests were disaggregated by removing low discretion situations, such as involving citizens with a warrant for their arrest, those involved in violent crime, and DUI situations. Only examining arrests with high discretion levels reduced the likelihood of arrest for both Black and Hispanic citizens. The gender and age effects were relatively unchanged.

\textsuperscript{11} Non-discretionary reasons for the stop such as encounters in which the citizen was driving without a license or leaving the scene of an accident were removed. These encounters were required by policy, thus the officer had no discretion.
Collectively, the results suggest no pervasive pattern of disparity although there were some clear indications that racial/ethnic, gender, and age disparities exist despite relevant controls (Alpert et al., 2006). The introduction of other variables generally reduced the effect for these citizen demographics, and the results also suggest that these effects are stronger for non-gang officers. Despite these findings, it is possible that model misspecification exists, as measures of suspect demeanor (Klinger, 1996; Worden & Shepard, 1996), vehicle condition (Engel et al., 2006), the presence of bystanders and/or the victim (Engel et al., 2000) were not available for analysis. Furthermore, no analyses were conducted based on combinations of driver demographics. Nevertheless, the Los Angeles study is one of the more thorough and elaborate analyses of police-citizen encounters published to date and offers good insight into the impact of citizen demographics on traffic stop outcomes.

In 2004, the Alpert Group (2004) released an evaluation of all traffic stops conducted between February 12 and October 31, 2001 in the Miami-Dade area of Florida. This study included measures of neighborhood factors, officer characteristics, and stop characteristics. Based on these data, the authors report a general pattern of racial/ethnic disparity in post-stop outcomes (i.e., verbal warnings, citations, and arrests); however, an examination of the regression tables in their report only suggests minority disparities for verbal warnings. Specifically, Black and Hispanic drivers were more likely than Whites to receive a verbal warning, and female drivers were more likely than male drivers to receive a verbal warning. Conversely, analysis of citations demonstrated that Black motorists were less likely than White drivers to receive a summons and no statistical difference between Hispanic and White drivers.

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12 Neighborhood factors included the percent minority population, the percent owner-occupied housing, and a measure of residential stability. Officer characteristics included the race/ethnicity, gender, and age of the officer, and their years of experience, number of citizen complaints, frequency of use of force, and record of disciplinary action. Finally, stop characteristics included if the stop was for an investigative reason, if contraband was discovered, and if a record check was conducted on the occupants.
drivers. Further, no statistically significant relationship was reported between gender and the likelihood of receiving a citation.

For arrest, Black and Hispanic drivers were statistically no more likely than similarly situated White drivers to receive a custodial arrest\textsuperscript{13}. In other words, in cases where there was no officer discretion (i.e., an existing warrant for the arrest of the citizen), there was no race/ethnicity effect on the likelihood of arrest. Male drivers however were 3.6 times more likely to be arrested than female drivers after controlling for other relevant factors.

These findings need to be interpreted with acknowledgement of several caveats. The authors report a considerable amount of missing data regarding the arrest of the driver, which can introduce bias into the analysis. The study also did not consider the impact of the driver’s age on traffic stop outcomes, which could have had an independent or interactive impact on the traffic stop outcomes. Finally, apart from the gender effect on custodial arrests, the effect sizes of all the relationships are relatively small.

Engel et al. (2006) examined 43,707 traffic stops collected in Cleveland, OH. Initial analyses reported that 96\% of all recorded traffic stops involved the issuance of a citation to the citizen. The authors caution that this dataset may not reflect all traffic stops, but rather all traffic stops that ended in the issuance of, at minimum, a citation. Hierarchical analyses were conducted only on traffic stops ending in an arrest while controlling for driver, vehicle, stop, officer, and community characteristics\textsuperscript{14}. These analyses reported no racial/ethnic group

\textsuperscript{13} The authors defined a custodial arrest as any arrest that is not conducted due to a warrant (i.e., policy mandated). Therefore, a custodial arrest was based on officer discretion.

\textsuperscript{14} Driver characteristics included the race/ethnicity, gender, and age of the driver, and the driver’s demeanor. Vehicle characteristics included the state of registration, any after-market vehicle modifications, the vehicle’s operating condition, and the number of passengers in the vehicle. Stop characteristics included the time of day, the day of the week, the roadway type, the reason for the stop, the number of reasons for the stop, if contraband was discovered as a result of a search, and the police zone where the stop occurred. Officer characteristics included the race/ethnicity, gender, assignment, and years of service of the officer. Finally, community
effects. Male drivers were 2.6 times more likely to be arrested compared to female drivers and young drivers were marginally more likely to be arrested compared to older drivers. This study did measure driver’s demeanor and vehicle condition, which are generally not available in other data sets, but were important factors in predicting an arrest. A noticeable limitation is the 96% citation rate, which suggests that it is unlikely that all traffic stops were included in the data set. This study also did not explore the impact of interaction terms based on driver demographics.

The Eugene Police Department (EPD) collected data on all traffic stops between January 1, 2002 and December 31, 2003 resulting in 36,011 cases for analysis. Analyses focused on all traffic stops that resulted in an enforcement action (i.e., a summons or citation) or an arrest of the citizen. The study included measures of the geographic and temporal characteristics of the stop, the reason for the stop, the number of passengers, the presence of a language barrier, and if the officer could determine the race/ethnicity of the driver prior to the stop (Gumbhir, 2004).

For traffic stops that result in an enforcement action, no race/ethnicity effect was reported. Male drivers were slightly more likely to receive an enforcement action compared to female drivers, while drivers over the age of 40 were more likely to receive enforcement action than drivers between the ages of 16 and 29. For arrests, Asian drivers were significantly less likely to receive that outcome, while no other race/ethnicity had a statistically significant relationship with arrest when compared to White drivers. Male drivers were more likely to be arrested than female drivers, and drivers between the ages of 30 and 39 were more likely than drivers between the ages of 16 and 29 to be arrested.

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characteristics included the population characteristics of the neighborhood and a factor representing level of poverty in that neighborhood.
One limitation of this research is the traffic stop data set contained only 70% of all the traffic stops based on a comparison with the EPD’s information record system that records information on all citations issued. Moreover, the data collection methodology also offered some categorization concerns for items such as reason for the stop (Gumbhir, 2004). Other limitations include the inability to measure several potentially relevant variables, such as citizen demeanor and vehicle characteristics, and no examination of driver demographic interaction terms.

Between January 17 and March 31, 2000, the Richmond Police Department (RPD) collected data on all traffic stops within the city of Richmond, VA. The city’s computer-aided dispatch system recorded slightly less than 7,000 traffic stops during this time period. Approximately 73% of those stops were recorded using the officer’s Mobile Data Terminal (MDT). Analyses of these data are reported in two separate studies at the encounter and aggregate levels (Smith & Petrocelli, 2001; Petrocelli, Piquero, & Smith, 2003).

The encounter analysis focused on the likelihood of a traffic stop resulting in an arrest or summons compared to a warning while measuring citizen, encounter, and officer characteristics\(^\text{15}\) (Smith & Petrocelli, 2001). The results indicate that non-White drivers were 1.5 times more likely to be arrested/receive a summons than White drivers. Moreover, male drivers were 1.1 times more likely than female drivers to be arrested/summoned and younger drivers were statistically more likely to receive such an outcome compared to older drivers.

Using the same data set, Petrocelli et al. (2003) aggregated the data to the neighborhood level for analysis. The analyses was informed by conflict theory and explored

\[^{15}\text{Citizen characteristics included the race/ethnicity, gender, and age of citizen. Encounter characteristics included the time of stop, the reason for the stop, the location of the stop, if a search was conducted, and the type of search conducted. Finally officer characteristics included the race/ethnicity, gender, age, and years of service of the officer.}\]
the rate of arrest/summons per neighborhood in relation to the rate of Black and Other\textsuperscript{16} populations, the level of poverty, unemployment, income, and crime rate of each neighborhood. The results suggested that areas with higher levels of Black residents had a lower likelihood of a traffic stop resulting in an arrest/summons. Gender and age were not included in the model.

These studies’ contributions must be assessed with an acknowledgement of several limitations. First, the data were collected only for a period of two and a half months, which raises concerns that the pattern of traffic stop outcomes may have been influenced by seasonal factors. A data audit was conducted between the computer-aided dispatch system and the MDT data and reported that over 25\% of the traffic stops were not included in the traffic stop data set. The aggregate level analysis did not include any measure of officer characteristics, citizen factors, or stop factors. While these are encounter level variables, it would have been informative to aggregate them to the neighborhood level to assess if they were related to the outcomes of interest. Furthermore, the race/ethnicity of the citizen involved in the traffic stop was not included at the aggregate level (i.e., the rate of racial/ethnic groups involved in traffic stops per neighborhood).

In a separate analysis, Withrow (2004) examined 37,454 traffic stops conducted by the Wichita Police Department (WPD) during a six-month period. Analyses focused on the likelihood of arrest while measuring citizen, officer, and encounter characteristics\textsuperscript{17} (Withrow, 2004). The results indicated that Black drivers were 1.8 times more likely to be arrested than non-Black drivers, Hispanic drivers were 1.3 more likely to be arrested than

\textsuperscript{16}All non-White & non-Black racial/ethnicity groups.

\textsuperscript{17}Citizen characteristics included the race/ethnicity and age of the citizen. Officer characteristics included the race/ethnicity, gender, age, and years of experience of the officer. Finally, encounter characteristics included the time of the day, if a search occurred, the duration of the stop, the crime rate of the area, if the stop was initiated by the officer, and if physical resistance occurred.
non-Hispanic drivers; however, the age of the driver had no effect on the likelihood of arrest. Unfortunately, several weaknesses limit this study. A data audit uncovered a noticeable reduction in the number of citations issued during the data collection period compared to the same time period during the previous year, indicating a potential failure to record all traffic stops. Further, the Hispanic effect was only significant at the .01 level of significance and based on over 37,000 cases suggesting that the effect may be a product of the number of cases rather than substantive disparity. The reason for the stop was not included in this analysis and has been demonstrated to be an important factor in understanding traffic stop outcomes.

Ingram (2007) examined the issuance of citations using data from an unnamed metropolitan area. This study offers a specific focus on neighborhood effects and continues the history of examining the impact of neighborhood effects on police decision-making (Smith, Visher, & Davidson, 1984; Smith, 1986). Data were collected between January and October of 1999 and included both neighborhood and encounter level variables. The analysis was conducted using a multi-level approach to properly parse out the effects of encounter and neighborhood levels; furthermore, a consideration of spatial autocorrelation was included to properly specify the effects of adjacent neighborhoods.

The results indicate that non-White drivers were 1.8 times more likely to be issued a citation compared to White drivers. Male drivers were 1.5 times more likely to receive a citation compared to female drivers, and younger drivers were more likely than older drivers to receive a citation. These findings are relatively consistent with other city-level analyses of

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18 Neighborhood measures included the violent crime rate, a measure of residential instability, a measure of socio-economic status, and population characteristics. The encounter characteristics included the race/ethnicity, gender, age, and residency of the citizen, the time of day of the encounter, and some limited measures of the reason for the stop.
traffic stop outcomes. Limitations of the study do exist; for example, the models have incomplete measures of reason for the stop and no measure of driver demographic interaction terms, officer characteristics, or citizen demeanor. No analyses of arrest were conducted.

Data were collected between February 2001 and February 2003 in a different unidentified urban location (Schafer et al., 2006). These data were analyzed to determine the likelihood of a minority citizen receiving only a warning while measuring the race/ethnicity, gender, and age of the citizen, and the legal reason for the stop. The results indicated that minority drivers were more likely to receive only a warning compared to White drivers, while male drivers and younger drivers were also more likely to receive only a warning when compared to female and older drivers, respectively. Unfortunately, no measures of officer information were included in the analysis, and combining Black and Hispanic drivers together into one category potentially hides important nuances regarding these racial/ethnic groups.

Research by Moon and Cooley (2007) examined all traffic stops initiated by a university police department located in a mid-western state between April 2001 and December 2002. This data collection effort resulted in 10,210 cases on which information was collected regarding drivers' demographics (i.e., race/ethnicity, gender, age and state of license of citizen) and situational factors (i.e., the reason for stop, location, date, and time of stop). This study differs from the analysis undertaken in other research studies. First, the dependent variable was developed from information on warnings, citations, and arrests. To create a dichotomous variable, all warnings were coded as “0”, while all citations and arrests (excluding warrant arrests) were coded as “1” and defined as legal sanctions. Second, the
analysis involved the development of interaction terms based on citizen demographics, which is of particular importance to this discussion.

The results indicated that in both 2001 and 2002 Asian drivers were 1.5 times more likely to receive a legal sanction compared to White drivers. No effect was reported for gender, but younger drivers were more likely to receive a legal sanction. As mentioned, the data were further examined by developing interaction terms between the race/ethnicity and gender of the citizen. Identical statistical models were run with interaction terms in place of the individual demographic characteristics. The results indicated that Asian males were more likely to receive a legal sanction in both years. This was the only result consistent across both years, but several other groups reached statistical significance in the individual years. In 2001, Black males were less likely to receive a legal sanction; in 2002, Asian females were more likely, and Black females less likely to receive a legal sanction.

This study offers a unique examination of university police officers’ decision-making and explored the impact of combining demographic terms when analyzing traffic stop outcomes. While both of these contributions are noteworthy, this study does suffer from some weaknesses. Officer, situation, and vehicle characteristics were not included in the model, which raises concerns of model misspecification. The dependent variable was the product of citations and arrests potentially disguising important differences between these two outcomes. Moreover, the sample was drawn from a university so it is difficult to assess the generalizability of these data to other settings. Finally, there was no discussion of an internal evaluation of the data to ensure that all traffic stops were included in the analysis.
CONCLUSION

This chapter outlined several reasons why traffic stops are an important decision point to study. It also summarized various data collection methods, and detailed the distinction between traffic stops and traffic stop outcomes for analysis purposes. Primarily, a thorough review of previous studies using multivariate analyses of official data was presented. Despite limitations that often accompany social science research, the results generally indicate that the race/ethnicity, gender, and age of the citizen is related to the likelihood of being warned, cited, or arrested at the conclusion of a traffic stop.

Specifically, all five studies examining the relationship between the race/ethnicity of the driver and the likelihood of being warned indicated a significant relationship. Two of the five studies suggested that minorities were more likely to be warned, while the other three had mixed results depending on the race/ethnicity of interest. Ten of twelve studies exploring citations reported a race/ethnicity effect for minority drivers. Five of those ten studies with significant race/ethnicity effects reported either Black or Hispanic drivers as less likely to receive a citation compared to White drivers, while the remaining five studies reported Asian or Other drivers as more likely to receive a citation. In six of the twelve studies, Black and Hispanic drivers were either less likely to receive a citation or did not demonstrate a relationship with citations. Finally, five of ten arrest studies reported that minority groups were more likely to be arrested, two of ten reported no effect, and the remaining three had mixed results depending on the race/ethnicity of the driver.

With regard to gender of the driver, the results are more consistent. Four of five studies indicated that females were more likely to be warned, eight of eleven studies reported that males were more likely to be cited (two studies reported no gender effect; one study
reported that females were more likely to be cited), and all eight studies examining arrests indicated that males were more likely to receive that outcome.

All four studies examining age and warnings reported that older drivers were more likely to receive a warning, eight out of ten studies reported that younger drivers were more likely to be cited, and five of eight studies examining arrests reported significant effects of age although the pattern of results is mixed. Collectively, drivers’ race/ethnicity, gender, and age was frequently related to the likelihood of particular traffic stop outcomes. In other words, drivers with different demographic characteristics receive different outcomes compared to their similarly situated peers.

Despite this conclusion, limitations do exist in these studies. Of particular interest to the current research is the sparse examination of driver demographic interaction terms. Only one study developed a measure of the combined effect of a driver’s race/ethnicity, gender, and/or age. The results demonstrated that the interaction terms were related to the dependent variable thus validating further study. Other limitations of the previous studies included officer disengagement, missing information, and model misspecification. These limitations should not detract from the general pattern of results offered by the summarized studies. All social science research has weaknesses that need to be acknowledged, contextualized, and considered when drawing conclusions. Importantly, these weaknesses need to be addressed in future research. The current research accepts this challenge by exploring the effect of driver demographic interaction terms on traffic stop outcomes. To heed the concerns raised by previous researchers (Engel et al., 2002; Hagan, 1989), the following chapter explores theoretical options for disparities in traffic stop outcomes.
Table 2.1: Summary of Traffic Stop Outcomes (p. 1 of 2)

<table>
<thead>
<tr>
<th>Author</th>
<th>Year</th>
<th>Race/Eth. Measured</th>
<th>Warnings Race/Ethnicity</th>
<th>Gender</th>
<th>Age</th>
<th>Citations Race/Ethnicity</th>
<th>Gender</th>
<th>Age</th>
<th>Arrests Race/Ethnicity</th>
<th>Gender</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alpert Group</td>
<td>Feb – Oct, 2001</td>
<td>B, H</td>
<td>B; H</td>
<td>F</td>
<td>--</td>
<td>B</td>
<td>No</td>
<td>--</td>
<td>No effect</td>
<td>M</td>
<td>--</td>
</tr>
<tr>
<td>Alpert et al.</td>
<td>July 2003 – June 2004</td>
<td>A, B, H, NA</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>All Stops: A; H; NA; B</td>
<td>F</td>
<td>Y</td>
<td>O</td>
<td>M</td>
<td>M; Y</td>
</tr>
<tr>
<td>Engel, et al. (2005)</td>
<td>May 2003 – April 2004</td>
<td>B, H, O</td>
<td>All Stops: H; O;</td>
<td>F</td>
<td>O</td>
<td>All Stops: H; O</td>
<td>M</td>
<td>Y</td>
<td>No effect</td>
<td>M</td>
<td>No effect</td>
</tr>
<tr>
<td>Engel, et al. (2007c)</td>
<td>2006</td>
<td>B, H, NA, O</td>
<td>NA; B; H; O</td>
<td>F</td>
<td>O</td>
<td>M</td>
<td>Y</td>
<td>M</td>
<td>Y</td>
<td>M</td>
<td>M</td>
</tr>
</tbody>
</table>

1 All studies included a measure of White drivers as the reference group. All entries indicate more likely than the comparison group unless otherwise indicated. For example, B indicates that Black drivers were more likely than White drivers to receive the outcome of interest.
2 Arrests do not include those conducted due to a warrant.
3 Excluded age group: 26-35 years of age.

A – Asian; B – Black; H – Hispanic; NA – Native American; NW – Non-White; No – No Effect
M – Male; F – Female
Y – Young; M – Middle Age; O – Old
Table 2.1: Summary of Traffic Stop Outcomes (p. 2 of 2)

<table>
<thead>
<tr>
<th>Author</th>
<th>Year</th>
<th>Race/Eth. Measured</th>
<th>Warnings</th>
<th>Citations</th>
<th>Arrests</th>
<th>A</th>
<th>B</th>
<th>Hy</th>
<th>NC</th>
<th>M</th>
<th>Y</th>
</tr>
</thead>
</table>

A – Asian; B – Black; H – Hispanic; NA – Native American; NC – Non-White; No – No Effect; M – Male; F – Female; Y – Young; M – Middle Age; O – Old

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4 Outcome measured as a Legal Sanction rather than a Citation.
5 Outcome measured at the aggregate level; thus, this result indicates areas of higher Black populations result in lower rates of arrest.
6 Arrests were combined with summons and compared directly with the likelihood of receiving a warning.
7 This study examined traffic stop outcomes by predicting Black citations with a variety of independent variables. Initial non-multivariate analysis did indicate a higher likelihood of issuing citations to Black citizens in some jurisdictions.
8 These race/ethnicity groups reflect a Black/non-Black and a Hispanic/non-Hispanic distinction.
CHAPTER 3: THEORETICAL EXPLANATIONS OF DEMOGRAPHIC DISPARITIES IN TRAFFIC STOP OUTCOMES

INTRODUCTION

Extant research demonstrates that traffic stops result in differential outcomes for citizens depending on their race/ethnicity, gender, or age (Alpert et al., 2006; Engel et al., 2006; Engel et al., 2007c; Lovrich et al., 2005; Lovrich et al., 2003; Smith & Petrocelli, 2001). Multivariate analyses of official data from state and local agencies across the county confirm this pattern. Understanding these results requires theoretical models either created broadly to illuminate officer decision-making or developed for the specific purpose of explaining racial/ethnic, gender, or age disparities in traffic stop outcomes. In either case, theory is the mechanism by which empirical findings are interpreted. Without a theoretical explanation for the empirical evidence, the processes causing the outcome are not clearly understood and the results are more difficult to interpret or explain. Traffic stop studies have received criticism for failing to offer adequate theoretical explanations (Engel et al., 2002). The processes leading to a traffic stop outcome require understanding due to the impact of these outcomes for citizens.

This chapter briefly reviews a series of theoretical models that offer explanations for the reported racial/ethnic, gender, and age disparities in traffic stop outcomes. The primary focus however is on the social conditioning model (Smith & Alpert, 2007). Developed as an explanation for racial/ethnic disparities in traffic stop outcomes, the social conditioning model informs the research questions posed in this research by encouraging an examination
of the relationship between young, minority males and traffic stop outcomes. Other theories of police decision-making or behavior exist and are included in this review if they have direct application to understanding driver demographic disparities in traffic stop outcomes. For example, racial bias, racial profiling, deployment, and cognitive stereotyping are four explanations for racial/ethnic disparities in officer decision-making, and are coupled with reviews of expectancy theory, gender-based explanations, the liberation hypothesis, and conflict theory to complete this chapter’s review of applicable theories.

RACIAL BIAS

The racial bias perspective suggests that disparities in traffic stop outcomes are rooted in knowing or intentional bias by the decision-maker against certain individuals or groups of individuals that result in a negative outcome for that individual or group (Tomaskovic-Devey et al., 2004; Warren et al., 2006). Most often this bias is assumed to center on the race/ethnicity of the individual or group reflected by its name; however, the principle of bias is also applicable to gender and age. Based on this perspective, decision-making rests on an underlying belief system that suggests some individuals or groups within society are of a lower status and therefore deserve differential, often negative, treatment. In the case of traffic stops, characteristics of the individual (i.e., their race/ethnicity, gender, or age) justify the differential exposure to law enforcement attention and explain the reported disparities in citations and arrests. Under this framework, some officers are racially motivated to treat minority groups different from White drivers. These few bad apples impact the overall rates of traffic stop outcomes for the agency (Tomaskovic-Devey et al., 2004). The racial bias perspective could also be applied to understanding differential outcomes for gender or age
disparities and disparities based on particular combinations of driver demographics, such as young, minority male drivers.

The racial bias explanation is limited due to some unlikely assumptions. For example, a large number of officers would have to be biased to produce overall disparate outcomes for particular groups across numerous studies. While possible, this appears implausible because not only would these “bad apples” have to be plentiful but they also would have to overshadow the rest of the officers. Non-racist officers would have to be unaware of this bias in their peers or be willing to ignore such behavior. Additionally, the bad apples theory has been criticized for not acknowledging the importance of organizational effects (Klockars, Kutnjak, & Haberfeld, 2003). Finally, it does not offer an explanation as to how or why this underlying bias was developed. As a result, the racial bias model for traffic stop outcomes is not considered a reasonable explanation for disparate traffic stop outcomes (Tomaskovic-Devey et al., 2004).

**RACIAL PROFILING**

Since the mid-1990s, concerns of racial profiling have been paramount for police agencies, politicians, civil rights groups, and society (Buerger & Farrell, 2002; Fridell et al., 2001; Fridell, 2005; GAO, 2000; Hickman, 2005; Institute on Race and Poverty, 2001). Racial profiling is a commonly accepted explanation for racial/ethnic disparities in traffic stop outcomes (Harris, 1997, 2002). From a holistic perspective, this approach is an improvement from the racial bias explanation because it offers a description of the motivation for considering race/ethnicity (Tomaskovic-Devey et al., 2004). In the racial profiling explanation, the race/ethnicity of the citizen is a key explanatory factor in decision-making because it is used as a **conscious** factor linked to perceived criminal activity or a
criminal profile, which stems from the drug interdiction profiling methodology connected to the war on drugs (Tonry, 1995). In the racial bias explanation, there is an underlying dislike or prejudice against certain groups, which is manifested in bias outcomes. Some researchers suggest that the organizational environment highlights the value of using such race/ethnicity “to identify typical traits of individuals who are thought to be associated with criminal propensity” (Tomaskovic-Devey et al., 2004: 11). From this perspective, the use of race/ethnicity is benign rather than as an outlet for discriminatory attitudes. It is not difficult to imagine extending this process to include the gender or age of the citizen or a combination of the citizen’s demographic characteristics to be used as components of a criminal profile. For example, the early claims of profiling on the interstates were based on race/ethnicity, but could also be interpreted as a focus on young, minority males (Harris, 1997; 2002).

One limitation of the racial profiling explanation is its failure to consider other plausible explanations for disparate outcomes. Extant research demonstrates that a number of different factors are related to traffic stop outcomes apart from just the race/ethnicity of the driver. It is possible that race/ethnicity is one of many variables that influence an officer’s decision to warn, cite, or arrest, but the existing empirical evidence suggests it is not the only factor.

**DEPLOYMENT**

The deployment perspective builds on the fact that some geographic areas exhibit higher concentrations of crime (Sherman, Gartin, & Buerger, 1989). From this perspective, officers are dispatched in response to the levels of crime or requests for service by citizens in those areas (Tomaskovic-Devey et al., 2004), and empirical research suggests that police often patrol those areas more aggressively (Smith et al., 1984). Moreover, areas with higher
crime rates also frequently possess higher levels of minority citizens (Krivo & Peterson, 1996). Thus, deployment patterns are not intentionally targeting groups of citizens but are responding to levels of criminal activity (Novak, 2004; Warren et al., 2006).

Racial/ethnic, gender, and age disparities in traffic stop outcomes occur as a result of geographically clustered pockets of minority citizens. It is argued that the relationship between police deployment and minority status is spurious; instead, it is the relationship between police deployment and criminal activity that explains the relationship between criminal activity and minorities (Smith et al., 1984; Smith, 1986). Police presence is correlated with crime rates (Jackson & Carroll, 1981), which in turn is correlated with race/ethnicity.

Empirical research on the relationship between neighborhoods and police activity includes work by Smith (1986) who reported that police responded differently to citizens depending on the characteristics of the neighborhood. Other empirical work has found that concentrated disadvantage may contribute to difficult police-citizen relations (Terrill & Reisig, 2003; Velez, 2001) or trump individual factors when examining police-citizen encounters (Reisig & Parks, 2000; Schafer, Huebner, & Bynum, 2003). Moreover, in areas of low socio-economic status, higher rates of police abuse are reported (Kane, 2002), police are more disrespectful (Mastrofski, Reisig, & McCluskey, 2002), and police engage in more misconduct (Fagan & Davies, 2000). Weitzer & Tuch (2006) argue that these neighborhoods provide greater opportunity to engage in misconduct because there is limited community restraint on the officers’ behavior.

The implication of this approach for traffic stop outcomes is that the race/ethnicity, gender, and age effect would be attenuated once a measure of the crime rate/calls for service
was introduced (Fagan & Davies, 2000). Ingram (2007) found that controlling for neighborhood factors such as the violent crime rate, residential instability, percent minority status, and spatial autocorrelation, non-Caucasians, males, and younger drivers were all more likely to receive a citation when compared to their counterparts. Further work is needed to explore the relationship between neighborhood characteristics, citizen characteristics, and traffic stop outcomes (Parker et al., 2004) prior to any definitive conclusions regarding the accuracy of the deployment hypothesis.

**COGNITIVE STEREOTYPING**

Cognitive stereotyping is a loosely connected series of ideas regarding human behavior predicated on emphasizing the psychological functioning of the individual as the primary determinate in decision-making. This approach suggests that individuals develop a perceptual shorthand to assist in decision-making (Tomaskovic-Devey et al., 2004; Warren et al., 2006). The social conditioning model, discussed later in this chapter, is built on this premise and offers a more comprehensive description of these processes. One theory of criminal justice decision-making that also relies on this framework is focal concerns theory (Steffensmeier et al., 1998), although to date it has not been applied directly to traffic stop outcomes.

Developed with the intention of explaining disparate outcomes in sentencing research, focal concerns theory is built upon three core elements (Steffensmeier et al., 1998). First, the notion of blameworthiness is a combination of the decision maker’s belief regarding the offender’s culpability and the degree of injury sustained as a result of the crime. Second, decision makers consider the need to protect the community, which may involve incarcerating the offender or sending a message of deterrence to the wider
community. Finally, decision-making is affected by considering practical constraints and consequences such as the flow of cases through the court, workgroup relationships within the court, and services available in the system to the offender. These three factors coalesce into a perceptual shorthand which is used when faced with uncertainty or the need to make a quick decision. Importantly, this perceptual shorthand relies on citizen characteristics such as race/ethnicity, gender, and age to assist in decision-making (Steffensmeier et al., 1998).

Focal concerns theory could be applied to traffic stop outcomes. During a traffic stop, officers often face situations of uncertainty, which require quick decisions. It is precisely in such situations that officers may rely on race/ethnicity, age, and gender as a tool to assist in determining the stop disposition through the use of the perceptual shorthand. Unfortunately, focal concerns theory does not fully describe the development of the perceptual shorthand. While a plausible explanation, focal concerns theory lacks a comprehensive explanation of the processes at work in developing the perceptual shorthand. Without such an explanation, focal concerns theory fails to adequately explain racial/ethnic differences in traffic stop outcomes.

**EXPECTANCY THEORY**

Expectancy theory suggests that workers’ perceptions regarding the value of their work affect how they complete their tasks. Changes in their perception of the reward structure change the value of their work, which indirectly affects their behavior (Campbell & Pritchard, 1976; Klein & Ritti, 1984; Mitchell, 1974). Specifically, the process by which this occurs is reflected in four interrelated elements as summarized by Mastrofski et al., (1994). First, effort-performance refers to the workers’ need to know what the work is, how to do the work, and an ability to accomplish the work. Second, the workers are influenced by their
perception of what the organization would like them to do (i.e., the instrumentality of performance). Third, employees need a clear understanding of the reward structure within the organization, and the reward structure needs to be calibrated to a level that the workers can see either in their own work or vicariously through their peers. This is referred to as the performance reward expectancy. Finally, these three components must coalesce to form a reward structure strong enough to motivate a worker, referred to as the reward-cost balance (Mastrofski et al., 1994).

Expectancy theory has been applied to police behavior (DeJong, Mastrofski, & Parks, 2001; Mastrofski et al., 1994). As Engel et al. (2002) describe, this theory has application to understanding racial/ethnic disparities in traffic stops. If officers believe they will be rewarded for identifying or interrupting criminal activity during a traffic stop, and if they also believe that minorities are more likely to be involved in such activities, more serious outcomes (i.e., citation or arrest) are likely to occur for those groups. Thus, disparities in traffic stop outcomes are the product of the officers’ perception of the reward structure within the organization based on a rational calculus. This explanation can also be extended to include gender and age disparities as operating through a similar process.

One challenge for linking expectancy theory to traffic stop outcomes is the need to measure organizational rewards. These types of data are generally not available in official data, observational data, or citizen surveys. Thus, it is difficult to assess the accuracy of expectancy theory. In addition, expectancy theory rests on the assumption that the agency is aware of officers’ behavior and responds with rewards (or punishments) in relation to the officer’s actions. Likewise, it assumes that officers understand the expectations of the organization, which may not always be the case. Finally, it assumes that the organization
functions in one cohesive direction. This may be a questionable assumption in large state police agencies where the size of the agency may create several smaller agencies each with their own agenda.

**GENDER-BASED THEORIES**

Within the broader criminal justice literature, decision-making explanations have also directly considered the impact of gender. These approaches have dotted the criminal justice landscape most frequently within the context of sentencing research (i.e., the initial decision to incarcerate and the subsequent length of sentence). To date, these explanations have not been applied to traffic stop outcomes.

As reported in Chapter 2, empirical research reports that females receive less severe outcomes (i.e., citations or arrests) during traffic stops compared to males. The chivalry/paternalism hypothesis suggests these outcomes may result from the desire of law enforcement officials to protect females from the invasive nature of either a citation or arrest and the stigma that is associated with receiving a citation or being arrested (Daly 1987, 1989). Alternatively, there may be a belief by the police that females require special treatment within the criminal justice system (Belknap, 2001). Others suggest that women do not need formal sanctioning because they are more likely to be under the influence of informal social control (Kruttschnitt, 1982). In the case of traffic stop outcomes, officers would be less likely to cite or arrest a female driver.

Not all theories focused on gender hypothesize such a relationship; some theories suggest that women should be expected to receive more severe outcomes. For example, the evil women hypothesis suggests that some women may deviate from their traditional social roles as homemakers and pro-social individuals (Chesney-Lind, 1987; Kruttschnitt, 1981).
Deviating from their traditional roles is also discussed in the chivalry/paternalism explanation, but the evil women hypothesis would explain harsher treatment of women as a means to correct this behavior rather than protect the women as suggested by the chivalry/paternalism hypothesis. Therefore, their presence within the criminal justice system represents an unacceptable form of behavior that must be punished. Even within the context of a traffic stop, females would be expected to receive a coercive outcome (i.e., citation or arrest) as a form of deterrence and formal social control. The disproportionate outcome conveys the message to the female that she has violated the expected social norms of behavior.

To effectively test these approaches and their ability to explain disparities in traffic stop outcomes, current traffic stop data collection efforts would need to collect additional information. For example, the chivalry/paternalism hypothesis requires a measurement of the officer’s belief toward females and their role in society. Collecting such additional information would put an increased burden on officers and is not likely to be accepted. Alternatively, addressing the evil women hypothesis would require a similar measure of the officer’s view of females in society. As a result, applying these theories to explaining traffic stop outcomes is not extremely realistic within current data collection efforts. Moreover, these explanations are not easily modified to explain racial/ethnic and age disparities in traffic stop outcomes.

**LIBERATION HYPOTHESIS**

Within the sentencing literature, the liberation hypothesis has been offered as an explanation for criminal justice decision-making. Based on a study of jury decision-making, the liberation hypothesis suggests that the seriousness of the case or offense dictates the
degree of discretion available to the decision maker (Kalven & Zeisel, 1966). In more serious cases, less discretion is available thereby making extra-legal factors less important, whereas in less serious cases, factors such as race/ethnicity, age, and gender are relied upon more heavily (Spohn & Cederblom, 1991). Support was found for this hypothesis in an analysis of death penalty cases by focusing on the race/ethnicity of the offender and the race/ethnicity of the victim (Spohn & Cederblom, 1991).

To date, the liberation hypothesis has not been applied to traffic stop outcomes. This hypothesis would suggest that traffic stops initiated for less serious reasons offer greater discretion leading to the higher likelihood of the officer relying on citizen demographics. That is, if the officer has the choice to write a warning or a citation, demographic factors will play a role in the outcome; conversely, in cases where there is a clear requirement of arrest and no discretion, these citizen characteristics are less relevant to the outcome¹. In those cases of increased discretion, the demographic factors are more likely to become pronounced and lead to disparate outcomes. Moreover, most traffic stops are initiated for minor offenses (Tyler, 1990); thus, using this hypothesis, demographics would be expected to effect traffic stop outcomes.

The liberation hypothesis is not well suited to explain racial/ethnic disparities in traffic stop outcomes. It is a reasonable explanation for expecting some differences in outcomes based on race/ethnicity, but it does not offer a thorough explanation for the processes underlying this expectation. The liberation hypothesis does not outline why in

¹ Alpert et al. (2006) examined traffic stop outcomes by the amount of discretion available to the officer. For traffic stops initiated with a high degree of discretion and resulting in a citation, the effect for Hispanic citizens was mixed, while the Black effect became stronger. For traffic stops initiated with a high degree of discretion and resulting in an arrest, any racial/ethnic effect was attenuated.
situations of less seriousness demographics (i.e., race/ethnicity, gender, and age) are more likely to be a factor in decision-making.

CONFLICT

Conflict theory is one of the most frequently used theories to explain social behavior throughout the last one hundred years. At its core, conflict theory is built on the premise that various groups exist within society, each with a level of power or influence. These groups use whatever power they possess to control or manipulate the other group (Bohm, 1982), and as a result, conflict between these groups is an ever-present and fundamental component of social relationships (Simmel, 1950). Specifically, the elites within society possess a greater level of power over the underclass (Turk, 1969). Conflict exists between these groups regarding the prevailing social structure. To effectively maintain social order and their dominant position within society, the elites leverage the resources of the criminal justice system (Chambliss, 1976; Taylor, Walton, & Young, 1973). In this manner, the law and the enforcers of the law (i.e., the police) become agents of the elites.

Under this structure, the police are not just used to enforce the law but also to maintain the power structure as it has been created (Weitzer & Tuch, 2006). From this perspective, police are a tool used to maintain the class, race, and gender divisions within society (Lynch, Michalowski, & Groves, 2006). As a result, the conflict perspective argues that the police contribute to the “us” vs. “them” or the “have” vs. “have not” mentality that exists in our society. As Lynch et al. (2006: 240) argue, “policing emerged as part of an ongoing effort to maintain the dominance of capital over labor, rich over poor, whites over minorities, and men over women.” Minority groups are viewed as “social dynamite” (Spitzer, 1975), a group of people who are volatile and need to be addressed through social
control mechanisms, such as the law. Similarly, the racial threat hypothesis argues that Whites perceive minority groups to be a threat to the prevailing order (Blalock, 1967; Liska, 1992).

Scheingold (1984) applied the conflict framework to the criminal justice system by suggesting that certain myths are perpetuated to maintain control over society. In particular, citizens’ fear of crime, media coverage, and the political climate interact to reinforce the simple dichotomy of good versus bad in society. This depiction encourages a response focused on addressing the evil components of society through the use of punishment. In particular, minority youths are viewed as the source of the “evil” and need to be the target of police attention and punishment. As a result, the public’s response to the myth of crime and punishment is the politics of law and order in which penalties for law violation are increased and a widening of the punishment net occurs (Engel & Calnon, 2004a).

Scheingold’s work would predict extra attention for young minority citizens within the context of traffic stop outcomes. These groups would be characterized as the “bad” people who contribute to the evils within society and for which law enforcement activity has a social responsibility to pay extra attention to in an effort to interrupt their criminal behavior. Thus, this approach would predict higher levels of citation and arrest for young minority citizens. Moreover, from a racial threat perspective, greater examination of minority behavior through citation or arrest restricts their ability to challenge or overthrow the dominant White group.

While offering a thorough explanation of the processes underlying the outcomes, conflict theory presents challenges for empirical verification when examining traffic stop outcomes due to measurement difficulties. Law enforcement collected data, citizen survey
data, or data collected through observations of police-citizen interactions generally do not involve measures of the group dynamics hypothesized within conflict theory. Furthermore, conflict theory is a macro explanation of behavior, whereas traffic stop outcomes are often examined at the encounter level. This difference in focus requires that traffic stop outcomes be aggregated and compared with measures of group behavior and attitudes. While possible, this is an uncommon approach to examining traffic stop outcomes and may jeopardize the consideration of important encounter specific factors (c.f., Petrocelli et al., 2003).

**SOCIAL CONDITIONING MODEL**

Compared to the previously described theories, the social conditioning model offers the most comprehensive explanation for disparate racial/ethnic, gender, and age outcomes in traffic stops. Drawing from recent racial profiling research and the rich history of research in social psychology, Smith & Alpert (2007) synthesize these two literatures into a model developed specifically for explaining racial/ethnic disparities in traffic stop outcomes. The social conditioning model demarcates the process by which unconscious stereotypes are formed based primarily on the citizen’s race/ethnicity (Smith & Alpert, 2007). The model then specifies how these profiles affect officer behavior to produce racial/ethnic disparities in traffic stop outcomes (Smith & Alpert, 2007). These processes are easily extended to define more specific populations such as young, minority males; thus, the social conditioning model forms the theoretical foundation for this research and directly informs the hypotheses.

Smith & Alpert (2007) focus primarily on race/ethnicity as the key variable in the formation of these profiles, while paying less attention to gender and age. Other work on the formation of suspicion by officers has identified the importance of gender (Smith, Makarios, & Alpert, 2006). The current research adopts this general approach, but also focuses on
gender and age as important factors to consider in understanding the development of stereotypes. Gender and age are consistent with the principles of the social conditioning model, and arguably, strengthen the overall explanatory power of the model. Using the social conditioning model as a guide, this dissertation explores whether the combination of driver demographics is related to traffic stop outcomes. This section initially summarizes the social conditioning model by describing the process through which unconscious stereotypes are formed. Next, evidence is offered for the importance of citizen demographics in forming these stereotypes. Finally, these profiles are linked directly to police behavior to explain the racial/ethnic, gender, and age disparities reported in traffic stop outcomes.

Process

The process of developing unconscious stereotypes, schemas, or scripts is succinctly summarized by Smith & Alpert (2007). They outline the past research in social psychology that has documented the importance of stereotypes, schemas, or scripts (Allport, 1954; Mackie et al., 1996). Stereotypes are the most commonly recognized expression of this process and have been studied since the early 20th Century (Fontaine & Emily, 1978). Early descriptions of stereotyping involve a process “in which a person is placed in a social category and is perceived to possess all of the critical attributes associated with that category as well as a host of non-critical ones that members of that category may or may not possess” (Lippman, 1922 in Fontaine & Emily, 1978: 325). Allport (1954) characterized stereotyping as a product of an individual’s ego that is used to maintain one’s own self-esteem through a process of rationalization. Stereotypes are viewed as cognitive processes reflecting attitudes, beliefs, and expectations regarding specific groups (Mackie et al., 1996). In other words,
individuals categorize and view other groups in a manner that allows for quick processing when faced with similar situations in the future.

Schemas are often used interchangeably with stereotyping although schemas gained notoriety from a different background - within traditional learning theory (Smith et al., 2006). Schemas have been defined as a cognitive process that assists an individual in learning how to respond to particular situations based on past experience (Good & Brophy, 1990). The real power of schemas lie in their resistance to change once formed (Ross & Anderson, 1982) and that they are continually reinforced through everyday exposure (Drass & Spencer, 1987; Lurigio & Carroll, 1985). Moreover, information that runs contrary to the formed schema is often discounted or avoided. In this regard, outcomes are either amplified or diminished based on the schema applied, and these schemas are continually used as a cognitive tool to simplify complex situations that require a decision (Farrell & Holmes, 1991).

The role of cognition in decision-making has also been referred to as a script or typescript. Within the context of individual decision-making, typescripts “inform a processor that one class of actors (types) is more likely to show a trait or cluster of traits than is another class of actors (countertypes). Typescripts serve, in a word, as a heuristic that guides the processor in making likelihood and utility estimates” (Hill, Harris, & Miller, 1985: 149). According to Huesmann (1988:15), “a script suggests what events are to happen in the environment, how the person should behave in response to these events, and what the likely outcome of those behaviors would be.” Scripts present a set of rules for the interpretation of future events (Tomkins, 1992). Collectively, stereotypes, schemas, and scripts all refer to the development of a perceptual shorthand that assists in deciphering the world, categorizing experiences, and influencing decisions.
The formation of these profiles is influenced by a variety of sources including vicarious experiences and media exposure (Smith & Alpert, 2007). According to the social conditioning model, as an individual is exposed to the views, beliefs, and experiences of those around them, such as neighbors, friends, family, and colleagues, their own opinions and views are affected (Smith & Alpert, 2007). Individuals are affected by the stories and experiences of those with whom they have regular contact (Weitzer & Tuch, 2006). In some cases, however, experiences of others may be amplified, distorted, or provide incorrect information which leads to the formation of inaccurate profiles.

Exposure to the media also influences the formation of these unconscious beliefs. Research examining the role of the media in affecting individual beliefs has demonstrated that the media is a powerful force in shaping beliefs (Gerbner et al., 1980; Dahlgren, 1988). Moreover, opinions regarding particular groups are more intense following a traumatic event (Kaminski & Jefferis, 1998; Weitzer, 2002). Thus, more frequent exposure to devastating events is likely to increase the attitudes or beliefs regarding a particular group (Leiber et al., 1998; Scaglion & Condon, 1980; Skogan, 2005; Smith & Hawkins, 1973; Walker et al., 1972; Weitzer & Tuch, 2006). This process may have a stronger effect on police officers who are more frequently exposed to criminal activity.

Once formed, other psychological processes reinforce these profiles. As summarized by Smith & Alpert (2007), social identity theory\(^2\) suggests that group membership bolsters opinions of oneself to the detriment of those in other groups (Brewer, 1979; Hinton, 1993; Tajfel & Turner, 1979). In this manner, an individual begins to place the characteristics of his/her group above the characteristics of other groups. Coupled with this process, the illusory correlation principle suggests that individuals overestimate behaviors associated with

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\(^2\) Social identity theory has considerable overlap with social attribution theory.
a minority group relative to the same behaviors associated with the majority group
(Chapman, 1967). For example, in experimental situations, subjects overestimated the
negative behaviors of minority citizens and underestimated the negative behavior of majority
citizens (Hamilton, 1976). In these experiments, a pre-existing profile of minority citizens
was used to assist in decision-making and was exacerbated by the illusory correlation
resulting in an incorrect conclusion regarding the behavior of the minority group. Evidence
of the illusory correlation’s effect was substantiated by a recent meta-analysis, which found it
to be robust (Mullen & Johnson, 1990).

Furthermore, the ecological fallacy suggests that aggregate group characteristics are
applied to individuals (Robinson, 1950). In other words, an individual of a particular group
is assigned the characteristics of that group regardless of whether or not those characteristics
are accurate reflections of the individual. This scenario can be problematic as not all
members of a group possess the aggregate attributes of the group. For example, if White
drivers as a group are characterized as speeders, it would be an ecological fallacy to assume
that all individual White drivers drive faster than the speed limit. If the ecological fallacy is
used, profiles may be reinforced.

In sum, stereotypes, schemas, or scripts are formed through vicarious experiences or
through media exposure. Repeated contacts with particular segments of society reinforce the
formation of this perceptual shorthand (Smith et al., 2006). These views are reinforced by
social identity theory, the illusionary correlation principle, and the ecological fallacy. As a
result of these influencers, an unconscious psychological profile is developed which
influences behavior (Smith & Alpert, 2007).
Role of Demographics

The aforementioned process describes how these unconscious profiles are developed, but what are the characteristics that define this cognitive tool? In order to explain racial/ethnic, gender, and age differences in traffic stop outcomes, the social conditioning model must establish that these unconscious profiles characterized by race/ethnicity, gender, and age exist. Within society, individuals must be grouped according to these demographic characteristics if the social conditioning model is accurate.

Several different strands of research indicate that individuals are grouped together by their demographic characteristics. For example, Smith & Alpert (2007: 1,276) summarize several prominent policing researchers when they note that, “police beliefs about which citizens are likely to be involved in crime are based on a variety of individual, behavioral, and situational cues, including race and gender (Bittner, 1970; Rubenstein, 1973; Skolnick, 1994).” Other research suggests that the media portrays minorities as closely linked to crime (Barlow, 1998) and in ways that reinforce the pre-existing stereotypes (Entman, 1992; 1990). Thus, crime is more likely to be linked with minority citizens than with any other group. This is also evidenced by the racial typification literature.

Racial typification refers to the notion that crime is seen as a typical component of the Black culture and that there is an implicit link between crime and race that fuels higher incarceration rates and responses to crime within society and the criminal justice system (Chiricos et al., 2004; Scheingold, 1984). In essence, racial typification speaks to an intricate cultural linkage between race and crime that has been forged with the assistance of the media. This impression of race and crime is responsible for a large portion of the punitive attitudes towards crime within society (Chiricos et al., 2004). As Weitzer & Tuch (2006: 10-
argue, racial typification is “a generalization that colors popular thinking and discourse and leads people, particularly whites, to overstate the amount of crime among blacks.” Moreover, they suggest that a vicious cycle ensues in which citizens stereotype minorities and place expectations on law enforcement to address their concerns, which can lead to a harsher response by police to minorities.

Historically, there has been considerable discussion regarding racism and societal views on race/ethnicity. More recently, authors argue that the U.S. is in transition from a society of overt racism to one that still has racist overtones but which are presented in a covert manner. Bobo et al. (1997:16) argue that traditional racism has been replaced with a laissez-faire racism in which there remains a “persistent negative stereotyping of African-Americans.” Importantly, the change to laissez-faire racism is consistent with the group position thesis (Blumer, 1958), which acknowledges that Blacks are not directly a target; rather, the target is any group that occupies a minority role and is viewed as a threat to the majority. Therefore, it is the nature of the current political and economic culture that reinforces the racist attitudes toward minority groups and is not just a pure racist mentality.

Further evidence suggests that White Americans believe in racial equality but oppose policies that are intended to achieve such harmony (Kluegel, 1990). More specifically, this viewpoint suggests that Whites believe that Black citizens are less intelligent, do not work as hard, are less patriotic, and are more likely to accept living off welfare, which contributes to an overall undercurrent of racism despite improvements in opinions regarding minorities (Bobo & Kluegel, 1997; Massey & Denton, 1993). In sum, there is evidence that the population views Blacks differently from Whites and that certain attributes (i.e., laziness, lack of effort, etc.) are associated with minorities (Katz & Braley, 1933). Moreover, groups
are not only defined by race/ethnicity, but also by gender and age. Certain combinations of race/ethnicity, gender, and age create sub-groups that are attributed particular characteristics; for example, young, Black males are treated differently within the criminal justice system (Spohn & Holleran, 2000; Steffensmeier et al., 1998; Steffensmeier & Demuth, 2006).

Collectively, this research documents how society distinguishes between individuals based on demographics. Through the process of stereotype formation, these messages are communicated to individuals and become the foundation for group-based profiles. The final component of applying the social conditioning model to disparate traffic stop outcomes is to describe how police officer behavior is impacted by these group differences.

**Impact on Officers**

The application of the aforementioned processes to police officers is straightforward. Officers are no different than any other citizen and are exposed to societal conceptions regarding particular groups (Alpert et al., 2005; Smith & Alpert, 2007). Just as any individual is influenced by vicarious experiences or media representations of particular groups, law enforcement personnel are affected in a similar fashion. The formation of stereotypes for officers may even be stronger due to their working conditions.

In addition to the impact of vicarious experiences and media exposure, personal experience is hypothesized to affect the formation of these unconscious profiles. In developing the social conditioning model to explain racial/ethnic, gender, and age disparities in traffic stop outcomes, Smith & Alpert (2007) argue the personal experience of the officer also plays a substantial role in the formation of these unconscious beliefs. Unlike other citizens, officers are more likely to be exposed to criminal situations; thus, they are regularly faced with negative and potentially dangerous situations (Smith & Alpert, 2007). As
previously mentioned, negative experiences are likely to have a stronger impact on the
development of these unconscious profiles (Leiber et al., 1998; Scaglion & Condon, 1980;
Skogan, 2005; Smith & Hawkins, 1973; Walker et al., 1972; Weitzer & Tuch, 2006).
Moreover, criminal activity is concentrated among certain population groups. Officers who
regularly confront criminal activity may have greater exposure to these groups, thus
associating crime with particular populations. For example, if the police disproportionately
encounter minority citizens, younger citizens, or individuals with specific combinations of
demographic characteristics, it is likely they will internalize those experiences and develop
beliefs regarding those groups.

Further, training has an influential role in affecting an officer’s view of the world
(Rubenstein, 1973). If training programs introduce or reinforce any bias against a group, the
officer is likely to strongly internalize that information and interpret it as evidence to support
their unconscious schema.

The application of this process to police officers is reasonable considering it has been
applied to other criminal justice actors. It has been argued that difficult decisions are often
affected by the stereotypical view of criminal justice actors (Luirgio & Carroll, 1985). Steen,
Engen, & Gainey (2005) link this process to Sudnow’s classic work (1965) on courtroom
decision-making in which cases that match particular expected criteria are processed as
“routine,” while cases with unique characteristics are more difficult to process. They applied
the concept of stereotypes to criminal justice actors’ perceptions of criminality and
punishment through a series of interviews and suggest “racial stereotypes affect attributions
of responsibility and perceptions of responsibility and perceptions of danger and threat”
cognitive theories in social psychology emphasize that ideal cognitive states are simple, coherent, and relatively enduring structures (frequently termed *schemata*) that provide *a priori* organization for interpreting new experiences. Normative patterns of court organization include crime stereotypes that are shared in court actors’ cognitive schemata. These definitions evolve their distinctive quality and are reaffirmed continuously through the everyday interaction of court actors as they deal with alleged offenders (italics in original).

Thus, behavior is influenced by the actors’ stereotypical view; in addition, the schemas are further reinforced by daily exposure to events that conform to the pre-existing stereotype as explained by social identity theory, the illusory correlation, and the ecological fallacy.

Smith & Alpert (2007) argue that previous research supports the link between these unconscious profiles and behavior. In particular, they describe experiments conducted by Graham & Lowery (2004), which provide evidence that unconscious stereotyping may influence the discretion of law enforcement personnel. These results were also partially supported in an earlier meta-analysis (Dovidio et al., 1996).

In sum, the social condition model argues that racial/ethnic disparities in traffic stop outcomes are the product of unconscious cognitive schemas (Smith & Alpert, 2007). As described by Smith & Alpert (2007), police form these profiles through repeated contacts with particular demographic groups often involved in criminal activity. These unconscious stereotypes are reinforced due to the officer’s vicarious experiences and media exposure to messages regarding these groups. Furthermore, social identity theory, the illusory correlation, and the ecological fallacy combine to strengthen the stereotype. These stereotypes reflect the categorization of individuals into groups identified by demographic characteristics, specifically race/ethnicity. As explained by Smith et al. (2004: 28-29),
police officers are unaware of their own bias toward subgroups, but their behavior belies their attitudes. For example, an officer may profess no racial bias, yet the officer may look harder for signs of drugs without being consciously aware that he/she is doing so when stopping a vehicle driven by a young African American male. Cognitive bias can take many forms, including presumptions about the likelihood that a person’s gender, age or race/ethnicity would make one more “suspicious” or subject to scrutiny.

Smith & Alpert (2007) do not discount the potential of active racism as the explanation for racial/ethnic disparities in traffic stop outcomes; however, they suggest it is more likely the case that unconscious stereotypes formed through the process described above influence officer behavior in highly discretionary situations such as traffic stops.

The social conditioning model emphasizes the importance of demographic characteristics as factors in traffic stop outcomes. Within society, race/ethnicity, gender, and age are often linked together to form specific groups, such as young, minority males. The social conditioning model offers a comprehensive and thorough explanation for the potential relationship between such groups and traffic stop outcomes. The current research adopts the social conditioning model as the theoretical framework to directly inform the creation of specific, testable research hypotheses regarding disparities in traffic stop outcomes for young, minority male drivers.

**CONCLUSION**

This chapter reviewed a variety of theoretical explanations for racial/ethnic disparities in traffic stop outcomes. Among these, the social conditioning model (Smith & Alpert, 2007) offers the most comprehensive description of the process by which unconscious cognitive schemas are formed. These profiles reflect group differences within society and are reinforced through personal, vicarious, and media experiences. The explanation offered by the social conditioning model is thorough and supported by decades of research in social
psychology. Moreover, the social conditioning model was developed specifically for explaining traffic stop outcome disparities. Thus, the social conditioning model answers the call for theoretical development in understanding police behavior during a traffic stop (Engel et al., 2002), and offers a framework for developing specific, testable hypotheses regarding differential outcomes in traffic stops.

In particular, these hypotheses investigate not only racial/ethnic disparities in traffic stop outcomes, but also those disparities reported in gender and age. The social conditioning model is well suited to explain such disparities, and supports the investigation of the potential relationship between specific driver groups, such as young, minority males, and traffic stop outcomes.

While the social conditioning model operates as foundation for this research, this dissertation does not test the theory. To accomplish this goal, data would be required on a variety of the theory’s central constructs and these data are not available. Instead, confirmation of theoretically informed hypotheses would offer support for the principles of the social conditioning model. In other words, if the data analyzed here are consistent with the theoretical predictions of the model, greater confidence will be established in the accuracy of the social conditioning model. The specific hypotheses consistent with the social conditioning model, the traffic stop data used to test these hypotheses, and the analytic techniques employed are described in the following chapter.
CHAPTER 4: METHODOLOGY

INTRODUCTION

Chapters 2 and 3 discussed the extant literature on traffic stop outcomes and potential theoretical explanations for those findings, respectively. Using this information as a backdrop, this chapter addresses three methodological issues of this research. First, specific hypotheses are presented regarding the relationship between driver demographics and traffic stop outcomes. These hypotheses are based on past research and informed by the social conditioning model. In particular, emphasis is placed on the interaction between the race/ethnicity, gender, and age of the driver and the likelihood of being warned, cited, or arrested. Second, data used in the analyses are described, including the variables contained within the data set, their basic descriptive statistics, and the limitations of these data. The chapter concludes with a description of the analytic techniques chosen to address the research hypotheses. Bilevel multivariate regression models are the primary technique used in this research.

RESEARCH HYPOTHESES

This research investigates the potential interactive effects of driver demographics on traffic stop outcomes. This specific topic has received limited attention in the extant literature. Previous studies have demonstrated disparities in warnings, citations, and arrests for particular race/ethnicity, gender, and age groups (e.g., Alpert et al., 2006; Engel et al., 2006; Engel et al., 2007c; Smith & Petrocelli, 2001), but have often failed to examine how race/ethnicity, gender, and age may interact to form specific groups that have differing likelihoods of being warned, cited, or arrested (c.f., Moon & Cooley, 2007). This research addresses such a gap in the literature.
Previous research has also been criticized for lacking a theoretical framework (Engel et al., 2002); however, various theoretical explanations for racial/ethnic disparities in traffic stop outcomes have been offered (e.g., Mastrofski et al., 1994; Smith & Alpert, 2007; Tomaskovic-Devey et al., 2004, Warren et al., 2006). Unfortunately, these theories are used infrequently in the creation of specific testable hypotheses (Engel et al., 2002). The current research addresses this criticism by adopting the social conditioning model (Smith & Alpert, 2007) as its primary theoretical framework. This research does not directly test the social conditioning model; rather, it uses the social conditioning model as a guide to inform the research questions and interpret the outcomes.

Two sets of research hypotheses pertaining to the impact of driver demographics on traffic stop outcomes are explored in this research. The analytic strategy of this research is to move from descriptive statistics to bilevel multivariate models that explore the relationship between interaction terms and the dependent variables. This process is common among other traffic stop studies (e.g., Alpert et al., 2006; Engel et al., 2007c; Smith et al., 2003).

Initially, basic descriptives describe the data set by specifying the range, mean, and standard deviation for each dependent and independent variable. Thereafter, zero order analyses will address if any relationships exist between driver demographics and traffic stop outcomes. Based on the existing empirical evidence regarding racial/ethnic, gender, and age disparities in traffic stop outcomes and the theoretical direction offered by the social conditioning model, this research will then address the following research question: Do driver demographics exert an influence on the likelihood of receiving a warning, citation, or
arrest, net of stop, officer, vehicle, and other driver characteristics? The following specific research hypotheses will be tested:

- Minorities, males, and younger drivers will be more likely to receive a warning compared to White, females, and older drivers, net of controls.
- Minorities, males, and younger drivers will be less likely to receive a citation compared to White, females, and older drivers, net of controls.
- Minorities, males, and younger drivers will be more likely to be arrested compared to White, females, and older drivers, net of controls.

Previous research confirmed that individuals possessing certain demographic characteristics, such as being a minority, young, or male, are at an increased likelihood to receive more severe outcomes when compared to similarly situated individuals (Alpert et al., 2006; Engel et al., 2006; Engel et al., 2007c; Lovrich et al., 2005; Lovrich et al., 2003; Smith & Petrocelli, 2001). In addition, the social conditioning model suggests that racial/ethnic, gender, and age groups may be viewed differently by officers depending on their personal, vicarious, and media exposure to images of those groups (Smith & Alpert, 2007). Moreover, other factors, such as stop, officer, vehicle, and other driver characteristics, are also related to the likelihood of receiving a particular traffic stop outcome (Alpert et al., 2006; Engel et al., 2007c; Ingram, 2007; Lovrich et al., 2003; Lovrich et al., 2005; Smith & Petrocelli, 2001). Therefore, analysis of the relationship between driver demographics and traffic stop outcomes must include measures of these other variables as outlined in the research hypotheses (Fridell et al., 2001; Fridell, 2004; Ramirez et al., 2000).

This research, however, is specifically focused on investigating the combined effect of driver demographics on traffic stop outcomes. In other words, the interactions between driver demographics are assessed to identify if they possess a collective effect on traffic stop

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3 In the data analyzed in this research, all cases result in one of these three outcomes.

4 Theoretical reasons and empirical evidence for including these factors in this analysis is provided in the following section of this chapter.
outcomes beyond the independent effect of driver demographics demonstrated in previous research. Thus, the following research hypotheses are tested in this research:

- The interaction of being minority, male, and young will lead to more warnings compared to other combinations of demographics, net of other factors.
- The interaction of being minority, male, and young will lead to fewer citations compared to other combinations of demographics, net of other factors.
- The interaction of being minority, male, and young will lead to more arrests compared to other combinations of demographics, net of other factors.

This set of research hypotheses offer a contribution to the existing literature by exploring the interactive effects of driver demographics. Collectively, these two sets of research hypotheses will be tested in this research.

Two issues remain to be discussed. First, and specific to the interaction hypotheses, what evidence is available to suggest that such interaction terms are related to traffic stop outcomes? Second, and related to both sets of hypotheses, what is the justification for predicting the direction of the relationship between driver demographics and traffic stop outcomes?

Exploring interaction terms are justified by the social conditioning model and other criminal justice research. The social conditioning model offers a process by which combinations of demographics coalesce to form a negative stereotype and influence how these specific groups are viewed and treated by society (Smith & Alpert, 2007). Specifically, minority, young males are often stereotyped within our society as more likely to be involved in criminal activity (Bobo & Kluegel, 1997; Harris, 1999). This stereotype may frequently lead to an arrest (Hepburn, 1978). The social conditioning model suggests that officers are exposed to these messages and internalize them to form an unconscious perceptual shorthand regarding young, minority males (Smith & Alpert, 2007). This shorthand is used as a tool in decision-making during a traffic stop. For example, due to the unconscious belief of
increased criminal activity by these groups, a young, Black male is stereotyped as more deserving of an arrest than other individuals with a different set of demographic characteristics. Thus, the combination of being a minority, male, and young leads to a heightened likelihood of arrest above the likelihood associated with each independent demographic (i.e., race/ethnicity, gender, and age).

In other words, as particular characteristics interact in an individual, they have a greater influence than any one characteristic has by itself. This is analogous to the saying that the whole is greater than the sum of its parts. The specific meaning attached to the collective properties of being a young, minority male are transmitted to the officer through their personal and vicarious experience and through media exposure. As a result, officer decision-making is influenced by these unconscious stereotypes regarding specific groups in society.

The notion of interaction terms is not only suggested by the social conditioning model, but also in other criminal justice research. For example, interactions based on citizen demographics have been important in previous research on criminal justice decision-making (Moore & Miethe, 1986; Spohn & Cederblom, 1991; Steffensmeier et al., 1998). Research on sentencing decisions has demonstrated the importance of examining citizen demographic interaction terms (e.g., Spohn & Holleran, 2000; Steffensmeier et al., 1998 for research on sentencing decisions). It is conceivable that if demographic interactive effects were related to sentencing outcomes, it is possible that they may also affect traffic stop outcomes. As Zatz suggests (1987:83), “research that tests only for main effect and does not investigate all of the possible manifestations of discrimination may erroneously conclude that discrimination does not exist.”
Moreover, failure to investigate the importance of these interactions has been a weakness of traffic stop studies to date (Kowalski & Lundman, 2007). As mentioned, extant research has demonstrated the relationship between the independent effects of these variables (i.e., race/ethnicity, gender, and age) and traffic stop outcomes (Engel et al., 2005; Engel et al., 2006; Lovrich et al., 2003; Lovrich et al., 2005; Smith & Petrocelli, 2001), but research has not adequately examined the interactive effect of these demographics on traffic stop outcomes.

Thus, based on the social conditioning model, the evidence generated from research on other criminal justice decision points, and the gap in previous traffic stop literature, the current research explores the relationship between young, minority male drivers and traffic stop outcomes. In other words, these research hypotheses suggest a quantitative difference between the independent effects of being young, a minority, or a male (1st set of hypotheses) and the collective effect of being a young, minority male (2nd set of hypotheses).

Both sets of research hypotheses specify that the variables of interest will possess a positive relationship with warnings and arrests, and a negative relationship with citations. The relationship between arrest and young, minority males (both independently and collectively) is relatively straightforward and supported by the social conditioning model and previous research. For example, males were more likely to be arrested in the majority of studies (Alpert Group, 2004; Engel et al., 2004; Engel et al., 2007c; Lovrich et al., 2003; Moon & Cooley, 2007), minorities were more likely to be arrested in some studies (e.g., Alpert et al., 2006; Engel et al., 2004; Engel et al., 2007c; Withrow, 2004) and not in others (Alpert Group, 2004; Engel et al., 2005), and age had variable results (Alpert et al., 2006).
The hypothesized relationship between these driver characteristics and warnings and citations, however, needs further discussion.

Previous research reports the likelihood of receiving a warning is frequently inversely related to the likelihood of receiving a citation (e.g., Alpert Group, 2004; Engel et al., 2004; Engel et al., 2007c). For example, in most cases, males and younger drivers are more likely to be cited (Ingram, 2007; Lovrich et al., 2003; Lovrich et al., 2005) and less likely to be warned (Engel et al., 2004; Engel et al., 2005). In regard to driver’s race/ethnicity, in some cases, Black and Hispanic drivers are less likely to be warned and more likely to be cited (Engel et al., 2004; Engel et al., 2007c) whereas in other research the race/ethnicity effect is variable or non-significant (Alpert Group, 2004; Lovrich et al., 2003; Moon & Cooley, 2007). For example, Alpert et al. (2006) report that Blacks were more likely to be cited, while Hispanic and other race/ethnicities were less likely to be cited.

Based only on this evidence, the two sets of research hypotheses in the current research should indicate a lower likelihood of warning and a higher likelihood of citation for young, minority, or male drivers. These research hypotheses, however, imply an inverse relationship – warnings more likely and citations less likely. What is the justification for such hypotheses? To answer this question, it is important to assess if one of the three demographic characteristics is dominant. This is particularly important for the interaction hypotheses. For example, if males were more likely to be cited, but minority drivers less likely to be cited, what type of relationship is to be expected between an interaction term of minority male driver and citation?

This research relies on an assumption that race/ethnicity is the most salient demographic factor. In other words, the expectation is that minority status outweighs the
impact of gender and/or age in relation to traffic stop outcomes. This belief is based on non-traffic stop research suggesting that minorities may actually receive less severe outcomes (i.e., warnings) because their contact with the criminal justice system is a product of a pre-existing belief that they are involved in criminal activity (Hepburn, 1978). This evidence is consistent with the explanation offered by the social conditioning model (Smith & Alpert, 2007), which also predicts that unconscious stereotypes affect traffic stop outcomes. As mentioned in Chapter 3, the formation of unconscious stereotypes is predicated on personal, vicarious, and media exposure. In particular, the media often emphasizes the relationship between race/ethnicity and criminal activity (Barlow, 1998; Chiricos et al., 2004; Entman, 1992; 1990; Scheingold, 1984), which elevates this factor above the others. Thus, it is suggested that driver’s gender and/or age will be overridden by the race/ethnicity of the driver.

Furthermore, if unconscious stereotypes are operating as hypothesized by the social conditioning model, young, minority, male groups are likely to receive more scrutiny by officers. This attention is likely to result in traffic stops initiated for pre-textual reasons relating to the officer’s unconscious perspective that criminal activity may be occurring. In other words, a vehicle driven by a young, minority male is more likely to be seen as involved in criminal activity. The reason for the traffic stop is a pre-text for an investigation into potential criminal activity. These unconscious stereotypes may be incorrect and result in no discovery of elevated rates of criminal activity for these groups. In other words, the underlying, unconscious assumptions of the officer may not be valid.

This is particularly relevant for interdiction or canine officers who are focused on the discovery of contraband. These officers are more likely to warn a driver if there is no
criminal activity occurring because issuing a citation raises the possibility of a court challenge and reduced time on the highway for interdiction work. Furthermore, if no obvious reason is found for an arrest, issuing a warning to the driver is likely to make them feel at ease and be more likely to allow their vehicle or person to be searched.

Most vehicles violate a traffic law for which they can be legally stopped, although this is not explicitly discussed within the social conditioning model. Thus, like any other driver, young, minority males violate the law while driving and are stopped for legal reasons. They may receive greater attention due to the officer’s unconscious stereotype regarding this group. If no criminal activity is discovered, a warning may be more likely than a citation due to the less severe impact on the citizen, and a warning removes the potential court appearance for the officer.

Thus, young, minority male drivers are hypothesized to have a positive relationship with warnings and a negative relationship with citations. This is in contrast to previous traffic stop literature but based on the dominance of race/ethnicity (Hepburn, 1978; Smith & Alpert, 2007) and the use of pre-textual traffic stopping procedures.

Testing these research hypotheses provides a more nuanced understanding of the relationship between driver demographics and traffic stop outcomes. Moreover, confirmation of these hypotheses will lend support to the social conditioning model as a viable explanation for any racial/ethnic, gender, and age disparities in traffic stop outcomes.

**DATA**

Confidentiality restrictions do not allow for the source of these data to be identified, however, a generic description of the data collection effort is permitted. These data were drawn from a multi-year data collection effort to assess the pattern of traffic stops and traffic
stop outcomes for all officer-initiated traffic stops. All data were collected by a single law enforcement agency and analyzed by an independent research team. Monthly and year-end reports are generated to inform the agency of their traffic stop and traffic stop outcome patterns. The data used in this research were collected in 2006 and were checked for accuracy and completeness through a series of data audits completed during the data collection phase.

This data collection effort originated as a response to growing concerns regarding potential racially biased behavior by law enforcement agencies in traffic stops (Harris, 2002; Ramirez et al., 2000). This attention stemmed partially from court decisions that mandated data collection for law enforcement agencies in New Jersey and Maryland (see State of New Jersey v. Soto, 1996; Wilkins v. State of Maryland, 1993). Within this legal environment, the law enforcement agency also initiated its own department policy against using race/ethnicity as a tool in decision-making. As a result, the agency initiated a voluntarily data collection effort to assess their traffic stopping practices.

Prior to data collection, an internal agency committee was formed in conjunction with the research team to create the data collection instrument and decide on the mechanism for data collection. Decisions regarding the data fields were a product of guidelines developed by the National Institute of Justice, consultations between the agency and the research team, and recognition of the practical limitations of a large, statewide data collection effort. The committee decided on collecting stop, driver, and vehicle characteristics, and an officer identifier.

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5 Stop information included the date/time, the location of the stop—county and municipality, the type of roadway, the reason(s) for the stop, the duration of the stop, and the outcome of the stop, and the number of passengers in the vehicle. Driver characteristics included their gender, age, race/ethnicity, and zip code of residency. Vehicle characteristics included the state of registration.
Once the specific data fields were decided, all personnel were trained on the data collection instrument\(^6\) and a pilot test was initiated. Other issues addressed by the committee were minimizing officer disengagement and developing a data auditing system. Once initiated, the data collection system required agency personnel to complete a traffic stop form after completion of an officer-initiated traffic stop. The method of collection included a paper option and an electronic option. The paper option required a multi-step process including recording all pertinent information on a bubble form, transferring those forms by mail to the research team, and entering the forms into the electronic database by using a Scantron machine. The electronic option required the officer to enter all information directly into a software program using either his/her Mobile Data Terminal (MDT) in the cruiser or at the post on a computer. The information was then electronically transmitted to the research team. Information collected on the paper and electronic systems are identical and allowed merging of the data sets without loss of information.

Data used in this research represent all officer-initiated traffic stops by the agency in 2006 and recorded on the traffic stop form\(^7\). These data do not include any encounters in which a motorist requested assistance, collisions, or if the officer was responding to a dispatch. The agency’s size and service demands contributed to a total of 283,827 officer-initiated traffic stops conducted in 2006.

**Measures**

The data set represents all officer-initiated traffic stops and includes information on driver, stop, officer, and vehicle characteristics. Table 4.1 lists the measures collected on the traffic stop form and the variables used in the analysis. Each of the 283,827 traffic stops

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\(^6\) Training of officers included viewing a video from the agency explaining the research project, a training video from the researchers, and the completion of forms during practice traffic stops.

\(^7\) The use of the phrase “traffic stop form” refers to information recorded through the paper or electronic option.
equal one case in the data set. Of those traffic stops, 3,260 cases (1.1%) were discarded due to missing information on at least one variable, an invalid organizational code, and/or the driver was under the age of 15. Analysis of these cases showed a random pattern of variables excluded; thus, removing these cases will not bias the analysis. The final number of cases in the data set is 280,567 and all variables are dichotomous unless otherwise noted.

Dependent Variables

The dependent variables are based on the traffic stop outcome and recorded as a non-mutually exclusive category on the traffic stop form. Therefore, a single traffic stop may result in multiple outcomes such as a warning and an arrest. Of the 280,567 traffic stops, 25.7% of those cases resulted in at least one warning issued to the driver. The large majority of traffic stops concluded with at least one citation issued to the driver (87.2%), while 1.5% of the traffic stops ended with an arrest of the driver.

Traffic stop outcomes were also coded as mutually exclusive categories based on the most severe outcome issued to the driver. Thus, a traffic stop that ended with a warning and a citation would be considered a citation and would not be classed as a warning. Based on this categorization, 12.1% of traffic stops resulted in only a warning, 86.4% ended in only a citation, and 1.5% concluded with an arrest.

The primary difference between these two methods is the definition of the dependent variable. A traffic stop with multiple outcomes is counted in all relevant models in the non-mutually exclusive method. In the mutually exclusive method, the traffic stop outcome is

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8 Variables were coded as a “1” when the characteristic was present and “0” when the characteristic was not present.
9 This method used the same number of cases as the non-mutually exclusive method.
10 The severity of traffic stop outcomes moves from warnings to arrests (least to most severe).
determined by the most severe outcome. All descriptive statistics for the dependent and independent variables are reported in Table 4.2.
<table>
<thead>
<tr>
<th>Variable Type</th>
<th>Variable Category</th>
<th>Information Collected on Traffic Stop Form</th>
<th>Variables Created for Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variables</strong></td>
<td>Stop Outcomes</td>
<td>Warning Issued</td>
<td>Any Warning Issued (1=Yes; 0=No); Only Warning Issued (1=Yes; 0=No)</td>
</tr>
<tr>
<td></td>
<td>Citation Issued</td>
<td>Citation Issued</td>
<td>Any Citation Issued (1=Yes; 0=No); Citation Most Severe (1=Yes; 0=No)</td>
</tr>
<tr>
<td></td>
<td>Driver Arrested</td>
<td>Driver Arrested</td>
<td>Any Driver Arrested (1=Yes; 0=No); Arrest Most Severe (1=Yes; 0=No)</td>
</tr>
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<td>Race/Ethnicity of Driver</td>
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<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Black (1=Yes; 0=No)</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>Hispanic (1=Yes; 0=No)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Other1 (1=Yes; 0=No)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Gender of Driver</td>
<td>Gender (1=Male; 0=Female)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Age of Driver</td>
<td>Age (1=15-29 Years of Age; 0=30 Years of Age and Older)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Age (1=15-29 Years of Age; 0=30 Years of Age and Older)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Black Male (1=Yes; 0=No)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hispanic Male (1=Yes; 0=No)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Male 15-29 Years of Age (1=Yes; 0=No)</td>
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<td></td>
<td></td>
<td>Hispanic 15-29 Years of Age (1=Yes; 0=No)</td>
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<tr>
<td></td>
<td></td>
<td>Young, Black Male (1=Yes; 0=No)</td>
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<tr>
<td></td>
<td></td>
<td>Young, Hispanic Male (1=Yes; 0=No)</td>
<td></td>
</tr>
<tr>
<td><strong>Other Driver Characteristics</strong></td>
<td>Driver Lives in County of Stop</td>
<td>County residency (1=Yes; 0=No)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>In-State Resident</td>
<td>State residency (1=Yes; 0=No)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Time of Day</td>
<td>Daytime (1=Yes; 0=No)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Date, Month</td>
<td>Weekday (1=Yes; 0=No)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>County &amp; Municipality</td>
<td>Season (1=Summer; 0=Else)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Stop Characteristics</td>
<td>Interstate (1=Yes; 0=Else)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Roadway Type</td>
<td>Speeding (1=Yes; 0=Else)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Reason for the Stop</td>
<td>Number of reasons for the stop (range 1-6)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Passengers Discovered</td>
<td>Contraband Discovered (1=Yes; 0=No)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Passengers in Vehicle</td>
<td>Number of passengers in the vehicle (range 1-5)</td>
<td></td>
</tr>
<tr>
<td><strong>Vehicle Characteristics</strong></td>
<td>Vehicle Registration</td>
<td>Vehicle registered in state (1=Yes; 0=No)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>White (1=Yes; 0=Else)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Gender (1=Male; 0=Female)</td>
<td></td>
</tr>
<tr>
<td><strong>Officer Characteristics</strong></td>
<td>Officer Employee Identifier</td>
<td>Experience (1=less than 5 years; 0=5 years or more)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Education (range 1-6) – 1-Some H.S.; 2-Some College; 3 – 2 Yr Degree; 4 – 4 Yr Degree; 5 – Some Grad; 6 – 2+ Grad</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Assignment (1=patrol; 0=non-patrol)</td>
<td></td>
</tr>
</tbody>
</table>

1 “Other” drivers consist of Asian/Pacific Islander, Middle Eastern, Native American, and Unknown drivers.
Independent Variables

Drivers’ race/ethnicity was recorded on the traffic stop form based on the officer’s perception of the driver rather than the actual race/ethnicity of the driver. This method is preferred because it is the officer’s perception of the drivers’ race/ethnicity that is central for identifying bias, rather than the drivers’ actual race/ethnicity (Fridell, 2004). There are eight categories of race/ethnicity to select including: Asian/Pacific Islander, Black, Black Hispanic, Middle Eastern, Native American, White, White Hispanic, and Unknown. These eight options were re-categorized into four new categorical variables representing White, Black, Hispanic\(^{38}\), and Other\(^{39}\) drivers.

Drivers’ gender was also collected based on the perception of the officer, and measured as a dichotomous variable where 0 = female and 1 = male. Year of birth was recorded from the driver’s license and used to create two measures of driver’s age. Collected as a metric variable, age of the driver was calculated from the driver’s year of birth. Drivers’ age was transformed into a dichotomous variable where 1 = drivers between the ages of 15 & 29 and 0 = drivers aged 30 thirty years of age and older. Drivers’ age was also grouped as an ordinal variable where 1 = 15-29 years of age, 2 = 30-49 years of age, and 3 = 50+ years of age. These variables were created to explore the potential of a non-linear relationship between driver’s age and the traffic stop outcomes (Steffensmeier, Kramer, & Ulmer, 1995). Descriptive statistics report that White drivers were the most frequent race/ethnicity to be stopped (84.5%), male drivers comprised 68.8% of the traffic stops, and drivers between the ages of 15 & 29 comprised 28.7% of the traffic stops. The other age groups’ descriptive statistics are reported in Table 4.2.

\(^{38}\) The Hispanic category represents any driver recorded as White Hispanic or Black Hispanic.

\(^{39}\) The Other category represents any driver recorded as Asian/Pacific Islander, Middle Eastern, Native American, or Unknown.
To test the research hypotheses, seven interaction terms were created. The first five interaction terms were created as follows: Black and male, Black and young (i.e., 15-29 years of age), male and young, Hispanic and male, and Hispanic and young. The final two interaction terms were young, Black males and young, Hispanic males. Descriptive analyses demonstrate that males between 15 and 29 years of age were the most common group stopped (28.7%). Black male drivers were the second most common group (5.9%), followed by young, Black drivers (3.5%), and Hispanic male drivers (2.8%). Young, Black males comprised 2.3% of all traffic stops, and young, Hispanic males represented 1.3% of all traffic stops.

To accurately assess the relationship between driver demographics and traffic stop outcomes, all other potentially explanatory factors must be considered. The remaining independent variables are included in the analysis because they are theoretically associated with the traffic stop outcomes and/or because empirical evidence has demonstrated such a relationship. Thus, not all the independent variables are directly linked with the social conditioning model.

Apart from demographics, other driver characteristics were collected, such as if the driver lives within the county of the traffic stop and if the driver lives within the state. These dichotomous variables tap the influence of a driver’s home jurisdiction on traffic stop outcomes. For example, out-of-jurisdiction drivers are potentially less likely to contest a ticket due to the distance required to attend a court hearing. Thus, it is hypothesized that out-of-county and out-of-state drivers are more likely to receive a citation, but less likely to receive a warning. Moreover, the agency engages in enforcement of all laws, not just driving violations, on both highways and urban streets. Thus, their knowledge regarding the criminal

40 The specific analytic strategy for using these interaction terms is described in the following section.
activity of local residents is hypothesized to lead to higher levels of arrest for in-county and in-state residents. Descriptive statistics show that slightly more than a third of the drivers stopped (35.7%) reside in the jurisdiction of the stop, and 75.2% of the drivers stopped live in the state.

Stop characteristics collected on traffic stop forms include time, date, and location of the stop, reason for the stop, if contraband was discovered as a result of a vehicle or driver search, and the number of passengers in the vehicle (Alpert et al., 2006; Engel et al., 2004; Engel et al., 2005; Engel et al., 2007d; Ingram, 2007). Time of the day was used to create a dichotomous variable for daytime traffic stops\(^{41}\). Previous research suggests that the resolution of a traffic stop may differ between daytime and nighttime; for example, Alpert et al. (2006) found that arrests were more likely during the evening, whereas citations were less likely in the evening. Conversely, Ingram (2007) reported citations were more likely to be issued in the evening. In these data, the majority of traffic stops (70.4%) occurred during daytime hours.

The date of the traffic stop was used to create two dichotomous variables indicating whether or not the stop occurred on a weekday and the season of the stop (i.e., four separate dichotomous variables were created for each season). The first variable provides a recognition that the driving population may differ between weekdays and weekends. Research supports this claim; for example, Alpert et al. (2006) found that arrests were more likely on weekends while citations were less likely. Seasonal variation may also exist in traffic stop outcomes, in particular for arrests. Crime varies by season, and if arrests are related to actual criminal activity, it is plausible to consider that arrest rates may also vary by

\(^{41}\) Daytime traffic stops were coded as a 1 and all other traffic stops coded as 0 indicating a nighttime traffic stop. This distinction was defined by the time of the day and based on the season of the traffic stop.
Descriptive statistics of these data indicate that 71.3% of the traffic stops occurred on a weekday, and that traffic stops were approximately evenly dispersed across all four seasons.\footnote{The dichotomous variable representing traffic stops summer was included in the analysis as this was the season with the fewest traffic stops.}

The location of the traffic stop was used to create a dichotomous variable indicating if the stop occurred on an interstate. The type of roadway is important to consider as the driving populations may differ between highways and city roads (Meehan & Ponder, 2002). In their analysis of data collected by the Washington State Highway Patrol, Lovrich et al. (2003; 2005) included a measure of roadway and reported that citations were more likely to be issued for traffic stops occurring on an interstate. In these data, almost half of the traffic stops occurred on an interstate (47.5%).

The reason for the stop is consistently collected in traffic stop data collection effort due to its impact on officer discretion. Traffic stop outcomes are influenced by the level of discretion available to the officer (Ramirez et al., 2000), and the reason for the stop dictates the degree of autonomy available to the officer (Batton & Cadleck, 2004; Engel et al., 2002; Klinger, 1996). Moreover, Alpert et al. (2005) report that certain traffic violations predict whether or not a traffic stop will be initiated. This leads to an indirect effect on those receiving an outcome. Therefore, the reason for the stop is a crucial contextual variable related to traffic stop outcomes (Lovrich et al., 2003). Past research reports that traffic stops initiated due to equipment violations are less likely to lead to an arrest, but more likely to result in a citation (Alert et al., 2006), and that speeding is negatively related to the likelihood of being arrested (Engel et al., 2007d).
Various reasons for the stop are included in the data set as dichotomous variables. For example, speeding, moving violations, equipment violations, pre-existing information regarding criminal activity, or registration and/or license violations are coded as a 1 when that reason was identified and 0 when it was not the reason for the stop. Of all these reasons for a stop, this research includes speeding as a dichotomous variable due to the frequency of occurrence in these data (70.0%). The other reasons for the stop are excluded from the analysis, although the interpretation of the speeding variable is in relation to the occurrence of any other reason for the stop. Furthermore, a multitude of reasons for the stop are associated with a higher likelihood of citation or arrest (Engel & Calnon, 2004b), with Lovrich et al. (2003) reporting that including the number of reasons for the stop attenuated the racial/ethnic effects. Thus, the number of reasons for the stop is included in this analysis, and hypothesized to be positively related to citations and arrests. Descriptive statistics indicate that the average number of reasons for the stop in 2006 ranged from 1 to 7, with 88.2% of the traffic stops initiated due to one reason, and the average traffic stop initiated as a result of 1.1 reason.

Discovery of contraband has a documented relationship with arrests (Engel & Calnon, 2004b). Past research indicates that when contraband is discovered during a traffic stop, the outcome of the encounter is more likely to be an arrest (Engel et al., 2004; Engel et al., 2005; Engel et al., 2007d). Thus, it is hypothesized that discovery of contraband will be positively related to the likelihood of arrest. Contraband was discovered in 0.4% of all traffic stops.

Finally, the number of passengers in the vehicle was also collected. Past research on the impact of bystanders during police-citizen encounters indicate that an arrest is more likely when there are more bystanders and the citizen is disrespectful (Engel et al., 2000).
The presence of passengers in a vehicle is analogous to the presence of bystanders in other police-citizen encounters; thus, the number of passengers is included in the analysis. The number of passengers ranged from 0 to 9 in a traffic stop with an average of 0.6 passengers per traffic stop.

Vehicle characteristics are also important to consider because officers may use these factors in their decision-making (Alpert et al., 2006; Batton & Kadlec, 2004). For example, vehicles that look out of place may be higher risk of being stopped, or drivers that do not “match” their vehicle raise the suspicion of officers (Ramirez et al., 2000). These data include a measure of vehicle registration. Descriptive statistics show that 77.7% of vehicles stopped were registered within the state.

The final set of variables measure the impact of officer characteristics on traffic stop outcomes. For every traffic stop, officers were required to attach their unique employee numbers. This identifier was used to merge the officer’s race/ethnicity, gender, experience, education, and assignment information into each case in the database. This information is strictly confidential and provided to the researchers under the conditions outlined in the research contract. Once officer characteristics were associated to each traffic stop, the employee identifier was deleted and destroyed. In this manner, no individual officer can be identified or associated with a specific traffic stop, but the analysis still allows for an examination of the impact of officer characteristics.  

Recent research demonstrated that officer characteristics possess a relationship with traffic stop outcomes; for example, male officers were less likely to arrest, while those officers with less experience were more likely to arrest (Alpert et al., 2006). Moreover,  

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43 This method precludes the use of officer characteristics as level 2 predictors in the bilevel analyses discussed in the next section of this chapter.
officer assignments may influence the populations that an officer interacts with based on geographic and/or temporal variations (Batton & Kadleck, 2004), which could impact the relationship between driver demographics and traffic stop outcomes. Alpert et al. (2006) also reports that officers assigned to patrol were less likely to arrest. Finally, officer education has been theorized as a factor related to officer decision-making (Alpert et al. 2005; Walker & Katz, 2002).

In these data, officer gender was a dichotomous variable coded as 0 = female and 1 = male. The large majority of officers initiating traffic stops were male (97.0%). Officer race/ethnicity was measured as a series of dichotomous variables for White, Black, Hispanic, American Indian, and Asian officers. In the analysis, only a measure of White officers will be included as this group represents the large majority of officers and thus serves as a logical referent (91.9%). Officer assignment was also represented by a series of dichotomous variables including patrol, crime, staff, canine, or other. The significant majority of officers were assigned to patrol (97.6%), and this is the only assignment variable to be included in the analysis. Officer experience was represented by a dichotomous variable indicating those with five years of experience or more coded as a 1 and those with less than five years experience coded as a 0. Forty percent of officers had less than five years of experience at the time of traffic stop. Finally, officer education was measured by a categorical variable ranging from 1 to 6 and representing officers with some high school coded as a 1 to officer with more than 2 years of graduate school coded as a 6. On average, officers in this dataset possess at least some college education experience (mean = 3.0; standard deviation = 1.3). For further information on any of these descriptive statistics, please refer to Table 4.2.
### Table 4.2: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Variables</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean</th>
<th>Std. Dev.</th>
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<tbody>
<tr>
<td><strong>Dependent Variables (n = 280,567)</strong></td>
<td></td>
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<td></td>
<td></td>
<td><strong>Other Driver Characteristics</strong></td>
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<td>Citation Most Severe</td>
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<td>0.343</td>
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<td>0.123</td>
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<td>Hispanic Driver</td>
<td>0</td>
<td>1</td>
<td>0.035</td>
<td>0.183</td>
<td>Summer Stop</td>
<td>0</td>
<td>1</td>
<td>0.232</td>
<td>0.422</td>
</tr>
<tr>
<td>Other Driver</td>
<td>0</td>
<td>1</td>
<td>0.036</td>
<td>0.185</td>
<td>Interstate Stop</td>
<td>0</td>
<td>1</td>
<td>0.475</td>
<td>0.499</td>
</tr>
<tr>
<td>Male Driver</td>
<td>0</td>
<td>1</td>
<td>0.688</td>
<td>0.463</td>
<td>Speeding is Reason for Stop</td>
<td>0</td>
<td>1</td>
<td>0.700</td>
<td>0.458</td>
</tr>
<tr>
<td>Drivers’ Age</td>
<td>0</td>
<td>1</td>
<td>0.287</td>
<td>0.452</td>
<td>Number of Reasons for Stop</td>
<td>1</td>
<td>7</td>
<td>1.135</td>
<td>0.393</td>
</tr>
<tr>
<td>Drivers’ Aged 15-29</td>
<td>0</td>
<td>1</td>
<td>0.434</td>
<td>0.496</td>
<td>Contraband Discovered during Stop</td>
<td>0</td>
<td>1</td>
<td>0.004</td>
<td>0.064</td>
</tr>
<tr>
<td>Drivers’ Aged 30-49</td>
<td>0</td>
<td>1</td>
<td>0.400</td>
<td>0.490</td>
<td>Number of Passengers</td>
<td>0</td>
<td>9</td>
<td>0.643</td>
<td>0.987</td>
</tr>
<tr>
<td>Drivers’ Aged 50 and Over</td>
<td>0</td>
<td>1</td>
<td>0.166</td>
<td>0.372</td>
<td><strong>Vehicle Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Interaction Terms</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>State Registration</td>
<td>0</td>
<td>1</td>
<td>0.777</td>
<td>0.416</td>
</tr>
<tr>
<td>Black Male</td>
<td>0</td>
<td>1</td>
<td>0.059</td>
<td>0.235</td>
<td><strong>Officer Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic Male</td>
<td>0</td>
<td>1</td>
<td>0.028</td>
<td>0.165</td>
<td>Male Officer</td>
<td>0</td>
<td>1</td>
<td>0.970</td>
<td>0.171</td>
</tr>
<tr>
<td>Black 15-29 Years of Age</td>
<td>0</td>
<td>1</td>
<td>0.035</td>
<td>0.182</td>
<td>Caucasian Officer</td>
<td>0</td>
<td>1</td>
<td>0.919</td>
<td>0.273</td>
</tr>
<tr>
<td>Male 15-29 Years of Age</td>
<td>0</td>
<td>1</td>
<td>0.287</td>
<td>0.452</td>
<td>Officer with Less than 5 Years Experience</td>
<td>0</td>
<td>1</td>
<td>0.404</td>
<td>0.491</td>
</tr>
<tr>
<td>Hispanic 15-29 Years of Age</td>
<td>0</td>
<td>1</td>
<td>0.016</td>
<td>0.126</td>
<td>Officer’s Education(^2)</td>
<td>1</td>
<td>6</td>
<td>2.955</td>
<td>1.321</td>
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<tr>
<td>Young, Black Male</td>
<td>0</td>
<td>1</td>
<td>0.023</td>
<td>0.150</td>
<td>Patrol Assignment</td>
<td>0</td>
<td>1</td>
<td>0.976</td>
<td>0.154</td>
</tr>
<tr>
<td>Young, Hispanic Male</td>
<td>0</td>
<td>1</td>
<td>0.013</td>
<td>0.114</td>
<td><strong>Interaction Terms</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

1 Asian/Pacific Islander, Middle Eastern, Native American, or Unknown drivers
2 1-Some High School; 2-Some College; 3 – 2 Yr. Degree; 4 – 4 Yr. Degree; 5 – Some Graduate School; 6 – 2+ Yr. Graduate School
Data Limitations

Official data present some limitations that need to be acknowledged. For example, the use of official data can be burdensome due to the reliance on cooperation from the agency (Lundman & Kaufman, 2003; Tomaskovic-Devey et al., 2006). This concern is mitigated in this data collection effort as the agency voluntarily initiated data collection and offered their full support since the inception of the research project.

A second potential limitation of official data is ensuring that all information was recorded accurately and completely for all traffic stops (Lundman, 2004; Walker, 2001). Several precautionary steps were taken in this data collection effort including constant monitoring and feedback to the agency. In particular, a data auditing procedure was instituted at the inception of this research which offered a statistical report on missing data and information that was logically inconsistent within each traffic stop form. Whenever possible these errors were corrected, and on-going feedback was provided to agency administrators regarding the error rate. The standard error rate recommended by the Police Executive Research Forum (PERF) is 10% for data collected by law enforcement agencies (Fridell et al., 2001). In the case of these data, the error rate was targeted at 5% and each year of the data collection effort met and exceeded that goal (i.e., the error rate was lower than 5%). For example, only 1.9% and 2.9% of the data collected in 2004 and 2005, respectively, was missing information or contained inconsistent data, and in 2006, the error rate was 2.5%. The combination of the data auditing procedures and the support of agency supervisors and administrators provide greater confidence in the accuracy of these data.

Third, the potential of officer disengagement presents a challenge to official data collection efforts (Ramirez et al., 2000; Walker, 2001). This concern arises whenever an
officer alters his or her behavior as a result of the data collection effort (Fridell et al., 2001). The data used in this analysis were collected in the fifth year of the project. Thus, using official data from a research project that has become a regular component of an officer’s job substantially reduces concerns of officer disengagement.

Finally, official data is not always collected for the purpose of understanding decision-making. As a result, the data collection effort may not include measures of all pertinent variables related to the subject under study. This leads to the potential of model misspecification, as some variables that have explanatory power may not be collected for consideration in the analysis. For example, previous research was critiqued for not measuring driver demeanor as a possible important explanatory predictor. This is a legitimate criticism of the current research as well.

These limitations aside, collecting information on all officer-initiated traffic stops throughout one year across an entire law enforcement agency results in a large number of cases for analysis. These data were collected specifically for the purpose of identifying any potential racial/ethnic biases in traffic stop outcomes. As a result and as outlined in this chapter, there are several variables to consider in the analysis. To properly investigate these data for patterns of disparity, specific analytical techniques appropriate for large samples with multiple variables need to be used. These techniques are described below.

**ANALYTICAL TECHNIQUES**

The analytical method of this research begins with descriptive statistics (as reported above), followed by zero-order analyses using the chi-square statistic, and concludes with various bilevel multivariate models. Descriptive statistics can indicate if there are raw differences between the driver groups in traffic stop outcomes; however, they do not provide
evidence of disparity based on statistical testing (Batton & Kadleck, 2004). Zero-order analyses fill this void by statistically comparing the rate of the dependent variables of interest (i.e., warnings, citations, and arrests) in relation to the primary independent variables of interest (i.e., the race/ethnicity, gender, and age of the driver). These analyses offer basic information regarding statistically significant correlations between the independent and dependent variables, and can be used to run some basic diagnostic checks for correlations and skew of the variables. Zero-order analyses may, however, result in misleading conclusions because they fail to consider the impact of other potentially important variables on traffic stop outcomes (Batton & Kadleck, 2004).

Multivariate analyses address this limitation by offering a robust analysis of the dependent variables while measuring a variety of potential explanatory variables. Effective study of a social science phenomenon, such as traffic stop outcomes, invariably involves the collection of multiple pieces of information to assess all correlates of the outcome (Fridell, 2004; Ramirez et al., 2000), and multivariate analysis is a key technique for parsing out the effects of each independent variable (Hanushek & Jackson, 1977; Weisburd & Britt, 2004). Simply put, the individual impact of one variable on the outcome can be measured while considering all the other variables simultaneously. For example in the case of traffic stop outcomes, the individual impact of drivers’ race/ethnicity on the outcome (e.g., a warning, a citation, or an arrest) is examined while controlling for the impact of any of the other variables, such as driver, stop, vehicle, or officer characteristics (Batton & Kadleck, 2004). In short, to understand a phenomenon, all potential, reasonable explanations need to be examined and all factors that could contribute to the outcome need to be considered in the analysis.
Multivariate models vary depending on the data available for analysis. One of the more common types of multivariate analysis is logistic regression. This technique is appropriate for data that contains a dichotomous dependent variable (Pampel, 2000). The results of logistic regression are interpreted as the change in logged odds of receiving the outcome of interest for a one-unit change in the independent variables (Hanushek & Jackson, 1977; Pampel, 2000).

Although appropriate and useful for studying traffic stop outcomes (Fridell, 2004), multivariate analyses, including logistic regression, have limitations such as specification error (Hanushek & Jackson, 1977). This occurs when the multivariate model does not include measures of constructs that are related to the dependent variable. For example, citizens’ demeanor has been linked to officer behavior (Klinger, 1996; Worden & Shepard, 1996), but if this variable is not measured, the results derived from the analysis may be misspecified. Thus, model misspecification potentially occurs when important explanatory variables are not included. Researchers are generally more confident in the findings of statistical analyses that examine traffic stop dispositions using multivariate analysis because at least some, if not all, influential factors contributing to officer decision-making are statistically controlled (Fridell, 2004).

Another limitation of multivariate analyses is the requirement of uncorrelated error between the independent variables (Hanushek & Jackson, 1977). Multivariate regression models produce valid parameters estimates when no correlated error is present across predictor variables (Hanushek & Jackson, 1977). This may be a concern when analyzing traffic stop outcomes because the same officer frequently conducts multiple traffic stops. For example, driver, stop, and vehicle characteristics all operate at the encounter level, whereas
officer characteristics exist at a higher level of aggregation. Thus, the impact of one officer is spread across multiple cases, which potentially violates the assumption that each case is independently affected by the independent variables. This concern is mitigated by the use of a multilevel model.

Multilevel modeling is a form of multivariate regression that is appropriate for data collected across different units of aggregation (Raudenbush & Bryk, 2002). In other words, multilevel modeling allows an examination of data collected at different levels of aggregation by controlling and distinguishing between effects located at the individual/encounter level compared to those occurring at a higher unit of aggregation (Luke, 2004). This type of regression model is particularly relevant to traffic stop studies because independent variables that are empirically or theoretically relevant to traffic stop outcomes exist at different levels of aggregation.

These data may possess correlated error because one officer initiated multiple stops. Thus, the characteristics of one officer are not equally spread across multiple cases in the dataset thereby violating the underlying assumption of regression models that each case is independently affected by the independent variables (Hanushek & Jackson, 1977). Multilevel models correct for this potential threat by including a higher unit of analysis in the analysis (Luke, 2004). In traffic stop analyses, the officer characteristics are ideally included in the model at level two. For example, in an ideal situation, traffic stop characteristics would be modeled at level 1 and officer characteristics entered at level 2. Unfortunately, it is not possible to model officer characteristics at level 2 due to confidentiality concerns.

Officer characteristics are modeled at level one rather than pooled at level two due to confidentiality requirements. The confidentiality requirements of the research contract restrict the identification of specific officer identifiers, which would be necessary to model the officer characteristics at level two.

46 Officer characteristics are modeled at level one rather than pooled at level two due to confidentiality requirements. The confidentiality requirements of the research contract restrict the identification of specific officer identifiers, which would be necessary to model the officer characteristics at level two.
Instead, the multilevel models examine traffic stop outcomes nested within the smallest organizational unit.

Using the smallest organizational unit offers a rough proxy for officer characteristics because officers working within that unit influence the behavior within that unit. Organizational effects have been hypothesized to form and possess an influence on the behavior and decision-making of officer (Klinger, 1997). Organizational effects are likely a product of individual officer characteristics coalescing at small organizational units to form an aggregate impact on traffic stop outcomes. Moreover, due to the large area patrolled by this law enforcement agency, each unit operates to some degree independently within the larger organization. In addition, traffic patterns are different depending on the geographic location. While specific organizational factors are not specified in these models, any organizational effect on traffic stop outcomes is controlled in the bilevel models.

These data will be analyzed using bilevel models by nesting traffic stop outcomes within the smallest organizational unit to correct for potential correlated error. Using this bilevel strategy, a series of regression models will be calculated to address the research hypotheses. There are several different methods by which interaction terms can be considered in a multivariate model\(^{47}\). This research considers their impact by examining the full sample using the following steps. Initially, bilevel, Bernoulli regression models will be run to examine the three outcomes of interest (i.e., warning, citations, and arrests). For each of these models, all the aforementioned independent variables will be included. These base models offer a baseline to compare with the subsequent models, which include the interaction terms. Next, interaction terms will be entered to model young, Black male drivers and

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\(^{47}\) An alternative method would require the data set to be split on one of the demographic variables and interaction terms created based on the remaining two demographic categories. Depending on the results of the method described in this chapter, this alternative approach may be adopted during the analysis process.
young, Hispanic male drivers compared to other demographic interactions. Using this method, it can be determined if the combination of driver demographics are related to traffic stop outcomes beyond the main effect of these three driver characteristics.

Collectively, the aforementioned techniques offer simple (i.e., zero-order analyses) and more complex, sophisticated techniques (i.e., bilevel, multivariate analyses) for examining the relationship between the independent and dependent variables. This approach follows previous research on traffic stop outcomes that used multilevel modeling (see Engel et al., 2007c; Ingram, 2007).

CONCLUSION

This chapter outlined the specific research hypotheses to be tested in this research. Specifically, the analyses reported in Chapter 5 will assess if driver demographics interact to affect the likelihood of being warned, cited, or arrested, net of other factors. To address the research questions posed by this research, data from the fifth year of an on-going data collection project is examined. These data were collected on all officer-initiated traffic stop outcomes, and include driver, stop, vehicle, and officer characteristics. Official data have limitations, but many of these shortcomings are addressed in these data. A series of bilevel multivariate regression models will be run on these data to address the research hypotheses. The following chapter reports the results of these analyses.
CHAPTER 5: RESULTS

INTRODUCTION

This chapter reports the results of all data analyses conducted in this research. Initially, zero-order relationships were computed between driver demographics and traffic stop outcomes. Thereafter, these relationships were explored further by including other independent variables in a series of bilevel, Bernoulli models examining traffic stop outcomes nested within the smallest organizational unit. A traffic stop may have resulted in more than one outcome (e.g., a warning and a citation), and the traffic stop outcomes were analyzed as non-mutually exclusive and mutually exclusive variables. In the former, the case was considered a warning and a citation in their respective models. In the latter, only the most severe outcome of the case (i.e., the citation) was analyzed. In both the non-mutually exclusive and mutually exclusive models, all traffic stop outcomes were analyzed independently as dichotomous values (e.g., 1=any type of warning was issued; 0=no warning was issued, etc.). Conclusions and implications of the results are addressed in the following chapter.

ZERO-ORDER ANALYSES

Zero-order analyses measure the relationship between one independent variable and one dependent variable without any other “control” variables (Weisburd & Britt, 2004). One measure of statistical significance for these relationships is the chi-square statistic. This statistic is appropriate for categorical independent and dependent variables (Weisburd & Britt, 2004), such as driver demographics and traffic stop outcomes. In this research, a
critical region of .0001 level was selected and indicated the odds of a statistically significant result even if the relationship does not truly exist in the population.

Zero-order analyses for drivers’ race/ethnicity, gender, age, and interaction terms and traffic stop outcomes were conducted and reported in Table 5.1. For simplicity, a single asterisk is presented in the table to indicate a statistically significant relationship between the independent and dependent variables. In the case of drivers’ race/ethnicity, an asterisk beside “White” identifies a statistically significant difference between some or all of the races/ethnicities and the outcome. In such a situation, the percentages for each group should be reviewed to identify the differences.

For warnings, there was a statistically significant relationship between drivers’ race/ethnicity and warnings. Traffic stops involving White drivers resulted in a warning in 26.0% of the cases, while traffic stop involving Other drivers ended in a warning in 17.7% of all occurrences. Drivers over the age of 30 received more warnings (26.3%) compared to those under 30 (24.9%). Also, young, Black male drivers received more warnings (27.8%) compared to non-young, Black male drivers. No significant differences were reported between drivers’ gender and warnings, or between young, Hispanic male drivers and warnings.

Analyses of citations indicated statistical significance for drivers’ race/ethnicity, gender, age, and one interaction term. Traffic stops involving Other (92.3%), Hispanic (89.5%), and Black (88.3%) drivers resulted in a citation more frequently than traffic stops involving White drivers (86.8%). Male drivers received a citation (87.4%) more frequently than female drivers (86.8%), and drivers under the age of 30 received citations more frequently (89.2%) than drivers 30 years of age or older (85.6%). Young, Hispanic male
drivers were cited more frequently (90.7%) compared to non-young, Hispanic male drivers (87.2%). No effect was reported for young, Black male drivers.

For arrest, Hispanic drivers experienced the highest rate (2.2%) compared to traffic stops involving White (1.6%) and Black (1.5%) drivers. Traffic stops of male drivers end in arrest twice as often as traffic stops of female drivers (1.8% compared to 0.9%), and drivers under the age of 30 were arrested at a slightly higher rate than drivers 30 years of age and older (1.6% compared to 1.5%). Both young, Black male drivers and young, Hispanic male drivers had higher rates of arrest compared to non-young, Black male drivers and non-young, Hispanic male drivers, respectively.

Conclusions based on bivariate analyses are limited because they do not consider the effect of any other independent variables (Batton & Kadlec, 2004). Thus, multivariate models were computed to assess if the statistically significant differences noted in the zero-order analyses are also present when other independent variables are introduced.

Table 5.1: Zero-Order Analyses of Driver Demographics & Traffic Stop Outcomes (N=280,567)

<table>
<thead>
<tr>
<th>Race/Ethnicity</th>
<th>Warnings</th>
<th>Citations</th>
<th>Arrests</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>26.0*</td>
<td>86.8*</td>
<td>1.6*</td>
</tr>
<tr>
<td>Black</td>
<td>25.8</td>
<td>88.3</td>
<td>1.5</td>
</tr>
<tr>
<td>Hispanic</td>
<td>25.8</td>
<td>89.5</td>
<td>2.2</td>
</tr>
<tr>
<td>Other</td>
<td>17.7</td>
<td>92.3</td>
<td>0.4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Gender</th>
<th>Warnings</th>
<th>Citations</th>
<th>Arrests</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>25.7</td>
<td>87.4*</td>
<td>1.8*</td>
</tr>
<tr>
<td>Female</td>
<td>25.8</td>
<td>86.8</td>
<td>0.9</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Age</th>
<th>Warnings</th>
<th>Citations</th>
<th>Arrests</th>
</tr>
</thead>
<tbody>
<tr>
<td>15-29 Years of Age</td>
<td>24.9*</td>
<td>89.2*</td>
<td>1.6*</td>
</tr>
<tr>
<td>30 Years of Age and Older</td>
<td>26.3</td>
<td>85.6</td>
<td>1.5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Interactions</th>
<th>Warnings</th>
<th>Citations</th>
<th>Arrests</th>
</tr>
</thead>
<tbody>
<tr>
<td>Young, Black Males</td>
<td>27.8*</td>
<td>88.3</td>
<td>2.1*</td>
</tr>
<tr>
<td>Non-Young, Black Males</td>
<td>25.6</td>
<td>87.2</td>
<td>1.5</td>
</tr>
<tr>
<td>Young, Hispanic Males</td>
<td>27.0</td>
<td>90.7*</td>
<td>3.0*</td>
</tr>
<tr>
<td>Non-Young, Hispanic Males</td>
<td>25.7</td>
<td>87.2</td>
<td>1.5</td>
</tr>
</tbody>
</table>

Note: Young drivers are between 15 and 29 years of age
Note: * = p < .0001
MULTIVARIATE ANALYSES

A series of bilevel models were estimated to further explore the relationship between driver demographics and traffic stop outcomes. Bilevel multivariate models consist of a lower unit of analysis nested within an upper unit of analysis (Raudenbush & Bryk, 2002), and offer an adjustment for correlated error in the multivariate relationships, such as spatial autocorrelation. In this research, all traffic stops were nested within the smallest organizational unit as a rough proxy for an organizational work group (Klinger, 1997).

All models were computed using a significance level of .0001^{48} due to the size of the sample (N = 280,567). All bilevel models were computed using the Bernoulli setting, which is appropriate for bilevel analyses involving dichotomous outcome variables (Raudenbush & Bryk, 2002). The warning and arrest models required a correction for overdispersion, which occurs when the standard error of the dependent variable is larger than the mean of that variable (Hanushek & Jackson, 1977). The level one coefficients for all models were fixed with the intercept left to vary randomly across level two units because the research hypotheses did not predict that these effects would differ significantly in magnitude across the level two units (Raudenbush & Bryk, 2002). All level one units were group mean centered for analysis. Group mean centering allows for interpretation within aggregates units by controlling for contextual effects across level two units (Raudenbush & Bryk, 2002). No predictor variables were entered at level two due to a lack of availability of theoretically relevant variables.

All multivariate models report coefficients and odds ratios for the independent variables. Bilevel, Bernoulli coefficients are interpreted similar to logistic regression

^{48} p < .0001 = The odds of observing a statistically significant relationship when none exists in the population.
coefficients and represent a change in the log of the odds ratio of the dependent variable for a one-unit change in the independent variable (Hanushek & Jackson, 1977). The odds ratio is interpreted as the change in likelihood of receiving the outcome based on the presence of the independent variable (Hanushek & Jackson, 1977). Odds ratios are only reported for statistically significant independent variables. All independent variables possessing a statistically significant negative relationship with the dependent variable have their odds ratios inverted for ease of interpretation (e.g., an odds ratio of 0.99 was inverted to 1.01).

As mentioned, traffic stop outcomes were examined as non-mutually exclusive and mutually exclusive variables. While these models contain the same independent variables, they differ in interpretation of the results. The non-mutually exclusive models report the occurrence of warnings, citations, and arrests even if the traffic stop encounter resulted in more than one outcome. The mutually exclusive models capture only the most severe outcome when examining the relationships between independent and dependent variables. Thus, the former models address the research questions posed initially in Chapter 4 (i.e., are driver demographics related to the likelihood of any warning, any citation, or any arrest?), while the latter models offer additional insight by exploring if driver demographics are related to the likelihood of receiving only a warning, a citation as the most severe outcome, or an arrest as the most severe outcome?

Non-Mutually Exclusive Models

Bilevel, Bernoulli models were computed for all three traffic stop outcomes and included driver, stop, vehicle, and officer characteristics. The specific variables, their coefficients, and their odds ratios are reported in Table 5.2. This table, and all subsequent

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49 The arrest models are identical in the non-mutually exclusive and mutually exclusive models. This is due to arrest being considered the most severe outcome. Thus, whether an arrest was accompanied by another outcome or was the sole outcome, the arrest models contain identical cases.
tables, are organized by dependent variable across the columns and by independent variables down the rows. The independent variables\textsuperscript{50} were grouped into driver demographics, other driver characteristics, stop characteristics, vehicle characteristics, and officer characteristics. Model statistics are provided at the bottom of the tables. For each dependent variable, all models were initially analyzed without any driver demographic interaction terms. These base models identified statistically significant associations between the independent variables and the traffic stop outcome. Thereafter, an additional set of models included driver demographic interaction terms to indicate if specific combinations of driver demographics have an effect beyond the independent effect of each variable. All base models and interaction models are reported in Table 5.2. These models generally did not differ in their effects; thus, they are discussed simultaneously below.

**Warnings**

Results from the bilevel warning model demonstrated no significant effect for minority drivers\textsuperscript{51} compared to White drivers (i.e., the excluded category). Male drivers were 1.1 times less likely to be warned and young drivers\textsuperscript{52} (i.e., under the age of 30) were 1.2 times less likely to be warned compared to female drivers, and drivers 30 years of age or older, respectively. In the interaction model, no statistically significant relationship was discovered for young, Black male drivers or for young, Hispanic male drivers and warnings.

\textsuperscript{50} All independent variables are dichotomous unless otherwise noted. Thus, any statistically significant results were interpreted in relation to the absence of that characteristic. Exceptions include drivers’ race/ethnicity – all groups relative to White drivers; number of reasons for the stop – results were interpreted relative to an additional reason for the stop; number of passengers – results were interpreted relative to an additional passenger in the vehicle.

\textsuperscript{51} Minority drivers refer to Black and Hispanic drivers only. Although Other drivers are comprised of minority races/ethnicities, it is difficult to assess their relationship with the dependent variable due to the multitude of groups in this category. Thus, results for Other drivers are reported with the other independent variables and are not discussed in relation to driver demographics.

\textsuperscript{52} All bilevel analyses reported in this chapter were also computed with drivers between the ages of 15 and 24 defined as young drivers. The results were generally identical with one important caveat – no interaction term reached statistical significance. Young drivers were defined as aged between 15 and 29 based on the age distribution of the variable.
The warning model results demonstrate the importance of examining the odds ratios for each statistically significant variable. Although, as noted, two driver demographic variables were statistically significant, neither had a particularly strong substantive relationship with the outcome. Thus, the results of all bilevel models should be interpreted with consideration of both the statistical and substantive significance.

Other independent variables possessing a negative relationship with warnings included traffic stops involving Other drivers (1.2 times less likely), traffic stops occurring during the daytime (1.2 times less likely), traffic stops conducted on an interstate highway (1.3 times less likely), traffic stops initiated due to speeding (2.1 times less likely), and traffic stops initiated by an officer assigned to a patrol function (2.3 times less likely). Independent variables positively related to warnings included traffic stops involving residents of the county in which the traffic stop was initiated (1.1 times more likely), traffic stops occurring on a weekday (1.1 times more likely), and traffic stops that were initiated for more than one reason (5.2 times more likely).

Citations

The base model and the interaction model differed slightly for citations. In the base model, neither Black nor Hispanic drivers were statistically related to citations compared to White drivers. In the interaction model, Hispanic drivers were 1.2 times more likely to be cited compared to White drivers. Moreover, the interaction model reported young, Black male drivers were 1.3 times less likely to be cited. No similar result was discovered for young, Hispanic male drivers. The lack of statistical significance for young, Hispanic male drivers requires a reinterpretation of the statistical significance of the main effect of Hispanic drivers – Hispanic drivers, who were not young and male, were 1.2 times more likely to be
cited compared to White drivers. Moreover, male drivers were 1.1 times more likely to be cited compared to female drivers, and young drivers were 1.5 times more likely to be cited compared to drivers 30 years of age or older.

Other independent variables positively related to citations included traffic stops involving Other drivers (1.4 times more likely), traffic stops occurring during the daytime (1.7 times more likely), traffic stops conducted on an interstate highway (1.5 times more likely), traffic stops initiated due to speeding (2.9 times more likely), traffic stops initiated for more than one reason (1.6 times more likely), and traffic stops initiated by an officer assigned to a patrol function (3.8 times more likely). Negative relationships between independent variables and citations included traffic stops involving residents of the county in which the traffic stop was initiated (1.2 times less likely), and traffic stops that resulted in the discovery of contraband (4.0 times less likely). The bilevel model examining citations has general similarities to the warning model in terms of the variables that achieved statistical significance; notably, the direction of these effects was frequently inverted.
Table 5.2: Non-Mutually Exclusive Bilevel Analyses of Traffic Stop Outcomes (N=280,567)

<table>
<thead>
<tr>
<th>Variables</th>
<th>WARNINGS</th>
<th></th>
<th></th>
<th>CITATIONS</th>
<th></th>
<th></th>
<th>ARRESTS</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-1.11</td>
<td>-1.11</td>
<td>2.14</td>
<td>2.14</td>
<td>-5.46</td>
<td>-5.46</td>
<td></td>
<td></td>
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</tr>
<tr>
<td><strong>Driver Demographics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>0.05</td>
<td>--</td>
<td>0.02</td>
<td>--</td>
<td>-0.06</td>
<td>--</td>
<td>0.01</td>
<td>--</td>
<td>-0.09</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.14</td>
<td>--</td>
<td>-0.12</td>
<td>--</td>
<td>0.18</td>
<td>--</td>
<td>0.22</td>
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<td>0.22</td>
</tr>
<tr>
<td>Other Race</td>
<td>-0.14*</td>
<td>1.15</td>
<td>-0.14*</td>
<td>1.15</td>
<td>0.32*</td>
<td>1.37</td>
<td>0.32*</td>
<td>1.37</td>
<td>-0.72</td>
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<td>Male</td>
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<td>1.09</td>
<td>-0.08*</td>
<td>1.09</td>
<td>0.12*</td>
<td>1.13</td>
<td>0.13*</td>
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</tr>
<tr>
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<td>-0.15*</td>
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<td>0.40*</td>
<td>1.49</td>
<td>-0.29*</td>
</tr>
<tr>
<td><strong>Other Driver Characteristics</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td>County resident</td>
<td>0.09*</td>
<td>1.10</td>
<td>0.09*</td>
<td>1.10</td>
<td>-0.14*</td>
<td>1.15</td>
<td>-0.14*</td>
<td>1.15</td>
<td>0.45*</td>
</tr>
<tr>
<td>State resident</td>
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<td>--</td>
<td>0.05</td>
<td>--</td>
<td>0.05</td>
<td>--</td>
<td>0.11</td>
</tr>
<tr>
<td><strong>Stop Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Daytime</td>
<td>-0.17*</td>
<td>1.19</td>
<td>-0.17*</td>
<td>1.19</td>
<td>0.50*</td>
<td>1.65</td>
<td>0.50*</td>
<td>1.65</td>
<td>-1.97*</td>
</tr>
<tr>
<td>Weekday</td>
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<td>1.12</td>
<td>0.11*</td>
<td>1.12</td>
<td>-0.02</td>
<td>--</td>
<td>-0.02</td>
<td>--</td>
<td>-0.85*</td>
</tr>
<tr>
<td>Summer</td>
<td>-0.00</td>
<td>--</td>
<td>-0.00</td>
<td>--</td>
<td>0.01</td>
<td>--</td>
<td>0.01</td>
<td>--</td>
<td>0.04</td>
</tr>
<tr>
<td>Interstate</td>
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<td>1.27</td>
<td>-0.24*</td>
<td>1.27</td>
<td>0.38*</td>
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<td>0.38*</td>
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<td>-0.75*</td>
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<td>1.06*</td>
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<td>1.65*</td>
<td>5.19</td>
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<td>0.49*</td>
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<tr>
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<td>-0.47</td>
<td>--</td>
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<td>4.00</td>
<td>-1.38*</td>
<td>4.00</td>
<td>4.47*</td>
</tr>
<tr>
<td>Number of Passengers</td>
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<td>0.02</td>
<td>--</td>
<td>-0.02</td>
<td>--</td>
<td>-0.02</td>
<td>--</td>
<td>-0.11*</td>
</tr>
<tr>
<td><strong>Vehicle Characteristics</strong></td>
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<td></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>State registration</td>
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<td>0.06</td>
<td>--</td>
<td>-0.04</td>
<td>--</td>
<td>-0.03</td>
<td>--</td>
<td>0.19</td>
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<tr>
<td><strong>Officer Characteristics</strong></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>-0.05</td>
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<td>-0.05</td>
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<td>-0.07</td>
<td>--</td>
<td>-0.08</td>
<td>--</td>
<td>0.31</td>
</tr>
<tr>
<td>White</td>
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<td>--</td>
<td>0.11</td>
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<td>-0.17</td>
<td>--</td>
<td>-0.17</td>
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<td>-1.17</td>
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<tr>
<td>Less than 5 Years Experience</td>
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<td>0.11</td>
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<tr>
<td>Patrol Assignment</td>
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<td>-0.86*</td>
<td>2.33</td>
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<td>3.82</td>
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<td><strong>Interactions</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young, Black Male</td>
<td>--</td>
<td>--</td>
<td>0.10</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>-0.26*</td>
<td>1.30</td>
<td>--</td>
</tr>
<tr>
<td>Young, Hispanic Male</td>
<td>--</td>
<td>--</td>
<td>-0.06</td>
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<td>--</td>
<td>-0.13</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td><strong>Model Chi-square</strong></td>
<td>24,171.78*</td>
<td>24,171.16*</td>
<td>18,174.27*</td>
<td>18,172.10*</td>
<td>3,012.33*</td>
<td>3,028.55*</td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Note: * = p ≤ .0001
Note: Young refers to drivers between the ages of 15 and 29.
Arrests

The bilevel model examining arrests reported no statistically significant effects for minority drivers compared to White drivers. Male drivers were 1.6 times more likely to be arrested compared to female drivers, and young drivers 1.4 times less likely to be arrested compared to drivers 30 years of age and older. No statistical significance was reported for either interaction term.

The strongest independent variable related to arrest was the discovery of contraband, which makes the likelihood of arrest 87.2 times more likely. Other variables positively related to arrest included traffic stops involving residents of the county in which the traffic stop was initiated (1.6 times more likely), and traffic stops initiated for more than one reason (1.5 times more likely). The remaining variables possessing statistical significance were negatively related to arrest and included traffic stops occurring during the daytime (7.1 times less likely), traffic stops conducted on a weekday (2.3 times less likely), traffic stops initiated due to speeding (3.0 times less likely), and traffic stops involving a vehicle with more passengers (1.1 times less likely).

Collectively, the multivariate models reflect mixed support for the results reported in the zero-order analyses. In regard to drivers’ race/ethnicity, the zero-order analyses reported statistically significant differences for all three traffic stop outcomes; conversely, the multivariate analyses reported Hispanic drivers were significantly more likely to receive citations (only once the interaction terms had been introduced), and Other drivers were related to warnings and citations. No other race/ethnicity effects were reported. The pattern for drivers’ gender and age was more consistent between the two analyses with the exception of drivers’ gender reaching statistical significance in the multivariate models, but not in the
zero-order analyses. Finally, the interaction terms were noticeably different between the two types of analyses. In the zero-order models, four of six relationships were statistically significant, whereas in the multivariate models, only one relationship was statistically significant (i.e., young, Black male drivers and citations). The bilevel models also differed slightly from the results of three logistic regression models, which analyzed warnings, citations, and arrests.

Mutually Exclusive Models

A second series of bilevel models were computed to identify any potential relationships between driver demographics and traffic stops that resulted in only a warning, a citation as the most severe outcome, or an arrest as the most severe outcome. These models differ from the previous bilevel models reported in Table 5.2 because of the change in definition of the dependent variable. All dependent variables reported in Table 5.3 are mutually exclusive; in other words, each traffic stop was only analyzed in one model. In the case of a traffic stop with more than one outcome, the most severe outcome was selected as the outcome to analyze. As a result, the least severe outcome, warnings, was reduced from occurring in 26% of the non-mutually exclusive outcomes to 12% of the mutually exclusive outcomes. Citations were only slightly reduced from 87% in the non-mutually exclusive outcomes.

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53 One final note on the bilevel non-mutually exclusive models is warranted. Logistic regression models were also computed using the identical independent and dependent variables included in the bilevel base model. The results of the logistic regression models were similar with two notable exceptions. First, the bilevel models identified fewer statistically significant variables suggesting that statistical significance in the logistic regression models was possibly a product of correlated error. For example, evidence discovered during the traffic stop and number of passengers switched to non-significance in the bilevel model for warnings. Second and related, the change in statistical significance was most pronounced in officer characteristics, but also evident in drivers’ race/ethnicity. For example, in the bilevel models, the only officer characteristic statistically related to any traffic stop outcome was officer assignment. In contrast, all five officer characteristics were significant in at least one of the logistic regression models. Moreover, Hispanic drivers were statistically less likely to be warned and Other drivers less likely to be arrested compared to White drivers in the logistic regression analyses.
outcomes to 86% in the mutually exclusive outcomes. The most severe traffic stop outcome, arrest, was unchanged in the two models.

**Warnings**

As a result of the changes in the frequency of the dependent variable, the mutually exclusive warning model demonstrated the greatest differences compared to the non-mutually exclusive models. Two important differences are worth noting. First, young, Black male drivers were 1.3 times more likely to be warned. This statistically significant result was not present in the non-mutually exclusive warning model. In addition, the main effect for Hispanic drivers indicated that this group was 1.3 times less likely to be warned compared to White drivers.

Second, a number of the other independent variables increased the strength of their relationship with warnings in the mutually exclusive model compared to the non-mutually exclusive model. For example, male drivers increased from 1.1 times less likely to 1.2 times less likely to be warned compared to female drivers. Younger drivers increased from 1.2 times less likely to 1.5 times less likely to be warned compared to drivers 30 years of age or older. Other increases were evident for Other drivers, traffic stops initiated during daytime hours, traffic stops initiated on interstates, traffic stops initiated due to speeding, and traffic stops initiated by officers assigned to patrol. Traffic stops involving county residents were no longer statistically significant, and number of reasons for the stop reversed statistical direction and resulted in a 1.7 times lower likelihood of warning for each additional reason. In the non-mutually exclusive warning model, each additional reason for the stop increased the likelihood of warning by 5.2 times.
Citations

The mutually exclusive citation model was virtually identical to the non-mutually exclusive citation model. One notable exception was the increase in strength of the evidence discovered variable. In the non-mutually exclusive citation model, traffic stops resulting in the discovery of evidence decreased the likelihood of citation by 4.0 times; however, the same relationship in the mutually exclusive model decreases the likelihood of citation by 14.3 times. This result is understandable as the discovery of evidence is the strongest predictor of arrest, and in the mutually exclusive models, traffic stops with citations and arrests are only analyzed in the arrest model.
Table 5.3: Mutually Exclusive Bilevel Analyses of Traffic Stop Outcomes (N=280,567)

<table>
<thead>
<tr>
<th>Variables</th>
<th>WARNINGS ONLY</th>
<th>CITATIONS ONLY</th>
<th>ARRESTS ONLY</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>Odds ratio</td>
<td>Coeff.</td>
</tr>
<tr>
<td>Intercept</td>
<td>-2.20</td>
<td>-2.20</td>
<td>2.07</td>
</tr>
<tr>
<td><strong>Driver Demographics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>0.07</td>
<td>--</td>
<td>-0.05</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.21</td>
<td>--</td>
<td>0.14</td>
</tr>
<tr>
<td>Other Race</td>
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<td>1.35</td>
<td>0.34*</td>
</tr>
<tr>
<td>Male</td>
<td>-0.15*</td>
<td>1.16</td>
<td>0.09*</td>
</tr>
<tr>
<td>Young</td>
<td>-0.37*</td>
<td>1.45</td>
<td>0.38*</td>
</tr>
<tr>
<td><strong>Other Driver Characteristics</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>County resident</td>
<td>0.11</td>
<td>--</td>
<td>-0.16*</td>
</tr>
<tr>
<td>State resident</td>
<td>-0.07</td>
<td>--</td>
<td>0.05</td>
</tr>
<tr>
<td><strong>Stop Characteristics</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Daytime</td>
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<td>0.58*</td>
</tr>
<tr>
<td>Weekday</td>
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<td>1.11</td>
<td>0.04</td>
</tr>
<tr>
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<td>--</td>
<td>0.00</td>
</tr>
<tr>
<td>Interstate</td>
<td>-0.37*</td>
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<td>0.39*</td>
</tr>
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<td>Speeding is the Reason for the Stop</td>
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<td>1.07*</td>
</tr>
<tr>
<td>Number of Reasons for Stop</td>
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<td>1.79</td>
<td>0.37*</td>
</tr>
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<td>Evidence found during Stop</td>
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<td>-2.61*</td>
</tr>
<tr>
<td>Number of Passengers</td>
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<td>--</td>
<td>-0.02</td>
</tr>
<tr>
<td><strong>Vehicle Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State registration</td>
<td>0.04</td>
<td>--</td>
<td>-0.05</td>
</tr>
<tr>
<td><strong>Officer Characteristics</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>0.06</td>
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<td>-0.11</td>
</tr>
<tr>
<td>White</td>
<td>0.18</td>
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<td>0.05</td>
</tr>
<tr>
<td>Less than 5 Years Experience</td>
<td>-0.09</td>
<td>--</td>
<td>0.07</td>
</tr>
<tr>
<td>Education Scale</td>
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<td>--</td>
<td>-0.05</td>
</tr>
<tr>
<td>Patrol Assignment</td>
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<td>3.85</td>
<td>1.34*</td>
</tr>
<tr>
<td><strong>Interactions</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young, Black Male</td>
<td>--</td>
<td>--</td>
<td>0.26*</td>
</tr>
<tr>
<td>Young, Hispanic Male</td>
<td>--</td>
<td>--</td>
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</tr>
<tr>
<td><strong>Model Chi-square</strong></td>
<td>17,877.27*</td>
<td>17,879.86*</td>
<td>17,951.64*</td>
</tr>
</tbody>
</table>

Note: * = p ≤ .0001
Note: Young refers to drivers between the ages of 15 and 29.
Additional Models

Several other bilevel models not reported in table form were computed to further explore if the results were consistent in other data configurations\textsuperscript{54}. One analysis examined only daytime traffic stops due to the possibility that the effect of drivers’ race/ethnicity, gender, and/or age was more prevalent during the daytime when these characteristics were more obvious to the officer. The results of the daytime only traffic stops analysis demonstrated no change in statistical significance for driver demographics and traffic stop outcomes. Thus, while traffic stops initiated during the daytime possess a relationship with being warned, cited, and arrested, the time of the day did not affect the relationship between driver demographics and traffic stop outcomes.

Assuming that officers have discretion with which to make decisions regarding traffic stop outcomes, the reason for the stop was targeted to specify the degree of discretion available to the officer. For example, traffic stops initiated based on pre-existing information (i.e., information provided prior to the traffic stop) may reduce the level of officer discretion and indirectly affect the traffic stop outcome. To test this supposition, analyses of traffic stops initiated only on pre-existing information were computed. In these models, pre-existing information was used as a proxy for the level of discretion available to the officer (i.e., these traffic stops had a lower level of discretion). These models did not demonstrate any change in the relationship between driver demographics and traffic stop outcomes.

Several alternative 3-way interaction models were also computed. One model included an interaction term for young, Black male drivers and 2-way interaction terms for young male drivers, Black male drivers, and young Black drivers. These 2-way

\textsuperscript{54} All additional analyses were computed with non-mutually exclusive dependent variables.
interaction terms were included to identify statistically significant relationships among the 2-way interactions that were potentially masked by only examining the 3-way interaction term. No significant effects were discovered for either the 2-way or the 3-way interaction terms with one exception. Young male drivers were actually 1.3 times less likely to be arrested. Identical processes were followed for young, Hispanic male drivers with the same result: young male drivers were 1.3 times less likely to be arrested.

One other set of analyses was computed to examine the impact of the large dataset under study. Rooted in the core principles of probability theory, statistical significance (i.e., the critical region necessary to reject the null hypotheses of no difference) is reached more easily as sample size increases (Hanushek & Jackson, 1977). This occurs because as sample size increases, the sample tested more closely resembles the true population. Any differences in the population would be treated as statistically significant. Although no statistical significance was discovered for the 3-way interaction terms using all 280,567 cases, a further test for significance was conducted using a sub-set of the data.

The large majority of cases in this dataset involved White drivers (i.e., slightly less than 90%). A smaller dataset was created that reflected a more even distribution of drivers’ race/ethnicity. To construct this smaller dataset, a sample of White drivers was randomly selected from all White drivers and set to match the number of Black drivers in the complete dataset. This sub-sample of White drivers was then merged with all remaining cases involving non-White drivers to form a data set of 67,196 cases. All previously described models were analyzed using this smaller dataset with similar results. Of note, some independent variables\(^{55}\) were no longer statistically significant in the

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\(^{55}\) Male drivers and county residents were no longer statistically related to warnings and citations.
analyses of the smaller sample. This indicates that some independent variables may be statistically significant due to sample size.

CONCLUSION

Collectively, the interaction models indicated a consistent pattern of main effects for drivers’ gender and age and traffic stop outcomes, but no main effect for drivers’ race/ethnicity (i.e., Black or Hispanic), with the exception of Hispanic drivers and citation. The interaction terms produced mixed results. Young, Black male drivers were more likely to be warned in the mutually exclusive model, and less likely to be cited in both the mutually and non-mutually exclusive models. No effect was reported for young, Black male drivers in any other model, and young, Hispanic male drivers had no relationship with traffic stop outcomes in any of the bilevel models. Other independent variables were significant predictors of traffic stop outcomes and their strength varied between the non-mutually exclusive and mutually exclusive models. The final chapter explores the implications of these results for traffic stop outcomes, the social conditioning model, and other research.
CHAPTER 6: DISCUSSION

INTRODUCTION

This research explored whether driver demographics were related to traffic stop outcomes. Using the social conditioning model as a theoretical foundation, officer-initiated traffic stops were analyzed using a series of bilevel, multivariate models. The analyses examined traffic stop outcomes as non-mutually exclusive and mutually exclusive variables. Both sets of models reported statistically significant relationships between drivers’ age and gender and traffic stop outcomes. The relationship between drivers’ race/ethnicity and traffic stop outcomes was mixed. Analyses involving interaction terms demonstrated that young, Black male drivers were less likely to be cited and more likely to be warned, although this latter effect was only present in the mutually exclusive model. No relationship was reported between young, Black male drivers and arrest or between young, Hispanic male drivers and any of the traffic stop outcomes. This chapter discusses the implications of these results for the research hypotheses, the social conditioning model, and future research.

RESEARCH HYPOTHESES

Two sets of hypotheses were presented and examined by operationalizing the dependent variables as non-mutually exclusive and mutually exclusive variables. The first set of research hypotheses predicted that drivers’ race/ethnicity, gender, and age were related to traffic stop outcomes, net of other factors. Specifically, the research hypotheses predicted:

- Minorities, males, and younger drivers will be more likely to receive a warning compared to White, females, and older drivers, net of controls.
- Minorities, males, and younger drivers will be *less* likely to receive a citation compared to White, females, and older drivers, net of controls.
- Minorities, males, and younger drivers will be *more* likely to be arrested compared to White, females, and older drivers, net of controls.

To test these hypotheses, bilevel regression models initially contained no interaction terms (i.e., base models). These models reported no statistically significant effects for minority (i.e., Black or Hispanic) drivers in any model, but consistent disparity was reported for drivers’ gender and drivers’ age. In both the non-mutually exclusive and mutually exclusive base models, drivers’ gender and drivers’ age were linked to arrests as hypothesized, but in the non-hypothesized direction for warnings and citations. These results offer partial support for the first set of hypotheses.

A second set of hypotheses focused on specific combinations of driver demographics (i.e., young, minority male drivers) and their relationships with the dependent variables, net of other factors and beyond the main effects of the independent variables. The research hypotheses predicted:

- The interaction of being minority, male, and young will lead to *more* warnings compared to other combinations of demographics, net of other factors.
- The interaction of being minority, male, and young will lead to *fewer citations* compared to other combinations of demographics, net of other factors.
- The interaction of being minority, male, and young will lead to *more* arrests compared to other combinations of demographics, net of other factors.

The estimation of the bilevel interaction models produced several notable results in addition to the statistical significance of drivers’ gender and drivers’ age. First, young, Black male drivers were *more* likely to be warned and *less* likely to be cited in the mutually exclusive models. Young, Black male drivers were also *less* likely to be cited in the non-mutually exclusive model. Both results support the research hypotheses.
Second, the main effects of drivers’ race/ethnicity were now statistically related to warnings and citations in the mutually exclusive interaction models. A main effect was also reported between Hispanic drivers and citations in the non-mutually exclusive models. Of note, these relationships only appeared in the interaction models and not in the base models; in other words, the inclusion of the interaction terms altered the main effect of drivers’ race/ethnicity on warnings and citations. These relationships, however, were in the opposite direction of the research hypotheses.

Third, no statistically significant relationships were found between young, minority, male drivers and arrest in either model. The zero-order analyses demonstrated a statistically significant relationship between arrest and these groups, but the inclusion of other variables in the multivariate analyses eliminated this effect. In particular, the measure of contraband discovered was an enormously strong predictor of arrest - increasing the likelihood of arrest by more than 80 times when present. Thus, it appears that the zero-order relationship was spurious and the presence of contraband discovered rendered the impact of these interaction terms non-significant. Young, Hispanic male drivers were also not statistically related to warnings or citations in either model. Both of these findings were contrary to the research hypotheses.

Finally, the main and interaction effects were more pronounced in the mutually exclusive models compared to the non-mutually exclusive models. In other words, the mutually exclusive models reported statistical significance in the relationships between Hispanics and warnings, and young, Black male drivers and warnings, and those relationships were not statistically significant in the non-mutually exclusive models.
Moreover, the effects of the other independent variables were stronger in the mutually exclusive models compared to the non-mutually exclusive models.

The cumulative effect of these findings generally supports the research hypotheses. Drivers’ gender and age were related to the traffic stop outcomes. Drivers’ race/ethnicity was associated with two of the three dependent variables for Hispanic drivers, and the interaction terms were also related to two of the three traffic stop outcomes for young, Black male drivers. As noted, these results are based on the mutually exclusive models; support for the research hypotheses was weaker when examining non-mutually exclusive traffic stop outcomes.

**Beyond Driver Demographics**

Several other independent variables were statistically related to the dependent variables. Some non-driver demographic variables were related to traffic stop outcomes in the hypothesized direction, while other variables exhibited statistical significance in the opposite direction of the hypotheses. For example, it was hypothesized that out of county drivers would be more likely to be arrested and less likely to be warned. The results indicated that out of county drivers were more likely to be warned and arrested, and less likely to be cited. There are two possible explanations for this result. It is possible that non-residents proportionately engage in more activities that can result in an arrest. Alternatively, it is possible that officers may treat non-residents more harshly (i.e., arrest) for similar activities that do not result in an arrest for residents. Data were not available to explore these explanations.

Eight stop characteristics were also included in the bilevel multivariate models. Of those eight variables, four variables were hypothesized to maintain a statistically
significant relationship with the dependent variables. In all cases, the predicted relationships were supported by empirical analysis. For example, consistent with the findings of Alpert et al. (2006), arrests were more likely to occur on a weekend compared to a weekday. Traffic stops initiated on an interstate were more likely to result in a citation than non-interstate traffic stops. This effect mirrors the results reported in analyses of data collected by the Washington State Highway Patrol (Lovrich et al., 2003; 2005). The discovery of contraband during a traffic stop had an extremely powerful positive relationship with the likelihood of arrest, which was evidenced in previous research (Engel et al., 2004; Engel et al., 2005; Engel et al., 2007d). Finally, the number of reasons for the stop was positively related to a citation or arrest. Only one hypothesized relationship was not supported – no statistical relationship was reported between traffic stops initiated on a weekday and issuance of a citation.

A series of other statistical relationships discovered were not specifically hypothesized. Some of these relationships are consistent with other research. For example, traffic stops initiated during the daytime were negatively related to warnings and arrests, and positively related to citations. Although the effects are weak, they are consistent with other research findings indicating arrests were more likely to occur during non-daytime hours and citations were less likely to be issued during those same hours (Alpert et al., 2006).

Other findings in the current research contradicted previous research results. The current research reported a positive relationship between daytime stops and citations. This is in contrast to Ingram (2006), who reported citations were more likely to be issued
during the evening. This discrepancy in results could potentially stem from jurisdictional differences.

The current research also reported traffic stops initiated on a weekday were positively related to warnings, but not related to citations. This result was unexpected for two reasons. First, it is not consistent with previous research showing citations were more likely to occur on weekdays (Alpert et al., 2006). Second, warnings and citations are frequently inversely related to one another. Thus, a negative relationship between warnings and weekdays would have been expected to accompany a positive relationship between citations and weekdays. One potential explanation for this difference is that Alpert et al.’s (2006) study was conducted in an urban environment, whereas nearly 50% of the officer-initiated traffic stops in this data set occurred on an interstate and likely in non-urban areas.

Other statistically significant relationships not initially hypothesized included interstate traffic stops, which produced fewer warnings, but more citations. The likelihood of warnings, citations, and arrests increased as the number of reasons for the stop increased. Traffic stops initiated due to speeding reduced the likelihood of warning or arrest, but increased the chance of citation. Traffic stops involving the discovery of contraband resulted in fewer citations, but more arrests. In such traffic stops, it is conceivable that the driver was more likely to be arrested than to receive a citation.

Finally, the likelihood of arrest was reduced as the number of passengers in the vehicle increased. This result is contradictory to past research on the impact of

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56 This trend was only reported in the non-mutually exclusive models; the mutually exclusive models indicated a negative relationship between number of reasons for the stop and warnings.
bystanders and the likelihood of arrest (Engel et al., 2000). Three possible explanations exist for such results. First, previous research on police-citizen encounters suggests that the likelihood of arrest increases with the number of bystanders. Importantly, this effect is accompanied by an increased level of disrespect toward the officer by the citizen. The demeanor of the citizen, which was not measured in these data, could be correlated with the number of passengers/bystanders. Therefore, without a measure of driver demeanor, the relationship between passengers/bystanders and traffic stop outcomes may not be properly specified. Second, it is possible that passengers in a vehicle during a traffic stop are not analogous to bystanders in a police-citizen encounter in non-traffic stop situations. Finally, vehicles with more passengers may not necessarily be involved in activities that warrant an arrest.

Officer characteristics were also hypothesized to possess a relationship with traffic stop outcomes. Two important findings emerged from the analyses involving officer characteristics. First, officers assigned to patrol were more likely than non-patrol officers to issue a citation and less likely to issue a warning. All other officer characteristics were not related to the likelihood of warning, citation, or arrest. Second, these results are based on the bilevel models and differ from the logistic regression models. In other words, officer characteristics became non-significant once the models included a correction for any spatial autocorrelation. The implications for this result are two-fold. First, analyses that do not consider organizational units may distort the relationship between officer characteristics and traffic stops outcomes. Second, further analyses should be conducted using organizational variables to assess if such variables are related to traffic stops outcomes.
These findings were consistent in both the non-mutually and mutually exclusive models, but stronger in the mutually exclusive models, with one exception\textsuperscript{57}. Although some variables differed slightly from previous research, the models generally produced results consistent with previous research, theoretical explanations, and/or logical arguments. Generalizability of these findings may be limited due to differences in geography or agency type. For example, traffic stop data sets primarily comprised of urban police-citizen encounters may produce slightly different results (e.g., Alpert et al., 2006).

**SOCIAL CONDITIONING MODEL**

The research findings have implications, not only for the research hypotheses, but also for the social conditioning model. The social conditioning model underpinned the research hypotheses; therefore, any research hypotheses receiving empirical support also indirectly validated the social conditioning model. Furthermore, as the social conditioning model is an explanation for disparity, it can be applied to understanding differences in results, such as between young, Black male drivers and young, Hispanic male drivers. The findings also present implications for future use of the social conditioning model.

The social conditioning model describes a process by which unconscious stereotypes are formed, and subsequently, these unconscious schemas impact decision-making (Smith & Alpert, 2007). In essence, this is a two-stage process involving acquisition of the stereotype and the effect of that stereotype. It is conceivable that the formation of stereotypes is an on-going, iterative process that is dynamic over time.

\textsuperscript{57} The relationship between number of reasons for the stop and warnings differed between the non-mutually exclusive and mutually exclusive models.
rather than a linear process. Due to a lack of measures, not all assumptions and propositions of the model were tested in this research. For example, the existence and intensity of stereotypes were not measured in the available data.

**Research Findings**

Several propositions of the social conditioning model were addressed indirectly through the research hypotheses. In other words, the social conditioning model implied specific relationships and those relationships were frequently uncovered by examining the research hypotheses. For example, drivers’ gender and drivers’ age were related to traffic stop outcomes and the specific driver demographic interaction terms were statistically significant, with minor exceptions. Young, Black male drivers were more likely to be warned and less likely to be cited, however the same relationships were not reported for young, Hispanic drivers. Collectively, a considerable number of testable predictions regarding the relationship between specific demographic groups and traffic stop outcomes were supported. Indirectly, these findings are consistent with the general tenets of the social conditioning model.

While general support is offered for the social conditioning model, some conclusions derived from the analyses require additional discussion. At first glance, the social conditioning model may have been expected to predict that young, minority male drivers would receive more severe outcomes. The interpretation would be as follows: the model suggests that unconscious processes underlie disparities in traffic stop outcomes, and these unconscious processes fuel extra scrutiny for young, minority male drivers leading to more severe outcomes. In such cases, the reason for the traffic stop is a pretext
for an investigation into potential criminal activity, and the traffic stop result would be higher rates of young, minority male drivers receiving more severe outcomes.

These unconscious stereotypes may be incorrect, however, and result in no discovery of elevated rates of criminal activity for these groups. In other words, the underlying, unconscious assumptions of the officer may not be valid. Thus, young, minority male drivers may be stopped as a means to interrupt criminal activity; however, if no such activity is occurring, the traffic stop is more likely to result in a warning rather than a citation. The results of this research support this explanation, as young, Black male drivers were less likely to be warned and more likely to be cited.

Further, the results reported statistically significant interaction terms for young, Black male drivers, but not for young, Hispanic male drivers. What are plausible explanations for this difference? It is possible that the source of these data do not present an opportunity for disparity to manifest. The state in which all traffic stops occurred is primarily comprised of White citizens (86%), with Black and Hispanic residents representing 11% and 4% of the population, respectively (US Census Bureau, 2004). While some areas may possess a greater concentration of Hispanic residents, Hispanics comprise a small percentage of the population. Applying this fact to the social conditioning model would suggest that officers working in this jurisdiction may not have personal or vicarious experience with Hispanic drivers. Moreover, the majority of media and societal images regarding young, minority male involvement in criminal activity centers on young, Black males. Thus, officers may not have formed unconscious stereotypes regarding young, Hispanic male drivers and criminal involvement, which
translates into less scrutiny for this group and no statistically significant disparity in results.

**Implications for the Future**

The research findings also present implications for the on-going use of the social conditioning model in research. Initially, the aforementioned difference in relationship strength between the non-mutually exclusive and mutually exclusive models may have repercussions for the social conditioning model. Differences between non-mutually exclusive and mutually exclusive models only arise when a traffic stop results in more than one outcome. Practically, if any differences exist between the two models, they will most likely be visible when analyzing the least severe traffic stop outcome (e.g., warnings). The key difference between these approaches is in the interpretation of the results; recognizing that disparity in traffic stop outcomes may be discovered using either the non-mutually exclusive or the mutually exclusive method.

As noted, the research findings differed slightly between the non-mutually exclusive and mutually exclusive models. The mutually exclusive models demonstrated more statistically significant relationships (e.g., interaction terms) and produced stronger effects for non-driver demographic variables. The mutually exclusive model identified disparities for Hispanic drivers and warnings, and young, Black male drivers and warnings. Such results offer greater support for the social conditioning model compared to that provided by the non-mutually exclusive models. Using the mutually exclusive method, two of the three interaction models reported statistically significant effects for the interaction terms, whereas one of the three models identified statistically significant effects for the interaction terms using the non-mutually exclusive approach.
As a result, the social conditioning model gained more corroboration from the mutually exclusive models. The non-mutually exclusive models also showed some driver demographic based disparities; however, the more consistent disparities reported in the mutually exclusive models indicate that the social conditioning model may be more appropriately applied to analyses examining the most severe outcome. Thus, using both operationalization methods would not violate the principles of the social conditioning model, but preference should be given to the mutually exclusive approach.

Another avenue of future exploration for the social conditioning model would be to examine data from different sources. One method of categorizing traffic stop data is to separate highway patrol data from urban, municipal data due to the different focus of these agencies. Highway patrol agencies often are concerned with speeding, DUI enforcement, or drug interdiction and perform less crime control, whereas urban, municipal agencies focus primarily on crime control and may place less emphasis on traffic related issues. Rather, the majority of their work may be focused on crime control rather than speeding or DUI enforcement. This distinction, while variable across agencies, may have implications for the social conditioning model.

It is conceivable that unconscious stereotypes may form differently in officers who primarily work in a highway patrol function compared to officers who work in an urban environment. According to the social conditioning model, two of the three sources of stereotype creation are personal and vicarious experiences (Smith & Alpert, 2007). These coalesce with media exposure to form schemas regarding specific citizen groups. Officers primarily working in a highway patrol function may form completely different stereotypes regarding young, minority males and their involvement in criminal activity.
compared to stereotypes formed by officers working in urban areas. Officers working on interstates and state routes likely have different personal experiences with these specific groups, and their vicarious experiences mainly influenced by their peers who also patrol similar locations. This is not to suggest that officers frequently working in a highway patrol function are not exposed to personal or vicarious images of young, minority males and crime, but the frequency of these interactions is likely lower compared to officers regularly working urban areas. This alteration in frequency may still result in the formation of unconscious stereotypes, but the intensity of these schemas is likely to be weaker. Thus, based on the principles of the model, a weaker stereotype regarding specific groups would lead to less disparity in traffic stop outcomes.

This dataset exemplifies such a case. While the organization is a full service agency and includes a variety of crime-related functions, such as investigations, the majority of the cases in this dataset are reflective of a highway patrol function. This is due to the nature of the data collection effort, which targets officer-initiated traffic stops and does not include calls for service or other forms of non-officer initiated enforcement. A significant portion of the dataset does not reflect criminal activity with the exception of proactive criminal interdiction activity. Thus, the officers initiating traffic stops analyzed in this dataset may not have had extensive exposure to minority groups involved in crime, which according to the social conditioning model is a key component to forming intense unconscious stereotypes regarding specific demographic groups.

The findings report that disparities were still discovered in the dataset even though it represents a primarily highway patrol function. The implication for the social conditioning model is that it does have applicability to explaining highway patrol type
activity in a non-urban area, as disparities were still evident for young, Black male drivers. Thus, the social conditioning model may be most applicable to officer decision-making in urban locales, but it is relevant even in locations where the development of unconscious stereotypes may be weaker. Future studies using the social conditioning model could test this hypothesis by examining data collected from an urban area.

In sum, the social conditioning model offers an explanation for disparity in traffic stop outcomes. The research findings offer general support for such an explanation. Furthermore, future analyses using the social conditioning model need to consider the operationalization of the dependent variable and the source of the data. Such considerations may result in additional support for the social conditioning model.

**RESEARCH IMPLICATIONS**

Finally, the research findings of this study have implications for other research even though they are not directly generalizable to other agencies due to organizational and geographic differences. Specifically, the findings offer insight for other research regarding the importance of theory, the use of different analytical techniques, and sources of data.

As evidenced by the reliance on the social conditioning model of this research, research on biased policing would benefit from a greater emphasis on theoretical frameworks. Originally argued by Engel et al. (2002), traffic stop research generally lacks a consistent theoretical foundation. Exceptions to this trend are beginning to surface, such as the social conditioning model. As described in this chapter, the existence of a theoretical framework assisted in developing testable hypotheses and provided an explanation for the results. Although the social conditioning model has not been fully
tested, this research has demonstrated its utility in conducting empirically sound and robust analyses.

Such theoretical frameworks feed the development of new research questions and challenge empirical studies to examine issues such as biased policing in new ways. For example, the maximum utility of analyzing traffic stop data may soon be reached (i.e., no greater knowledge is gained from continued analyses of traffic stop data), thus requiring new methods of studying police-citizen encounters. Theoretical frameworks, such as the social conditioning model, can inform and direct new avenues of research on potential disparities in traffic stop outcomes. Despite progress in the past fifteen years, there are numerous unanswered questions regarding the relationship between driver demographics and traffic stop outcomes. Grounding research in a theoretical framework is key to improved empirical understanding.

The current research also employed analytical techniques not often used in past research. For example, bilevel modeling was used as a correction for correlated error. The majority of previous research has not used bilevel modeling, thus raising a concern of potential model misspecification. Moreover, bilevel modeling offers the potential to study organizational effects that may be related to traffic stop outcomes. Organizational effects have not been fully explored in traffic stop research, but have been suggested as a potentially important set of factors related to officer decision-making (Klinger, 1997). The characteristics of traffic stop data require that traffic stops be nested with a higher unit of analysis, and bilevel modeling offers the most appropriate method to analyze these data.
Another analytical technique used in the current analyses applicable to future research was the non-mutually exclusive and mutually exclusive operationalization of the dependent variables. These methods produced slightly different results and highlight the need for future research to clearly specify how and why the dependent variable(s) is operationalized. The theoretical framework and specific research questions should be consulted whenever possible to guide this decision recognizing that the selection of one method instead of the other is not a zero sum outcome. Instead, the two approaches offer different information regarding the potential existence of disparity in traffic stop outcomes.

Previous research has most frequently used the non-mutually exclusive method (Alpert Group, 2004; Engel et al., 2004; Engel et al., 2005; Gumbhir, 2004; Lovrich et al., 2003; Lovrich et al., 2005) or not discussed the importance of this distinction. In so doing, such research may have missed identifying potential disparities. Moreover, the interpretation of the findings is more straightforward when using the mutually exclusive method. Thus, future research exploring for disparity would benefit from examining the most severe outcome using the mutually exclusive method.

Finally, these research findings are based on data collected from an agency often engaged in a highway patrol function. While some of the officer-initiated traffic stops were conducted in urban locations, the majority of police-citizen encounters occurred on interstates and state highways. Knowledge regarding traffic stop outcome disparities would increase by comparing data collected from a highway patrol type agency to data collected in an urban environment. Such results would offer insight into the processes described by the social conditioning model.
CONCLUSION

Concerns of biased policing in traffic stops have entered the public and research realms in recent years. Racial/ethnic, gender, and age disparities in traffic stop outcomes have been evidenced in previous research. The current research explored these issues by examining the cumulative effect of driver demographics on the likelihood of being warned, cited, or arrested. Guided by the social conditioning model, the analyses uncovered disparities for young, Black male drivers in warnings and citations, and for drivers’ gender and drivers’ age in association with all traffic stop outcomes.

These findings support continued exploration of disparity using the social conditioning model, bilevel modeling, and the mutually exclusive method of operationalizing traffic stop outcomes. Moreover, the discovery of a relationship between driver demographic based interactions and traffic stop outcomes has key implications for future research. Previous research has generally not examined the importance of considering these specific groups, and most of the discussion regarding disparity has been rooted in drivers’ race/ethnicity, with only a passing mention of drivers’ gender or age. Not only do future studies need to consider the main effects of driver demographics, but they must also investigate the existence of interactive effects.

In effect, the discovery of interactive effects based on all three demographics introduces a whole new series of research questions for exploration, such as: Are these findings unique to this dataset? Does disparity exist for young, Hispanic male drivers in other locations where Hispanic citizens comprise a greater percentage of the population? Are there other combinations of driver demographics that also experience disparities in traffic stop outcomes? Which of the three characteristics, if any, are more influential in
the disparate outcomes? Many additional research questions exist regarding the relationship between driver demographics and traffic stop outcomes. Theory, methodological rigor, and sound analytical techniques need to guide this new area of research to fully explicate these relationships.
CHAPTER 7: REFERENCES


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