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THE ROLE OF DRIVING BEHAVIOR IN THE DEBATE OVER RACIALLY BIASED POLICING

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ABSTRACT

The most frequently explored question in traffic stop data analysis studies is whether drivers' race/ethnicity influences police officers' stopping behavior. The public perceptions of racially biased policing are entirely focused on the behavior of police officers. Thus, it is not surprising that negative perceptions of the police contributed to the push for official traffic stop data collection. The limitation of this data collection has been to assume that the offending behavior of drivers that comes to the attention of police is equivalent across demographic groups, when little evidence exists to support this assumption. Research on racially biased policing has less frequently examined whether driver's offending behavior has an impact on stopping behavior by police. This neglect in previous work is particularly troublesome considering that most research on police behavior has found legally relevant offending behavior and offense severity to be among the strongest and most consistent predictors of various types of police actions.

Building on previous research that has documented demographic differences in travel patterns, illegal and risky driving behavior, the current study seeks to explore three research questions: 1) Does driving behavior vary by driver race, age, and gender? 2) Does severity of offending behavior vary based on demographic characteristics? 3) Do contextual level factors influence driving behavior? The general hypothesis to be tested by the current study is that racial / demographic groups are not equivalent in the nature and extent of their traffic law violating behavior.

To address these research questions, this study uses data collected for the Pennsylvania State Police Project on Police-Citizen Contacts during field observations of roadway usage and law-violating speeding behavior in 27 sampled counties across the state. Hierarchical multivariate models explore the influence on observed driving behavior of driver demographic characteristics, situational and contextual characteristics. Results indicate support for the hypotheses regarding the impact of driver demographic characteristics and contextual factors on driving behavior. These findings provide an alternative explanation for demographic disparities in police outcomes that is not based on officer bias, but rather legitimate offending differences. The implications of these findings for future traffic stop research are also discussed.

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CHAPTER 1: INTRODUCTION

The hostility of police-minority relations is often traced back to the volatile Civil Rights Movement and race riots of the 1960s, but the issues of race and policing are rooted much deeper in history (Jones-Brown & Maule, 2010; Walker & Katz, 2002; Williams & Murphy, 1990). Early in United States history, the nation's legal order sanctioned slavery and segregation; the police were agents of that order and bound to enforce it. The entire criminal justice system was predicated upon the subordination and legal inequality of African Americans. Therefore, it is not surprising that the pattern of policing that emerged and endured from this era was characterized by fewer civil rights for minorities, little police responsibility for protecting minorities from crime, and generally unrestrained police abuse against minorities (Harris 1999a; Kennedy, 1997; Walker, Spohn, & DeLone, 2000; Williams & Murphy, 1990). An understanding of the persisting degree of racial bias in policing today depends upon recognizing how this history inextricably links police, minority communities, and the broader social context of racism and discrimination (Fridell, Lunney, Diamond, & Kubu, 2001; Jones-Brown & Maule, 2010; Walker & Katz, 2002; Williams & Murphy, 1990).

The Civil Rights Movement in the 1960s challenged race discrimination in all areas of public life, but paid specific attention to the problem of racial discrimination in the criminal justice system. A number of reforms were instituted to eliminate racial discrimination and improve police-minority relations (e.g., community-oriented policing, or special police-community relation units, increased representation of minorities as agents of the criminal justice system, training in race relations, etc.); nevertheless, problems remain (Walker et al., 2000; Walker & Katz, 2002). Police-minority relations remain hostile partially because many reforms did not change daily police work and partly because positive gains were often overshadowed by high-profile failures like the incidents involving Rodney King, Abner Louima, Amadou Diallo, and LAPD's Rampart unit (Walker & Katz, 2002). Although institutionalized racial discrimination and overt prejudice that characterized earlier history is no longer officially sanctioned (Bernard, Engel, Calnon, & Hays, 2005), the fact is that at least the perception exists that the police continue to use race and ethnicity as an indicator of criminal behavior in law enforcement practices, including as part of the most current issue of racial profiling (Harris, 1999a; Kennedy, 1997).

As is clear from this brief overview, racial profiling is just the latest chapter in a long history of unequal treatment by police and hostile police-minority relations (Harris, 1999a; Kennedy, 1997; Walker & Katz, 2002; Walker et al., 2000). Indeed, scholars argue that racial profiling is a microcosm of the larger problem of current police-community relations that includes charges of inadequate police protection for minority communities, complaints of aggressive overenforcement and excessive force against minorities, and unwarranted stops and frisks, all of which contribute to minorities' higher distrust and fear of police (Fridell et al., 2001; Kennedy, 1997; Walker & Katz, 2002).

WHAT IS RACIAL PROFILING?

Racial profiling has become one of the most controversial and central topics in the practice of criminal justice and criminal justice research in the last decade (Ekstrand, 2000; Engel, Calnon, & Bernard, 2002; Fridell et al., 2001; Ramirez, McDevitt & Farrell, 2000). A consensus on its definition, however, has remained somewhat elusive. The term profiling can be traced back to the drug courier profiles used in the War on Drugs. As part of police efforts to interdict drug trafficking on the nation's highways, police agencies developed guidelines or "profiles" to help officers identify characteristics of drug couriers that could be used to target drivers and vehicles (Harris, 1999a). The problem of "racial profiling" developed when driver race and/or ethnicity began to be explicitly included as relevant indicators of involvement in drug trafficking by police departments across the nation, including in Florida, Maryland, Colorado, and New Jersey (Harris, 1997, 1999a, 2002; Tonry, 1995). Furthermore, the drug interdiction training materials associated with the DEA's Operation Pipeline, which encouraged targeting minority drivers with pretext stops as an effective tool of drug law enforcement, reached police officers in 48 states (Harris, 1999a).

The argument behind these types of policies was that, based on the racial distribution of particular types of offending behavior, profiling using driver race/ethnicity would ensure more efficient use of police resources than would random stops (Cole, 1999; Harris, 1999a; Kennedy, 1997; Taylor & Whitney, 1999; Walker & Katz, 2002). The most notorious example of this argument in defense of profiling was New Jersey's Chief of Troopers Carl Williams, who in 1999, was fired after publicly arguing that, "The drug problem is cocaine or marijuana. It is most likely a minority group that is involved with that" (Donahue, 1999).

Despite this rather narrow definition of profiling that began with drug trafficking, the growing consensus became that any and all decisions made by officers based solely or partially on the race of the suspect should be considered racial profiling (Ramirez et al., 2000). Fridell and her colleagues (2001), however, developed a new term instead of profiling—racially biased policing—because they argued that some past definitions of profiling may have been too restrictive, focusing exclusively on "sole" reliance on race. Their argument was that police decision making is rarely based on any *sole* factor, including race. Furthermore, in focus groups with citizens and police officers, Fridell et al. (2001) noted that citizens defined profiling as encompassing any and all demonstrations of racial bias in policing and viewed it as widespread. On the other hand, for police officers "profiling" connoted only the narrow definition of sole reliance on race; therefore, they viewed it as a much rarer occurrence. The differing definitions of profiling led to defensiveness and frustration as the two groups talked past each other (Fridell et al., 2001), thus the development of the new term. For the purposes of the current research, the term and definition of *racially biased policing* provided by Fridell and her colleagues (2001, 5) is adopted: "Racially biased policing occurs when law enforcement inappropriately considers race or ethnicity in deciding with whom and how to intervene in an enforcement capacity."

PUBLIC PERCEPTIONS, LEGISLATION, LITIGATION, AND DATA COLLECTION

Overall, media coverage, legislation, litigation, data collection, and scholarly research on the subject of racially biased policing have exploded in the last decade. A primary catalyst behind much of the legislative, judicial, and data collection activities reviewed here was the growing negative public perceptions of profiling as a tactic of law enforcement. The media were instrumental in bringing racially biased policing to the forefront of the nation's public consciousness by reporting about traffic stops of minorities, particularly high profile minority celebrities, and their treatment by police during such stops (Harris, 2002; Russell, 1999; Trende, 2000). Front page newspaper articles and lead stories on the evening news became commonplace in media coverage during the late 1990s and into the new century, undoubtedly contributing to negative public perceptions (Harris, 1999a; Ramirez et al., 2000). Negative public opinion, however, was not limited to minorities. Although perceptions of the police and racially biased policing are more negative and more widespread among Blacks, the public in general is dissatisfied with this tactic of policing. Several studies have also noted that the public disapproval of racially biased policing is contributing to less positive general public perceptions of police legitimacy and fairness (Engel, 2005; Lundman & Kaufman, 2003; Newport, 1999; Tyler & Wakslak, 2004; Weitzer & Tuch, 2002).

The recognition by government officials and police administrators that this legitimacy crisis threatened already tenuous police-minority relations spurred considerable government activity in the debate over racially biased policing (Engel & Calnon, 2004a). On the heels of the 1999 *Strengthening Police-Community Relationships* conference in Washington, D.C., legislators at all levels of government across the country initiated, and in many cases passed, two types of proposals: 1) those defining and prohibiting racial profiling or racially biased policing as a tactic of law enforcement, and 2) those initiating police departments' data collection on driver race and ethnicity for traffic stops (Hickman, 2005; Jones-Brown & Maule, 2010; National Conference of State Legislatures, 2001; Police Foundation, 2005; Ramirez et al., 2000; Strom, Brien & Smith, 2001; Strom & Durose, 2000).

Civil rights groups including the ACLU and NAACP have also played a role in pushing for government activity on racially biased policing. Though they have supported and lobbied for the legislation noted above, they have also invoked the judicial branch of government. These groups actively inform citizens of their rights during traffic stops and support legal cases that have arisen from police stops and searches perceived by minority citizens to be overly aggressive or unwarranted (Beck & Daly, 1999; Harris, 1999b; Russell, 1999). Civil and criminal litigation alleging racially biased policing has emerged in both state and federal courts (Ekstrand, 2000; Engel et al., 2002; Gabiddon, Marzette, & Peterson, 2007; Tillyer, Engel & Wooldredge, 2008; Smith & Alpert, 2002). These cases most frequently raise the question of selective enforcement by police officers on the basis of race, a violation of the Equal Protection Clause of the 14th Amendment (Tillyer et al., 2008; Smith & Alpert, 2002).

To successfully claim selective enforcement, petitioners must show both discriminatory effect and discriminatory purpose (*U.S. v. Armstrong*, 1996). Discriminatory effect is demonstrated by showing that "persons of another race violated the same law, but that the law was not enforced against them" (*U.S. v. Armstrong*, 1996). The courts have stated that statistical evidence may be used to establish discriminatory effect (*Castaneda v. Partida,* 1976; *Turner v. Fouche,* 1970; *U.S. v. Armstrong,* 1996; *Wo v. Hopkins,* 1886). What was quickly realized by petitioners and the courts, however, was that existing police statistics usually were not capable of addressing this question (Beck & Daly, 1999; Ekstrand, 2000; Tillyer et al., 2008; Smith & Alpert, 2002). In order to adequately challenge and adjudicate claims of racially biased policing, litigants must have access to data that can establish valid comparisons between those drivers stopped versus drivers eligible to be stopped (Smith & Alpert, 2002). Therefore the data necessary for answering the question of discriminatory effect is two-pronged—police collection of data on actual stops as well as benchmark estimates of those eligible to be stopped.

In response to this lack of appropriate statistical data, many courts requested that police departments collect traffic stop and benchmark data by race (e.g., *Chavez v. Illinois State Police*, 2001; Tillyer et al., 2008; *State of New Jersey v. Kennedy*, 1991; *State of New Jersey v. Smith*, 1997). A few selective enforcement cases, most relatively recent, have included data collection for rates of actual roadway usage and/or violating behavior as part of a comparison of stops and benchmark data deemed necessary by the courts (see *State of New Jersey v. Ballard*, 2000; *State of New Jersey v. Smith*, 1997; *State of New Jersey v. Soto*, 1996; *U.S. v. Alcaraz-Arellano*, 2004; *U.S. v. Lindsey*, 2003; *U.S. v. Parada*, 2003; *U.S. v. Stanley*, 2003; *U.S. v. Williams*, 2004). Civil and criminal litigation, thus, has contributed to the growing body of data collected on traffic stops and benchmark comparisons.

In summary, the increase in data collection on traffic stops is a result of three primary factors: the legislative push toward mandating police agencies to collect stop and benchmark data, the judicial decisions and federal consent decrees demanding the same, and proactive responses by police departments trying to respond to negative public opinion and keep pace with the national trend toward data collection (Engel et al., 2002; Hickman, 2005; Ramirez et al., 2000; Strom et al., 2001). The federal government tried to lead the push for data collection and obtain national level information on the characteristics of individuals subject to traffic stops by introducing the Police Public Contact Survey, initially completed in 1999 and repeated in 2002 and 2005 (Durose, Schmitt, & Langan, 2005, 2007; Ekstrand, 2000; Langan, Greenfeld, Smith, Durose, & Levin, 2001).

Analyses of the self-report data from these surveys revealed somewhat troubling results regarding stop outcomes and citizen perceptions of stops. First, blacks reported significantly more traffic stops than did whites (Lundman & Kaufman, 2003). Second, even controlling for other extra-legal and legal factors, the police were significantly more likely to cite, arrest, search, and use force during traffic stops against African Americans compared to Whites (Durose et al., 2005, 2007; Engel & Calnon, 2004a; Lundman, 2004). Third, searches of African-Americans were no more likely, and were actually less likely in the 2002 survey, to produce contraband than searches of other racial groups (Durose et al., 2005;

Engel & Calnon, 2004a; Lundman, 2004). Finally, African Americans were less likely to perceive stops as legitimate and more likely to say police acted improperly during stops than were whites (Engel, 2005; Lundman & Kaufman, 2003; Durose et al., 2005, 2007).

The growing amount of traffic stop data being collected by hundreds of police agencies nationwide required qualified social scientists to analyze and interpret such data and provided an opportunity for academic researchers to become involved in this public policy debate. Until about five years ago, scholarly reference to the issue of racially biased policing was virtually nonexistent, when only limited analyses had just begun (Ekstrand, 2000; Russell, 2001). At the present time, however, academic scholars are partnered with police departments across the nation in their data collection efforts. The increased participation of academic scholars in the collection, analysis, and interpretation of traffic stop data has led to a rapid improvement in the quality of data that addresses concerns about racially biased policing (Engel & Calnon, 2004b).

Nevertheless, it is important to understand that most of the initial traffic stop data collection efforts were undertaken due to fears of litigation, political pressure, local & state statutes, or court orders (Tillyer, Engel, Wooldredge, 2008). That is, citizens, legislators, and the courts demanded data collection to determine how prevalent the problem was, while departments wanted to show it was not happening. The overriding purpose, however, was not to understand or explain police behavior and decision making, which stands in contrast to the overwhelming majority of research on police behavior in the last 30 years that has sought to explain officers' decision making and behavior (Engel et al., 2002; Tillyer et al., 2008). Instead, much empirical research on the topic grew out of studies to support expert testimony to be used in lawsuits (Tillyer et al., 2008; Ramirez et al., 2000). As a result, the data collected were limited in what they could tell the public, the police, and researchers, and were easily subject to misinterpretation (Engel et al., 2002).

DISPARITY VS. DISCRIMINATION

Overall, early data collection efforts reported differences in aggregate rates of stops and stop outcomes, but researchers could only note that differences existed because, as stated above, they had not measured *why* they exist. The standard basis for determining that particular demographic groups are overrepresented in police stops is the difference between a group's *actual* proportion of stops and the same group's representation in a comparison group of the *expected* probability of such actions, assuming no police officer bias (Engel et al., 2002; Fridell et al., 2001; Ridgeway & MacDonald, 2010). This comparison is known as a benchmark. The most frequently utilized reference group for expected stops is one based on population statistics (Engel et al., 2002; Fridell, 2004; Ridgeway & MacDonald, 2010). Researchers and police departments must rely on the estimated population of drivers not stopped because the actual population of drivers not stopped but eligible to be stopped is unknown. Census data, however, are limited in their ability to measure alternative explanations of racial disparities including factors influencing drivers' risk of being stopped (e.g., where and when they drive, frequency of driving, what and how they drive) (Engel et al., 2002; Engel & Calnon, 2004b; Fridell, 2004; Ridgeway & MacDonald, 2010).

The Census' lack of measures of alternative explanatory factors, however, did not prevent some of the initial studies of traffic stops from prematurely interpreting disparity as discrimination and attributing racial disparities in stops and/or stop outcomes to unmeasured officers' racial prejudice (Engel et al., 2002). Most researchers in the field began to realize, however, that the hypothesis that police are racially biased in their stopping decisions is just one of numerous possible hypotheses or explanations for disparity in stops (Engel et al., 2002; Fridell, 2004; Wilson, Dunham, & Alpert, 2004). In addition to officer bias, scholars have offered the following alternative, race-neutral factors as possible explanations of racial and ethnic disparities in stops and stop outcomes: racial differences in travel patterns, location, frequency, and/or severity of law-violating driving behavior, as well as spatial characteristics like police deployment patterns (Cordner, Williams, & Velasco, 2002; Cox et al., 2001; Engel et al., 2002; Engel & Calnon, 2004a; Farrell et al., 2003; Fridell, 2004; Lansdowne, 2000; Rojek et al., 2004; Smith, Tomaskovic-Devey, Zingraff, Mason, Warren, & Wright, 2003; Washington State Patrol, 2001; Zingraff, Mason, Smith, Tomaskovic-Devey, Warren, McMurray, & Fenlon, 2000).

Without the measurement of any of these alternative explanatory factors, it simply cannot be determined whether differences in traffic stops and stop outcomes reflect disparity or discrimination (Engel et al., 2002; Ridgeway & MacDonald, 2010; et al., 2001; Rojek et al., 2004; Zingraff et al., 2000). That is, not all differences in outcomes mean that the police acted inappropriately. If a difference in groups' outcomes can be explained by legitimate factors, then it is merely considered a disparity, whereas a difference in groups' outcomes, which is unrelated to legally relevant considerations and instead based on some extralegal factor(s), is appropriately called discrimination (Walker et al., 2000). This question of disparity versus discrimination is not unique to traffic stops. Indeed, in the criminal justice system as a whole, one of the most compelling questions for researchers is whether disparity in outcomes involves legitimate differential behavior by particular groups or illegitimate differential selection by agents of the criminal justice system (Bernard et al., 2005; Lauritsen & Sampson, 1998; Walker et al., 2000).

Though data collection efforts across the country are more precisely capturing police behavior before, during, and after traffic stops, very little work is being undertaken to understand drivers' offending behavior that precedes police involvement. This is particularly troublesome considering that a General Accounting Office report in 2000 identified this type of data collection (and alternative explanation) as one of the most important avenues for future research to better explore (Ekstrand, 2000). Perhaps due to the politically volatile nature of even suggesting that disparity may be the result of citizens' behavior rather than police behavior (MacDonald, 2002), only a few studies, including the current research, have tried to assess whether driver offending behavior varies by demographic characteristics (Engel, Frank, Tillyer, & Klahm, 2006; Lamberth, 1994 1996; Lange, Blackman, & Johnson, 2001, 2005; Lundman & Kowalski, 2009; Smith et al., 2003).

PRESENT STUDY

Given the political environment of racially biased policing, it is very timely to question whether demographic differences in driving behavior exist that may explain disparate patterns in official police behavior. Charges of profiling are based on a seemingly inappropriate overrepresentation of racial groups in police stops. Demographic disparities in criminal justice outcomes, however, do not necessarily mean that criminal justice officials have acted inappropriately, although this has been the most frequently touted explanation with regard to the debate on racially biased policing (see Engel et al., 2002; Smith et al., 2003). As noted above, an alternative explanation to discrimination is that demographic disparities in traffic stops, just as with many other outcomes of the criminal justice system, may reflect differences in legally relevant offending behavior by members of different demographic groups (Walker et al., 2000).

A key question in the examination of racially biased policing has long been "does driver's race/ethnicity have an impact on vehicle stopping behavior by police" (Fridell, 2004, 4). The public perceptions of racially biased policing are entirely focused on the behavior of police officers. Thus, it is not surprising that the increasingly negative perceptions of police contributed to the push for collecting data on police behavior during traffic stops. The limitation of this data collection has been to assume that offending behavior of drivers that come to the attention of police is equivalent across demographic groups, when in fact, little evidence exists to support this assumption.

Much less research has asked whether driver's offending behavior (irrespective of race) has an impact on stopping behavior by police. The current study examines this much neglected question in research on racially biased policing: whether driving behavior may vary by race, age, and gender, thus providing, at least partially, legitimate explanations for demographic disparities in police outcomes. The neglect of offending behavior in most studies of racially biased policing is particularly troublesome considering that most other research on police behavior has found legally relevant offending behavior and offense severity to be one of the strongest and most consistent predictors of various types of police actions (Brooks, 2001; Engel, Sobol, & Worden, 2000; Klinger, 1994, 1996; Mastrofski, Worden, & Snipes, 1995; Mastrofski, Snipes, Parks, & Maxwell, 2000; National Research Council, 2004; Novak, Frank, Smith, & Engel, 2002; Riksheim & Chermak, 1993). Indeed, Fridell (2004, 17) argues that "driving behavior is a critical component of any model that seeks to explain decisions by police to stop drivers."

The legitimate differential offending explanation of the disparity in traffic stops is also important to explore because of the policy ramifications associated with this type of research. That is, each of the various possible explanations for disparity requires a different response by police. For example, if members of a particular demographic group tend to be more serious driving offenders, then we of course do not want police ignoring legally relevant offending behavior in order to eliminate the appearance of impropriety. On the other hand, if driving behavior and other race-neutral explanations of disparity are ruled out, then perhaps the appropriate policy response is for police officers to undergo racial sensitivity training or a review of appropriate stopping and searching procedures. The exploration of various explanations of disparity in traffic stops, therefore, is crucial to understanding how best to respond to such disparity (Engel et al., 2002).

OVERVIEW

The current study is organized into six remaining chapters. In Chapter 2, the bodies of research highlighted in the introduction are discussed in greater detail. Specifically, the two main catalysts behind traffic stop data collection are reviewed. First, this chapter describes how the prevalence of citizen perceptions of racially biased policing motivated many police agencies to collect data in order to counter these perceptions and show that their traffic enforcement behavior is legitimate, not based on racial status. Second, this chapter details how the rise in civil and criminal challenges to law enforcement practices perceived to be racially biased prompted the courts to call for data collection efforts that could effectively address the questions of discriminatory effect before them.

Chapter 3 describes the general trends in traffic stop data collection that were prompted by the negative citizen perceptions and judicial decisions described in Chapter 2. Specifically, this chapter outlines the overwhelming move among state and local police departments across the country toward the collection of official data for all traffic stops as well as the details of these collection efforts (Fridell et al., 2001; Hickman, 2005; Institute on Race and Poverty, 2001; Police Foundation, 2005; Strom et al., 2001). This chapter also reviews the various alternatives for benchmark data collection utilized by police agencies and researchers, including population estimates, surveys of roadway usage and drivers' violating behavior. Taking the position that these latter two types of benchmarks—based on drivers' roadway usage and violating behavior—are preferable to Census-based baselines, other research on drivers' behavioral differences are reviewed in the latter half of Chapter 3.

Chapters 2 and 3 provide the framework for the research questions and hypotheses presented in Chapter 4. Given the salient role of driving offending behavior in the debate over benchmarks and racially biased policing, this study builds on previous research that has documented demographic differences in travel patterns and various types of illegal or risky driving behavior. It explores these primary research questions: 1) Does driving behavior vary by driver race, age, and gender? 2) Does severity of offending behavior vary based on demographic characteristics? 3) Do contextual level factors influence driving behavior?

To address these questions, this study uses data collected through direct field observation of roadway usage and law-violating speeding behavior in 27 counties across the state of Pennsylvania. The data collection procedures utilized and data at the state and county level are described in the latter half of Chapter 4. The strengths and weaknesses of these data are assessed, with particular attention given to comparing the current study with previous observational data collection efforts.

Chapter 5 begins with a description of the measures. The dependent variable is speeding, a driving behavior that is objectively measured and whose severity is easily quantifiable. The independent measures include driver characteristics, vehicle characteristics, and situational characteristics. The chapter concludes with the explanation of the analytical strategy to be employed. The focus of this latter section is on the hierarchical or nested nature of the observation data and the complexities that using data at two levels of aggregation introduces.

Following this, the results of the bivariate and multivariate analyses of drivers' speeding behavior are presented in Chapter 6. First, this chapter examines bivariate differences in speeding behavior by gender, age, and race. Bivariate crosstabulation analyses examining speeding behavior by driver demographic characteristics are presented for each of the individual observed counties as well as for the overall statewide sample. Second, this chapter presents hierarchical Poisson and logistic analyses examining the influence of drivers' demographic characteristics, as well as situational and contextual characteristics, on observed speeding behavior.

Finally, Chapter 7 summarizes the study's results and discusses the impact of these findings within the context of the debate on racially biased policing and future traffic stop research. This discussion is specifically focused on the relationship between driver demographic characteristics and speeding behavior, and the implications of those relationships for traffic stop benchmark research.

CHAPTER 2: REVIEW OF ISSUES IN RACIALLY BIASED POLICING

Two interconnected issues contributed to the rise in data collection on racially biased policing: 1) citizen perceptions of police behavior, and 2) judicial assessments of actual police behavior. In this chapter, the research on citizen perceptions of police and racially biased policing is reviewed. These studies demonstrate that citizens' perceptions of racially biased policing constitute a real crisis of legitimacy for police agencies across the country. Countering these perceptions, therefore, was a major motivation behind police agencies' data collection on traffic stops. The other important catalyst behind traffic stop data collection efforts came from the judicial branch. This chapter documents the rise in civil and criminal challenges brought by minorities to law enforcement practices and describes how the questions of discrimination before the courts prompted calls for data collection of stops and benchmark populations.

CITIZEN PERCEPTIONS

As noted earlier, for minority citizens, racially biased policing during traffic stops is just the latest problem in a long history of unequal treatment by police (Fridell et al., 2001; Harris, 1999a; Kennedy, 1997). Scholars note that historical factors like underenforcement in minority communities and the mistreatment of minorities at the hands of police have contributed to minorities' lack of faith and distrust in police (Kennedy, 1997; Smith et al., 2003; Walker et al., 2000). Police use of race as an indicator of suspicion or criminality, in the past and in the current practice of racially biased policing, compounds the existing distrust and fear of the police by minority citizens (Harris, 1999a; Kennedy, 1997). Citizen perceptions of police thus take on an importance separate from the objective reality of police behavior, as perceptions of police illegitimacy may persist, even in the absence of actual police behavior that is inappropriate or illegitimate (Engel, 2005; Lundman & Kaufman, 2003; Smith et al., 2003; Weitzer & Tuch, 2002). The implications of such perceptions cannot be underestimated. Citizens who view the criminal justice system as unjust are less likely to cooperate with police and to participate in community problem-solving efforts, further isolating the police and minority communities from each other (Fridell et al., 2001; Tyler, 1990).

Scholars examining citizens' perceptions of the police have produced a long-standing and considerable body of research that has found minority attitudes and perceptions of police are more negative than Whites. Given the historical factors that contributed to the formation of such attitudes, it is not surprising that more dated studies show that, compared to White citizens, minority citizens had more negative general attitudes toward police, perceived that they were treated unfairly, and were less likely to support the legitimacy of the police (Albrecht & Green, 1977; Bayley & Mendelsohn, 1969; Carter, 1983; Decker, 1981; Dunham & Alpert, 1988; Jacob, 1971; Scaglion & Condon; 1980).

The disparity between Whites and minority groups' attitudes about the police, however, is not merely a historical relic. Research in the last 10 years continues to confirm earlier findings. Specifically, Blacks and Hispanics hold less favorable attitudes toward police than Whites do, are less likely to be satisfied with the overall performance of police than Whites are, and express less confidence in police than Whites do (Hurst, Frank, & Browning, 2000; Leiber, Nalla, & Farnworth, 1998; Taylor, Turner, Esbensen, & Winfree, 2001; Tuch & Weitzer, 1997; Webb & Marshall, 1995; Weitzer & Tuch, 1999). This continuing gap between Whites and minorities' attitudes toward police can be partially attributed to well-publicized incidents of police brutality like the Rodney King incident, which produce a greater decline in general support for police among Blacks and Hispanics than Whites, and tend to have more staying power for minorities' attitudes toward police than Whites (Lasley, 1994; Tuch & Weitzer, 1997).

Furthermore, racial differences in opinion are also evident in citizens' evaluations of police misconduct in general, and police treatment of minorities in particular. Whites are significantly less likely than Blacks and Hispanics to believe that police engage in a variety of types of misconduct (e.g., corruption, unwarranted stops, excessive physical force, and verbal abuse) and are less likely to see the need for reforms in policing (Weitzer & Tuch, 2004a; Weitzer & Tuch, 2004b). On the other hand, in comparison to Whites, Blacks are more likely to report that they are differentially hassled or mistreated by police, to feel that police protection in their neighborhoods is worse, to view racism among police as more prevalent, and to believe that they are generally treated differently by police (Browning et al., 1994; Tuch & Weitzer, 1997; Weitzer, 2000; Weitzer & Tuch, 1999). Other studies, however, have suggested that it is one's neighborhood context, rather than individual race and ethnicity, that is a stronger predictor of citizens' attitudes toward police (Frank et al., 1994; Reisig and Parks, 2000; Sampson and Bartusch, 1998; Weitzer, 2000).

The most recent additions to this literature focus on attitudes about and perceptions of racially biased policing and citizens' treatment by police during traffic stops. Anecdotal stories on minorities' personal experiences during police stops are abundant (Harris, 1999a, 1999b), but considerably fewer studies have empirically assessed citizens' experiences and perceptions of traffic stops and racially biased policing. A handful of recent studies are notable and reviewed below.

Using nationwide data from a 1999 Gallup telephone survey, Weitzer & Tuch (2002) discovered that the overwhelming majority of respondents, whether White or Black, reject racial profiling as a valid tool for police enforcement of the law. Respondents' race and personal experiences with profiling, however, were strong predictors of more specific attitudes toward police and profiling. Blacks were more likely than Whites: 1) to think that police treat Blacks in their community less fairly than they treat Whites during vehicle stops, 2) to hold unfavorable opinions of their local and state police, and 3) to report less favorable treatment during contacts with local and state police. Weitzer & Tuch (2002) also reported that Blacks were more likely than Whites to view racial profiling as widespread, to disapprove of it, and to claim to have been victims of it. Finally, they found that respondents who perceived they had had personal experience with profiling were significantly less satisfied with police and more likely to hold the opinion that profiling is widespread.

Using survey data from North Carolina residents, Smith et al. (2003) explored racial differences in general trust in the police, beliefs in profiling, and treatment during traffic stops. Examining trust in police first, African Americans were significantly more likely than Whites to distrust police, which the researchers showed was a function of not only their personal stop experiences, but also the reported stop experiences of their friends and family. Higher levels of distrust for police were evident for both African American and White drivers who were treated disrespectfully during a police stop. Moving to respondents' beliefs in profiling, Smith et al. (2003) found that African Americans were more likely than Whites to believe that police are more likely to pull over African American or Latino drivers. African Americans' belief that racial profiling exists was also dramatically increased by the experiences of their friends and family members. Similar to the findings for trust in police, both African American and White drivers treated with disrespect during a police stop were more likely to believe police racially profile. Finally, Smith et al. (2003) examined treatment by police during traffic stops. African Americans were more likely than their White counterparts to report being treated with less respect during stops and to report higher levels of disrespect in stops of household members and friends.

Reitzel, Rice, & Piquero (2004) examined perceptions of police profiling among Hispanics and non-Hispanics using data from a random sample of over 700 New York City residents aged 18-26 who were administered a *New York Times* New York Police Department Poll in January 2001. Respondents were asked whether they believed racial profiling was widespread, whether it was justified, and whether they felt they were ever stopped by police because of their race / ethnicity. Their findings indicated that both Blacks and Hispanics were more likely than non-Black and non-Hispanics to believe profiling is widespread, as were respondents who believed police to be disrespectful or who reported bad previous experiences with police (Reitzel et al., 2004). Blacks were less likely than non-Blacks to believe that profiling is justified, while Hispanics and non-Hispanics did not differ significantly on this question. Finally, both Blacks and Hispanics were more likely than their non-Black and non-Hispanic counterparts to believe they had been profiled.

In a series of four surveys that asked respondents about personal experiences with police, as well as general perceptions of racial profiling, police performance, and the legitimacy of police, Tyler & Wakslak (2004) examined whether citizens' perceptions of racial profiling and their inferences about the motives underlying police behavior affected their support for police. They found that support for police was significantly lessened among those who view profiling as more prevalent and not justified, and among those who think they have been personally profiled. Furthermore, those who felt profiled were less willing to accept police authority as legitimate and had more negative assessments of police performance.

Not surprisingly, minorities were more likely than Whites to believe profiling occurs (Tyler & Wakslak, 2004). Both minorities and Whites, however, viewed profiling as reflecting negatively on police and as undermining their legitimacy. Racial differences were evident in their attributions about police motives underlying profiling behavior. Whites were more likely to attribute profiling to being a natural byproduct of neutral crime fighting, a finding Tyler & Wakslak (2004) suggest may be due to the post-September 11th debate about profiling, whereas minorities were more likely to say profiling occurs as the expression of police prejudice.

Based on Tyler's (1990) procedural justice model, Tyler & Wakslak (2004) also expected that citizens' perceptions of profiling would be associated with their assessments of whether the police were procedurally fair during their experiences. Indeed, both minorities and Whites made determinations of profiling based on procedural elements of the quality of police decision making (e.g., neutrality, objectivity, consistency) and the quality of police treatment (e.g., politeness, respect). That is, if police were procedurally fair in respondents' past personal experiences then they were less likely to perceive that they had been profiled and less likely to say profiling was prevalent.

The 1999, 2002, and 2005 Police Public Contact Surveys asked national samples of citizens about their interactions with police, including during traffic stops (Durose et al., 2005, 2007; Langan et al., 2001). Two similar studies analyzed the 1999 data to examine citizens' perceptions of police legitimacy and appropriate behavior during traffic stops

(Engel, 2005; Lundman & Kaufman, 2003).[1] Their findings indicate that African Americans, those stopped more frequently, those searched, and those receiving a citation were significantly more likely to perceive stops as illegitimate and to say that police acted improperly during the stop (Engel, 2005; Lundman & Kaufman, 2003). African Americans' perceptions of injustice remained strong & consistent even after controlling for other extralegal and legal factors. Like Tyler & Wakslak (2004), Engel (2005) found that citizens were concerned with the fairness of the police procedures and outcomes, rather than just whether outcomes were favorable to them.

Understanding the implications of a loss of police legitimacy is crucial to an understanding of why police agencies have become so actively involved in data collection efforts to refute negative citizens' perceptions. Tyler (1990) explains that police agencies have to be concerned with citizens' perceptions because they influence citizens' willingness to defer to, accept as legitimate, and abide by the legal authority of police. Without citizens' voluntary compliance with police and other legal authorities, the criminal justice system would be effectively crippled, as it does not have the resources to rely only on the manipulation of costs and benefits to influence citizens' behavior (Tyler, 1990).

COURTS

Minority experiences with what they perceived to be overly aggressive and/or unwarranted traffic stops and searches contributed to an increase in the number of civil lawsuits and criminal appeals brought before the courts (Beck & Daly, 1999; Gabiddon et al., 2007; Jones-Brown & Maule, 2010; Russell, 1999). These challenges to police behavior initially were largely based on the 4th Amendment's prohibition of unreasonable searches and

[1] The Department of Justice reports on the 2002 and 2005 survey data are the only published reports available for these data. Any secondary analyses of these data are heretofore unpublished. The DOJ reports indicate similar findings between the 1999 and more recent surveys (Durose et al., 2005, 2007).

seizures. The legal issues associated with racially biased policing, however, were changed dramatically with the Supreme Court's rendering of its decision in *Whren v. U.S.* (1996). The issue before the Court in *Whren* was a question of the constitutionality of pretextual stops, stops that are made based on commonly occurring traffic violations with the subjective intention of investigating other potentially more serious legal violations (*Whren v. U.S.*, 1996). As described by Smith & Alpert (2002, 683):

> The primary issue in *Whren* was whether a traffic stop that was made with reasonable suspicion of a traffic infraction was nonetheless unlawful if the officer had an ulterior motive in making the stop.

In *Whren,* the Supreme Court upheld the legality of pretextual stops, stating that as long as the police officer had a legal basis for making the stop, there was no violation of the Fourth Amendment protection against unreasonable searches and seizures. The Court ruled that it was simply irrelevant whether the decision to stop was also based on racial bias if the officer could have made the stop for a legal violation (Tillyer et al., 2008; Smith & Alpert, 2002, *Whren v. U.S.*, 1996).

Numerous legal scholars (e.g., Beck & Daly, 1999; Harris, 2001; Lyle, 2001; Trende, 2000; Williamson, 2003) have noted that the *Whren* decision effectively closed the door to Fourth Amendment claims of unreasonable searches based on police racial bias, which Smith & Alpert (2002, 683) noted is the "primary mechanism for checking overly intrusive police behavior in most other contexts." Since *Whren*, most litigation alleging racially biased policing is now brought before the courts on the grounds of selective enforcement, a violation of the Equal Protection clauses of the Fifth and Fourteenth Amendments to the U.S. Constitution (Tillyer et al., 2008; Smith & Alpert, 2002). As Justice Scalia noted in writing the unanimous opinion of the Supreme Court:

> We of course agree with petitioners that the Constitution prohibits selective

> enforcement of the law based on considerations such as race. But the constitutional basis for objecting to intentionally discriminatory application of laws is the Equal Protection Clause, not the Fourth Amendment (Whren v. U.S. 517 U.S. 806, at 813).

Litigation based on selective enforcement requires the plaintiff to show that: 1) the police officers unequally enforced a facially neutral law with a "discriminatory purpose" in mind, and 2) their actions had a "discriminatory effect" (Tillyer et al., 2008; Smith & Alpert, 2002; *U.S. v. Armstrong*, 1996; *U.S. v. Bell*, 1996). Proving discriminatory purpose is often problematic, as police officers are unlikely to admit such behavior and evidence of overtly discriminatory policies is equally unlikely. In the absence of explicit admissions of discrimination, persons alleging selective enforcement usually must rely on some inference of discriminatory intent from a totality of circumstances in the case, which often includes some presentation of statistical evidence (*Chavez v. Illinois State Police*, 2001; Tillyer et al., 2008; Smith & Alpert, 2002; *Village of Arlington Heights v. Metro Housing Development Corp*, 1977).

As for the second prong of selective enforcement, the Supreme Court previously established in *U.S. v. Armstrong* (1996) that to show discriminatory effect "citizens must demonstrate that persons of another race violated the same law, but that the law was not enforced against them" (Smith & Alpert, 2002, 683). Tillyer, Engel, and Wooldredge (2008) note that the courts have long accepted statistical evidence about "similarly situated individuals" to establish discriminatory effect (*Castaneda v. Partida,* 1976; *Turner v. Fouche,* 1970; *U.S. v. Armstrong,* 1996; *Wo v. Hopkins,* 1886). The accepted use of statistics as proof of equal protection violations, however, generally has been limited to cases involving employment discrimination and the selection of jury venires (Tillyer et al., 2008; *McClesky v. Kemp*, 1987; The Alpert Group, 2004).

With the Supreme Court's decision in *Whren*, however, statistical evidence about similarly situated individuals became particularly important in cases dealing with traffic stops, as it is difficult, if not impossible, to name a similarly situated driver that was not stopped (Tillyer et al., 2008). It was quickly evident that the legal requirements for proving discriminatory effect would necessitate new data collection efforts to provide relevant statistical evidence about similarly situated individuals. More specifically, to be applicable for cases involving selective enforcement, statistical research needed to be "able to adequately measure and compare rates of racial/ethnic groups' traffic stops to their representation in the population *eligible* for traffic stops" (Tillyer et al., 2008, 148, emphasis added). Such a comparison requires two types of data: police stop data (the numerator) and some type of baseline comparison data (the denominator) (Smith & Alpert, 2002). The details of both stop and benchmark data collection are reviewed in the following chapter, but the discussion below highlights how the legal requirements for proving selective enforcement drove the development of data collection efforts on racially biased policing.

Data for all stops, broken down by race, are necessary to establish the numerator in the similarly situated persons comparison described above. Although police document many stops, often existing official data was and continues to be insufficient for addressing claims of racially biased policing because it does not include racial data for all stops regardless of their outcome (Beck & Daly, 1999; *Chavez v. Illinois State Police, 2001*; Ekstrand, 2000; Hickman, 2005; Smith & Alpert, 2002; Strom et al., 2001; Strom & Durose, 2000). Recognizing the need for accurate official data on stops, however, growing numbers of state police agencies have begun mandating the collection of racial data for all traffic stops in the last ten years (Hickman, 2005; Strom et al., 2001; Strom & Durose, 2000).

Obtaining racial data for the denominator of the similarly situated persons comparison was even more complex. The primary issue was no agreement from the courts or researchers on what benchmark population would be most appropriate for comparisons with official stop data (Engel et al., 2002; Farrell et al., 2003; Fridell et al., 2001; Fridell, 2004). Indeed, cases that have introduced statistical evidence in order to show discriminatory effect in selective enforcement cases have introduced four different types of comparison data: 1) population estimates based on the Census (*Chavez v. Illinois State Police*, 2001; *Commonwealth of Massachusetts v. Lora*, 2003; *Harris v. City of Virginia Beach*, 2001), 2) internal comparisons among officers (*U.S. v. Alcarez-Arellano*, 2004; *U.S. v. Hare*, 2004; *U.S. v. Mesa-Roche*, 2003), 3) surveys of road usage (*State of New Jersey v. Smith*, 1997; *State of New Jersey v. Soto*, 1996; *U.S. v. Alcaraz-Arellano*, 2004; *U.S. v. Lindsey*, 2003; *U.S. v. Parada*, 2003; *U.S. v. Stanley*, 2003), and 4) surveys of violating behavior (*State of New Jersey v. Ballard*, 2000; *State of New Jersey v. Soto*, 1996; *U.S. v. Williams*, 2004).

To further complicate matters, Tillyer et al. (2008) noted that statistical comparisons based on benchmark data from the *same* research methodologies have been accepted as sufficient evidence of discriminatory effect in some courts, but not others. Specifically, while not unanimous, growing numbers of both state and federal cases have concluded that population statistics do not provide reliable comparisons of similarly situated persons against which traffic stops can be compared. Furthermore, the opinions in these cases have suggested that, for the purposes of showing discriminatory effect, they would find statistical comparisons of stops and benchmark data most compelling when the comparison populations were based not on population baselines, but rather rates of drivers' actual roadway usage or, even more preferable, violating behavior (*Chavez v. Illinois State Police*, 2001; *State of New*

Jersey v. Kennedy, 1991; *State of New Jersey v. Smith*, 1997; *U.S. v. Alcaraz-Arellano*, 2004; *U.S. v. Lindsey*, 2003; *U.S. v. Mesa-Roche*, 2003).

Indeed it was the recommendations of one of the earliest of these cases (*State of New Jersey v. Kennedy*, 1991) that Dr. John Lamberth was following when he initiated the first attempts to establish a driving population of "similarly situated individuals." He did so for the purposes of fulfilling the discriminatory effect prong of selective enforcement in separate legal cases in New Jersey and Maryland (*State of New Jersey v. Soto,* 1996; *Wilkins v. Maryland State Police,* 1994). The methodological details of these benchmark data collection efforts are described in the following chapter, but the implications of this work for the collection of data on similarly situated individuals are discussed here.

In both cases, litigants challenged the state police use of traffic stops as racially biased on particular limited access highways: the New Jersey Turnpike and Interstate 95 in Maryland. Lamberth (1994, 1996) used observation teams on these highways to collect data on the racial and ethnic distribution of motorists using and speeding on these roadways. The results indicated that the overwhelming majority of drivers were violating the posted speed limits, that there were no significant differences in the speeding behavior of White and Black drivers, and that the percentages of minorities observed and/or speeding was significantly smaller than their representation among official stop and arrest statistics.

Despite a number of important limitations (detailed in the following chapter) in Lamberth's violator survey methodology, Lamberth created statistical evidence on similarly situated individuals that successfully supported claims of selective enforcement (see *State of New Jersey v. Ballard 2000; State of New Jersey v. Clark 2001; State of New Jersey v. Francis 2001; State of New Jersey v. Soto 1996).* Although federal court cases have subsequently dismissed Lamberth's more recent work as insufficient for establishing discriminatory effect (see *U.S. v. Alcaraz-Arellano* 2004; *U.S. v. Duque Nava* 2004; *U.S. v. Mesa-Roche* 2003), his studies in New Jersey and Maryland became the model for benchmarking of similarly situated individuals. Indeed, his work provoked studies that furthered this type of methodology and now sets the standard for benchmarking data collection in the field of research on racially biased policing. It is important to note, however, that the methodological development and collection of racial data for traffic stops and benchmark comparisons did not result from a desire to understand police behavior, but rather were entirely driven by the need to provide evidence of discrimination in the legal arena (Tillyer et al., 2008).

SUMMARY

This chapter reviewed how citizen perceptions of racially biased policing and judicial decisions have contributed to the increase in data collection on traffic stops and benchmark comparisons. The desire to counter citizen perceptions' of the prevalence of racially biased policing and show that their enforcement behavior was legitimate, not based on racial status, motivated many police agencies to begin to collect data on their traffic stops. The other important catalyst behind traffic stop data collection efforts came from the judicial branch. As a result of minorities' experiences with police, some began to bring civil and criminal challenges to law enforcement practices they perceived to be racially biased. Legal requirements for statistical evidence of discriminatory effect prompted courts to call for data collection of stops and benchmark populations because existing police data could not adequately address the questions before the courts. The resulting data collection efforts are reviewed in the next chapter.

CHAPTER 3: TRAFFIC STOP & BENCHMARK DATA COLLECTION

The first part of this chapter documents the main elements of the traffic stop and benchmark data collection that resulted from the public pressure and judicial decisions reviewed in Chapter 2. As will be reviewed, this overwhelming push toward data collection left most police agencies with an abundance of data that was not particularly meaningful, as stop data was overwhelmingly being compared to residential population figures to determine whether disparity exists (Engel & Calnon, 2004b; Fridell, 2004; Ridgeway & MacDonald, 2010). The main issue is that the measurement of drivers' behavior, to which presumably police behavior is in response, was neglected in the vast majority of these studies.

The second half of this chapter reviews the extant research on demographic differences in driving behavior as the background for the central question this study examines: Are there racial differences in legally relevant offending behavior that might explain seemingly inappropriate racial disparities in traffic stops based on comparison with population statistics? Without the exploration of such a possibility, conclusions of racially biased policing are simply unfounded (Engel et al., 2002).

TRAFFIC STOP DATA COLLECTION

The pervasive and continuing perceptions that police officers inappropriately use race as a factor in traffic stop decision making has prompted an overwhelming move toward the ongoing collection of official data for all traffic stops by state and local police departments across the country (Fridell et al., 2001; Hickman, 2005; Institute on Race and Poverty, 2001; Police Foundation, 2005; Strom et al., 2001). As noted by Engel et al. (2002), some of these data collection efforts were a result of court and legislative mandates. Increasing numbers of police agencies each year, however, are voluntarily implementing programs that require their officers to record the race of drivers that are stopped and/or searched (Fridell et al., 2001; Hickman, 2005). This is a direct effort by police agencies to address public perceptions of biased-based police behavior. It sends a message to their communities that they are concerned both about their credibility with the public and with maintaining effective and fair methods of policing that do not include race-based decision making (Ramirez et al., 2000). Furthermore, data collection has been spurred by a real desire on the part of police administrators to move past a reliance on the anecdotal stories and evidence to a more systematic and objective empirical analysis of the role of race, if any, in police traffic stops (Ramirez et al, 2000; Fridell et al., 2001).

Two primary resources exist for police agencies and researchers determining what to include in their traffic stop data collection efforts: *A Resource Guide on Racial Profiling Data Collection Systems* (Ramirez et al., 2000) and *Racially Biased Policing: A Principled Response* (Fridell et al., 2001). Although the question of what data police agencies should collect varies with their definition of racial profiling or racially biased policing, there is a growing consensus that any and all decisions made by officers based solely or partially on the race of the suspect should be included (Ramirez et al., 2000). Thus, we have witnessed a movement from some earlier studies that only collected data for stops with particular outcomes (i.e., only if citation/search/arrest occurred) toward data collection for all vehicle stops (Engel et al., 2002; Fridell et al., 2001). The following list of data fields is generally representative of the recommended items for police agencies to include in their officer-involved data collection efforts:

- Time and date of stop, the location where stop occurs, and duration of stop,
- Reason for stop and outcome of stop
- Drivers' characteristics (age, gender, race/ethnicity, residency)
- Vehicle registration and/or state of license

- Whether search of vehicle or person is initiated, reasons or authority for search, and whether and what type of property/evidence is seized
- Employee and/or barracks identification (Fridell et al., 2001; Ramirez et al., 2000).

Findings from virtually all data collection efforts have indicated that some disparities exist for police stops, citations, searches, and arrests of different racial groups, though the size of disparity varies widely by agency, type of stop outcome, and most importantly, the type of data to which stops are compared (for review, see Engel et al., 2002; Kowalski & Lundman, 2007).[2] That is, examining how often police stop members of various racial groups is merely an exercise in descriptive statistics and not particularly meaningful until those percentages are compared to some "expected probability" of being stopped for different racial groups. For example, if a police department collects data and determines that 20% of their stops are of Blacks, the interpretation of whether that 20% is disparate or discriminatory depends on what percent of Blacks are in the comparison population. This type of comparison, known as a benchmark or base rate, is an attempt to quantify how much disparity exists (Fridell et al., 2001; Rojek et al., 2004).

BENCHMARK DATA COLLECTION

As noted above, the standard basis for determining if particular demographic groups are over or under represented in police stops is a benchmark—the difference between a group's *actual* proportion of stops and the same group's representation in a comparison group of the *expected* probability of such actions, assuming no police officer bias (Engel et al., 2002; Fridell et al., 2001; Fridell, 2004; Ridgeway & MacDonald, 2010). However,

[2] A specific review of the hundreds of jurisdictions collecting traffic stop data and the findings of the publicly available reports for various police agencies is beyond the scope of this literature review. For a thorough listing of these data collection efforts and available final reports, see the website developed and updated by the Institute on Race and Justice at Northeastern University: http://www.racialprofilinganalysis.neu.edu.

simply demonstrating a disparity between, for example, the percent of minorities stopped and the percent living in a particular area, does not necessarily indicate police officers have acted inappropriately. Rather, an alternative explanation is that disparities may reflect differences in unmeasured legally relevant behavior by racial groups (Walker et al., 2000). Benchmark comparisons represent researchers' attempts to isolate race as an explanatory factor for disparity in traffic stops from the driving quality explanation and other possible alternative factors, including driving quantity, driving location, and time of travel (Fridell, 2004). While alternative explanatory factors are typically examined in multivariate analyses, benchmark comparisons are necessary for analyses of stops. Unlike analyses of stop outcomes where the comparison population—all stopped drivers—is known and multivariate analyses can be estimated, with stops the similarly situated population (drivers eligible for stops but not) is unknown and can only be approximated (Tillyer et al., 2008; Fridell, 2004).

In this effort to rule out factors other than racial discrimination in traffic stop research, social scientists have utilized several different data sources to measure comparison groups, some of which were readily available and others that involved initiating new data collection (Engel et al., 2002). Although there is general agreement upon the elements of data collection for actual traffic stops, there is little consensus on what constitutes a valid benchmark measure of "expected" rate of stops against which official stop data can be compared (Engel et al., 2002; Farrell et al., 2003; Fridell et al., 2001; Fridell, 2004; Ridgeway & MacDonald, 2010). The most common types of benchmark data include: adjusted and unadjusted Census data, official accident data, DMV records of licensed drivers, citizen surveys, internal departmental comparisons, observations of roadway usage, and assessments of traffic violating behavior (Engel & Calnon, 2004b; Fridell et al., 2001;

Fridell, 2004; Ridgeway & MacDonald, 2010). Each benchmark is an attempt to most closely approximate the pool of drivers from which drivers eligible to be stopped are selected. As noted in the review of legal considerations of racially biased policing, the benchmark is comparable to the "similarly situated individuals" used in statistical analyses to demonstrate discriminatory effect in selective enforcement cases (Tillyer et al., 2008). Each type has strengths and limitations in their ability to actually represent the group of people at risk of being stopped, and none has the ability to adequately measure *all* the risk factors associated with the likelihood of being stopped (Engel & Calnon, 2004b; Tillyer et al., 2008; Fridell et al., 2001; Fridell, 2004; Ridgeway & MacDonald, 2010). Three of the benchmarks listed above—population estimates, surveys of roadway usage, and surveys of offending behavior—and their strengths and weaknesses are reviewed below.

Population Estimates

Most of the initial studies of traffic stops by police relied on population estimates to determine "expected probabilities" (e.g., ACLU, 2000; Cordner et al., 2002; Cox et al., 2001; Lansdowne, 2000; Smith & Petrocelli, 2001; Spitzer, 1999; TDPS, 2000; Verniero & Zoubek, 1999). Indeed, Census estimates of population figures—both total population and driving-age population—are still the most widely used benchmark measures for studies of police-citizen contacts. These types of benchmarks are heavily relied on, at least partially, because they are cost efficient and readily available (Fridell et al., 2001; Fridell, 2004; Smith & Petrocelli, 2001).

Relying on Census data as a benchmark comparison for traffic stops, however, involves making a number of important assumptions including:

- Residents of an area drive only where they live,

- People of all races are equally likely to have a driver's license and/or access to a vehicle,
- Drivers of all races do not differ in their frequency, time, or locations of travel,
- Drivers of all races do not differ in the quality of their driving.

The first assumption has been discredited by a number of scholars conducting research on racially biased policing. Specifically, researchers have noted that there are a number of factors that influence whether population estimates can be considered accurate representations of the driving population in those areas, including the percentage of residents without drivers' licenses, the presence of major highways, commuting patterns, college or university student populations, and the availability of tourist attractions (*Chavez v. Illinois State Police*, 2001; Cordner et al., 2002, Cox et al., 2001; Engel, Calnon, Liu, & Johnson, 2004; Farrell et al., 2003; Fridell et al., 2001; Fridell, 2004; Morgan, 2002; Rojek et al., 2004; Smith et al., 2003).[3] Importantly, these factors may differentially affect whether racial / ethnic groups drive in areas in which they are not residents (Fridell, 2004). Indeed, researchers have demonstrated that residential populations frequently over or underestimate the percentages of Black, Hispanic, or other minority drivers observed in the driving population or those in the population of drivers stopped by police (Cordner et al., 2002; Engel, Calnon, Liu, & Johnson et al., 2004; Greenwald, 2001; Lamberth 2003a; Rojek et al., 2004; Thomas & Carlson, 2001).

The second and third assumptions--people of all races are equally likely to have a driver's license and/or access to a vehicle, and drivers of all races do not differ in their frequency, time, or locations of travel—are also not consistent with the literature on travel

[3] A number of researchers have recently been improving estimates of driving populations with spatial statistics, weighting techniques, and modified Census measures (Eck, Liu, & Bostaph, 2003; Farrell et al., 2003; Novak, 2004; Rojek et al., 2004). While these techniques are promising endeavors for better use of Census data, they still lack a measure of drivers' offending behavior, which this study and other scholars (Fridell, 2004; The Alpert Group, 2004) advocate as the preferable benchmark.

patterns of minorities, which has noted important relationships between race/ethnicity and travel behavior.[4] For example, data from the 2002 Police Public Contact Survey show that Blacks and Hispanics are significantly less likely than Whites are to indicate that they drive a motor vehicle at least a few times a year (Durose et al., 2005). Similarly, analyses using the 1995 Nationwide Personal Transportation Survey (NPTS) data show that Blacks and Hispanics were less likely than Whites to have a driver's license (Chu et al., 2000; Polzin et al., 2000), are more likely to live in households with fewer vehicles than Whites are, and are more likely than Whites to use public transit rather than personal use vehicles as their primary means of transportation, particularly among older minorities (Bureau of Transportation Statistics, 1997; Burkhardt, McGavock, Nelson, & Mitchell, 2002; Chu et al., 2000; FHA, 1995; Krovi & Barnes, 2000; Polzin et al., 2000; Rosenbloom, 1998; Ross & Dunning, 1997). African Americans, in particular, are over-represented in households without a vehicle (FHA, 1995).

Racial differences are also evident for people of color who rely on travel in their personally owned vehicles, as they have been found to make fewer trips than Whites, travel fewer miles, and spend less time traveling (Polzin et al., 2000; Smith et al., 2003). Other recent research suggests that the time of travel may vary by driver race, as Black drivers were found to make up higher percentages of those driving during the late night and early morning hours as compared to White drivers (Lange et al., 2005; Smith et al., 2003).

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[4] Similar behavioral differences are evident for gender and age, as men and younger people participle more in travel in comparison to women and older people. Specifically, national surveys indicated that men are more likely than women to drive every day, to make more trips per person, to make more trips for work, to make longer trips, on average, and to be licensed drivers (FHA, 1995; Boyle et al., 1998; Polzin et al., 2000). Older persons, by contrast, have a lower participation rate in travel; compared to younger people, persons 65 and older are less likely than younger people to drive every day and make fewer trips per day than younger persons (FHA, 1995).

The final assumption of whether demographic groups drive differently has been somewhat more controversial. Indeed, Heather MacDonald (2001) suggests that even asking this taboo question of whether racial groups might differentially offend behind the wheel, is perceived as revealing one's racism (see also Taylor & Whitney, 1999). Some researchers have defended the use of population figures as an appropriate comparison group for stop data, suggesting that no research has indicated that there are racial differences in driving or travel behavior (ACLU, 2000; Verniero & Zoubek, 1999). Fridell (2004, 13), however, argues that we cannot presume the null hypothesis to be true and that "unless research shows that there are no differences between groups as pertains to (alternative) hypotheses we must assume that there are differences." Furthermore, there is at least moderate empirical evidence that counters the claim that driving behaviors do not significantly differ with race. A brief review of the travel and transportation literature reveals differences in driving behavior by driver's age, gender, and race or ethnicity.

Differences in Illegal and/or Risky Driving Behavior

In addition to the above-noted differences in travel patterns, demographic differences in several types of driving behavior are also evident. Although studies of illegal driving behavior in the criminological/criminal justice literatures are limited, studies completed with accident statistics, Department of Transportation Statistics, or other data collected by the National Highway Transportation Safety Administration (NHTSA) are abundant in other research fields and are reviewed here.

Seat belt and child restraint use

Studies of drivers' seat belt use have produced fairly uniform findings with respect to driver gender and age. In general, women are more likely to use seatbelts than men are, although one recent study suggested that this gender gap is diminishing as males are increasing their seat belt use (Everett et al., 2001; Glassbrenner, 2003; Lerner et al., 2001; Reinfurt et al., 1996; Wells et al., 2002). The relationship between age and seat belt use is also consistent across several studies. Although the studies varied slightly in their operationalization of older (65 vs. 70) and younger (16-24 v. under 35), younger people are significantly less likely than middle age and older drivers to use their seat belts (Glassbrenner, 2003; Lerner et al., 2001; Reinfurt et al., 1996; Wells et al., 2002).

Racial differences in the use of seat belts are not as clear. Some studies indicate that Whites, and sometimes Hispanics, are more likely than Blacks to use seat belts (Braver, 2003; Everett et al., 2001; Harper et al., 2000; Lerner et al., 2001; Wells et al., 2002). Other studies reported no significant racial differences, suggesting that the racial gap in seal belt use that had previously existed is virtually gone, as Blacks, Whites, and other minorities all had similar rates of seat belt use (Glassbrenner, 2003; Reinfurt et al., 1996). African Americans in North Carolina report higher seat belt use than Whites (Smith et al., 2003). These researchers note, however, that in the same self-report survey Blacks underreported being stopped for speeding stops the research team knew to have occurred, and suggest that greater social desirability effects among African American respondents may have influenced their willingness to self-report other illegal behaviors as well (Tomaskovic-Devey, Wright, Czaja, & Miller, 2006). Recently, the NHTSA (2007a) reported that African American children were significantly more likely than children of other racial/ethnic groups to be involved in fatal traffic accidents when the child was not properly restrained. In general, child restraint use is lower for Hispanics and Blacks compared to Whites (NHTSA, 2007b).

Alcohol-related and other accidents

Studies examining accidents have reported generally higher involvement by men in accidents. More male drivers than female drivers reported crash experience in the past five years (Boyle et al., 1998), males were more likely to be driving when children and teenage passengers were unrestrained by seat belts and injured in vehicle crashes (Miller et al., 1998), and males were more likely to be involved in fatal crashes and alcohol-related accidents than females (Abdel-Aty & Abdelwahab, 2000; Braver, 2003; Massie et al., 1995; Zador et al., 2000). Females, on the other hand, were more likely than males to report that they or someone else had been injured in a crash (Boyle et al., 1998; Massie et al., 1995).

In general, age is negatively related to the risk of accidents, as the likelihood of being involved in crashes decreases with age. Indeed, the most important predictor of crashes was being between the ages of 16 and 24; people in this age group were more likely than all other age groups to be involved in crashes (Boyle et al., 1998; Massie et al., 1995). Older drivers also had a lower risk of being fatally injured in a single-vehicle crash than younger drivers (Zador et al., 2000). Alcohol-related accidents, however, involve a slightly different effect of age, since the youngest drivers cannot legally purchase or consume alcohol. These studies found that the next age group, of 25-34 year olds, experienced the highest accident rate when drugs or alcohol were involved. Involvement in alcohol-related accidents declined steadily with age, but seemed to have a stronger effect for males than females (Abdel-Aty & Abdelwahab, 2000).

Research on the influence of race on accident involvement has produced somewhat inconsistent findings across studies. Some research has found that African Americans and Hispanics had higher rates of involvement in alcohol-related and other fatal accidents (Baker et al., 1998; Braver, 2003; Harper et al., 2000; Royal, 2000). Other researchers, however, found that White drivers were more likely to be involved in alcohol/drugs-related traffic accidents than Hispanics or Blacks (Abdel-Aty & Abdelwahab, 2000). There were important interaction effects discovered in this study, however, as it was younger White drivers (under 45) that had higher alcohol-related accident involvement, while drivers of other races had higher rates for people 45 and above. Finally, other research has noted similar alcohol-related fatality rates and non-alcohol related fatal accident rates for Whites, Hispanics, and Blacks (NHTSA, 2007a; Voas et al., 2000). Recent research from the NHTSA (2007a), however, showed that Native Americans had a significantly higher accident fatality rate and a higher alcohol-involved accident fatality rate than other racial/ethnic groups.

Drinking and driving

Research on the influence of gender on drunk driving generally has shown that males were more likely than females to be driving after drinking, but that females were more likely than males to have been the passenger of a drunk driver (Caetano & Clark, 2000; Everett et al., 2001; Harre et al., 1996; Voas et al., 1998). As with the studies of alcohol-related crashes, increases in age have been found to decrease the likelihood of drinking before driving (Berger & Snortum, 1986). The influence of race/ethnicity is mixed, as some research suggests Blacks are less likely than Hispanics and Whites to drive drunk, while others found that Hispanics were more likely than their White and Black counterparts to drink and drive or that race was not an important predictor of drinking and driving (Caetano & Clark, 2000; Everett et al., 2001; Mustaine & Tewksbury, 1999; Voas et al., 1998)

Driving aggression

Studies of aggression or road rage have also examined demographic differences in these types of behaviors. Some research has found that male and female drivers tend to be similarly aggressive, particularly in terms of less serious types of mild aggression, as men and women were equally likely to engage in behaviors like horn honking, yelling, or purposely tailgating, and reported similar levels of anger or frustration while driving (Harre, Field, & Kirkwood, 1996; Hennessy & Wiesenthal, 1997; 1999; 2001; Lawton and Nutter, 2002). Hennessy & Wiesenthal (2001) suggested that it might be the anonymous environment of driving that permits women to be more aggressive than traditional gender roles might expect. In studies that do find significant differences in aggressive behavior, men are more likely to express frustration, engage in angry or threatening driving behavior, and externalize frustration through verbally and physically aggressive actions, whereas women tend to internalize aggression and refrain from severely aggressive actions (Hennessy and Wiesenthal, 2001; Lawton & Nutter, 2002; Shinar & Compton, 2004; Wells-Parker et al., 2002).

Research on the influence of age on driving aggression has consistently found that younger drivers are more likely to experience road rage, drive aggressively, and express anger or frustration at the driving behavior of others (Shinar & Compton, 2004; Wells-Parker et al., 2002; Yu et al., 2004). The only study found that examined racial differences in aggressive driving and road rage found no significant difference in verbal frustration or angry/threatening driving among Whites, Blacks, and Hispanics (Wells-Parker et al., 2002).

Summary

The body of research reviewed above suggests the possibility of racial/ethnic differences in travel and driving patterns (including frequency and quality) to the point that the null hypothesis (i.e., no demographic differences) cannot be sustained. Therefore, the lack of measures of driving behavior in Census data is a major weakness in its utility as a benchmark for traffic stops because, as noted above, differences in this behavior may account for racial disparity in stops. Indeed, Fridell (2004, 28) concluded that "researchers can draw no definitive conclusions regarding racially biased policing" from Census benchmarks. Therefore, it is necessary for studies examining differences in rates of police-public contacts during traffic stops to utilize more precise benchmarks that capture differences in the frequency and patterns of actual driving behavior by gender, age, and race.

Observational Assessments of Drivers' Roadway Usage and Offending Behavior

The growth in observational studies of driving behavior is largely due to the recognition, by courts and social scientists alike, that population statistics do not provide reliable benchmark comparisons against which stops and stop outcomes can be compared. As noted above, the reliance on Census data as a benchmark for traffic stops involves making a number of false assumptions about people's travel and driving behavior. These acknowledged weaknesses of Census data have caused some traffic stop researchers to initiate more costly and time-intensive observational studies of roadway usage and driving behavior to better determine who is driving where and how they are driving (Engel et al., 2002; Engel et al., 2006; Farrell et al., 2003; Lamberth, 1994, 1996; Lange et al., 2005; Smith et al., 2003). As noted earlier, both state and federal courts adjudicating claims of racially biased policing also have commented on the fact that they would find more compelling benchmark data that included rates of actual roadway usage and/or violating behavior for comparisons to stop data (e.g., *Chavez v. Illinois State Police*, 2001; *State of New Jersey v. Kennedy*, 1991; *State of New Jersey v. Smith*, 1997).

Surveys of Roadway Usage

The first study to focus on assessing drivers' roadway usage occurred in New Jersey. As noted in the previous chapter, John Lamberth (1994) was commissioned by defense attorneys in *State of New Jersey v. Soto* (1996) and used observation teams on the New Jersey Turnpike to collect data on the race and ethnicity of motorists using this roadway. On randomly selected dates and times over a very limited data collection period of two weeks in June of 1993, Lamberth had observers alternate between four stationary observation posts on the Turnpike, recording the race of the driver and any visible passengers, as well as the state of registration for the vehicle.

A total of 42,706 cars were observed between 8 am and 8 pm on the selected days. The results indicated that the percentage of minorities observed (13.5%) was significantly smaller than their representation (35.6%) among official stop and arrest statistics for a 3 year period beginning in April 1988. Note, however, that offending behavior was not captured by this data collection technique, and it is a logical assumption that stops and arrests are based, in large part, on offending behavior. Lamberth argued that the reasoning behind conducting both traffic and violator surveys was to test the "assumption that the population of turnpike traffic violators will mirror the population of travelers as a whole on the NJ Turnpike."

A more recent assessment of roadway usage also focused on the New Jersey Turnpike, although it relied primarily on drivers' self-reported race/ethnicity rather than observation by researchers. This survey came about following a number of high profile incidents involving allegations of racially biased policing and the New Jersey State Police (NJSP), particularly on the New Jersey Turnpike. Facing a potential federal civil rights suit for racial bias in police stops and searches, the state of New Jersey entered into a consent decree with the U.S. Department of Justice that mandated data collection for traffic stops and searches and monitored the State Police for racially discriminatory behavior (Lange et al., 2005; Ramirez et al., 2000). The consent decree provided for a contract with an independent research team that would survey drivers on the Turnpike in order to establish a benchmark population of drivers to be compared to NJSP stop rates. The argument was that an estimate of actual Turnpike drivers would provide a better standard of comparison than estimates based on Census data.

Lange and his colleagues (2005) conducted a month-long roadway usage survey at various exit tollbooths along the New Jersey Turnpike in 2000. Research assistants interviewed a random sample of drivers (n=4,656) exiting tollbooths, of which 86.8% agreed to participate. For those who agreed, interviewers collected drivers' age, race/ethnicity, sex, where they entered the Turnpike, and state of vehicle registration. For those who refused, observers estimated drivers' race/ethnicity and age. Data collection varied by weekend/weekday, segments of the turnpike, and time of day. The strength of this self-report methodology is in the elimination of measurement error by observers, particularly for Hispanic drivers.

The demographics of this driving population were compared to police stops during the same time period and Lange et al. (2005) reported that in the Southern and Central segments of the turnpike, Blacks were overrepresented among police stops while there was no significant difference in the Northern segment. Hispanics were underrepresented in police stops in all geographic segments, although this may be a function of police difficulty in assessing Hispanic ethnicity of stopped drivers. It is also interesting to note that the driving population captured by this survey did not significantly differ from the population of all drivers—that is, not taking into account drivers' speeding status—captured by the Speed Survey to be reviewed below.

Researchers in Rhode Island were fortunate enough to be able to conduct rolling road survey observations on the entirety of the North and South routes of I-95 due to the small size of the state (Farrell et al., 2003). Over an eighteen-month period, spanning 2001 to 2003, an average of three surveys were taken each month, yielding a total of 9,584 observations over the 44 mile stretch of interstate. The length of the data collection period was advantageous in that it allowed for observations to be spaced out across weekdays and weekends; the observations also followed a staggered start and stop methodology to vary the possible times of day for observations. During observation periods, the research vehicle traveled at approximately 60-65 miles per hour, depending on the posted speed limit, which varied between 55 & 65 mph. Interrater reliability was examined during the pilot test of this observational survey method, with each of two observers independently recording their observations of the license plate, race, gender and number of occupants in vehicles traveling on the road. Tests of interrater reliability indicated that in almost all cases, observers' independent observations were nearly identical for license information, gender and occupants, and very high (about 95%) for race.

The racial demographics of highway drivers established by the rolling road survey were compared against the racial makeup of Rhode Island State Police stops from the same time period during which observations were conducted. Using this most comparable stop data to the observation data, Farrell et al. (2003) found that the State Police stopped a higher proportion of Nonwhite drivers (average of 10.8% more) on I-95 than were observed by the research team in the driving population on I-95, although the size of the disparity varied by sections of the interstate.

Although using observations of roadways to gather benchmark data is a useful method in areas where residential and driving populations are unlikely to be the same (and Census data would be particularly inappropriate as a benchmark), the lack of a measure of offending behavior is an important limitation of the roadway usage benchmark. That is, if driver-violating behavior varies by demographic characteristics, then simply assessing who is using the roadways is a less valid benchmark for comparison to stopped drivers because it does not address the paramount question of who is more likely to be stopped by police for traffic violating behaviors.

<u>Surveys of Driver Offending Behavior</u>

As noted above, a few scholars argue that collecting data on law-violating behavior is unnecessary, suggesting that the driving population as a whole is subject to being stopped and therefore that is the appropriate population to measure for benchmarking purposes (Lamberth, 2003a, 2003b, 2004; Lamberth, Harris, McDevitt, & Ramirez, 2004; Rickabaugh, 2003). The problem with this strategy is that it ignores drivers' differential risks of being stopped based on their driving behavior. Several scholars have countered the above argument with the proposition that it is logical to assume that those who violate traffic laws and violate them to a more serious degree are at higher risk of being stopped by police than those who do not (Engel & Calnon, 2004b; Fridell, 2004; Smith et al., 2003; The Alpert Group, 2004). Indeed, Fridell (2004, 17) points out that the rationale behind including demographic groups' driving behavior as part of benchmark data collection is that "police are asked to make driving behavior a key part of (stopping) decisions" as well.

In order to examine this question of racial differences in offending patterns, data collection on drivers' offending behavior is necessary. One of the most reliably observed driving offenses is speeding. Until recently, the existing research on the demographic differences in speeding has focused only on gender and age and has not examined racial differences in this behavior.[5] Given the lack of data on demographic differences, particularly racial differences, in driving behavior, social scientists have initiated observational studies to explore the possibility that particular types of citizens may drive differently and be more likely to violate traffic laws and/or commit more serious violations (Engel et al., 2006; Lamberth, 1994, 1996; Lange et al., 2005; Smith et al., 2003; The Alpert Group, 2004). These studies are discussed in detail below, but summarized briefly in Table 3.1.

[5] Generally, male and younger drivers were found to be more likely than their female and older counterparts to speed, particularly at higher speeds (Boyle et al., 1998; Harre et al., 1996; NCSA, 2002).

Table 3.1. Summary of Observational Studies of Driving Behavior

Location & Dates of Study	Violating Behavior Observed	Operationalization of Violating Behavior	Results
Maryland (1994)	Speeding, observed by rolling vehicle survey	Vehicles traveling one or more miles over the posted speed limit	93% of all drivers observed were speeding; no significant differences in speeding behavior of Whites and Blacks
New Jersey (1996)	Speeding, observed by rolling vehicle survey	Vehicles traveling more than 5 miles over the posted speed limit	98% of all drivers observed were speeding; no significant differences in speeding behavior of Whites and Blacks
North Carolina (2000)	Speeding, observed by rolling vehicle survey and stopwatches	Exact amount of miles over the posted speed limit captured. Three speeding thresholds established: 1) low (above first decile of speeds at which drivers are cited); 2) high (above citation median); 3) 15 mph above limit	The percentage of drivers observed speeding at or above the low and high speeding thresholds varies across roadway segments. Black drivers were significantly more likely to exceed all three measures of "speeding thresholds" compared to White drivers. The overrepresentation of Blacks among speeders declined above 8 mph over the threshold speed.
New Jersey (2001)	Speeding, observed by random and speed-triggered RADAR and high-speed photography	Vehicles traveling at least 15 miles per hour over the posted speed limit	The vast majority of all drivers were found to be driving *less* than 15 mph over the posted speed limit. The average speed for each racial/ethnic group of drivers was very similar (Whites: 66.3 mph, Hispanics: 66.3 mph, Blacks: 66.8 mph). Black drivers were 64 percent more likely than White drivers to exceed the 65 mph limit by 15 or more mph. No statistically significant differences between Blacks and Whites were found at the 55 mph speed limit.
Miami (2001)	Speeding, observed from stationary observation points with RADAR. Running red lights and making illegal turns also observed from stationary observation point.	Vehicles traveling five or more miles over the posted speed limit	White males violated above their proportion in the driving sample. Black males violated at the same proportion as in the driving sample. White and Black females violated below their proportion in the driving sample.
Cleveland (2005)	Speeding, observed from stationary observation points with RADAR or LASER. Red light violations and illegal turns.	Vehicles traveling eight or more miles per hour over the posted speed limit (two standard deviations below the mean amount over the limit for Cleveland Division of Police speeding stops), but precise amount over the limit was captured	7.4% of the vehicles observed on the roadways were traveling 8 MPH or more over the legal limit. 45% of the vehicles observed were traveling at least one mile per hour over the speed limit. Blacks were more likely to be exceeding the speed limit than any other racial group.

Maryland & New Jersey

John Lamberth (1994; 1996) administered the first observational studies examining speeding behavior in the mid-1990s, emerging out of separate legal cases in Maryland and New Jersey (*State of New Jersey v. Soto*, 1996; *Wilkins v. Maryland State Police*, 1994). In order to determine who was speeding, Lamberth had trained observers ride in a vehicle traveling at a set speed (e.g., at the exact speed limit in Maryland and at five miles per hour over the speed limit in New Jersey), simultaneously recording the characteristics of the drivers in the cars that passed them (the speeders) as well as the drivers in cars that the research vehicle passed (the non-speeders). Using this technique, which Lamberth called the "carousel method," he reported that the overwhelming majority of drivers (98% and 93% in New Jersey and Maryland respectively) were violating the posted speed limits. The major finding reported from this study, however, was that there were no significant differences in the speeding behavior of White and Black drivers.

This finding, however, has been widely criticized by other researchers because: 1) the measurement of speeding was a simple dichotomy so there was no way to determine if the *severity* of speeding behavior varied by demographic groups, and 2) the speeding threshold measured was, at most, 5 miles per hour over the posted speed limit (Ekstrand, 2000; Engel & Calnon, 2004b). This is particularly significant because most police agencies have formal policies or informal norms regarding the level of speeding that merits a warning or citation.[6] The limitations of this technique, therefore, prohibit giving much credence to the argument that White and Black drivers drive indistinguishably. The lack of a measure of the degree of

[6] For example, the law of the Commonwealth of Pennsylvania requires that vehicles be traveling at more than six miles per hour above the posted speed limit in order for police to issue drivers a citation (75 Pa. C.S. § 3368).

the speeding violation does not capture (even at five miles per hour over the speed limit) drivers' real risk of being stopped for that behavior. As simply stated by Smith and his colleagues (2003, 255), "not all speeding is equal."

Lamberth's findings, unfortunately, have lead to more recent data collection efforts that only examine traffic observations and do not measure traffic violating behavior, based on the argument that the populations of traffic motorists and traffic law-violators are virtually identical (Lamberth, 2003a, 2003b, 2004; Lamberth et al., 2004; Rickabaugh, 2003). Not only does this stand in conflict with the growing body of research that suggests driving differences by race do exist, but several federal court cases have criticized Lamberth's failure to measure the violator population as well as many facets of his traffic observation methodology, including the sample size, duration of observational surveys, and the reliability of observers' perceptions of driver characteristics, particularly at nighttime (see *U.S. v. Alcaraz-Arellano*, 2004; *U.S. v. Duque Nava*, 2004; *U.S. v. Mesa-Roche*, 2003).

North Carolina

Since Lamberth's initial attempts to survey law-violating behavior, other researchers have altered these techniques and have advanced the observation methodology. A research team in North Carolina worked with the North Carolina State Highway Patrol, under legislative mandate, to collect data on the racial distribution of traffic stops. The NCSHP also cooperated with a more comprehensive examination of stops and outcomes that included observational benchmark data collection on speeding drivers (Smith et al., 2003).

In order to capture drivers' speeding behavior, the North Carolina research team improved upon Lamberth's carousel method by using stopwatches to more precisely measure the amount over the limit at which vehicles were speeding (Smith et al., 2003). Groups of observers assessed speeding behavior by relying on stopwatches to measure how long it took vehicles to pass the distance from their vehicle's rear bumper to the front bumper, while it was traveling at a set speed. The researchers determined that although this method systematically underestimated the actual speeds of vehicles, they were able to statistically correct for the underestimation to obtain accurate measures of the speed of passing vehicles (Smith et al., 2003). In addition to the speed of passing vehicles, observers also recorded information about the vehicle and its occupants (e.g., drivers' race, gender, approximate age, vehicle color, state of license plate, type of vehicle), so that they could analyze demographic differences in speeding.

Because speeding was captured as the exact amount over the limit, several different speeding "thresholds" were examined: 1) low (above first decile of speeds at which drivers are cited); 2) high (above citation median); 3) 15 mph above limit (Smith et al., 2003). The findings suggest that for particular roadway segments, Black drivers were significantly more likely to exceed all three measures of "speeding thresholds" compared to White drivers. This relationship, however, was not linear, as the overrepresentation of Blacks among speeders declined above approximately 8 mph over the threshold speed. In general, the findings of the observational study supported the proposition that NCSHP police officers' stopping behavior (at least for speeders) was largely determined by vehicular driving behavior.

As the authors of the North Carolina study acknowledge (Smith et al., 2003), their assessments of speeding are somewhat limited by their reliance on a convenience sample of only 14 highway segments that were 10-15 miles long across the entire state of North Carolina (48,711 square miles). Furthermore, the data collection period only lasted 6 weeks, was conducted 4 days a week and 6 hours a day. The external validity of this study, thus, is limited, particularly in terms of its small geographic representation and its inability to capture potential seasonal variation. This is particularly significant given that the research team found speeding thresholds varied by highway. Nevertheless, there is no reason to believe that the finding that Black motorists are more likely to speed than White motorists is invalid for the roadway segments selected.

The methods of the research conducted in North Carolina measure strict differences in the severity of speeding by demographic characteristics. For purposes of comparing observational data to official traffic stop data, this may be problematic. As the researchers in North Carolina suggest, drivers differ in their levels of "speeding savvy," which suggests that some drivers may speed in ways that minimize their risks of being detected and stopped by police. Therefore, citizens' risks of being stopped for speeding may not be fully captured through methods that strictly examine differences in the severity of speeding behavior. Methods to determine drivers' risks of being stopped for speeding would have to rely on the same techniques for detection of speeding as the police use.

New Jersey

The Speed Violation Survey of the New Jersey Turnpike did just that, assessing demographic differences in speeding behavior using the same method of detecting speeders that the police use—RADAR. This survey came about following the aforementioned Tollbooth Survey that estimated the racial distribution of Turnpike drivers irrespective of violating behavior (Lange et al., 2005). When the population survey of Turnpike drivers was completed, the State of New Jersey contracted the researchers to conduct a second survey along the Turnpike, this time focusing on an estimated racial distribution of traffic-speed violators. The rationale behind the Turnpike Speed Survey was that using a benchmark based on violators, rather than just drivers, would better capture the appropriate benchmark established in the *State of New Jersey v. Kennedy* (Lange et al., 2005).

Utilizing both random and speed-triggered RADAR and high-speed photography at 14 different locations along the 148-mile turnpike, this study considered the race, ethnicity, gender, and speeding behavior of drivers on the roadway (Lange et al., 2001). Each location yielded approximately 48 hours of data collection during a three-month period in 2001, which varied by weekend and weekday. A panel of three trained observers, who worked independently to identify the drivers' race, ethnicity, gender, and age, examined the photographs with no knowledge of the recorded speed of the vehicle. Cases with at least two identical ratings were treated as conclusive (about 68% of the photographs); the rest were treated as unclassifiable.[7] The researchers operationalized speeding as driving at least 15 miles per hour over the posted speed limit based on discussions with the New Jersey State Police and the consensus that 15 mph above the limit represented a speeding violation for which most state troopers would initiate a traffic stop (Lange et al., 2005). Although there are clearly similarities between this research and Lamberth's earlier work, the Speed Violation Survey is distinct in several ways: a more serious operationalization of "speeder" (15 mph v. 5 mph over), a broader sample of the Turnpike (not limited to just the southern section), and a methodology that relied on RADAR and photography rather than observers in a moving vehicle (Lange et al., 2005).

Overall, the vast majority of drivers were found to be driving less than 15 mph over the posted speed limit (97.3% of Black drivers; 98.6% of White drivers). Furthermore, the average speed for each racial/ethnic group of drivers was very similar (66.2 mph for drivers

[7] Lange et al. (2001) found no evidence to indicate that drivers' race was significantly related to the likelihood of unclassifiable data, indicating instead that unusable data was primarily due to technical problems associated with the positioning of cameras that produced glare and shadows on the windows of passing cars.

classified as “other” compared to 66.3 mph for White and Hispanic drivers, and 66.8 mph for Black drivers) (Lange et al., 2005). Nevertheless, Lange et al (2005) did find significant race, age, and gender differences in speeding behavior. Based on only the cases with conclusive driver data, their findings indicated that Black drivers were 64 percent more likely than White drivers to exceed the 65 mph limit by 15 or more miles per hour, controlling for age and sex. No statistically significant differences between Blacks and Whites, however, were found at the 55 mph speed limit. That is, racial differences in speeding were evident at the upper tail end of the speeding distribution (80 mph or more), but the disparity between Black and White drivers among speeders disappeared as the speeding criterion was lowered toward the legal limit.[8]

Differences in speeding behavior by age and gender were also discovered. In the 65 mph zone, people coded as younger than 45 were 3 times more likely to speed than those over 45 and men were 20% more likely to speed than women, controlling for other driver characteristics. Significant age differences were also found in the 55 mph zone, but the gender difference disappeared. An important contribution of this work was that it also attempted to examine how age and race influence speeding behavior. Initially, Lange et al. (2005) conducted logistic regression analyses predicting speeding including only race and then added in age as a covariate. Although race was statistically significant for both analyses, the strength of the odds ratio dropped from 1.96 to 1.64 with the inclusion of the

[8] Lange et al. (2005, 214) offered the following explanation for the lack of statistically significant racial differences in speeding in the 55 mph speed limit: “One possible explanation…is that, in those areas, a much larger proportion of the vehicles are traveling higher than the criterion set as the definition of speeder (13.0 percent vs. 1.7 percent in the 65 mph zone). It does not take a great deal of racial/ethnic differences in speeding rates to produce a dramatic overrepresentation in a small faction of the drivers, as is the case in the 65 mph zones. However, where a substantial number of speeders exist, very large disparities between the races would be required to produce similar overrepresentations.”

age variable. They argue that if the age variable had been more precisely measured,[9] the differences between Black and White drivers might have been reduced even further. To support this proposition, Lange et al. (2005) note that their previously conducted Tollbooth Survey of the NJ Turnpike, which surveyed the population of Turnpike drivers, found a lower average age for Black drivers than White drivers. They suggest it is possible that "age may account for the overrepresentation of Black drivers among speeders" (Lange et al., 2005, 219).

Overall, the racial/ethnic distribution of police stops closely approximated the proportions of observed speeding violators. This is what would be expected if police were stopping vehicles in an unbiased manner, based on driving behavior rather than driver race (Lange et al., 2005). Therefore, these data are supportive of the alternative race-neutral explanation for high police stop rates of Black drivers relative to census counts. It is important to note, however, that because the study was limited only to the New Jersey Turnpike, the external validity of these findings to other locations or other types of roads is minimal.

Miami-Dade County

As part of a study examining the traffic stop practices of the Miami-Dade police department, The Alpert Group (2004) conducted an observational assessment of the demographic data on traffic patterns to be used as benchmarks for police stops. Their goals were first to measure who is driving on the roads, and second to determine who is violating the traffic laws in unincorporated Miami-Dade County. Specifically, the traffic observations

[9] The age variable had to be collapsed from a 3 category variable (under 25, 25-45, and older than 45) to a simply dichotomy (45 and younger vs. older than 45) because of reliability problems particularly with the younger age categories.

were designed to: 1) obtain racial and gender data for a sample of drivers at various intersections, 2) record the race and gender of all speeders, and 3) record the race and gender of drivers violating other traffic laws, namely running red lights or making illegal turns.

In order to determine where observations would be conducted, a list of intersections in White, Black and mixed areas of unincorporated Miami-Dade County was compiled by the Miami-Dade Police Department. As the list included more than 30 intersections, a sample of neighborhoods to be observed was selected through an elaborate process involving several criteria (a racial balance of Black, White, and racially mixed neighborhoods, best geographical distribution across the county, avoiding intersections that represented the same pool of drivers, and avoiding observations of traffic on the largest and most complex highways). The 16 selected intersections were located in all eight police districts in Miami-Dade County and include high volume stop, ticketing, and crash locations. The research team acknowledged that the limitation of this observation benchmark is that data was only collected and analyzed for limited days, times, and locations, which given the selection criteria, cannot be considered a random or representative sample of intersections in Miami-Dade County (The Alpert Group, 2004). Nevertheless, for purposes of comparing to police traffic stops, these times and places probably provide a better distribution of the places that are patrolled consistently by the police and where most enforcement of traffic laws occurs than would randomly selected intersections.

Teams of two observers collected data on drivers' race and gender for three populations: baseline drivers on the road, drivers speeding, and drivers violating other traffic laws. First, observers collected baseline data for every driver on the road, except when heavy traffic flow prohibited accurate observations; in this case, observers collected data for only the two fastest lanes. This data collection site was located on the same side of the road as the observers collecting data on drivers' speeding to observe the same traffic flow. These observers were positioned several blocks from each intersection to allow for observation of traffic before it slowed down for the intersection. At this site, one observer would operate the radar gun while the other observed the gender and race of any driver who was speeding. Speeding was operationalized as any speed equal to or greater than five miles above the posted speed limit. Finally, two observers positioned directly at the intersection reported either drivers who went through a red light and/or drivers who made an illegal turn. Only the most obvious violations were to be recorded, thus eliminating the inclusion of questionable violations, which may not qualify as legal infractions or be serious enough to warrant police intervention (The Alpert Group, 2004). An important strength of this study is its systematic observation of traffic violations other than speeding; it is, however, still limited in its operationalization of speeding. As noted above, all speeding is not equal (Smith, 2003); measuring speeding at only five miles per hour over the posted limit ignores the possibility that there may be significant racial differences in more severe speeding violations.

Each intersection was observed for eight hours. For all observations, when the driver's race or gender was not obvious, observers were trained to record the characteristic as "unknown." Because observers have difficulty determining the ethnicity of all drivers, particularly violators at higher speeds, the racial categories they recorded were limited to Black and non-Black. Shifts of night observations were eliminated, as reliable assessments of driver demographic data was impossible (The Alpert Group, 2004).

The observers recorded 93,251 drivers and more than 12,000 violations in White, Black, and racially mixed neighborhoods. The Miami-Dade police made 535 traffic stops for the three types of observed violations (speeding, running a red light, and making an illegal turn) at or near the 16 observed locations between August and November 2001, recording information about the stop, and race and gender of the driver. First comparing the racial and gender percentages of all drivers to all violators, The Alpert Group (2004) showed that white males violated 7 percentage points above their proportion in the driving sample, white females were 3 percentage points below, black males were at the same proportion in both samples, and black females violated at 4 percentage points below their proportion in the driving sample. A comparison between the violators and stops indicates that while the rates of violation vary among these race and gender categories, the rates of police stops were very close to the rates of violation for each of the groups (The Alpert Group, 2004).

Cleveland

The Cleveland Division of Police (CDP) contracted with an outside research team from the University of Cincinnati to evaluate the agency's policing practices during traffic stops. As part of the data collection process, the UC research team conducted roadway observations in order to record the demographic distribution of drivers using the roads and violating traffic laws for purposes of creating a benchmark against which the traffic stop data could be compared (Engel et al., 2006).

Due to budgetary limitations, only ten locations throughout the City of Cleveland were selected for traffic observation data collection. These locations were selected through consultation between the CDP and the UC research team based on the following criteria: major thoroughfare in/out of city, high volume of infractions/enforcement, unobstructed view and safety for observers, and no major disruptions (i.e, construction). UC students were trained to conduct traffic observations and assess illegal moving violations, including red light violations and illegal turns, as well as speeding, which was captured through the use of RADAR or LASER equipment.

Observers recorded data concerning the behavior of drivers (e.g., speeding or non-speeding moving violation), vehicle characteristics (type, color, condition), modifications, and state of registration), and characteristics of the vehicles' occupants (driver race, gender, and age). Drivers' race and ethnicity were captured using the following categories: White, Black, Hispanic, Asian, Native American, Middle Eastern, Non-White, and Other. Observations were restricted to daylight hours to ensure that observers were collecting data under conditions that allowed them the best opportunity to accurately capture drivers' demographic characteristics.

Observers completed over 557 hours of traffic observations at the selected locations between May 5th and November 19th, 2005. Data collection varied by time of day and day of the week. All of the observations were conducted on local roadways within the city of Cleveland; however, the number of lanes and speed limit on roadways differed across the city. A total of 41,257 observations were made of drivers/vehicles using the roadways across all six policing districts. Although there were 41,257 vehicles included in the observation data, only 37,926 of those were used in the benchmarking calculations (78.5% of which included data on speeding behavior).[10]

The majority of violating behavior captured by observers involved speeding. In order to determine if a vehicle was violating the speed limit, the observed speed of the vehicle as recorded by the observers was compared to the legal speed limit on that road. However, it is unrealistic to assume that the risk of being stopped for speeding is heightened by driving one

[10] A small portion of observations (2,149 vehicles) were excluded from the benchmarking analyses because there were not enough observation hours at the specific locations where the observations took place to provide reliable benchmarks (Engel et al., 2006).

mile per hour over the limit. As a result, the research team determined that eight miles per hour over the posted speed limit (two standard deviations below the mean amount over the limit for CDP speeding stops) would be defined as speeding for the subsequent analyses. With regard to speeding in the observation data, 7.4% of the vehicles observed on the roadways were traveling 8 MPH or more over the legal limit. Notwithstanding this operationalization of speeding, 45 percent of the vehicles observed were traveling at least one mile per hour over the speed limit. With regard to the racial composition of speeders, African Americans were more likely to be exceeding the speed limit than any other racial group. Results from benchmark comparisons of traffic stop data to observation data suggest that there were racial and ethnic disparities in CDP stopping patterns.

Summary

Overall, both the observational studies and traffic/transportation research show considerable differences by driver gender, age, and race in driver offending behavior, including speeding. This suggests that demographic differences in drivers' offending behavior may at least partially account for racial disparity in police stops and stop outcomes. Until recently, however, the overwhelming focus of the debate on racially biased policing, whether in traffic stop studies or citizens' perceptions, has been on police behavior, while the legally relevant behavior of drivers has been largely ignored. The current research builds on the few studies that have begun examining demographic differences in driving behavior and furthers the methodology on violator-based benchmarks for traffic stop studies.

CHAPTER 4: RESEARCH QUESTIONS, HYPOTHESES, AND DATA

As noted in the literature reviews in Chapters 2 and 3, data collection efforts examining racial and ethnic disparities in traffic stops are becoming commonplace in police agencies across the United States. Unfortunately, the majority of these studies still compare stop data with Census data, in spite of its documented limitations as a valid benchmark. One of the major limitations of Census data is in the assumption that offending behavior of drivers that come to the attention of police is equivalent across demographic groups in the population. This assumption suggests that disparity in outcomes must be the result of police behavior, rather than driver behavior. In fact, some evidence on driving behavior counters this assumption. Findings from recent observational studies as well as in the traffic and transportation literature suggest that demographic differences in drivers' legally relevant behavior may account for at least some of the racial disparity in police stops and stop outcomes. Despite this possibility, benchmarks based on driver violating behavior are much less frequently utilized than Census benchmarks. The goal of the current research is to examine the relationships between driver demographic characteristics and offending behavior to better inform the debate on racially biased policing. The remainder of this chapter lays out the research questions and hypotheses to be explored, and describes the details of the observation data collection process.

RESEARCH QUESTIONS AND HYPOTHESES

While police behavior is certainly a crucial element of the question of disparity in traffic stops and stop outcomes, police actions do not occur in a vacuum. Police behavior is likely in response to drivers' behavior. Indeed, Fridell (2004, 17) argues that "driving behavior is a critical component of any model that seeks to explain decisions by police to stop drivers." The current study examines this much neglected question in research on racially biased policing of whether demographic disparities in police outcomes may, at least partially, reflect legally relevant behavioral differences by race, age, and gender. Understanding whether driving behavior is a possible explanation for disparity in stops and stop outcomes is crucial to effectively responding to allegations of racially biased policing. Building on previous research that has documented demographic differences in travel patterns and various types of illegal or risky driving behavior, this study seeks to explore three important research questions: 1) Does driving behavior vary by driver race, age, and gender? 2) Does severity of offending behavior vary based on demographic characteristics? 3) Do contextual level factors influence driving behavior?

The general hypothesis to be tested by the current study is that racial / demographic groups are not equivalent in the nature and extent of their traffic law violating behavior. More specific hypotheses to be tested are based upon both speculation by researchers in the field of racially biased policing (Ekstrand, 2000; Engel et al., 2002; Fridell, 2004) and previous empirical research on various types of driving behaviors.

Research Question 1

As reviewed in the previous chapter, most research on illegal or dangerous driving behavior (e.g., seat belt use, accident involvement, drinking and driving, angry or aggressive driving behavior) has noted fairly consistent relationships between driving behavior and driver gender and age.[11] That is, male drivers and younger drivers are more likely to engage

[11] See Abdel-Aty & Abdelwahab, 2000; Braver, 2003; Berger & Snortum, 1986; Boyle et al., 1998; Caetano & Clark, 2000; Everett et al., 2001; Glassbrenner, 2003; Harre et al., 1996; Hennessy & Wiesenthal, 2001; Lawton & Nutter, 2002; Lerner et al., 2001; Massie et al., 1995; Miller et al., 1998; Reinfurt et al., 1996; Royal, 2003; Shinar & Compton, 2004; Voas et al., 1998; Wells et al., 2002; Wells-Parker et al., 2002; Yu et al., 2004; Zador et al., 2000

in these various types of offending behavior than are their female and older counterparts. Furthermore, in addition to these findings regarding behavioral differences, other research has shown attitudinal differences toward speeding for young male drivers compared to female and older drivers. Young drivers and male drivers were more likely to: 1) indicate an affinity for speeding, 2) minimize the potential costs associated with speeding and the likelihood of having such behavior enforced, and 3) report that several needs were met by speeding including: expressing individuality and rebelliousness, impressing and being accepted by peers, proving masculinity, and releasing frustration (Corbett & Simon, 1992, Royal, 2003).

Therefore, it is hypothesized that:

H1: Male drivers are more likely to speed than are female drivers.

H2: Younger drivers are more likely to speed than are older drivers.

Though research on other driving behaviors is somewhat mixed on whether racial groups differ in driving offending behavior,[12] recent research consistently shows that when it comes to speeding behavior, Blacks disproportionately offend compared to White drivers (Engel et al., 2006; Lange et al., 2001, 2005; Lundman & Kowalski, 2009; Smith et al., 2003). Therefore, it is expected that:

H3: Non-White drivers are more likely to speed than are White drivers.

H4: Black drivers are more likely to speed than are non-Black drivers.

As noted above, youthfulness is consistently one of the strongest predictors of a variety of illegal and risky driving behaviors, while considerably less is known about the

[12] See Abdel-Aty & Abdelwahab, 2000; Baker et al., 1998; Braver, 2003; Caetano & Clark, 2000; Everett et al., 2001; Glassbrenner, 2003; Harper et al., 2000; Lerner et al., 2001; Mustaine & Tewksbury, 1999; Reinfurt et al., 1996; Royal, 2000; Smith et al., 2003; Voas et al., 1998; Voas et al., 2000; Wells et al., 2002; Wells-Parker et al., 2002

influence of race. As suggested by other scholars (Fridell, 2004; Lange et al., 2005), it is possible, relative to race, that the propensity to speed is influenced by a higher proportion of younger drivers among Black drivers. Research reviewed in the previous chapter supports the idea that older Blacks may be less likely to drive personally owned vehicles than older Whites, which could create a population of Black drivers that is more heavily weighted towards younger, more aggressive drivers. Fridell (2004, 19) noted that "If a racial/ethnic group has proportionately more young people than another, age becomes an important intervening variable in the analysis model." With the exception of the Speed Violation Survey in New Jersey (Lange et al., 2005), little research has examined how this important covariate works with race.

Given this prior research and speculation, it is hypothesized that:

H5: Age will attenuate the influence of race on driving behavior.

Research Question 2

Survey research of drivers and police officers suggests that while less serious speeding may be normative, more severe speeding is not. Royal (2003) reported that more than 75 percent of drivers admitted driving over the speed limit and 51 percent indicated driving 10 miles per hour over the speed limit, but less than 15% of surveyed drivers admitted driving 20 miles per hour over the speed limit or 20 miles per hour faster than most other vehicles. Similarly, Corbett & Simon (1991) found that, although surveyed police officers rated minor levels of speeding fairly low on a perceived seriousness scale, this tolerance did not extend to speeding more than 10 and 20 miles per hour over the limit as their perceived seriousness ratings for these behaviors were considerably higher. Therefore, the mere existence of demographic differences in driver offending behavior may not be as important as whether demographic differences in the severity of such behavior exist, as more severe violations are presumed to increase drivers' risks of police intervention than less severe or no offending (Engel & Calnon, 2004b; Fridell, 2004; Smith et al., 2003).

In addition to the importance of this question for benchmarking purposes, prior research also suggests we might expect such differences in severity of offending for racial and gender groups. For example, when examining criminal offending on a continuum of minor offending to more serious or severe offending, previous research notes important differences for both the racial and gender gaps in crime (i.e., Blacks and males disproportionately offend compared to Whites and females). That is, the racial and gender gaps are both greatest for serious offending, but tend to be smaller or even nonexistent for minor offending (Elliot & Ageton, 1980; Hindelang, Hirschi, & Weis, 1979; Steffensmeier & Allan, 1996). Furthermore, one of the recent observational studies of speeding behavior found this exact occurrence, as racial differences were evident at the upper tail end of the speeding distribution that did not exist as the speeding criterion was lowered closer to the actual speed limit (Lange et al. 2005). The survey research described above reported similar differences in the seriousness of speeding by driver gender and age, as males and younger drivers were more likely than female and older drivers to engage in speeding 20 miles per hour over the speed limit and other vehicles (Royal, 2003). Therefore, it is expected that:

H6: Men are more likely to drive at higher speeds than are women.

H7: Younger drivers are more likely to driver at higher speeds than are older drivers.

H8: Blacks are more likely to drive at higher speeds than are Whites.

Research Question 3

Finally, this study seeks to explore the impact of contextual factors on individual drivers' speeding behavior. It is likely that certain characteristics of roadways and local areas affect individuals' propensity toward speeding and/or their ability to speed. For example, the topography or presence of construction in a particular area might constrain or allow individuals to express their normal inclination toward speeding behavior. Unfortunately, not all contextual factors can be measured by the current data. These data do, however, provide the ability to explore the influence of two specific contextual factors.

First, it is possible that drivers' speeding behavior may be influenced by the behavior of those individuals driving in the same area. Royal (2003) reported that approximately half of surveyed drivers indicated other drivers' speeding behavior was an important factor in determining their own driving speed. As described above, previous research shows that youthfulness consistently and strongly predicts a variety of illegal and risky driving behaviors; indeed, driver age is hypothesized to be a strong predictor of speeding behavior in the current study. Therefore, it is hypothesized that:

> H9: Drivers in municipalities with a higher average proportion of younger drivers will be more likely to speed than drivers in municipalities with a lower average proportion of younger drivers.

Second, drivers' speeding behavior may also be influenced by local police norms about acceptable speeding. As noted earlier, most police agencies have formal policies or informal norms regarding the level of speeding that merits a warning or citation; furthermore, these norms may vary by location. For example, Smith et al. (2003) found that, in North Carolina, their observed highways had different "speeding thresholds," that is speeds that are likely to result in a traffic stop & citation. Variable police norms about what constitutes acceptable speeding are important for this study because it is likely that drivers familiar with specific locations or routes know how much speeding the police will tolerate and are more likely to drive accordingly. To explore this possibility, a measure of average police enforcement behavior for speeding in individual municipalities is examined. Specifically, it is hypothesized that:

> H10: Drivers in municipalities with higher average speeding thresholds are more likely to speed than drivers in municipalities with lower average speeding thresholds.

In order to address these research questions, this study uses data collected for the Pennsylvania State Police Project on Police-Citizen Contacts. Using direct field observation techniques, observers collected roadway usage and law-violating behavioral data in 27 sampled counties across the state of Pennsylvania. The remainder of this chapter details the observational data collection, including the sampling and selection of observation locations, the training of observers, the data collection instrument, and a county-by-county description of observation sessions.

PROJECT ON POLICE-CITIZEN CONTACTS

The data utilized for this study are part of a broader project "The Project on Police-Citizen Contacts" initiated in 2002 by the Pennsylvania State Police Department (PSP) to collect data during all proactive traffic stops (see Engel et al., 2004). As part of this project, the department contracted for an independent observational survey of driving behavior in the Commonwealth as one of several base rates to which the department-collected stop data would be compared.[13] The current study uses this observational data to explore demographic differences in driving behavior. The remainder of this chapter describes the observation data collection process.

[13] This study was approved by the Pennsylvania State University Institutional Review Board in January 2002.

Observation Data

<u>Selecting observation counties and locations</u>

The primary reason for collecting observational data on driving behavior was to establish a more appropriate benchmark for the trooper-collected traffic stop data, particularly in counties where it was unlikely that Census data would accurately reflect the driving population. Due to the considerable size of the Commonwealth of Pennsylvania (44,820 square miles), it was not feasible, financially or practically, to conduct observations in each of Pennsylvania's 67 counties. It was determined that a sampling procedure would be utilized to select a more realistic number of counties to represent statewide traffic patterns. The details of this sampling strategy are described below.

As noted above, observational studies of roadway usage and driving behavior have been implemented in studies of traffic stops primarily because of the argument that Census data is unlikely to represent the driving population in many areas. Given this purpose, counties were not randomly sampled for observation, but rather were selected based on three specific characteristics related to this concern:

1) The likelihood that county wide traffic patterns did not reflect the residential population,
2) The county's general roadway usage, and
3) The likelihood of roadway usage by minorities in particular.[14]

The next step in this strategy was to identify county characteristics that were related to these three constructs. Seven such characteristics were identified for all 67 Pennsylvania counties:

1) total county population (U.S. Census Bureau, 2002),
2) the number of interstate miles within each county (PennDOT, 2001),

[14] The latter two factors associated with the sampling process were based on practical concerns; i.e., it would not be cost effective to conduct observations in several counties that had low population density, very small minority populations, and/or no major interstate travel.

3) the total number of roadway miles within each county (PennDOT, 2001),
4) the population of Blacks within each county (U.S. Census Bureau, 2002),
5) the population of Hispanics within each county (U.S. Census Bureau, 2002),
6) the presence of tourist attractions, colleges and universities, or historical sites, and
7) the presence of seasonal attractions (e.g., amusement parks, water parks, ski resorts, etc.) (PA Office of Tourism, 2002).

These seven characteristics were analyzed using principal components factor analysis (see Kim & Mueller, 1978), and the analysis revealed a factor with an eigenvalue greater than one (eigenvalue=3.31), which explained 43.7% of the variance.[15] Individual factor scores were generated for each county, and the counties were ranked from high to low, based on these scores. That is, the counties were essentially ranked according to these three concerns—their overall traffic volume potential, possible minority roadway usage, and the likelihood that travel patterns would not match residential populations.

The ranked 67 counties were then divided into four groups (High, Medium, Medium/Low, and Low) based on their factor scores. Twenty counties were selected for observation, with an over-sampling of the "high" group to better examine the counties where there is likely to be more traffic, more minority roadway usage, and traffic patterns that may not reflect residential populations. The factor score rankings and group classification of all 67 counties are displayed in Table 4.1. As this table shows, of the 20 counties selected, 55% (11 counties) were from the high group, 20% (4 counties) were from the medium group, 15% (3 counties) were from the medium/low group, and 10% (2 counties) were from the low

[15] In addition, a second factor was extracted with an eigenvalue slightly greater than one (eigenvalue = 1.12). However, this factor only explained 16% of the variance and none of the factor loadings for individual variables was greater than .50. This factor was statistically weak and uninterpretable due to the small factor loadings. As a result, the factor analysis was interpreted as have only one significant underlying factor. The sampling procedures therefore were based on the factor scores generated from the main factor.

group. The final selection of counties from within the four groups was based on the amount of departmental activity within those counties and their geographic location.[16]

[16] The final selection of counties from the four categories determined by factor analysis was based on input from PSP administrators and the research team. Special consideration was given to the specific activities of the department. For example, some counties were not selected (e.g. Philadelphia County) because PSP has limited jurisdiction in those areas, while other counties were selected because of more PSP activities. In addition, consideration was given to geographic location in an effort to more effectively cover the entire state and all major interstates (see Figure 4.1).

Table 4.1 County groupings based on factor analysis (n=67 counties).

GROUP 1—HIGH	GROUP 2—MEDIUM	GROUP 3—MED/LOW	GROUP 4—LOW
Allegheny (2)	Beaver (30)	Adams (39)	Armstrong (57)
Berks (8)	Bedford (32)	Bradford (40)	Cameron (67)
Bucks (10)	Blair (29)	Cambria (38)	Elk (65)
Chester (11)	Butler (24)	Carbon (49)	Forest (64)
Crawford (17)	**Centre (26)**	Clarion (45)	Fulton (56)
Dauphin (5)	Clearfield (27)	Clinton (48)	Jefferson (53)
Delaware (12)	Cumberland (18)	**Columbia (46)**	**Juniata (62)**
Erie (7)	**Franklin (23)**	Fayette (35)	**McKean (58)**
Lancaster (3)	**Lackawanna (21)**	Greene (36)	Mifflin (66)
Lehigh (4)	Lebanon (25)	Huntington (41)	Montour (63)
Luzerne (14)	Lycoming (28)	**Indiana (42)**	Perry (61)
Monroe (16)	**Mercer (20)**	Lawrence (43)	Potter (60)
Montgomery (6)	Northampton (19)	Snyder (50)	Sullivan (51)
Philadelphia (1)	Northumberland (33)	Somerset (44)	Venango (55)
Washington (15)	Pike (31)	Susquehanna (37)	Warren (59)
Westmoreland (13)	Schuylkill (22)	**Tioga (47)**	Wayne (52)
York (9)	Union (34)		Wyoming (54)

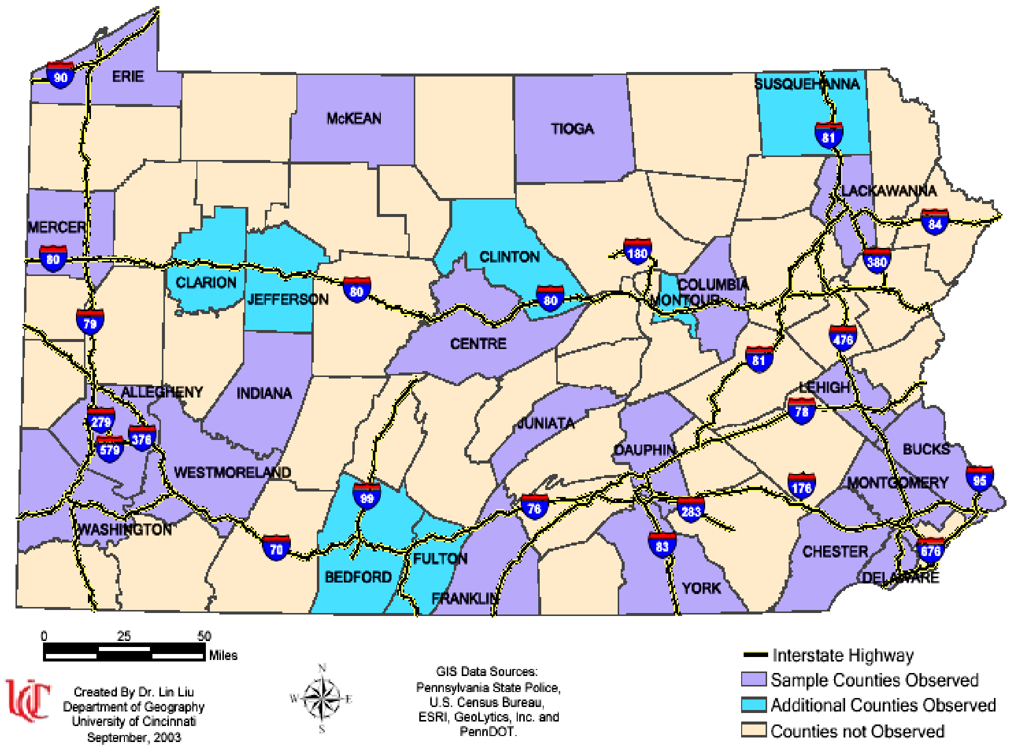
NOTE: Counties in bold were originally selected for observation. The numbers in parentheses indicate the counties' factor score rankings.

The twenty counties originally selected are displayed on the map in purple in Figure 4.1 and include:

Allegheny	Dauphin	Juniata	Montgomery
Bucks	Delaware	Lackawanna	Tioga
Centre	Erie	Lehigh	Washington
Chester	Franklin	McKean	Westmoreland
Columbia	Indiana	Mercer	York

As Figure 4.1 also indicates, additional observations were conducted for two days in seven other counties: Bedford, Clarion, Clinton, Fulton, Jefferson, Montour, and Susquehanna (shown on the map in blue). These counties were specifically identified based on preliminary analyses of the traffic stop data that indicated in those counties, all of which have significant interstate travel but small minority populations, that the percent of minorities that were stopped was substantially higher than the percent of minorities in the residential population. With one exception (Bedford County), these additionally selected counties were in the medium/low group (3 counties) or the low group (3 counties).

Figure 4.1. Counties with Observed Traffic Counts in Pennsylvania



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Once the counties were selected, PSP stations with jurisdiction in those areas were identified. The initial selection of roadways to be observed was the responsibility of the commanders at these stations, based on the guidance of detailed criteria (developed by the research team) that were deemed necessary for safety or data collection purposes. Specifically, station contacts were asked to select one location for each of the two initial days of observation that:

- Had a significant volume of traffic,
- Was generally representative of travel patterns in their jurisdiction,
- Generated a large number of citations,

- Was appropriate for use of RADAR while also allowing observers to see vehicle and driver characteristics, and
- Was safe for the observers to be stationed at all day.

After the first quarter (and each subsequent quarter) of traffic stop data collection was complete, the research team identified municipalities that had the highest percentages of stops and requested that locations in these municipalities be provided for subsequent observation sessions if they had not already been observed. Although occasionally it was not feasible to position observers at sites that were appropriate for Troopers in these municipalities, the stations did their best to accommodate requests, barring construction, weather, or safety hazards. For the additional observed counties, observed municipalities were selected by the research team based on the percent of stops generally, and the percent of stops of minorities in particular.

Data collection training and procedures

Undergraduate research assistants were recruited to serve as observers, whose primary responsibilities were to collect and enter data assessing roadway usage and traffic violating behavior. In order to be eligible to participate as a research assistant, undergraduate students were required to hold a minimum 3.0 GPA, to fill out an initial screening application, and to complete informal interviews with the project manager after passing the screening. During these interviews, the project manager explained the purpose of the overall study to provide the students with an understanding of the importance of the role of the roadway observations. Applicants that were selected to participate also had to pass the Pennsylvania State University Institutional Review Board's human subjects training, which focuses on the importance of confidentiality and protection of human subjects during the research process. Furthermore, all participants signed and were required to abide by the confidentiality and data integrity standards established in the project's own confidentiality agreement. Groups of 6-15 observers were recruited and trained each semester of the project's duration, with a total of 50 students participating over the course of 2002 and 2003.

Once students completed the hiring process, two mandatory training sessions were organized. First, PSP RADAR training instructors at the State Police Training Academy in Hershey, Pennsylvania spent four classroom hours explaining the philosophy, use, and limitations of RADAR technology to the team of observers. The PSP instructors then escorted several cars of observers to the nearby interstate where the observers practiced the techniques of RADAR learned earlier.

The project manager conducted the second training session, in several small groups, focusing on the specific procedures and techniques of data collection and data entry. The first part of this training documented the expectations of the observers before, during, and after each observation trip. Second, the data collection instruments were described and reviewed item by item (see Appendix A for the data collection instruments).[17] The majority of this part of the training session focused on the variables captured on the "RADAR Observation Form." Examples of each vehicle characteristic were offered, the different license plates available in Pennsylvania were reviewed, and the logic behind the order of the variables on the data collection instrument was explained (i.e., they were organized by the order in which they could usually be seen by observers).

Driver characteristics were reviewed extensively. To minimize error, observers were trained that *both* members of the observation team had to agree on the characteristics of the observed driver, including drivers' race/ethnicity. Race and ethnicity were captured using

[17] The project manager and data manager developed the data collection instruments during three 1-hour pilot test sessions on the nearby interstate, prior to the training of any undergraduate observers.

the following categories: White, Black, Hispanic, Asian, Native American, Middle Eastern, and other minority (Non-White). In cases where observers observed a Black Hispanic driver, they were trained that the observed driver should be coded based on skin color. If both observers agreed that the driver was a minority, but could not agree on a specific minority group, they were trained to record the race as simply "other Non-White." If the observers could not agree on the more general White / Non-White dichotomy, or if the driver's race was simply not discernible (e.g., tinted windows, sun visors, etc.), they were trained to record the driver's race as missing. Throughout the training, it was repeatedly emphasized to observers that missing data (on many items) was to be expected, and that they should always be confident in what was recorded; if they were not, they were trained to record the values for that variable(s) as missing.

Following the description of the data collection instrument, each group of observers practiced on the interstate, demonstrating their comprehension of the data collection process by showing that they could:

- plug in & test the RADAR set before starting,
- call out data to observation partner while running RADAR,
- call out data in order that it is on data sheet (less chance for error in recording data), and
- appropriately record data on the data collection instrument.

Each observer practiced calling out data and using RADAR with a minimum of 20 vehicles (some observers were more quickly adept at the data collection process than others). Each observer also practiced recording data (with the appropriate abbreviations) and agreeing on race, again with a minimum of 20 vehicles. All observers were evaluated in terms of their positioning and general use of RADAR, their ability to identify "good" RADAR situations (as defined by the PSP training personnel), their order of calling out data, their ability to also look at driver race while recording data, and their ability to accurately record the data. Following this roadway training, the training session also explained and demonstrated how the data collected would be entered into Microsoft Excel (for later transfer to SPSS), using one file for each type of data collected (i.e. one each for roadway usage and speeding observations).

The typical process of data collection consisted of the individual observation teams reporting to the host police barracks, being escorted to the pre-selected locations, and then setting up for data collection. During the data collection period, the two observers parked in a personal vehicle on the side or in the median of the roadway in order to collect information about the passing motorists and vehicles. Weather permitting, each day of observation was scheduled for between 7 and 8 hours of observation, which were divided approximately in half between observation of just roadway usage, and observation of speeding behavior (utilizing RADAR). Observers were scheduled for data collection only during daylight hours and during weather conditions that allowed proper visibility.

Sample

Within each of the originally selected twenty counties, research assistants completed a total of 10 days of observation (approximately 7-8 hours per day, for a planned total of about 1,500 hours of observation). Due to weather and daylight constraints, particularly during the winter months, some observation teams were not able to complete this amount of data collection. Observations were scheduled to vary by day of the week, time of day, and month of the year to allow for the possibility of variation in traffic patterns associated with day, time, and season. The observations conducted in the additional seven counties were scheduled for two consecutive 8-hour days in June 2003; therefore, these counties have smaller numbers of cases and do not have the same seasonal variation that the original sample of 20 counties offers.

Tables A.1 – A.21 in Appendix B document the data collected in each of the 27 sampled counties. As shown in Appendix B, each county's table lists the following specific information for each of the municipalities that was observed:

- the municipality name,
- each municipality's percent of PSP stops (during Year 1 of stop data collection, May 2002-April 2003) in that county,
- the dates of each of the county's observation sessions,
- the road type on which observation was conducted,
- the speed limit in which observation was conducted,
- the total number of vehicles and hours observed during each day of observation,
- the average number of vehicles observed per hour,
- and the percentage of the total number of vehicles for which speeding behavior was measured with RADAR.

Overall, across the 27 sampled counties, a total of 1577.5 hours of observation was conducted in 226 locations distributed across 148 municipalities. With few exceptions (e.g., weather, construction, or other safety hazards), municipalities selected for observation corresponded well to municipalities with the greatest amounts of PSP traffic enforcement activity in the select counties. Across the state, observations were made of 161,169 non-commercial vehicles between February 2002 and June 2003, of which observers captured drivers' speeding behavior with RADAR 41.4% of the time (n=66,741). Within this subset of observations, 6.5% (n=4,328) were missing information for at least one driver or vehicle characteristic. Over 40% of the cases with incomplete data were missing information regarding driver race (n=1,800, 2.7% of the full dataset) and one-third of those cases were also missing driver age and sex. Because the primary focus of this research is to examine the impact of driver demographic characteristics on speeding behavior and information regarding the vehicle may also be an important predictor of the dependent variable, all variables with missing data have been excluded from the multivariate analyses of speeding behavior that follow in Chapter 6.[18] Therefore, those analyses are based on 62,413 observations in 140 municipalities. Descriptive statistics for this subsample of speeding observations are provided in Chapter 6.

Strengths and Limitations

The data utilized in this study have a number of strengths in comparison to prior research. First, the approach of directly observing behavior in natural settings allows for the unobtrusive collection of data on drivers' offending behavior, minimizing the well-documented biases associated with official data collection and self-report methods (see Biderman & Lynch, 1991). Furthermore, this method allows for the collection of data on offenders' demographic characteristics for a much larger portion of the population than traditional self-report studies.

Second, the sampling procedures implemented to represent statewide travel patterns produce greater external reliability in terms of geography and road types than in the previous studies of this kind, which were often limited to only sections of interstates. Third, the year-long data collection and repeated observations in sampled counties also increases external validity in terms of seasonal variation, as most previous observational studies were limited to data collection periods of only a few weeks or months (Lamberth, 1994, 1996; Lange et al., 2005; Smith et al., 2003; The Alpert Group, 2004; for exception, see Farrell et al., 2003).

[18] Other than race/ethnicity, variables missing information for 1.0% or more of the cases include: driver age (1.6%), driver gender (1.6%), passengers in vehicle (1.3%), and state of vehicle license plate (2.7%). Because missing data is not randomly missing, there is no indication that any type of imputation method would be reliable. Additionally, the statistical software used for these analyses (HLM, discussed in more detail in Chapter 5) cannot handle missing data. Therefore, the exclusion of these cases was necessary.

Similarly, the length of the data collection period provided for observations to be varied by weekday and weekend, as well as staggered starting times, allowing for the possibility that the demographics of the driving population might differ by day of week and time of day.

Nevertheless, several limitations should be noted. A general limitation of traffic surveys that rely on the use of RADAR for speed detection may be that its use could slow down the speed of passing traffic (see Smith et al., 2003). Proponents of this approach, however, suggest that that the effect of observers' use of RADAR on traffic should be comparable to the effect of official use of RADAR on driver behavior (Lange et al., 2001; Engel & Calnon, 2004b). Furthermore, research sponsored by the National Highway Traffic Safety Administration indicates that only a small percentage of drivers (4%) use radar detectors regularly (Royal, 2003).

How often drivers' characteristics can be determined in stationary locations using RADAR is an empirical question that has not been addressed. As noted above, training sessions conducted prior to observers' participation in the study indicated that observers can determine the driver's race in good weather, during daylight hours, and when RADAR is conducted in locations with clear visibility to the roadway.[19] Therefore, if the goal of the research is to determine drivers' risk of being stopped for speeding, observers using RADAR in stationary vehicles may be a stronger method than observers in moving vehicles, or strategically placed video cameras.

Finally, it was practically and financially implausible to observe all counties across Pennsylvania or all roadways within each of the 27 sampled counties. Again, counties were

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[19] The research team also learned what troopers have argued all along – that the initial decision to stop a car for a speeding infraction cannot be based on characteristics of the driver alone. Observers (and troopers) are trained to identify a car and determine the speed of that car. It is only after a vehicle's speed has been determined and it passes the stationary vehicle using RADAR that drivers' characteristics can be determined.

sampled based on the likelihood of the largest discrepancies between residential and driving populations as well as general roadway usage and roadway usage by minorities in particular. It is possible that the sampling procedure could affect the results of the multivariate analyses if the seven variables on which the counties were sampled are related to driving behavior. In order to examine this possibility, later multivariate analyses incorporate individual counties' factor scores as a control variable. Within the sampled counties, observation sessions were concentrated on segments of roadways that generated the most traffic stop activity. Therefore, the roadway observations should not be considered a direct measure of who is using the roadways in each county, but rather who is using the roadways in areas where they are most likely to come to police attention. Thus, the county averages of driver characteristics are only estimates of the county driving population at the highest risk of police detection and do not include all possible roadways on which traffic stops may have occurred.

CHAPTER 5: METHODS

This chapter is organized in three sections. First, the creation of the dependent and independent measures is explained. Table 5.1 presents descriptive statistics for each of these variables. Second, this chapter details the hierarchical nonlinear modeling techniques used to estimate the dichotomous dependent variables. Finally, the strengths and limitations of the measures and analytical strategy are discussed.

MEASURES

Table 5.1 below displays the descriptive statistics for all the dependent and independent variables described below.

Dependent Variables

Although a number of different driving behaviors are illegal, this study focuses on the dependent variable—speeding—for several reasons. First, national survey data reveals that people have consistently reported speeding as the most frequent reason for which they are stopped by police (Boyle et al., 1998; Langan et al., 2001; Durose et al., 2005, 2007). Second, in terms of methodological considerations, the use of RADAR technology allows speeding to be measured more reliably and objectively than many other illegal driving behaviors. Finally, for many police agencies, particularly large state police departments and highway patrols, the most common offense for which traffic stops are made is speeding. Indeed, for the initial year-long period of traffic stop data collection simultaneously occurring during the observation data collection, the Pennsylvania State Police identified speeding as the reason for the stop in 75 percent of all traffic stops (Engel et al., 2004). Therefore, as a practical consideration, a survey of speeding behavior is probably the most appropriate type of benchmark data to be collected when the research goal is a comparison to the agency's traffic stops (Engel & Calnon, 2004b).

The dependent variable is operationalized in two ways. First, speeding is explored as a continuous measure of amount over the limit. Nearly 23% of all observed vehicles were traveling at or below the speed limit. Therefore, the distribution of this variable originally included negative values and had a mean amount over the limit of 5.43 mph. For the purpose of this analysis, the vehicles not speeding (i.e., negative values) were recoded as zero's. The recoded amount over the limit variable has a distribution that is highly skewed. As shown in Table 5.1, the mean and standard deviation of this variable are nearly equivalent. As a result, the use of a normal distribution is inappropriate because highly skewed distributions violate the normality (homeskedasticity) assumption of OLS regression. As will be described later, a Poisson distribution with log link function is utilized to adjust for this skewness problem. Once this variable is recoded, observed vehicles averaged speeds approximately 6.2 mph over the speed limit.

Second, speeding is examined as a series of dichotomous variables representing whether the driver was observed for exceeding the posted speed limit by 1) at least five miles per hour (mph), 2) at least 10 mph, 3) at least 15 mph, 4) at least 20 mph, and 5) at least 25 mph. Using a series of dichotomous variables allows for an examination of the influence of predictor variables across different degrees of speeding severity. As shown in Table 5.1, slightly over half of all observed drivers were speeding at least five mph over the limit. The percentage of speeding drivers decline considerably as speeding becomes more serious.

Table 5.1. Descriptive Statistics for Observations of Speeding (n=62,413)

	Mean	Standard Deviation	Minimum	Maximum
Dependent Variables				
Amount over limit	6.178	5.792	0	63
Speeding at ≥5 mph over	.535	.499	0	1
Speeding at ≥10 mph over	.255	.436	0	1
Speeding at ≥15 mph over	.097	.295	0	1
Speeding at ≥20 mph over	.027	.162	0	1
Speeding at ≥25 mph over	.006	.078	0	1
Independent Variables				
Level 1 Variables (observation)				
Driver Male	.667	.471	0	1
Driver Black	.035	.184	0	1
Driver Non-White	.066	.247	0	1
Driver 25 or under	.120	.325	0	1
Passengers	.413	.492	0	1
PA License Plate	.748	.434	0	1
Sports Car	.077	.266	0	1
Vehicle Red	.169	.375	0	1
Rush Hour	.225	.418	0	1
Weekday	.608	.488	0	1
Interstate Highway	.582	.493	0	1
Speed Limit 65mph	.358	.479	0	1
Level 2 Variables (municipality, n=140)				
Munic number of observed vehicles	445.807	262.003	50.0	1492.0
Munic mean % observed young drivers	11.745	4.176	3.4	23.3
Munic mean amount over limit for PSP speeding stops	19.107	2.632	12.8	26.9

Independent Variables

The independent variables can be categorized according to driver characteristics, vehicle characteristics, situational characteristics, and municipality characteristics. To accurately assess the relationship between driver demographics and speeding behavior, other potential explanatory factors must be considered. The remaining independent variables are included in the analysis to explore the influence of possible alternative explanations or because empirical evidence has previously demonstrated important relationships.

Driver Characteristics

The demographic characteristics of observed drivers represent the key independent variables of interest. Driver gender is coded as a dichotomous variable (male=1). Driver age, an important intervening variable since much research links age and violating behavior, is operationalized as a dichotomous variable, representing whether the driver was perceived to be 25 or under. Driver race is coded as two dichotomous variables with Black as 1 and Non-White as 1. The Non-White category includes the following specific minority groups: Black, Hispanic, Native American, Asian or Pacific Islander, Middle Eastern, and other.[20] As shown in Table 5.1, the majority of observed drivers were male, over 25, and White.

Vehicle Characteristics

The presence of passengers in a vehicle was coded as a simple dichotomy (Yes=1). Whether the vehicle displayed a Pennsylvania license plate is also coded as a dichotomous variable (PA=1). In addition, the type of vehicle and vehicle color are measured as dichotomous variables, comparing sports cars to all other vehicles (sports car=1) and red vehicles to all other colors (red=1). As shown in Table 5.1, the majority of vehicles displayed a Pennsylvania license plate, while approximately 40 percent had passengers. Only eight percent of the observed vehicles were sports cars, and 17 percent were red in color.

Situational Characteristics

The time of the observation is measured as a dichotomous variable comparing morning and evening rush hour time blocks to the rest of the day (rush hour=1). Whether the

[20] Although observers, when possible, did capture these more specific racial categories during their observations, the most reliable measures of observation are based on White / Black and White / non-White dichotomies. As previously noted, observers were trained to identify drivers as "non-White" if they were certain the driver was of some racial or ethnic minority group (i.e., not White), but were unclear or could not agree on the precise racial/ethnic group classification.

observation occurred on a weekday or during the weekend is measured as a dichotomous variable, with weekday (Monday through Friday) =1. The type of road on which the observation occurred is coded as a dichotomous variable: interstate=1, which is compared to state, county, or local roads. Finally, speed limit is measured as a dichotomous variable with 65 miles per hour compared to all lower speed limits. As shown in Table 5.1, most observed vehicles were traveling not during rush hours, on weekdays, and on interstate highways. About 36 percent of vehicles were observed in a 65 mph speed limit.

Municipality Characteristics

Finally, the influence of contextual factors on drivers' speeding behavior is explored. First, the study controls for the number of observed vehicles in each municipality. The average number of vehicles observed per municipality was approximately 446, with a large range from 50 to 1,492 vehicles. Second, the impact of the municipality average percent of young drivers is examined, based on the hypothesis that the demographic characteristics of the observed driving population might impact speeding behavior in that municipality. The average percent of young drivers observed per municipality was 11.7. Finally, the study explores whether drivers' speeding behavior may be influenced by the police enforcement behavior in individual municipalities. Therefore, a final predictor variable—the mean amount over the limit for PSP speeding stops within the municipality—is included. This variable is created from the PSP officer-collected traffic stop data that occurred simultaneously with the collection of observation data (see Engel et al., 2004). When PSP troopers stopped drivers for speeding offenses, they also recorded the amount over the posted limit at which the driver was speeding. The continuous measure of amount over the limit for PSP stops represents the municipality average for speeding stops. If drivers are aware of local "speeding thresholds" (i.e. the amount over the speed limit at which police typically issue citations for speeding), then speeding behavior may be predicted by that the municipality average amount over the limit. As shown in Table 5.1, the municipality average amount over the speed limit for which PSP troopers initiated speeding stops was 19.1, but the range for these informal speeding thresholds varied from a low of 12.8 to a high of 26.9. Higher average amounts for PSP speeding stops represent a less strict speeding threshold, while lower amounts indicate more stringent control of speeding behavior.

ANALYTICAL STRATEGY

The observation data collected in this study are hierarchical in nature, nested within two levels. The first level is that of the observation, of which there are 62,413 cases. The second level includes 140 municipalities within which the observation sessions were conducted. Given the hierarchical structure of these data, ordinary regression techniques are not appropriate. That is, the addition of measures at more than one level of aggregation introduces a statistical dilemma. Specifically, regression residuals for the level 1 cases (observations) within the same level 2 unit (municipalities) may be correlated, which violates the assumption of independence that underlies most ordinary regression techniques. The implications of violating this assumption are substantial, as dependence can lead to inefficient estimates and biased test statistics, making the analyses appear to have more power than they do (Guo & Zhao, 2000; Raudenbush & Bryk, 2002).

Hierarchical linear modeling (HLM) is a modeling procedure that can overcome this statistical dilemma. HLM includes an additional error term, Ui, that reflects the extra variation common to all level 1 cases within the level 2 unit, so the level 1 error term (Rij) can be independent. That is, HLM explicitly models the dependence of the residuals through this error term. In addition to allowing for the random variation in the dependent variable, this statistical technique also partitions the total variance into within and between components, which allows for measurement of contextual effects (Raudenbush & Bryk, 2002). More specifically, the 2 level HLM models to be estimated in this study divide the total variability in the dependent variables into two components: 1) σ^2, the proportion of variance across level 1 cases (observations), and 2) tau, the proportion of variance between level 2 cases (municipalities).

In Chapter 6, a two-level HLM model with the Poisson distribution is used to estimate the amount over limit dependent variable, which is, as described above, highly skewed. In order to estimate the dichotomous speeding dependent variables (over10, over15, etc.), a nonlinear model was required. The predicted value of binary outcome variables is constrained to be one of two values, either 0 or 1, which prohibits a normal distribution. For analyses examining only one level of data, logistic regression, which estimates the probability of the occurrence of the dependent variable, is appropriate for such restrictions on the value of Y (Liao, 1994). Analyses that include data at more than one level of aggregation utilize HLM, but with binary outcome variables cannot rely on a standard level 1 model because it assumes a linear model and normally distributed errors at level 1, once the additional error term is included (Raudenbush & Bryk, 2002). To account for these characteristics of the dependent variables, a nonlinear form of hierarchical modeling is used. Binary outcome models use a binomial sampling model with a Bernoulli distribution, as opposed to a normal sampling model, and a logit link instead of an identity link (Guo & Zhao, 2000; Raudenbush & Bryk, 2002). Both standard and hierarchical nonlinear models produce the predicted log-odds of the outcome variable, which can be transformed through exponentiation into the odds or probability of Y.

STRENGTHS AND LIMITATIONS

The measures and analytical strategy utilized in this study have a number of strengths and limitations that are important to note. First, capturing speeding behavior with the actual miles per hour over the limit is a particularly strong methodology because it allows for the examination of differences in severity of offending that previous dichotomous measures of "speeding/not speeding" did not. Second, the methodology the observation teams utilized for assessing violating behavior replicates actual PSP tactics for apprehending speeding drivers. Unlike previous data collection efforts that used photography or observers traveling in moving traffic, the location and visibility of observers in this study allowed for data collection in conditions that are similar to what PSP Troopers actually experience.

The most important limitations of the methodology surround the observers' categorization of drivers' demographic characteristics. Observers' subjective assessments may inaccurately categorize drivers, particularly when assessing drivers' race and/or ethnicity. The possibility that some minority drivers were incorrectly classified by observers as White, is particularly likely in the case of the identification of Hispanic drivers during roadway observations. Other observational and traffic studies have reported the difficulties associated with the observation of Hispanics, particularly with reliably distinguishing Hispanics from White drivers (Eck et al., 2003; Farrell et al., 2003; Lange et al., 2001, 2005; Smith & DeFrances, 2003; Smith et al., 2003; The Alpert Group, 2004). In New Jersey, Lange et al. (2001, 2005) were able to compare the percentages of Turnpike drivers identified as Hispanic by observers (The Speed Survey) with the percentages of those drivers who self-reported Hispanic ethnicity (The Tollbooth Survey). Only 4.8 percent of drivers were identified by observers as Hispanic, compared to 14.2 percent in the self-report survey. Similar differences between the Black and White populations of the two surveys were not found. Unfortunately, it is not possible to directly assess the incorrect classification of Hispanics in our roadway survey. It is one of the limitations of this type of benchmark data collection. To be cautious with the findings, analyses based specifically on observations of Hispanic drivers are not presented. Drivers coded as Hispanic by observers are included in the overall non-White category of drivers.

In order to minimize the possibility of inaccurate racial categorization in this data collection effort, observers were trained that both members of an observation team had to agree on drivers' characteristics or record the information as missing data. Observers were trained that when a driver's race/ethnicity was identifiable as "minority" or "not White" but a more specific racial/ethnic category was not determinable, the race/ethnicity of the driver should be recorded as non-White. Zatz (2000) argued that studies of racial differences that only examine White-Black or White-Nonwhite differences might be oversimplifying the influence of race. With this in mind, the data collection instrument (see Appendix A) was created to include several specific minority groups: White, Black, Native American, Asian or Pacific Islander, Hispanic, Middle Eastern, other minority, and unknown. Although observers, when possible, did capture these more specific racial categories during their observations, the most reliable measures of observation are based on White / Black and White / non-White dichotomies. While these data collection procedures ensure that the overall minority group classification is as reliable as possible, it increases the likelihood of underestimating particular minority groups (e.g. Hispanic, Asian, etc.) by including them in the non-White group, but not identifying them more specifically.

In addition to the limitations of racial/ethnic identification of drivers, the measure of drivers' age as a dichotomy of 25 years old or younger versus 26 years or older is rather crude. Although a dichotomous measure for age provides less precision, it is likely to have more validity compared to a measure with more discrete categories. Nevertheless, observation of drivers' age for this dichotomy is somewhat subjective, particularly for drivers who are in their mid-20s. Other observational studies have suffered from the same difficulties in categorizing driver age. Lange et al. (2005) originally started with three categories of driver age: younger than 25, 25-45, and older than 45 years. Facing serious problems with interrater reliability among the two younger age categories, they recategorized to a less precise, but more reliable, dichotomous variable (45 and younger vs. older than 45).

As is the case with race and ethnicity, the possible inaccurate classification of age is one of the limitations of roadway observations and the amount of inaccuracy in classifications cannot be determined. Unfortunately, the reliability and validity of observers' identification of drivers' demographic characteristics is a weakness of all data collection efforts of this type.

CHAPTER 6: RESULTS

This chapter presents the results of bivariate and multivariate analyses of drivers' speeding behavior in Pennsylvania. First, this chapter examines bivariate differences in speeding behavior by gender, age, and race. Specifically, Tables 6.1 - 6.27 present the results of bivariate crosstabulation analyses examining speeding behavior by driver demographic characteristics for each of the observed counties; the same relationships are presented at the state-level in Table 6.28. Second, multivariate analyses addressing the study's main research questions are presented in Tables 6.29 – 6.40. Specifically, hierarchical Poisson and logistic two-level models examine the influence of drivers' demographic characteristics, as well as vehicle, situational, and municipality characteristics, on observed speeding behavior. A detailed discussion of the results presented in this chapter and the implications of these findings are addressed in the concluding chapter.

BIVARIATE RELATIONSHIPS

Zero order correlations were computed for all variables to determine their relationship to one another at the bivariate level. The bivariate correlation matrices for Level 1 and Level 2 variables are presented in Table A.22 in Appendix B.

County Level Crosstabulations of Demographic Differences in Speeding

The tables below document the bivariate relationships between driver demographic characteristics and speeding in each of the 27 sampled counties. Within each county, the table lists the following information:

- the number of drivers within each demographic category (i.e., gender, age, and race),
- the percent of missing data for each demographic characteristic (i.e., the percent of all RADAR data collection for which observers were not able to capture one or more characteristics of the driver), and
- the percentage of each demographic category observed to be speeding at 5, 10, 15, and 20 mph over the posted speed limit.

Table 6.1 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Allegheny County. The data from Allegheny County suggest no significant gender differences in observed speeding behavior. Age differences, however, are strong and statistically significant for each operationalization of speeding. The effects of age on speeding behavior are stronger at higher speeds. Drivers identified as 25 years or younger are about 1.1, 1.2, 1.5, and 2.1 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. There are no statistically significant racial differences in observed speeding behavior in Allegheny County.

Table 6.1 Speeding in Allegheny County by Driver Characteristics (n=3,849)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	1,170	1.2	70.9	45.6	21.0	6.1
Male	2,632		71.7	44.0	21.2	6.5
25 years old or under	339	1.4	78.8**	52.5**	30.1***	12.1***
Over 25 years old	3,455		70.8	43.8	20.3	5.8
White	3,559	2.3	71.0	44.5	21.4	6.4
Non-White	201		76.1	44.3	16.4	6.0

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.2 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Bedford County. The data from Bedford County suggest no significant gender differences in observed speeding behavior. Age differences, however, are strong and statistically significant for three of the four operationalizations of speeding. The effects of age on speeding behavior are stronger at higher speeds in Bedford County. Drivers identified as 25 years or younger are about 1.3, 1.7, and 2.5 times more likely than drivers over 25 to exceed the speed limit by 10, 15, and 20 miles per hour, respectively. Statistically significant differences by race are evident for observed speeding behavior in

Bedford County and the effects of race on speeding behavior are stronger at higher amounts over the limit. Drivers identified as non-White are about 1.1, 1.5, 1.8,and 2.3 times more likely than white drivers to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively.

Table 6.2 Speeding in Bedford County by Driver Characteristics (n=1,323)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	417	1.2	83.5	54.2	26.6	9.6
Male	906		82.5	54.4	28.3	10.5
25 years old or under	1,100	1.6	84.9	65.1***	42.7***	20.6***
Over 25 years old	218		82.3	52.1	24.8	8.1
White	1,115	1.6	81.3***	50.8***	24.8***	8.5***
Non-White	203		90.6	73.4	44.3	19.2

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.3 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Bucks County. The data from Bucks County suggest no significant gender differences in observed speeding behavior. Age differences, for the most part, are statistically significant. Drivers identified as 25 years or younger are about 1.2, 1.4, and 1.9 times more likely to exceed the speed limit by 5, 10, and 15 miles per hour, respectively, compared to drivers identified as over 25 years old. Therefore, the effects of age on speeding behavior are somewhat stronger for more serious speeding. Although there is a difference of nearly six percentage points between younger and older drivers at 20 mph over the limit, the difference does not reach statistical significance. Statistically significant differences by race are evident for observed speeding behavior in Bucks County, particularly at higher amounts over the limit. Racial differences in speeding at 5 mph over the limit are not as strong and do not reach statistical significance. In contrast, drivers identified as non-White are approximately 1.2, 1.5, and 2.1 times more likely than white drivers are to exceed the speed limit by 10, 15, and 20 miles per hour, respectively.

Table 6.3 Speeding in Bucks County by Driver Characteristics (n=4,063)

Driver Characteristics	# of drivers	% Missing1	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	1,328	2.0	63.3	35.1	13.9	3.8
Male	2,653		65.6	35.5	13.9	4.2
25 years old or under	471	1.9	73.2***	47.3***	23.8***	9.1
Over 25 years old	3,513		63.8	33.8	12.6	3.4
White	3,446	3.0	64.3	34.4**	13.1***	3.5***
Non-White	496		68.8	40.3	19.4	7.3

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.4 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Centre County. These data suggest only slight statistically significant gender differences in observed speeding behavior. Men are 1.3 times more likely to speed 10 miles per hour over the speed limit than women are. Age differences in Centre County are strong and statistically significant for all measurements of speeding. Drivers identified as 25 years or younger are about 1.2, 1.6, 2.8, and 4.2 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. Again, the effects of age on speeding behavior are stronger at higher amounts over the limit. Finally, there are no statistically significant racial differences in observed speeding behavior in Centre County.

Table 6.4 Speeding in Centre County by Driver Characteristics (n=2,429)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	772	1.2	45.6	13.3**	4.0	0.9
Male	1,628		49.3	17.6	5.2	1.7
25 years old or under	310	0.7	55.8**	23.9***	11.0***	4.2***
Over 25 years old	2,101		47.0	15.1	4.0	1.0
White	2,326	1.0	48.2	16.3	4.8	1.4
Non-White	78		47.4	17.9	7.7	1.3

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.5 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Chester County. These data suggest no significant gender differences in observed speeding behavior. Age differences, however, are statistically significant and stronger for higher amounts over the limit. Drivers identified as 25 years or younger are about 1.2, 1.6, 2.4, and 3.6 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. There is only one significant racial difference in observed speeding behavior in Chester County; non-Whites are about 1.2 times more likely to exceed the speed limit by 10 miles per hour than whites.

Table 6.5 Speeding in Chester County by Driver Characteristics (n=2,636)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	1,012	1.1	64.6	33.9	13.6	4.1
Male	1,594		63.2	33.4	13.4	4.3
25 years old or under	281	1.3	72.6***	50.9***	27.8***	11.4***
Over 25 years old	2,320		62.6	31.3	11.7	3.2
White	2,371	2.3	63.6	32.8*	13.0	4.0
Non-White	205		66.8	40.0	17.6	4.9

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.6 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Clarion County. These data suggest that significant gender differences in observed speeding behavior are only evident at the highest amount over the limit. That is, men are approximately 20 times more likely to speed 20 mph over the limit than women are. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 2.0, 2.3, and 4.2 times more likely than drivers over 25 are to exceed the speed limit by 10, 15, and 20 miles per hour, respectively. Statistically significant race differences are also noted. Drivers identified as non-White in Clarion County are about 1.3, 2.0, and 2.5 times more likely than White drivers are to exceed the speed limit by 5, 10, and 15 miles per hour, respectively.

Table 6.6 Speeding in Clarion County by Driver Characteristics (n=931)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	295	3.5	57.3	20.3	3.1	0.0*
Male	636		53.9	19.7	5.2	2.0
25 years old or under	108	3.5	61.1	36.1***	9.3*	4.6**
Over 25 years old	823		54.4	17.9	4.0	1.1
White	791	5.5	53.2**	17.7***	3.9**	1.3
Non-White	121		66.9	34.7	9.9	3.3

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.7 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Clinton County. These data suggest no significant gender differences in observed speeding behavior. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.4, 2.1, and 2.6 times more likely than drivers over 25 are to exceed the speed limit by 5, 10, and 15 miles per hour, respectively. Race differences are also statistically significant in Clinton County. Drivers identified as non-White are about 1.3, 2.0, and 2.2 times more likely than White drivers are to exceed the speed limit by 5, 10, and 15 miles per hour, respectively.

Table 6.7 Speeding in Clinton County by Driver Characteristics (n=1,004)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	323	3.6	44.9	16.7	5.3	1.2
Male	681		48.6	17.5	6.0	0.9
25 years old or under	128	4.7	61.7***	32.0***	12.5***	2.3
Over 25 years old	864		45.4	15.2	4.9	0.8
White	806	6.2	44.8***	14.8***	4.7**	0.9
Non-White	171		60.2	29.2	10.5	1.8

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.8 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Columbia County. These data suggest no significant gender differences in observed speeding behavior. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.3, 2.4, 3.8, and 5.0 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. There are also racial differences in observed speeding behavior in Columbia County, but the differences only reach statistical significance for 10 and 15 miles per hour over the limit. Non-Whites are 1.8 and 2.1 times more likely than White drivers are to exceed the speed limit by 10 and 15 miles per hour, respectively.

Table 6.8 Speeding in Columbia County by Driver Characteristics (n=2,958)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	947	1.4	44.9	14.1	3.5	1.1
Male	1,971		45.4	13.5	3.8	1.1
25 years old or under	313	2.0	57.8***	28.4***	10.9***	3.5***
Over 25 years old	2,585		43.6	11.9	2.9	0.7
White	2,762	2.0	44.8	13.1***	3.5*	1.0
Non-White	138		52.9	23.9	7.2	1.4

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.9 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Dauphin County. These data suggest no significant gender differences in observed speeding behavior. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.3, 1.7, 2.3, and 3.2 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. There are also racial differences in observed speeding behavior in Dauphin County, but the differences only reach statistical significance for 15 miles per hour. Non-Whites are 1.9 times more likely than White drivers are to exceed the speed limit by 15 miles per hour.

Table 6.9 Speeding in Dauphin County by Driver Characteristics (n=2,374)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	724	0.9	49.7	22.4	10.2	2.6
Male	1,650		52.5	25.2	8.4	2.2
25 years old or under	277	0.9	63.2***	38.3***	18.4***	5.8***
Over 25 years old	2,096		50.1	22.5	7.9	1.8
White	2,263	1.4	51.2	23.8	8.7*	2.1
Non-White	99		57.6	32.3	16.2	5.1

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.10 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Delaware County. These data do show small, but statistically significant, gender differences in observed speeding behavior. Men are 1.1, 1.1, and 1.3 times more likely than women are to exceed the speed limit by 5, 10, and 15 miles per hour, respectively. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.1, 1.4, 1.8, and 2.5 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. There are also significant racial differences; non-Whites are about 1.2, 1.5, 1.9, and 1.8 times more likely than White drivers to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively.

Table 6.10 Speeding in Delaware County by Driver Characteristics (n=3,181)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	1,172	2.5	65.6***	35.5**	11.9*	2.9
Male	1,929		71.6	40.3	15.0	3.7
25 years old or under	328	2.0	76.5**	53.0***	22.9***	7.3***
Over 25 years old	2,789		68.4	36.7	12.8	2.9
White	2,571	5.7	66.7***	35.4***	12.1***	3.0*
Non-White	429		80.2	52.9	22.6	5.4

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.11 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Erie County. These data suggest slight gender differences in observed speeding behavior. In Erie County, men are significantly more likely than women are to exceed the speed limit by 10 or more miles per hour. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.4, 2.1, 3.2, and 22.0 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. There are no significant racial differences in observed speeding behavior in Erie County. This may partially be a result of the small percentage of non-Whites that were observed.

Table 6.11 Speeding in Erie County by Driver Characteristics (n=2,974)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	1,096	1.6	26.1	5.6*	1.2	0.4
Male	1,830		27.8	7.7	2.1	0.4
25 years old or under	404	1.1	35.1***	12.4***	4.2***	2.2***
Over 25 years old	2,537		25.7	6.0	1.3	0.1
White	2,882	1.2	27.1	6.8	1.7	0.4
Non-White	55		23.6	5.5	1.8	0.0

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.12 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Franklin County. These data suggest no significant gender differences in observed speeding behavior. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.4, 1.8, 3.2, and 4.0 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. There are no significant racial differences in observed speeding behavior in Franklin County. Again, this may partially be a result of the small percentage of non-Whites that were observed.

Table 6.12 Speeding in Franklin County by Driver Characteristics (n=2,871)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	1,083	0.9	30.4	10.3	2.2	0.3
Male	1,761		30.6	9.8	2.8	0.7
25 years old or under	313	1.2	40.6***	16.6***	6.4***	1.6**
Over 25 years old	2,525		29.1	9.1	2.0	0.4
White	2,764	1.6	30.2	10.0	2.6	0.5
Non-White	60		23.3	6.7	0.0	0.0

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.13 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Fulton County. These data suggest no significant gender differences in observed speeding behavior. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.3, 1.6, 1.9, and 2.1 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. Racial differences are also statistically significant and are stronger for higher amounts over the limit in Fulton County. Drivers identified as non-White are about 1.2, 1.5, 1.7,and 2.1 times more likely than White drivers to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively.

Table 6.13 Speeding in Fulton County by Driver Characteristics (n=1,304)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	361	1.5	60.9	38.0	17.5	9.7
Male	943		57.9	35.8	21.3	9.8
25 years old or under	200	1.9	70.5***	52.0***	33.0***	17.5***
Over 25 years old	1,099		56.4	33.5	17.8	8.3
White	1,086	2.4	56.6***	33.7***	18.2***	8.3***
Non-White	206		68.9	50.0	30.6	17.5

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.14 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Indiana County. These data show some statistically gender differences in observed speeding behavior. Specifically, men are 1.3 and 1.8 times more likely than women are to exceed the posted speed limit by 10 and 15 miles per hour, respectively. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.5, 2.1, 2.8, and 3.7 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. The only significant racial difference in observed speeding behavior indicates that at the lowest amount over the limit (5 or more miles per hour), non-Whites are 1.4 times more likely to exceed the speed limit than Whites are.

Table 6.14 Speeding in Indiana County by Driver Characteristics (n=2,742)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	905	1.1	42.0	16.2**	3.6**	1.1
Male	1,807		44.1	20.6	6.5	1.9
25 years old or under	311	0.8	62.7***	36.0***	12.9***	4.8***
Over 25 years old	2,409		40.8	17.0	4.6	1.3
White	2,639	1.9	42.9*	19.1	5.5	1.7
Non-White	51		58.8	21.6	5.9	2.0

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.15 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Jefferson County. These data suggest no significant gender differences in observed speeding behavior. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger in Jefferson County are about 1.3, 1.8, and 2.2 times more likely than drivers over 25 to exceed the speed limit by 5, 10, and 15 miles per hour, respectively. Similarly, race differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as non-White are about 1.2, 1.5, 2.8, and 4.0 times more likely than White drivers to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively.

Table 6.15 Speeding in Jefferson County by Driver Characteristics (n=1,105)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	352	3.1	47.4	13.4	3.4	0.3
Male	753		49.4	15.3	3.6	1.1
25 years old or under	149	3.7	60.4**	24.2***	6.7*	2.0
Over 25 years old	949		47.1	13.2	3.1	0.6
White	958	4.9	47.3*	13.6*	2.8**	0.6*
Non-White	126		58.7	20.6	7.9	2.4

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.16 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Juniata County. Unlike the trends in most other counties, the data from Juniata County show significant gender differences in observed speeding behavior in the opposite direction as is evident in other counties with significant gender differences. That is, women, not men, are 1.1, 1.3, and 1.7 times more likely to exceed the speed limit by 5, 10, and 15 miles per hour, respectively. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.4, 2.0, 3.3, and 5.5 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. There are also significant racial differences in observed speeding behavior in Juniata County that increase in strength for more serious speeding. Specifically, non-Whites are 1.3, 2.0, 3.1, and 7.8 times more likely than Whites are to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively.

Table 6.16 Speeding in Juniata County by Driver Characteristics (n=2,544)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	818	0.9	44.0*	17.4**	5.7**	1.1
Male	1,702		39.4	13.1	3.4	1.2
25 years old or under	251	0.8	54.2***	25.9***	11.2***	4.4***
Over 25 years old	2,272		39.5	13.2	3.4	0.8
White	2,454	1.0	40.7*	14.2**	4.0**	1.0***
Non-White	64		54.7	28.1	12.5	7.8

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.17 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Lackawanna County. These data suggest no significant gender differences in observed speeding behavior. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.1, 1.4, 1.9, and 2.0 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. There are also significant racial differences in observed speeding behavior in Lackawanna County that increase in strength for more serious speeding. Specifically, non-Whites are 1.4, 1.9, 2.3, and 3.2 times more likely than Whites to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively.

Table 6.17 Speeding in Lackawanna County by Driver Characteristics (n=4,594)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	1,380	1.1	49.9	23.8	8.0	2.4
Male	3,166		50.0	24.0	7.6	2.1
25 years old or under	853	1.2	54.7**	30.2***	12.4***	3.6**
Over 25 years old	3,687		48.9	22.4	6.6	1.8
White	4,211	1.6	48.7***	22.6***	7.1***	1.9***
Non-White	312		67.6	42.3	16.3	6.1

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.18 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Lehigh County. These data suggest no significant gender differences in observed speeding behavior. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.1, 1.4, 1.6, and 2.4 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. There are also significant racial differences in observed speeding behavior in Lehigh County, as non-Whites are 1.3, 1.4, and 2.3 times more likely than White drivers to exceed the speed limit by 10, 15, and 20 miles per hour, respectively.

Table 6.18 Speeding in Lehigh County by Driver Characteristics (n=3,147)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	1,024	2.7	72.9	46.2	19.6	4.7
Male	2,038		75.3	45.1	19.5	4.8
25 years old or under	464	3.2	82.5***	58.6***	28.2***	9.5***
Over 25 years old	2,584		73.0	43.0	17.8	3.9
White	2,817	3.9	74.0	44.6**	19.1*	4.4***
Non-White	206		79.1	55.8	26.2	10.2

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.19 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in McKean County. These data suggest no significant gender differences in observed speeding behavior. The effects of age on speeding behavior are only statistically significant at 5 and 15 mph over the speed limit, as drivers identified as 25 years or younger are about 1.4 and 1.6 times more likely than drivers over 25 to exceed the speed limit by 5 and 15 miles per hour, respectively. There are no significant racial differences in observed speeding behavior in McKean County. This may partially be a result of the very small number of non-Whites that were observed.

Table 6.19 Speeding in McKean County by Driver Characteristics (n=2,113)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	636	1.3	48.4	25.6	9.9	1.4
Male	1,450		44.3	23.0	9.7	2.2
25 years old or under	193	0.9	60.1***	26.9	14.5*	3.1
Over 25 years old	1,902		44.0	23.2	9.1	1.8
White	2,074	0.2	45.5	23.8	9.6	2.0
Non-White	25		44.0	16.0	16.0	0.0

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.20 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Mercer County. These data suggest no significant gender differences in observed speeding behavior. The effects of age on speeding behavior are statistically significant, but only for the lower two amounts over the limit. Specifically, drivers identified as 25 years or younger are about 1.4 and 2.1 times more likely than drivers over 25 are to exceed the speed limit by 5 and 10 miles per hour, respectively. There are significant racial differences in observed speeding behavior in Mercer County that increase in the strength of the effect with severity of speeding, as non-Whites are 1.2, 1.7, 3.0, and 6.0 times more likely than Whites to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively.

Table 6.20 Speeding in Mercer County by Driver Characteristics (n=3,494)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	1,018	1.3	42.5	10.5	2.8	0.3
Male	2,432		41.8	9.6	1.9	0.4
25 years old or under	398	1.4	55.3***	18.1***	3.3	0.5
Over 25 years old	3,047		40.2	8.8	2.0	0.4
White	3,253	2.1	41.4*	9.7**	2.0**	0.3**
Non-White	168		51.2	16.7	6.0	1.8

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.21 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Montgomery County. These data suggest no significant gender differences in observed speeding behavior. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.1, 1.2, 1.7, 2.1 times more likely than drivers over 25 are to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. There are no statistically significant racial differences in observed speeding behavior in Montgomery County.

Table 6.21 Speeding in Montgomery County by Driver Characteristics (n=2,847)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	817	0.9	79.4	50.6	21.8	6.3
Male	1,474		82.2	53.2	24.0	6.2
25 years old or under	335	0.9	88.7***	62.4***	36.7***	11.6***
Over 25 years old	2,486		80.1	50.8	21.2	5.5
White	2,523	1.5	80.7	51.8	22.8	6.0
Non-White	280		84.6	55.7	26.8	8.9

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.22 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Montour County. These data suggest no significant gender differences in observed speeding behavior. Although age differences in speeding behavior are apparent, there are likely too few cases to detect statistically significant differences. The main trend of the age-speeding relationship in other counties—younger drivers are more likely to speed than older drivers—is evident in Montour County even though it does not reach statistical significance. The effects of race on speeding behavior are consistent, but not statistically significant for all four amounts over the limit. Drivers identified as non-White are about 1.3 and 3.4 times more likely than White drivers are to exceed the speed limit by 5 and 15 miles per hour, respectively. The effects of race on speeding 10 and 20 mph over the limit are in the same direction—non-Whites are more likely than Whites to speed—despite the lack of statistical significance.

Table 6.22 Speeding in Montour County by Driver Characteristics (n=733)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	218	0.5	46.3	11.0	2.3	0.5
Male	515		54.0	13.6	2.9	0.4
25 years old or under	88	0.5	60.2	19.3	3.4	1.1
Over 25 years old	645		50.5	11.9	2.6	0.3
White	656	2.2	50.3*	12.2	2.3*	0.3
Non-White	65		64.6	20.0	7.7	1.5

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.23 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Susquehanna County. These data suggest some significant gender differences in observed speeding behavior, at both 5 and 10 mph over the limit. Men are 1.4 and 2.5 times more likely to speed 5 and 10 mph over the limit than women are. Strong age differences are not evident in Susquehanna County, as the only statistically significant difference between drivers identified as 25 years or younger and drivers over 25 is at 10 mph over the limit, where younger drivers are 2.1 times more likely than older drivers to exceed the speed limit by 10 miles per hour. Statistically significant race differences are also not evident in Susquehanna County, although non-Whites are more than 2 times as likely to exceed the speed limit by 15 and 20 mph, which is consistent with racial differences in speeding in other counties.

Table 6.23 Speeding in Susquehanna County by Driver Characteristics (n=602)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	147	1.0	35.4**	4.8*	2.0	0.7
Male	455		47.7	12.1	2.4	0.4
25 years old or under	95	1.0	50.5	17.9**	2.1	0.0
Over 25 years old	507		43.6	8.7	2.2	0.6
White	514	3.6	44.2	9.3	1.9	0.4
Non-White	72		45.8	12.5	4.2	1.4

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.24 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Tioga County. These data suggest no significant gender differences in observed speeding behavior. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.2, 1.6, and 2.0 times more likely than drivers over 25 to exceed the speed limit by 5, 10, and 15 miles per hour, respectively. Similarly, racial differences are statistically significant and the strength of the effect increases with the amount over the limit. Non-Whites are 1.4, 3.1, and 7.0 times more likely than Whites are to exceed the speed limit at 5, 15, and 20 miles per hour, respectively.

Table 6.24 Speeding in Tioga County by Driver Characteristics (n=1,448)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	464	1.2	43.3	20.5	4.7	1.3
Male	967		46.0	17.6	5.4	0.9
25 years old or under	115	1.2	54.8*	27.8**	9.6*	1.7
Over 25 years old	1,316		44.1	17.6	4.8	1.0
White	1,392	1.7	44.4*	18.0	5.0**	0.9**
Non-White	32		62.5	31.3	15.6	6.3

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.25 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Washington County. These data suggest no significant gender differences in observed speeding behavior. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.1, 1.5, 2.1, and 5.2 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. There are also significant racial differences in observed speeding behavior in Washington County. Specifically, non-Whites are 1.5, 1.8, and 2.5 times more likely than Whites to exceed the speed limit by 10, 15, and 20 miles per hour, respectively.

Table 6.25 Speeding in Washington County by Driver Characteristics (n=2,845)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	845	3.0	61.5	27.3	8.9	1.8
Male	1,914		61.3	25.9	8.0	1.3
25 years old or under	276	2.9	67.4*	37.3***	15.2***	4.7***
Over 25 years old	2,488		60.6	24.9	7.4	0.9
White	2,518	6.1	60.4	25.3**	7.8**	1.3*
Non-White	155		67.7	36.8	14.2	3.2

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.26 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in Westmoreland County. These data suggest only slight gender differences in observed speeding behavior, as women are 1.1 times more likely to exceed the speed limit by 5 or more miles per hour than men. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.3, 1.5, 2.1, and 2.8 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. There is only a small statistically significant difference in observed speeding behavior by race in Westmoreland County, although it is in the opposite direction of most of the observed racial differences. Whites are 1.3 times more likely to exceed the speed limit by at least 5 miles per hour than non-Whites are.

Table 6.26 Speeding in Westmoreland County by Driver Characteristics (n=2,805)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	934	2.2	51.7**	24.9	9.0	3.2
Male	1,810		45.7	22.5	9.3	2.8
25 years old or under	274	2.1	60.6***	33.9***	17.2***	6.9***
Over 25 years old	2,471		46.1	22.0	8.3	2.5
White	2,461	7.8	48.8**	23.8	9.2	2.8
Non-White	134		36.6	19.4	6.7	3.0

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Table 6.27 presents crosstabulations of drivers' gender, age, and race with speeding behavior from the observations in York County. These data suggest no significant gender differences in observed speeding behavior. Age differences are statistically significant and stronger as the amount over the limit increases. Drivers identified as 25 years or younger are about 1.3, 1.8, 2.7, and 3.6 times more likely than drivers over 25 to exceed the speed limit by 5, 10, 15, and 20 miles per hour, respectively. Small racial differences in observed speeding behavior are evident in York County. Non-Whites are 1.2, 1.5, and 1.6 times more likely to exceed the speed limit by 5, 10, and 15 miles per hour, respectively.

Table 6.27 Speeding in York County by Driver Characteristics (n=3,652)

Driver Characteristics	# of drivers	% Missing[1]	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph
Female	1,181	1.0	49.9	21.0	6.9	1.7
Male	2,435		47.5	20.2	7.7	2.3
25 years old or under	466	1.4	60.7***	33.5***	16.5***	5.8***
Over 25 years old	3,134		46.5	18.7	6.1	1.6
White	3,269	2.1	47.4***	19.6***	7.0**	2.0
Non-White	308		57.1	28.6	11.4	3.6

Note: Asterisks identify statistically significant chi-square bivariate associations. * p<.05 ** p<.01 ***p<.001

Summary of Speeding Observations in All Counties.

As reviewed above in the county-by-county analysis, drivers' speeding behavior was significantly predicted by drivers' demographic characteristics. The strength of the association between driver demographic characteristics and speeding also varied by county and by severity of speeding. Some of the speeding survey's major trends at the county level are summarized below:

- In contrast to the hypothesized relationship between gender and speeding, 19 of the 27 observed counties display no statistically significant gender differences in speeding behavior. In the few counties that do show differences, however, the relationship is in the expected direction, as males are slightly more likely than females to exceed the speed limit. The exception is Juniata County, where females are slightly more likely than males to exceed the speed limit.

- As was hypothesized, the relationship between driver age and speeding behavior is statistically significant and in the expected direction in almost all observed counties. That is, virtually all county-level crosstabulations suggest that drivers 25 and younger are significantly more likely to speed than are older drivers.

- The evidence for racial differences in speeding behavior was somewhat mixed.
  - Supporting the hypothesis that minorities are more likely to speed, nineteen counties (e.g., Bedford, Bucks, Chester, Clarion, Clinton, Columbia, Dauphin, Delaware, Fulton, Indiana, Jefferson, Juniata, Lackawanna, Lehigh, Mercer, Montour, Tioga, Washington, and York counties) showed statistically significant differences in speeding behavior between Whites and non-Whites at various amounts over the limit.
  - In a smaller number of counties, (e.g., Allegheny, Centre, Erie, Franklin, McKean, Montgomery, Susquehanna, and Westmoreland counties), however, the hypothesis of racial differences in speeding is not supported.

- The hypotheses on demographic differences in the severity of speeding behavior find support in the county-by-county analysis with respect to age and race, but not gender.
  - As noted above, nearly all counties demonstrated statistically significant age differences in speeding behavior, and the strength of that association increases as the amount over the limit increases in each of those counties.
  - In the majority of the nineteen counties with statistically significant racial differences, the strength of that association increases as the amount over the speed limit becomes more severe.
  - In a few counties, the relationship between gender and speeding is slightly stronger with increasing amounts over the limit, but in only one county (Clarion) does the relationship become significantly stronger at higher amounts over the limit.

Statewide Crosstabulations of Demographic Differences in Speeding

The crosstabulations presented in Table 6.28 show the bivariate relationships between speeding and driver demographic characteristics at the state level. The findings represent statistically significant chi-square bivariate associations, and confirm that drivers' characteristics are associated with speeding behavior. Multivariate analyses to follow examine whether the associations between drivers' characteristics and speeding behavior remain once other characteristics likely associated with speeding behavior are statistically controlled.

Turning to Table 6.28, the crosstabulations show that the only significant gender difference in speeding is at the highest level of speeding severity; men are slightly more likely than females to speed 25 mph over the limit. This does not provide much support to hypothesis number one, which proffered a general relationship between gender and speeding. It is consistent, however, with hypothesis number six, which proposed that men are more likely to speed at the higher amounts over the limit.

Age differences between drivers 25 and younger and older drivers, on the other hand, are evident for all measured amounts over the speed limit. Drivers identified as 25 years or younger are about 1.5 times more likely to exceed the speed limit by 10 miles per hour, and 2.0, 2.8, and 4.8 times more likely to exceed the speed limit by 15, 20, and 25 miles per hour, respectively. These findings offer strong support for the second hypothesis.

Non-Whites are also consistently more likely to speed across all measured amounts over the speed limit than are Whites. These results suggest that non-White drivers are about 1.6 times more likely to exceed the speed limit by 10 miles per hour or more compared to White drivers. The association is stronger for more serious amounts over the limit, as non-Whites are 1.9, 2.5, and 3.2 times more likely to exceed the speed limit by 15, 20, and 25 miles per hour, respectively, compared to Whites. These findings are supportive of hypothesis number three.

Similar to the results for Non-Whites, Black drivers are also consistently more likely to speed across all measured amounts over the speed limit than are Whites. These results suggest that Blacks are about 1.7 times more likely to exceed the speed limit by 10 miles per hour or more compared to Whites. As with the relationship between Non-White drivers and speeding, the association between Black drivers and speeding is also stronger for serious offending, as non-Whites are 2.2, 2.8, and 3.6 times more likely to exceed the speed limit by 15, 20, and 25 miles per hour, respectively, compared to Whites. These findings offer strong support for hypotheses four and eight.

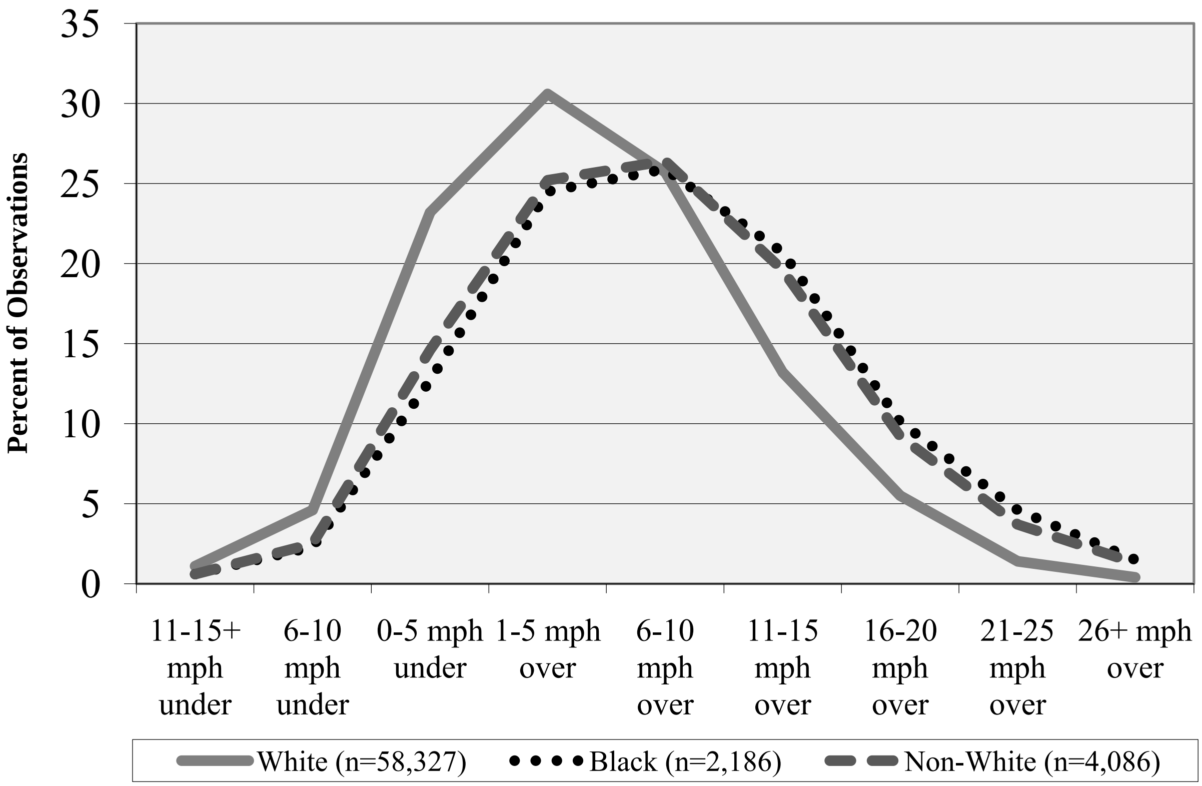
Table 6.28 Differences in Observed Speeding Behavior by Driver Characteristics (n=62,413)

Driver Characteristics	# of drivers	% over 5 mph	% over 10 mph	% over 15 mph	% over 20 mph	% over 25 mph
All Drivers	62,413	53.5	25.5	9.7	2.7	0.6
Female	20,784	53.2	25.4	9.3	2.6	0.5**
Male	41,629	53.6	25.5	9.8	2.8	0.7
25 years old or under	7,512	63.3***	36.4***	17.2***	6.2***	1.9***
Over 25 years old	54,901	52.1	24.0	8.6	2.2	0.4
White	58,327	52.6***	24.5***	9.1***	2.5***	0.5***
Non-White	4,086	66.3	38.8	17.2	6.1	1.6
White	58,327	52.6***	24.5***	9.1***	2.5***	0.5***
Black	2,186	69.0	41.7	19.6	7.1	1.8

Note: Asterisks identify statistically significant chi-square bivariate associations. * $p<.05$ ** $p<.01$ *** $p<.001$

In order to explore whether severity of speeding differs by race, Figure 6.1 shows the racial distributions of the amount over the speed limit at which drivers were observed. White drivers have the lowest average amount over the speed limit at 5.3 mph. Minorities, in general, had significantly higher mean amounts over the limit (7.8 mph), and Blacks, in particular, had the highest mean amount over the limit (8.4 mph). The *t test* analyses indicate that these racial differences are statistically significant ($p < .000$); this supports this study's general hypothesis that violating behavior is not equivalent across racial groups. Furthermore, the distributions of amount over the limit also support hypothesis number eight that there may be racial differences in speeding severity, as significantly higher percentages of Blacks and other minorities are represented in the most severe amounts over the limit. This will be explored further in the multivariate analyses below.

Figure 6.1 Differences in Amount over the Speed Limit by Driver's Race (n=62,413)



MULTIVARIATE RELATIONSHIPS

A series of bilevel models were estimated using HLM to further examine the relationship between observed drivers' speeding behavior and driver, vehicle, situational, and municipality characteristics. Throughout these analyses, the statistical significance of Level 1 relationships is assessed at the 0.001 level due to the large sample size. It is prudent to use a more stringent threshold for statistical significance when examining larger numbers of observations because as the sample size increases, there is a stronger possibility that the relationships reported are due to chance alone (Allison, 1999). Due to the substantially smaller number of Level 2 units, statistical significance for Level 2 variables and variables involved in cross-level interactions is assessed at the .05 level. Marginally significant results are noted when appropriate.

In each model presented, all level 1 predictors are group mean centered, which has the effect of controlling contextual variation and comparing the 0 and 1 categories of the dichotomous predictors on amount over the limit within the same municipality (i.e., do males speed more than females within the same municipality?). That is, the interpretation of the level 1 coefficient included in the model is: the effect of being in the 1 category versus the reference category, within the same level 2 unit, increases the amount over the speed limit by *beta* when holding all other predictors constant at their group mean. Finally, since the primary interest of this study is in understanding racial differences in speeding behavior, in all models only the slope for race and the intercept are allowed to randomly vary across level two units. All other coefficients were fixed.

The first analysis explores speeding behavior operationalized as a continuous measure of amount (in miles per hour) over the posted speed limit. The first step in the HLM analysis is to estimate a null model without any explanatory variables to determine whether there is significant between-municipality variation on the dependent variable, necessitating the use of HLM. As shown in Table 6.29, the results of this analysis yielded significant variation across municipalities in drivers' amount over the speed limit (τ_{00} = 0.37, p = .000). Specifically, the calculation of the intraclass correlation coefficient – $u_{oj} / (u_{oj} + r_{ij})$ – (Raudenbush & Bryk, 2002) indicates that 8.13% of the variance in amount over the limit is between municipalities. This indicates that the use of HLM will be necessary to take into account the nesting of observations within municipality.

Table 6.29 HLM Null Model of Drivers' Amount over the Speed Limit

Fixed effects	*Coefficient*	*Standard Error*	*T-ratio*	*df*
Intercept	1.77*	0.05	39.68	139
Random effects	***Variance Component***	***Standard Deviation***	X^2	***df***
Between municipality u_{oj}	0.37*	0.60	30823.47	139
Within municipality r_{ij}	4.18	2.04		

NOTE: * p < .001

Tables 6.30 and 6.31 present the results of two-level hierarchical Poisson analyses examining observed drivers' amount over the posted speed limit, with Table 6.30 examining all Non-White drivers in the race variable and Table 6.31 focusing only on Black drivers. In the upper half of these tables, the first column for each model is the coefficient or predicted log-odds for each independent variable. Since the interpretation of log-odds is not intuitively straightforward, these coefficients are exponentiated to allow for interpretation in terms of odds (Liao, 1994). The second column for each model—the odds ratio—represents this antilog transformation of the coefficient into the multiplicative odds of speeding based on the predictor variable, all else being equal. In cases where the coefficient is negative, the odds ratio is inverted by dividing by 1 for ease of interpretation. In the lower half of these tables, the variance components and standard deviations for the error terms included in the models are displayed. In order to explore hypothesis number five, Model 1 in each of these tables examines the influence of race and the other independent variables *excluding age* on amount over the limit; Model 2 includes age to see whether some of the race effect is attenuated by its inclusion in the model. Model 2 provides a baseline against which the subsequent models with Level 2 variables (Model 3) and cross-level interaction terms (Model 4) can be compared.[21]

The models in Table 6.30 examine observed drivers' amount over the speed limit. The results indicate significant relationships between driver demographic characteristics and amount over the speed limit in the expected directions. Although the effect of gender on amount over the limit is statistically significant, the strength of this effect is substantively small (odds ratio=1.04). The effect of being a young driver versus a driver over 25 increases the number of miles per hour over the speed limit by 1.31. In Model 1, without age as a covariate, the effect of being a non-White driver as opposed to a White driver increases the amount over the speed limit by 1.14. In Model 2, the race effect is virtually unchanged with the inclusion of age (odds ratio = 1.12). Although statistically significant, the substantive impact of this race effect is only modest. This table also shows that the variance component for driver non-White is significant across all models, indicating that the non-White effect on amount over the limit randomly varies by municipality. Other significant Level 1 effects suggest that the mean level of drivers' amount over the speed limit is lower for vehicles with passengers, in-state license plates, and vehicles traveling in 65 mph speed limits, and higher for sports cars.

In terms of contextual variables, Model 3 shows that the level 2 coefficient for percent of drivers 25 and younger is essentially zero, indicating that the proportion of young drivers at the municipality level does not affect an individual driver's number of miles per hour over the limit. On the other hand, the level 2 coefficient for average amount over the

[21] The full Model 4 shown in Table 6.30 was also run with an additional Level 2 variable that accounted for the sample selection factor scores for individual counties (see Table 4.1) in order to control for the possibility that the research design's sampling procedure might affect the results. This variable was not statistically significant and the substantive effects of the statistically significant relationships shown in Table 6.30 remain unchanged.

limit for PSP speeding stops is statistically significant. Specifically, for every one mile increase in the average amount over the limit for PSP speeding stops the observed drivers' amount over the speed limit is increased by 1.10. As demonstrated in the null model above, only 8 percent of the variance resides at level 2; therefore, even the moderate strength of PSP speeding threshold can wash out the effect of average speeding at the municipality level. Compared to Model 2, the intercept becomes statistically insignificant in Models 3 and 4. In other words, the main effect of PSP speeding threshold explained all the substantial variance for the intercept. That is, drivers only displayed speeding behavior in certain municipalities where the police have a higher tolerance threshold for speeding.

Model 4 shows that the municipality average speeding threshold exhibits a statistically significant cross-level interaction with driver race. This result is an important outcome for the study because it suggests that speeding behavior for non-Whites is contextual. Specifically, non-Whites are more likely than Whites to exceed the posted speed limit in municipalities where the PSP has more strict speeding thresholds. When this interaction between PSP speeding threshold and driver race is controlled, the main effect of driver race on the average drivers' amount over the limit increases in size from an odds ratio of 1.1 to 1.4.

Table 6.30 HLM Poisson analyses predicting Non-White drivers' amount over the limit (n=62,413)

	Model 1		Model 2		Model 3		Model 4	
Fixed Effects	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***
Intercept	1.76***		1.76***		-0.48		-0.52	
Municipality # observed vehicles	--	--	--	--	0.00*	1.00	0.00	1.00
Municipality average % observed young drivers	--	--	--	--	0.02	1.02	0.02	1.02
Municipality average amount over limit for PSP speeding stops	--	--	--	--	0.10***	1.10	0.10***	1.10
Driver Demographics								
Driver Male	0.02	1.02	0.04***	1.04	0.04***	1.04	0.04***	1.04
Driver 25 years old or under	--	--	0.27***	1.31	0.27***	1.31	0.27***	1.31
Driver Non-White	**0.13*** **	**1.14**	**0.11*** **	**1.12**	**0.11*** **	**1.12**	**0.33** **	**1.39**
Municipality # observed vehicles	--	--	--	--	--	--	0.00**	1.00
Munic. % young drivers * Driver NW	--	--	--	--	--	--	0.01	1.01
Munic. PSP amount over * Driver NW	--	--	--	--	--	--	-0.02***	1.02
Vehicle Characteristics								
Passengers	-0.05***	1.05	-0.03***	1.03	-0.03***	1.03	-0.03***	1.03
PA License Plate	-0.13***	1.14	-0.13***	1.14	-0.13***	1.14	-0.13***	1.14
Vehicle Red	-0.02	1.02	-0.03	1.03	-0.03	1.03	-0.03	1.03
Sports Car	0.15***	1.16	0.09***	1.09	0.09***	1.10	0.09***	1.10
Situational Characteristics								
Rush Hour	-0.02	1.02	-0.02	1.02	-0.02	1.02	-0.02	1.02
Weekday	-0.12	1.13	-0.11	1.12	-0.11	1.12	-0.11	1.12
Interstate	-0.13	1.14	-0.13	1.14	-0.13	1.14	-0.13	1.14
Speed Limit 65 mph	-0.79***	2.20	-0.79***	2.20	-0.79***	2.20	-0.80***	2.20
Random Effects	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***
Between municipality u_{oj}	0.37*	0.61	0.37***	0.61	0.26***	0.51	0.26***	0.51
Within municipality r_{ij}	4.07	2.02	3.99	2.00	3.98	2.00	3.99	2.00
Driver Non-White Slope	0.02***	0.12	0.02***	0.12	0.02***	0.13	0.02***	0.10

NOTE: * p < .05 ** p < .01 *** p < .001

Turning to Table 6.31, these models also examine drivers' amount over the limit, but focus on Black drivers in the race variable as opposed to all non-White drivers. The findings are very similar to those for the models examining non-White drivers. Although the effect of gender on amount over the limit is statistically significant, the substantive strength of this effect is negligible (odds ratio=1.04). The effect of being a young driver versus a driver over 25 increases the number of miles per hour over the speed limit by 1.31. In Model 1, without age as a covariate, the effect of being a Black driver as opposed to a non-Black driver increases the amount over the speed limit by 1.18. In Model 2, the race effect is virtually unchanged with the inclusion of age. This table also shows that the variance component for driver Black is significant across all models, indicating that the Black effect on amount over the limit randomly varies by municipality. Other significant Level 1 effects suggest that drivers' amount over the speed limit is lower for vehicles with passengers, in-state license plates, and vehicles traveling in 65 mph speed limits, and higher for sports cars.

In terms of contextual variables, Model 3 shows that the level 2 coefficient for percent of drivers 25 and younger is essentially zero, indicating that the proportion of young drivers at the municipality level does not affect an individual driver's number of miles per hour over the limit. On the other hand, the level 2 coefficient for average amount over the limit for PSP speeding stops is statistically significant. For every one mile increase in the average amount over the limit for the PSP speeding stops the observed drivers' amount over the speed limit is increased by 1.10 mph. Much like the results in Table 6.30, due to the fact that only 8 percent of the variance resides at level 2 even the moderate strength of PSP speeding threshold can wash out the effect of average speeding at the municipality level. Compared to Model 2, the intercept becomes statistically insignificant in Models 3 and 4. In other words, the main effect of PSP speeding threshold explained all the substantial variance for the intercept. That is, drivers only displayed speeding behavior in certain municipalities where the police have a higher tolerance for speeding. Model 4 also shows that with the addition of the cross-level interaction terms, the race effect that was significantly and positively associated with the average speeding level at the municipality level in Model 3 now becomes statistically insignificant in Model 4. Unlike in Table 6.30 for nonwhites, the cross-level interaction between PSP speeding threshold and driver Black is also not statistically significant.[22]

[22] As with Table 6.30, the full Model 4 shown in Table 6.31 was also run with an additional Level 2 variable that accounted for the sample selection factor scores for individual counties (see Table 4.1) in order to control for the possibility that the research design's sampling procedure might affect the results. This variable was not statistically significant and the effects of driver demographic characteristics remain unchanged. The only substantive difference in the model not shown was an increase in the strength of the cross-level interaction between driver Black and municipality percent of young drivers.

Table 6.31. HLM Poisson analyses predicting Black drivers' amount over the limit (n=62,413)

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Fixed Effects	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b)]***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b)]***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b)]***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b)]***
Intercept	1.76*		1.76*		-0.48		-0.52	
Municipality # observed vehicles	--	--	--	--	0.00*	1.00	0.00	1.00
Municipality average % observed young drivers	--	--	--	--	0.02	1.02	0.02	1.02
Municipality average amount over limit for PSP speeding stops	--	--	--	--	0.09***	1.10	0.10***	1.10
Driver Demographics								
Driver Male	0.02	1.02	0.04***	1.04	0.04***	1.04	0.04***	1.04
Driver 25 years old or under	--	--		1.31	0.27***	1.31	0.27***	1.31
Driver Black	**0.17******	**1.18**	**0.16******	**1.17**	**0.15******	**1.16**	**0.22**	**1.24**
Municipality # observed vehicles	--	--	--	--	--	--	0.00*	1.00
Munic. % young drivers * Driver Black	--	--	--	--	--	--	0.01*	1.01
Munic. PSP amount over * Driver Black	--	--	--	--	--	--	-0.02	1.02
Vehicle Characteristics								
Passengers	-0.05***	1.05	-0.03***	1.03	-0.03***	1.03	-0.03***	1.03
PA License Plate	-0.13***	1.14	-0.13***	1.14	-0.13***	1.14	-0.13***	1.14
Vehicle Red	-0.02	1.02	-0.03	1.03	-0.03	1.03	-0.03	1.03
Sports Car	0.15***	1.16	0.09***	1.09	0.09***	1.10	0.09***	1.10
Situational Characteristics								
Rush Hour	-0.02	1.02	-0.02	1.02	-0.02	1.02	-0.02	1.02
Weekday	-0.12	1.13	-0.11	1.12	-0.11	1.12	-0.11	1.12
Interstate	-0.13	1.14	-0.13	1.14	-0.13	1.14	-0.13	1.14
Speed Limit 65 mph	-0.79***	2.20	-0.80***	2.23	-0.79***	2.20	-0.80***	2.20
Random Effects	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***
Between municipality u_{oj}	0.37***	0.61	0.37***	0.61	0.26***	0.51	0.26***	0.51
Within municipality r_{ij}	4.07	2.02	3.99	2.00	3.99	2.00	3.99	2.00
Driver Black Slope	0.02***	0.15	0.02***	0.15	0.02***	0.15	0.02***	0.13

NOTE: * p < .05 ** p < .01 *** p < .001

The following analyses explore speeding behavior operationalized as a series of dichotomous variables. As noted above, the first step in an HLM analysis is to estimate a null model to determine whether there is significant between-municipality variation on the dependent variable. Table 6.32 presents the null models estimated for four dichotomous dependent variables: speeding at least 10, 15, 20, and 25 miles per hour over the limit.

Table 6.32 HLM Null Models of Drivers' Speeding 10, 15, 20, & 25 MPH over the Speed Limit

Null Model 10 mph over	***Fixed effects***	***Coefficient***	***Standard Error***	***T-ratio***	***df***
	Intercept γ_{00}	-1.55*	0.11	-14.03	139
	Random effects	***Var. Comp.***	***Standard Dev.***	X^2	***df***
	Between municipality u_{oj}	1.67*	1.29	14920.33	139
	Within municipality r_{ij}	0.98	0.99		
Null Model 15 mph over	***Fixed effects***	***Coefficient***	***Standard Error***	***T-ratio***	***df***
	Intercept γ_{00}	-3.01*	0.12	-24.99	139
	Random effects	***Var. Comp.***	***Standard Dev.***	X^2	***df***
	Between municipality u_{oj}	1.90*	1.38	13598.20	139
	Within municipality r_{ij}	0.93	0.97		
Null Model 20 mph over	***Fixed effects***	***Coefficient***	***Standard Error***	***T-ratio***	***df***
	Intercept γ_{00}	-4.43*	0.13	-35.55	139
	Random effects	***Var. Comp.***	***Standard Dev.***	X^2	***df***
	Between municipality u_{oj}	1.83*	1.35	6336.07	139
	Within municipality r_{ij}	0.83	0.91		
Null Model 25 mph over	***Fixed effects***	***Coefficient***	***Standard Error***	***T-ratio***	***df***
	Intercept γ_{00}	-5.80*	0.13	-44.24	139
	Random effects	***Var. Comp.***	***Standard Dev.***	X^2	***df***
	Between municipality u_{oj}	1.66*	1.29	1930.79	139
	Within municipality r_{ij}	0.67	0.82		

NOTE: * $p < .001$

The results of the estimation of the null models show significant variation across municipalities for each measure of speeding (10 mph over: τ_{00} = 1.67, p = .000; 15 mph over: τ_{00} = 1.90, p = .000; 20 mph over: τ_{00} = 1.83, p = .000; 25 mph over: τ_{00} = 1.66, p = .000). This indicates that the use of HLM is necessary in order to take into account the nesting of observations within municipality.

Tables 6.33 - 6.40 present the results of two-level hierarchical Bernoulli nonlinear analyses examining observed drivers' speeding at 10, 15, 20, and 25 miles per hour over the posted speed limit. These tables are similar, with the exception of the driver race variable, which is non-White (including Blacks, Hispanics, Middle Easterners, Asians/Pacific Islanders, Native Americans, and other minorities) for Tables 6.33 through 6.36 and Black for Tables 6.37 through 6.40. In the upper half of these tables, the first column for each model is the coefficient or predicted log-odds for each independent variable. As with the Poisson models above, these coefficients are exponentiated to allow for interpretation in terms of odds (Liao, 1994). The second column for each model—the odds ratio—represents this antilog transformation of the coefficient into the multiplicative odds of speeding based on the predictor variable, all else being equal. In cases where the coefficient is negative, the odds ratio is inverted by dividing by 1 for ease of interpretation.

The lower half of these tables displays the variance components and standard deviations for the error terms included in the models. In order to explore hypothesis number eight, Model 1 in each of these tables examines the influence of race and all other variables besides age on amount over the limit; Model 2 then includes age to see whether the race effect is attenuated by its inclusion in the model. Model 2 provides a baseline against which the subsequent models with Level 2 variables (Model 3) and cross-level interaction terms (Model 4) can be compared.

The models in Table 6.33 examine whether observed drivers were exceeding the speed limit by 10 or more miles per hour. Driver gender does not have a statistically significant influence on speeding more than 10 miles over the limit. Age and race, on the other hand, do exert significant effects on speeding behavior in the expected directions. The odds of exceeding the speed limit by at least 10 miles per hour are 1.7 times higher for drivers 25 and younger compared to older drivers. In Model 1, without age as a covariate, the odds of exceeding the speed limit by at least 10 miles per hour are 1.35 times higher for non-White drivers than Whites. In Model 2, the race effect is only slightly diminished with the inclusion of age. Specifically, in the full model, the odds of exceeding the speed limit by at least 10 miles per hour are 1.30 times higher for non-Whites than Whites. Table 6.33 also shows that the variance component for the driver non-White slope is statistically significant across all models, indicating that the non-White effect on the odds of exceeding the speed limit by at least 10 mph randomly varies by municipality. Other independent variables showing a significant relationship with exceeding the speed limit by at least 10 miles per hour included: vehicles with in-state license plates (1.3 times less likely), sports cars (1.2 times more likely), and vehicles traveling in a 65 mph speed limit (4.6 times less likely).

In Model 3, the only Level 2 variable that significantly predicts the odds of exceeding the speed limit by at least 10 miles per hour is the average amount over the limit for PSP speeding stops. Specifically, the odds of exceeding the speed limit by at least 10 miles per hour are 1.2 times higher for every one mile-per-hour increase in the average municipality speeding threshold.

Model 4 shows that the municipality number of observed vehicles and average speeding threshold exhibit statistically significant cross-level interactions with driver race. The size of this effect for number of observed vehicles is negligible. For the relationship between driver race and average speeding threshold, however, this is an important result because it indicates, as the results in Table 6.30 did, that speeding behavior for non-Whites is contextual. That is, non-Whites are more likely than Whites to exceed the posted speed limit in municipalities where the PSP has more strict speeding thresholds. With the addition of cross-level interaction effects in Model 4, the race effect increases in size but is no longer statistically significant. This is possibly due to the fact that, at the municipality level, some Level 2 units had few or no non-White drivers observed.[23]

[23] For Tables 6.33 – 6.40, the full Model 4's shown were also run with an additional Level 2 variable that accounted for the sample selection factor scores for individual counties (see Table 4.1) in order to control for the possibility that the research design's sampling procedure might affect the results. For Table 6.33, this variable was not statistically significant and the substantive effects of the statistically significant relationships shown remain unchanged.

Table 6.33 HLM analyses predicting Non-White drivers' speeding behavior at 10 mph over the limit (n=62,413)

	Model 1		Model 2		Model 3		Model 4	
Fixed Effects	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b)]***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b)]***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b)]***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b)]***
Intercept	-1.19***		-1.19***		-5.91***		-6.02***	
Municipality # observed vehicles	--	--	--	--	0.00	1.00	0.00	1.00
Municipality mean % observed young drivers	--	--	--	--	0.04	1.04	0.04	1.04
Municipality mean amount over limit for PSP speeding stops	--	--	--	--	0.21***	1.23	0.22***	1.24
Driver Demographics								
Driver Male	0.01	1.01	0.05	1.05	0.05	1.05	0.05	1.05
Driver 25 years old or under	--	--	0.53***	1.70	0.57***	1.78	0.57***	1.78
Driver Non-White	**0.30*** **	**1.35**	**0.26*** **	**1.30**	**0.25*** **	**1.28**	**0.57**	**1.77**
Municipality # observed vehicles	--	--	--	--	--	--	0.00*	1.00
Munic. % young drivers * Driver NW	--	--	--	--	--	--	0.01	1.01
Munic. PSP amount over * Driver NW	--	--	--	--	--	--	-0.04*	1.04
Vehicle Characteristics								
Passengers	-0.06	1.06	-0.04	1.04	-0.04	1.04	-0.04	1.04
PA License Plate	-0.26***	1.30	-0.26***	1.30	-0.28***	1.32	-0.28***	1.32
Vehicle Red	-0.05	1.05	-0.05	1.05	-0.06	1.06	-0.06	1.06
Sports Car	0.30***	1.35	0.20***	1.22	0.21***	1.23	0.21***	1.23
Situational Characteristics								
Rush Hour	-0.07	1.07	-0.06	1.06	-0.07	1.07	-0.07	1.07
Weekday	-0.25	1.28	-0.23	1.26	-0.26	1.30	-0.26	1.30
Interstate	-0.08	1.08	-0.07	1.07	-0.15	1.16	-0.15	1.16
Speed Limit 65 mph	-1.50***	4.48	-1.52***	4.57	-1.59	4.90	-1.61***	5.00
Random Effects	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***
Between municipality u_{oj}	1.70***	1.30	1.73***	1.32	1.17***	1.08	1.17***	1.08
Within municipality r_{ij}	0.99	0.99	0.98	0.99	0.98	0.99	0.98	0.99
Driver Non-White Slope	0.13***	0.37	0.13***	0.36	0.13***	0.36	0.10**	0.31

NOTE: * $p < .05$ ** $p < .01$ *** $p < .001$

The models presented in Table 6.34 examine whether observed drivers were exceeding the speed limit by 15 or more miles per hour. Unlike the previous table for 10 mph over the limit, the effect of driver gender is now statistically significant. It is a weak effect, however, as the odds of men exceeding the speed limit by 15 or more miles per hour are only 1.1 times the odds for women. Although this is the expected direction of the relationship between gender and speeding, the substantive impact of this relationship is minimal. The influences of age and race are stronger, in comparison to gender, as well as in comparison to the effects in the 10 mph over model. The odds of exceeding the speed limit by at least 15 miles per hour are 1.9 times higher for drivers 25 and younger compared to older drivers. In Model 1, without age as a covariate, the odds of non-Whites exceeding the speed limit by at least 15 miles per hour are 1.45 times higher than the odds for Whites. In Model 2, the race effect is only slightly diminished with the inclusion of age. Specifically, in the full model, the odds of exceeding the speed limit by at least 15 miles per hour are 1.39 times higher for non-Whites than Whites. Unlike the model for speeding at least 10 mph over the limit, the slope for the non-White effect is not statistically significant, indicating there is no significant between-municipality variation in the racial effect on speeding at least 15 mph over the limit. Model 2 shows the following other Level 1 independent variables have a significant relationship with exceeding the speed limit by at least 15 miles per hour included: vehicles with in-state license plates (1.3 times less likely), sports cars (1.3 times more likely), and vehicles traveling in a 65 mph speed limit (4.3 times less likely).

As shown in Model 3, the only Level 2 variable that significantly predicts the odds of exceeding the speed limit by at least 15 miles per hour is the average amount over the limit for PSP speeding stops. Specifically, the odds of exceeding the speed limit by at least 15 miles per hour are 1.2 times higher for every one mile-per-hour increase in the average municipality speeding threshold.

Model 4 shows that the municipality percent young and average speeding threshold exhibit statistically significant cross-level interactions with driver race, indicating, as the results in Table 6.30 did, that speeding behavior for non-Whites is contextual. The interaction between municipality percent young and driver race indicates that non-Whites are more likely than Whites to exceed the posted speed limit in municipalities with a higher proportion of young drivers. For the relationship between driver race and average speeding threshold, this indicates that non-Whites are more likely than Whites to exceed the posted speed limit in municipalities where the PSP has more strict speeding thresholds. With the addition of cross-level interaction effects in Model 4, the main effect of driver race increases in size as the odds of speeding at least 15 miles per hour are 2.2 times higher for non-Whites than Whites.[24]

[24] For Tables 6.33 – 6.40, the full Model 4's shown were also run with an additional Level 2 variable that accounted for the sample selection factor scores for individual counties (see Table 4.1) in order to control for the possibility that the research design's sampling procedure might affect the results. For Table 6.34, this variable was not statistically significant and the only substantive difference in the statistically significant relationships shown was an increase in the strength of the cross-level interaction between driver non-White and municipality percent of young drivers.

Table 6.34 HLM analyses predicting Non-White drivers' speeding behavior at 15 mph over the limit (n=62,413)

	Model 1		Model 2		Model 3		Model 4	
Fixed Effects	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***
Intercept	-2.28***		-2.29***		-6.85***		-7.04***	
Municipality # of observed vehicles					0.00	1.00	0.00	1.00
Municipality average % observed young drivers	--	--	--	--	0.04	1.04	0.04	1.04
Municipality average amount over limit for PSP speeding stops	--	--	--	--	0.19***	1.21	0.21***	1.23
Driver Demographics								
Driver Male	0.05	1.05	0.10***	1.12	0.11***	1.12	0.11***	1.12
Driver 25 years old or under	--	--		1.93	0.70***	2.02	0.70***	2.02
Driver Non-White	**0.37*****	**1.45**	**0.33*****	**1.39**	**0.31*****	**1.37**	**0.80***	**2.23**
Municipality # of observed vehicles	--	--	--	--	--	--	0.00	1.00
Munic. % young drivers * Driver NW	--	--	--	--	--	--	0.02*	1.02
Munic. PSP amount over * Driver NW	--	--	--	--	--	--	-0.04**	1.04
Vehicle Characteristics								
Passengers	-0.10***	1.11	-0.07	1.07	-0.07	1.07	-0.07	1.07
PA License Plate	-0.26***	1.30	-0.28***	1.32	-0.29***	1.34	-0.28***	1.32
Vehicle Red	-0.06	1.06	-0.07	1.07	-0.08	1.08	-0.07	1.07
Sports Car	0.40***	1.49	0.26***	1.30	0.28***	1.32	0.28***	1.32
Situational Characteristics								
Rush Hour	-0.09	1.09	-0.08	1.08	-0.09	1.09	-0.09	1.09
Weekday	-0.38	1.46	-0.35	1.42	-0.37	1.45	-0.37	1.45
Interstate	0.15	1.16	0.15	1.16	0.10	1.10	0.10	1.10
Speed Limit 65 mph	-1.43***	4.18	-1.46***	4.31	-1.59***	4.90	-1.59***	4.90
Random Effects	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***
Between municipality u_{oj}	1.94***	1.39	1.97***	1.41	1.35***	1.16	1.36***	1.17
Within municipality r_{ij}	0.94	0.97	0.93	0.96	0.93	0.96	0.93	0.96
Driver Non-White Slope	0.13	0.36	0.13	0.36	0.11	0.33	0.09	0.29

NOTE: * p < .05 ** p < .01 *** p < .001

The models in Table 6.35 present the results of analyses examining whether observed drivers were exceeding the speed limit by 20 or more miles per hour. All three driver demographic characteristics exert statistically significant effects on the odds of drivers' exceeding the speed limit, but the predictive power of gender is still weak. Men have odds only 1.1 times greater than women do of speeding by 20 or more miles per hour. Age remains the strongest demographic predictor of speeding behavior. The odds of exceeding the speed limit by at least 20 miles per hour for drivers 25 and younger are 2.2 times the odds for older drivers. In Model 1, without age as a covariate, the odds of non-Whites exceeding the speed limit by at least 20 miles per hour are 1.55 times higher than the odds for Whites. In Model 2, the race effect is only slightly diminished with the inclusion of age. Specifically, in the full model, the odds of exceeding the speed limit by at least 20 miles per hour are 1.48 times higher for non-Whites than Whites. Like the model for speeding at least 15 mph over the limit, the slope for the non-White effect is not statistically significant, indicating there is no significant between-municipality variation in the racial effect on speeding at least 20 mph over the limit.

Model 2 shows the following other independent variables have significant, negative relationships with exceeding the speed limit by at least 20 miles per hour included: vehicles with passengers (1.2 times less likely), vehicles with in-state license plates (1.2 times less likely), and vehicles traveling in a 65 mph speed limit (3.0 times less likely). Vehicle type, on the other hand, has a significant positive effect on the odds of speeding at least 20 mph over the limit, as drivers of sports cars have odds 1.3 times the odds of drivers of all other vehicle types.

In Model 3, two of the three Level 2 variables significantly predict the odds of exceeding the speed limit by at least 20 miles per hour: the percent observed young drivers and the amount over the limit for PSP speeding stops. The effect of the municipality average proportion of young drivers is quite small, but in the expected positive direction. The effect of PSP average amount over the limit for speeding stops is somewhat stronger as the odds of exceeding the speed limit by at least 20 miles per hour are 1.2 times higher for every one mile-per-hour increase in the average municipality speeding threshold. These effects are unchanged in Model 4.

Model 4 shows that the municipality percent young and average speeding threshold exhibit statistically significant cross-level interactions with driver race, indicating, as the models for 10 mph and 15 mph over the limit did, that speeding behavior for non-Whites is contextual. The interaction between municipality percent young and driver race indicates that non-Whites are more likely than Whites to exceed the posted speed limit in municipalities with a higher proportion of young drivers. For the relationship between driver race and average speeding threshold, this indicates that non-Whites are more likely than Whites to exceed the posted speed limit in municipalities with a lower average amount over the limit for PSP speeding stops. With the addition of cross-level interaction effects in Model 4, the race effect increases in size as the odds of speeding at least 20 miles per hour are 2.8 times higher for non-Whites than Whites.[25]

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[25] For Tables 6.33 – 6.40, the full Model 4's shown were also run with an additional Level 2 variable that accounted for the sample selection factor scores for individual counties (see Table 4.1) in order to control for the possibility that the research design's sampling procedure might affect the results. For Table 6.35, this variable was not statistically significant and the only substantive differences in the statistically significant relationships shown were an increase in the strength of the Level 2 main effect of the municipality percent of young drivers and an increase in the strength of the cross-level interaction between driver non-White and municipality percent of young drivers was observed.

Table 6.35 HLM analyses predicting Non-White drivers' speeding behavior at 20 mph over the limit (n=62,413)

	Model 1		Model 2		Model 3		Model 4	
Fixed Effects	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***
Intercept	-3.39***		-3.42***		-8.26***		-8.32***	
Municipality # of observed vehicles	--	--	--	--	0.00	1.00	0.00	1.00
Municipality average % observed young drivers	--	--	--	--	0.05*	1.05	0.05*	1.05
Municipality average amount over limit for PSP speeding stops	--	--	--	--	0.20***	1.22	0.20***	1.22
Driver Demographics								
Driver Male	0.08***	1.08	0.13***	1.14	0.14***	1.15	0.14***	1.15
Driver 25 years old or under	--	--	0.77***	2.16	0.82***	2.27	0.81***	2.25
Driver Non-White	**0.44*****	**1.55**	**0.39*****	**1.48**	**0.43*****	**1.54**	**1.03***	**2.80**
Municipality # of observed vehicles	--	--	--	--	--	--	0.00	1.00
Munic. % young drivers * Driver NW	--	--	--	--	--	--	0.03*	1.03
Munic. PSP amount over * Driver NW	--	--	--	--	--	--	-0.05**	1.05
Vehicle Characteristics								
Passengers	-0.19***	1.21	-0.15***	1.16	-0.16***	1.17	-0.16***	1.17
PA License Plate	-0.20***	1.22	-0.21***	1.23	-0.22***	1.25	-0.22***	1.25
Vehicle Red	-0.01	1.01	-0.03	1.03	-0.03	1.03	-0.02	1.02
Sports Car	0.45***	1.57	0.28***	1.32	0.29***	1.37	0.29***	1.37
Situational Characteristics								
Rush Hour	-0.06	1.06	-0.05	1.05	-0.05	1.05	-0.05	1.05
Weekday	-0.34	1.40	-0.30	1.35	-0.32	1.38	-0.32	1.38
Interstate	-0.38	1.46	-0.36	1.43	-0.44***	1.55	-0.44***	1.55
Speed Limit 65 mph	-1.08***	2.94	-1.11***	3.03	-1.24***	3.46	-1.24***	3.46
Random Effects	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***
Between municipality u_{oj}	1.87***	1.37	1.90***	1.38	1.32***	1.15	1.33***	1.15
Within municipality r_{ij}	0.82	0.91	0.80	0.89	0.80	0.89	0.80	0.90
Driver Non-White Slope	0.13	0.36	0.15	0.39	0.12	0.35	0.12	0.34

NOTE: * p < .05 ** p < .01 *** p < .001

The models in Table 6.36 present the results of analyses examining whether observed drivers were exceeding the speed limit by 25 or more miles per hour. All three driver demographic characteristics exert statistically significant effects on the odds of drivers' exceeding the speed limit. In addition, all three effects are stronger than in the previous three tables. Men have odds 1.3 times greater than women do of speeding by 20 or more miles per hour. While this is the strongest gender effect for any of the operationalizations of speeding, substantively, it still represents only a modest effect of gender on exceeding the speed limit by at least 25 mph.

Age continues to be the strongest demographic predictor of speeding behavior. The odds of exceeding the speed limit by at least 25 miles per hour for drivers 25 and younger are 2.7 times the odds for older drivers. In Model 1, without age as a covariate, the odds of non-Whites exceeding the speed limit by at least 25 miles per hour are 1.6 times higher than the odds for Whites. In Model 2, the race effect is only slightly diminished with the inclusion of age. Specifically, in the full model, the odds of exceeding the speed limit by at least 25 miles per hour are 1.5 times higher for non-Whites than Whites. Again, the slope for the non-White effect is not statistically significant, indicating there is no significant between-municipality variation in the racial effect on speeding at least 25 mph over the limit. Model 2 shows the following other independent variables have significant relationships with exceeding the speed limit by at least 25 miles per hour included: vehicles with passengers (1.1 times less likely) and sports cars (1.3 times more likely).

In Model 3, two of the three Level 2 variables significantly predict the odds of exceeding the speed limit by at least 25 miles per hour: the percent observed young drivers and the amount over the limit for PSP speeding stops. The effect of the municipality average proportion of young drivers is quite small, but in the expected positive direction. The effect of PSP average amount over the limit for speeding stops is somewhat stronger as the odds of exceeding the speed limit by at least 25 miles per hour are 1.2 times higher for every one mile-per-hour increase in the average municipality speeding threshold. These effects are unchanged in Model 4.

Model 4 shows that the municipality percent young and average speeding threshold exhibit statistically significant cross-level interactions with driver race, indicating, as the previous models for 10, 15, and 20 mph over the limit did, that speeding behavior for non-Whites is contextual. The interaction between municipality percent young and driver race indicates that non-Whites are more likely than Whites to exceed the posted speed limit in municipalities with a higher proportion of young drivers. For the relationship between driver race and average speeding threshold, this indicates that non-Whites are more likely than Whites to exceed the posted speed limit in municipalities with a lower average amount over the limit for PSP speeding stops. With the addition of cross-level interaction effects in Model 4, the race effect increases considerably in size as the odds of speeding at least 25 miles per hour are 4.5 times higher for non-Whites than Whites.[26]

[26] For Tables 6.33 – 6.40, the full Model 4's shown were also run with an additional Level 2 variable that accounted for the sample selection factor scores for individual counties (see Table 4.1) in order to control for the possibility that the research design's sampling procedure might affect the results. For Table 6.36, this variable was not statistically significant and the only substantive differences in the statistically significant relationships shown were an increase in the strength of the Level 2 main effect of the municipality percent of young drivers and an increase in the strength of the cross-level interaction between driver non-White and municipality percent of young drivers was observed.

Table 6.36 HLM analyses predicting Non-White drivers' speeding behavior at 25 mph over the limit (n=62,413)

	Model 1		Model 2		Model 3		Model 4	
Fixed Effects	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***
Intercept	-4.47***		-4.54***		-8.61***		-8.66***	
Municipality # of observed vehicles	--	--	--	--	0.00	1.00	0.00	1.00
Municipality average % observed young drivers	--	--	--	--	0.03*	1.03	0.03*	1.03
Municipality average amount over limit for PSP speeding stops	--	--	--	--	0.18***	1.20	0.18***	1.20
Driver Demographics								
Driver Male	0.21***	1.23	0.29***	1.34	0.31***	1.36	0.31***	1.36
Driver 25 years old or under	--	--	0.99***	2.69	1.06***	2.89		2.86
Driver Nonwhite	**0.48*****	**1.62**	**0.43*****	**1.54**	**0.60*****	**1.82**	**1.51****	**4.53**
Municipality # of observed vehicles	--	--	--	--	--	--	0.00	1.00
Munic. % young drivers * Driver NW	--	--	--	--	--	--	0.03*	1.03
Munic. PSP amount over * Driver NW	--	--	--	--	--	--	-0.07**	1.07
Vehicle Characteristics								
Passengers	-0.19***	1.21	-0.12***	1.13	-0.13	1.14	-0.13	1.14
PA License Plate	-0.04	1.04	-0.05	1.05	-0.06	1.06	-0.05	1.05
Vehicle Red	-0.07	1.07	-0.09	1.09	-0.09	1.09	-0.09	1.09
Sports Car	0.53***	1.70	0.27***	1.31	0.29***	1.34	0.28***	1.32
Situational Characteristics								
Rush Hour	0.05	1.05	0.05	1.05	0.06	1.06	0.06	1.06
Weekday	-0.15	1.25	-0.07	1.07	-0.08	1.08	-0.08	1.08
Interstate	-0.51***	1.67	-0.50	1.65	-0.58***	1.79	-0.58***	1.79
Speed Limit 65 mph	-0.13	1.14	-0.13	1.14	-0.15	1.16	-0.16	1.17
Random Effects	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***
Between municipality u_{oj}	1.76***	1.33	1.80***	1.34	1.44***	1.20	1.46***	1.21
Within municipality r_{ij}	0.62	0.79	0.59	0.77	0.61	0.78	0.61	0.78
Driver Nonwhite Slope	0.24	0.49	0.30	0.55	0.25	0.50	0.26	0.51

NOTE: * p < .05 ** p < .01 *** p < .001

Turning now to Black drivers, Table 6.37 examines whether observed drivers were exceeding the speed limit by 10 or more miles per hour. The findings are similar to those for Table 6.33. Driver gender does not have a statistically significant influence on speeding more than 10 miles over the limit. Age and race, on the other hand, do exert significant effects on the odds of drivers' exceeding the speed limit by 10 or more miles per hour in the expected directions. The odds of exceeding the speed limit by at least 10 miles per hour are 1.7 times higher for drivers 25 and younger compared to older drivers. In Model 1, without age as a covariate, the odds of exceeding the speed limit by at least 10 miles per hour are 1.44 times higher for Black drivers than non-Blacks. In Model 2, the race effect remains virtually the same (odds ratio = 1.40) with the inclusion of age. Table 6.37 also shows that the variance component for the driver Black slope is statistically significant, indicating that the Black effect on the odds of exceeding the speed limit by at least 10 mph randomly varies by municipality. Model 2 shows the following other independent variables have significant relationships with exceeding the speed limit by at least 10 miles per hour: vehicles with in-state license plates (1.3 times less likely), vehicles traveling in a 65 mph speed limit (4.6 times less likely), and sports cars (1.2 times more likely).

In Model 3, the only Level 2 variable that significantly predicts the odds of exceeding the speed limit by at least 10 miles per hour is the average amount over the limit for PSP speeding stops. Specifically, the odds of exceeding the speed limit by at least 10 miles per hour are 1.2 times higher for every one mile-per-hour increase in the average municipality speeding threshold. This relationship remains unchanged in Model 4.

Model 4 shows that the municipality percent young exhibits a statistically significant cross-level interaction with driver race, indicating that speeding behavior for Blacks is contextual. Specifically it suggests that Blacks are more likely than non-Blacks to exceed the posted speed limit by 10 or more mph in municipalities with a higher proportion of young drivers. With the addition of cross-level interaction effects in Model 4, the race effect increases in size but is no longer statistically significant. This is possibly due to the fact that, at the municipality level, some Level 2 units had few or no Black drivers observed.[27]

[27] For Tables 6.33 – 6.40, the full Model 4's shown were also run with an additional Level 2 variable that accounted for the sample selection factor scores for individual counties (see Table 4.1) in order to control for the possibility that the research design's sampling procedure might affect the results. For Table 6.37, this variable was not statistically significant and the only substantive difference in the statistically significant relationships shown was an increase in the strength of the cross-level interaction between driver Black and municipality percent of young drivers was observed.

Table 6.37 HLM analyses predicting Black drivers' speeding behavior at 10 mph over the speed limit (n=62,413)

	Model 1		Model 2		Model 3		Model 4	
Fixed Effects	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***
Intercept	-1.19***		-1.19***		-5.97***		-6.01***	
Municipality # observed vehicles	--	--	--	--	0.00	1.00	0.00	1.00
Municipality mean % observed young drivers	--	--	--	--	0.05	1.05	0.04	1.04
Municipality mean amount over limit for PSP speeding stops	--	--	--	--	0.21***	1.23	0.22***	1.24
Driver Demographics								
Driver Male	0.02	1.02	0.05	1.05	0.05	1.06	0.06	1.06
Driver 25 years old or under	--	--	0.54***	1.71		1.78	0.58***	1.78
Driver Black	**0.37*** **	**1.44**	**0.34*** **	**1.40**	**0.33*** **	**1.39**	**0.26**	**1.30**
Municipality # observed vehicles	--	--	--	--	--	--	0.00	1.00
Munic. % young drivers * Driver Black	--	--	--	--	--	--	0.03*	1.03
Munic. PSP amount over * Driver Black	--	--	--	--	--	--	-0.03	1.03
Vehicle Characteristics								
Passengers	-0.06	1.06	-0.03	1.03	-0.04	1.04	-0.04	1.04
PA License Plate	-0.26***	1.30	-0.27***	1.31	-0.29***	1.34	-0.29***	1.34
Vehicle Red	-0.05	1.05	-0.05	1.05	-0.06	1.06	-0.06	1.06
Sports Car	0.31***	1.36	0.20***	1.22	0.21***	1.23	0.21***	1.23
Situational Characteristics								
Rush Hour	-0.07	1.07	-0.07	1.07	-0.07	1.07	-0.07	1.07
Weekday	-0.25	1.28	-0.23	1.26	-0.26	1.30	-0.26	1.30
Interstate	-0.06	1.06	-0.06	1.06	-0.13	1.14	-0.13	1.14
Speed Limit 65 mph	-1.51***	4.53	-1.53***	4.62	-1.60***	4.95	-1.61***	5.00
Random Effects	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***
Between municipality u_{oj}	1.70***	1.30	1.73***	1.32	1.17***	1.08	1.17***	1.08
Within municipality r_{ij}	0.99	0.99	0.99	0.99	0.98	0.99	0.98	0.99
Driver Black Slope	0.19***	0.44	0.19***	0.43	0.20***	0.45	0.16**	0.40

NOTE: * p < .05 ** p < .01 *** p < .001

Table 6.35 examines whether observed drivers were exceeding the speed limit by 15 or more miles per hour. The effect of driver gender is now statistically significant, but it is a relatively weak effect as the odds of men exceeding the speed limit by 15 or more miles per hour are only 1.1 times the odds for women. Although this is the expected direction of the relationship between gender and speeding, the substantive impact of this relationship is minimal. The influences of age and race are stronger, in comparison to gender, as well as in comparison to the effects in the 10 mph over model. The odds of exceeding the speed limit by at least 15 miles per hour are 1.95 times higher for drivers 25 and younger compared to older drivers. In Model 1, without age as a covariate, the odds of Blacks exceeding the speed limit by at least 15 miles per hour are 1.61 times higher than the odds for non-Blacks. In Model 2, the race effect remains virtually the same (odds ratio = 1.56) with the inclusion of age. Table 6.37 also shows that the variance component for the driver Black slope is not statistically significant, indicating there is no significant between-municipality variation in the racial effect on speeding at least 15 mph over the limit. Model 2 shows the following other independent variables have significant relationships with exceeding the speed limit by at least 15 miles per hour: vehicles with in-state license plates (1.3 times less likely), vehicles traveling in a 65 mph speed limit (4.3 times less likely), and sports cars (1.3 times more likely).

The only Level 2 variable that significantly predicts the odds of exceeding the speed limit by at least 15 miles per hour is the average amount over the limit for PSP speeding stops. Specifically, the odds of exceeding the speed limit by at least 15 miles per hour are 1.2 times higher for every one mile-per-hour increase in the average municipality speeding threshold. This relationship remains unchanged in Model 4.

Model 4 shows that the municipality percent young exhibits a statistically significant cross-level interaction with driver race, indicating that speeding behavior for Blacks is contextual. Specifically it suggests that Blacks are more likely than non-Blacks to exceed the posted speed limit by 15 or more mph in municipalities with a higher proportion of young drivers. With the addition of cross-level interaction effects in Model 4, the race effect is no longer statistically significant.[28]

[28] For Tables 6.33 – 6.40, the full Model 4's shown were also run with an additional Level 2 variable that accounted for the sample selection factor scores for individual counties (see Table 4.1) in order to control for the possibility that the research design's sampling procedure might affect the results. For Table 6.38, this variable was not statistically significant and the only substantive difference in the statistically significant relationships shown was an increase in the strength of the cross-level interaction between driver Black and municipality percent of young drivers was observed.

Table 6.38 HLM analyses predicting Black drivers' speeding behavior at 15 mph over the speed limit (n=62,413)

	Model 1		Model 2		Model 3		Model 4	
Fixed Effects	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b)]***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b)]***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b)]***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b)]***
Intercept	-2.28***		-2.30***		-6.99***		-7.03***	
Municipality # of observed vehicles					0.00	1.00	0.00	1.00
Municipality average % observed young drivers	--	--	--	--	0.04	1.04	0.04	1.04
Municipality average amount over limit for PSP speeding stops	--	--	--	--	0.20***	1.22	0.21***	1.23
Driver Demographics								
Driver Male	0.06	1.06	0.11***	1.12	0.11***	1.12	0.11***	1.12
Driver 25 years old or under	--	--		1.95	0.70***	2.02	0.70***	2.02
Driver Black	**0.48*****	**1.61**	**0.44*****	**1.56**	**0.43*****	**1.53**	**0.30**	**1.36**
Municipality # of observed vehicles	--	--	--	--	--	--	0.00	1.00
Munic. % young drivers * Driver Black	--	--	--	--	--	--	0.04**	1.04
Munic. PSP amount over * Driver Black	--	--	--	--	--	--	-0.02	1.02
Vehicle Characteristics								
Passengers	-0.10***	1.11	-0.07	1.07	-0.07	1.07	-0.07	1.07
PA License Plate	-0.27***	1.31	-0.28***	1.32	-0.29***	1.34	-0.29***	1.34
Vehicle Red	-0.06	1.06	-0.07	1.07	-0.08	1.08	-0.08	1.08
Sports Car	0.41***	1.50	0.27***	1.31	0.28***	1.32	0.28***	1.32
Situational Characteristics								
Rush Hour	-0.09	1.09	-0.09	1.09	-0.09	1.09	-0.09	1.09
Weekday	-0.38	1.46	-0.35	1.42	-0.37	1.45	-0.37	1.45
Interstate	0.16	1.17	0.16	1.17	0.11	1.11	0.11	1.11
Speed Limit 65 mph	-1.43***	4.18	-1.46***	4.31	-1.59***	4.90	-1.59***	4.90
Random Effects	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***
Between municipality u_{oj}	1.93***	1.39	1.97***	1.40	1.35***	1.16	1.35***	1.16
Within municipality r_{ij}	0.94	0.97	0.93	0.96	0.93	0.96	0.93	0.97
Driver Black Slope	0.11	0.34	0.11	0.33	0.11	0.33	0.05	0.23

NOTE: * p < .05 ** p < .01 *** p < .001

The models in Table 6.39 present the results of analyses examining whether observed drivers were exceeding the speed limit by 20 or more miles per hour. All three driver demographic characteristics exert statistically significant effects on the odds of drivers' exceeding the speed limit, but the predictive power of gender is still weak. Men have odds only 1.15 times greater than women do of speeding by 20 or more miles per hour. Age remains the strongest demographic predictor of speeding behavior. The odds of exceeding the speed limit by at least 20 miles per hour for drivers 25 and younger are 2.2 times the odds for older drivers. In Model 1, without age as a covariate, the odds of Blacks exceeding the speed limit by at least 20 miles per hour are 1.72 times higher than the odds for non-Blacks. In Model 2, the race effect is virtually unchanged with the inclusion of age. Specifically, in the full model, the odds of exceeding the speed limit by at least 20 miles per hour are 1.67 times higher for Blacks than non-Blacks. Like the model for speeding at least 15 mph over the limit, the slope for the Black effect is not statistically significant, indicating there is no significant between-municipality variation in the racial effect on speeding at least 20 mph over the limit.

Model 2 shows the following other independent variables have significant, negative relationships with exceeding the speed limit by at least 20 miles per hour: vehicles with passengers (1.2 times less likely), vehicles with in-state license plates (1.3 times less likely), vehicles traveling on an interstate (1.5 times less likely), and vehicles traveling in a 65 mph speed limit (3.0 times less likely). Vehicle type, on the other hand, has a significant positive effect on the odds of speeding at least 20 mph over the limit, as drivers of sports cars have odds 1.3 times the odds of drivers of all other vehicle types.

In Model 3, two of the three Level 2 variables significantly predict the odds of exceeding the speed limit by at least 20 miles per hour: the percent observed young drivers and the amount over the limit for PSP speeding stops. The effect of the municipality average proportion of young drivers is quite small, but in the expected positive direction. The effect of PSP average amount over the limit for speeding stops is somewhat stronger as the odds of exceeding the speed limit by at least 20 miles per hour are 1.2 times higher for every one mile-per-hour increase in the average municipality speeding threshold. These effects are unchanged in Model 4.

Finally, in Model 4, none of the estimated cross-level interactions between driver race and the municipality-level variables are statistically significant. With the addition of cross-level interaction effects in Model 4, however, the main effect of driver race increases in size as the odds of speeding at least 20 miles per hour are 3.0 times higher for Blacks than non-Blacks.[29]

[29] For Tables 6.33 – 6.40, the full Model 4's shown were also run with an additional Level 2 variable that accounted for the sample selection factor scores for individual counties (see Table 4.1) in order to control for the possibility that the research design's sampling procedure might affect the results. For Table 6.39, this variable was not statistically significant and the only substantive difference in the statistically significant relationships shown was an increase in the strength of the Level 2 main effect of the municipality percent of young drivers.

Table 6.39 HLM analyses predicting Black drivers' speeding behavior at 20 mph over the speed limit (n=62,413)

	Model 1		Model 2		Model 3		Model 4	
Fixed Effects	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***
Intercept	-3.40***		-3.43***		-8.32***		-8.32***	
Municipality # of observed vehicles	--	--	--	--	0.00	1.00	0.00	1.00
Municipality average % observed young drivers	--	--	--	--	0.05*	1.05	0.05*	1.05
Municipality average amount over limit for PSP speeding stops	--	--	--	--	0.20***	1.22	0.20***	1.22
Driver Demographics								
Driver Male	0.08***	1.08	0.14***	1.15	0.15***	1.16	0.15***	1.16
Driver 25 years old or under	--	--	0.78***	2.18	0.82***	2.27	0.82***	2.27
Driver Black	**0.54*****	**1.72**	**0.51*****	**1.67**	**0.55*****	**1.73**	**1.10***	**3.01**
Municipality # of observed vehicles	--	--	--	--	--	--	0.00	1.00
Munic. % young drivers * Driver Black	--	--	--	--	--	--	0.01	1.01
Munic. PSP amount over * Driver Black	--	--	--	--	--	--	-0.04	1.04
Vehicle Characteristics								
Passengers	-0.19***	1.21	-0.15***	1.16	-0.16***	1.17	-0.16***	1.17
PA License Plate	-0.21***	1.23	-0.22***	1.25	-0.23***	1.26	-0.23***	1.26
Vehicle Red	-0.01	1.01	-0.03	1.03	-0.03	1.03	-0.03	1.03
Sports Car	0.46***	1.58	0.28***	1.32	0.30***	1.35	0.30***	1.35
Situational Characteristics								
Rush Hour	-0.06	1.06	-0.05	1.05	-0.05	1.05	-0.05	1.05
Weekday	-0.35	1.42	-0.30	1.35	-0.32	1.38	-0.32	1.38
Interstate	-0.38***	1.46	-0.37***	1.45	-0.44***	1.55	-0.45	1.57
Speed Limit 65 mph	-1.09***	2.97	-1.11***	3.03	-1.24***	3.46	-1.24***	3.46
Random Effects	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***
Between municipality u_{oj}	1.85***	1.36	1.88***	1.37	1.32***	1.15	1.32***	1.15
Within municipality r_{ij}	0.82	0.91	0.80	0.89	0.80	0.90	0.80	0.90
Driver Black Slope	0.28	0.52	0.30	0.55	0.29	0.54	0.31	0.56

NOTE: * p < .05 ** p < .01 *** p < .001

Finally, the models presented in Table 6.35 present the results of analyses examining whether observed drivers were exceeding the speed limit by 25 or more miles per hour. Turning first to driver gender, the analyses reveal men have odds 1.35 times greater than women do of speeding by 25 or more miles per hour. This is the strongest gender effect evident in any of the presented analyses. The influences of age and race remain stronger, in comparison to gender and in comparison to the less serious operationalizations of speeding behavior. The odds of exceeding the speed limit by at least 25 miles per hour are 2.7 times higher for drivers 25 and younger compared to older drivers. In Model 1, without age as a covariate, the odds of Blacks exceeding the speed limit by at least 25 miles per hour are 2.0 times higher than the odds for Whites. In Model 2, the race effect is unchanged with the inclusion of age. Again, the slope for the Black effect is not statistically significant, indicating there is no significant between-municipality variation in the racial effect on speeding at least 25 mph over the limit.

Model 2 shows the following other independent variables have significant, negative relationships with exceeding the speed limit by at least 25 miles per hour: vehicles with passengers (1.1 times less likely) and vehicles traveling on an interstate (1.7 times less likely). Vehicle type, on the other hand, has a significant positive effect on the odds of speeding at least 25 mph over the limit, as drivers of sports cars have odds 1.3 times the odds of drivers of all other vehicle types.

In Model 3, two of the three Level 2 variables significantly predict the odds of exceeding the speed limit by at least 25 miles per hour: the percent observed young drivers and the amount over the limit for PSP speeding stops. The effect of the municipality average proportion of young drivers is quite small, but in the expected positive direction. The effect of PSP average amount over the limit for speeding stops is somewhat stronger as the odds of exceeding the speed limit by at least 25 miles per hour are 1.2 times higher for every one mile-per-hour increase in the average municipality speeding threshold. These effects are unchanged in Model 4.

Model 4 shows that the average speeding threshold exhibits a statistically significant cross-level interaction with driver race, indicating that speeding behavior for Blacks is contextual. Specifically, this significant cross-level relationship between driver race and average speeding threshold indicates that Blacks are more likely than non-Blacks to exceed the posted speed limit by 25 or more mph in municipalities where the PSP has more strict speeding thresholds. With the addition of cross-level interaction effects in Model 4, the main effect of driver race substantially increases in size as the odds of speeding at least 25 miles per hour are over 18 times higher for Blacks than non-Blacks.[30]

[30] For Tables 6.33 – 6.40, the full Model 4's shown were also run with an additional Level 2 variable that accounted for the sample selection factor scores for individual counties (see Table 4.1) in order to control for the possibility that the research design's sampling procedure might affect the results. For Table 6.40, this variable was not statistically significant and the only substantive difference in the statistically significant relationships shown was an increase in the strength of the Level 2 main effect of the municipality percent of young drivers.

Table 6.40 HLM analyses predicting Black drivers' speeding behavior at 25 mph over the speed limit (n=62,413)

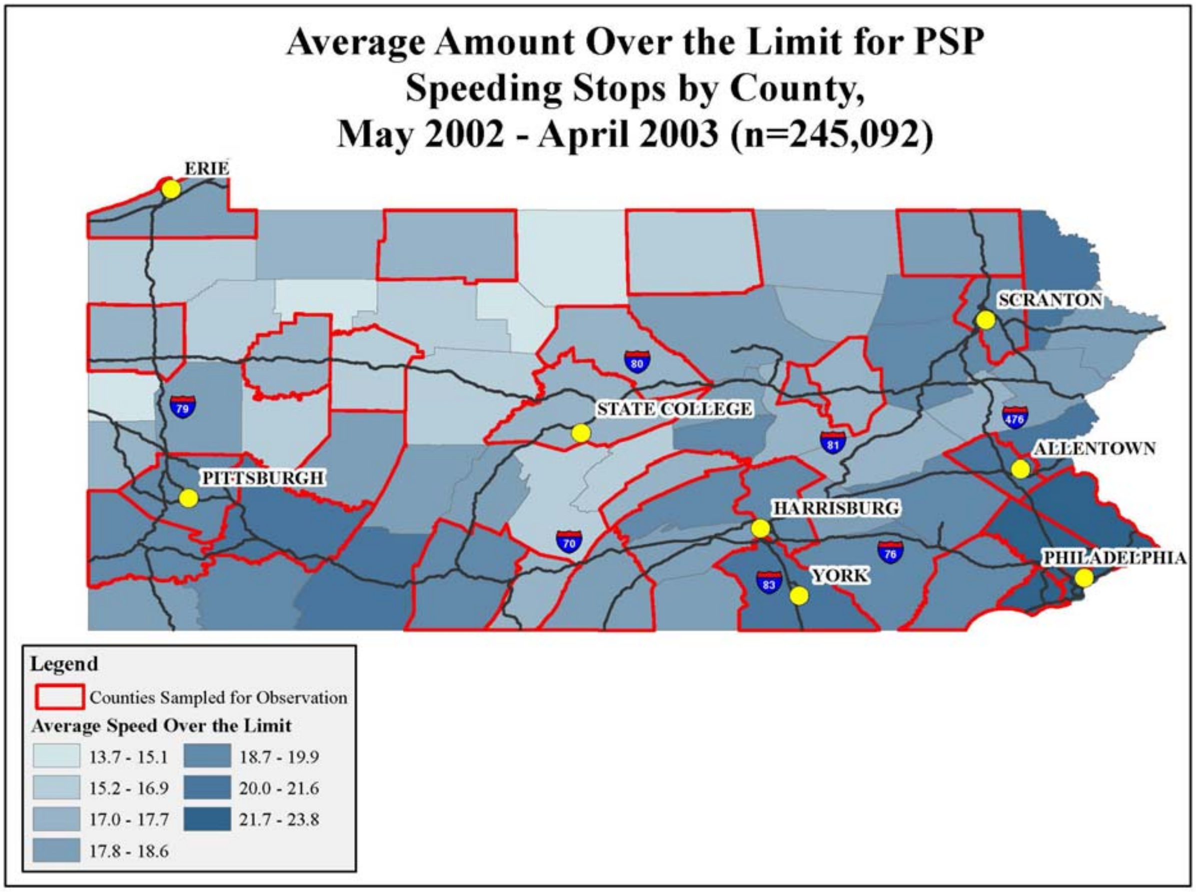
	Model 1		Model 2		Model 3		Model 4	
Fixed Effects	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***	***Coeff.***	***Odds Ratio [Exp(b) or 1/Exp(b])***
Intercept	-4.46***		-4.53***		-8.69***		-8.71***	
Municipality # of observed vehicles	--	--	--	--	0.00	1.00	0.00	1.00
Municipality average % observed young drivers	--	--	--	--	0.03*	1.03	0.03*	1.03
Municipality average amount over limit for PSP speeding stops	--	--	--	--	0.18***	1.20	0.19***	1.20
Driver Demographics								
Driver Male	0.22***	1.25	0.30***	1.35	0.32***	1.54	0.32***	1.38
Driver 25 years old or under	--	--	1.00***	2.72	1.06***	2.89	1.06***	2.89
Driver Black	**0.70*****	**2.01**	**0.72*****	**2.05**	**1.00*****	**2.72**	**2.90*****	**18.17**
Municipality # of observed vehicles	--	--	--	--	--	--	0.00	1.00
Munic. % young drivers * Driver Black	--	--	--	--	--	--	0.02	1.02
Munic. PSP amount over * Driver Black	--	--	--	--	--	--	-0.12***	1.13
Vehicle Characteristics								
Passengers	-0.18***	1.19	-0.11***	1.11	-0.12	1.13	-0.12	1.13
PA License Plate	-0.05	1.05	-0.06	1.06	-0.06	1.06	-0.06	1.06
Vehicle Red	-0.07	1.07	-0.08	1.08	-0.09	1.09	-0.09	1.09
Sports Car	0.53***	1.70	0.27***	1.31	0.29***	1.34	0.29***	1.34
Situational Characteristics								
Rush Hour	0.05	1.05	0.06	1.06	0.06	1.06	0.07	1.07
Weekday	-0.15	1.16	-0.08	1.08	-0.08	1.08	-0.08	1.08
Interstate	-0.51***	1.67	-0.51***	1.67	-0.58***	1.79	-0.59***	1.80
Speed Limit 65 mph	-0.12	1.13	-0.10	1.10	-0.13	1.14	-0.14	1.15
Random Effects	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***	***Var. Comp.***	***Stand. Dev.***
Between municipality u_{oj}	1.75***	1.32	1.80***	1.34	1.44***	1.20	1.45***	1.20
Within municipality r_{ij}	0.61	0.78	0.58	0.76	0.59	0.77	0.60	0.77
Driver Black Slope	1.22	1.10	1.37	1.17	1.35	1.16	1.23	1.11

NOTE: * p < .05 ** p < .01 *** p < .001

As discussed above, in municipalities where the PSP has more strict speeding thresholds (i.e., lower average amounts over the limit for PSP speeding stops), Nonwhites were more likely to exceed the posted speed limit by 10, 15, 20, and 25 mph and Blacks were more likely to exceed the posted speed limit by 25 mph. If perceptions of acceptable speed vary by driver race, then this may account for these findings. Royal (2003) found that males and younger drivers were more likely than their female and older counterparts to perceive that they could travel at higher speeds without being ticketed. While driver race was not examined in this survey research, it is plausible that perceptions of acceptable speeding also differ by race. Although Royal (2003) did not specify the thought process by which surveyed drivers arrived at their reported perceptions of acceptable miles per hour over the limit, it is possible that familiarity with speed thresholds near areas that drivers live are an important factor. In order to explore the significant cross-level interactions between driver race and PSP speeding thresholds, Figure 6.2 graphically displays the average amount over the limit for PSP speeding stops by county, with the 27 observed counties outlined in red.

As shown in Figure 6.2, the highest average amounts over the limit occurred in the counties in and around the metropolitan Philadelphia area. Other geographic areas that displayed above-average speeding thresholds include the counties in and around the Pittsburgh area, York County (near the I-83 corridor into Maryland), and the Northeast corner of the state; these areas are many of the most populated across the state. Furthermore, minorities are more likely to live in these geographic areas (U.S. Census Bureau, 2002). Therefore, it is possible that minority drivers may be accustomed to a higher tolerance for speeding in the areas near which they live. If and when these same drivers travel in other parts of the state but do not adjust their usual speeding behavior where the PSP has lower average speeding thresholds, this may be a plausible explanation for the significant cross-level interaction discovered in the bi-level models discussed above.

Figure 6.2 Average Amount Over the Limit for PSP Speeding Stops by County, May 2002-April 2003 (n=245,092)



Finally, in order to further explore the effect of race on speeding behavior, I estimated race-specific models (not shown) and explored whether the independent variables had different effects across Black and non-Black drivers. While the models presented explore the extent to which driver race interacts with municipality-level variables, split sample models allows for an examination of how driver race interacts with *all* other independent variables of interest. Using the test of equality of regression coefficients (Paternoster, Brame, Mazerolle, & Piquero, 1998), the z-statistic results indicated that *no* significant differences between

Black and non-Black drivers were evident in the effect of driver age and gender, or any of the other predictor variables, on speeding behavior.

Collectively, the hierarchical multivariate models presented in this chapter reflect mixed support for the expected relationships laid out by the hypotheses in Chapter 4. The final chapter summarizes these results and explores their implications for theoretical understandings of offending behavior, as well as future traffic stop research, policy, and racially biased policing legal challenges.

CHAPTER 7: DISCUSSION

Framed within the context of understanding the role of driver behavior in racially biased policing, the current study examined whether demographic disparities in police stops reported nationwide may, at least partially, reflect legally relevant behavioral differences by race, age, and gender. Understanding whether driving behavior is a plausible explanation for disparity in stops and stop outcomes is crucial to effectively responding to allegations of racially biased policing. Building on previous research that has documented demographic differences in travel patterns and various types of illegal or risky driving behavior, this study explored three research questions: 1) Does driving behavior vary by driver race, age, and gender? 2) Does severity of offending behavior vary based on driver demographic characteristics? 3) Do contextual level factors influence driving behavior? This final chapter reviews the support for these research questions and explores the implications of this study's results for theoretical understandings of offending behavior. Following this discussion, the implications of this study's findings for selective enforcement legal challenges, policy initiatives, and future research on racially biased policing are explored.

REVIEW OF FINDINGS

The general hypothesis tested by the current study was that racial / demographic groups are not equivalent in the nature and extent of their traffic law violating behavior. More specifically, based upon speculation by researchers in the field of racially biased policing and previous empirical research on various types of driving behaviors, the study's hypotheses predicted male drivers, drivers 25 years old and younger, non-White drivers, and Black drivers would be more likely to speed than their female, older, and White counterparts. Furthermore the study predicted that age would attenuate the influence of race on driving behavior. In terms of speeding severity, it was hypothesized that males, younger drivers, and Blacks would be more likely to drive at higher speeds than females, older drivers, and Whites. Finally, it was hypothesized that drivers in municipalities with a higher average proportion of younger drivers and in municipalities with higher average speeding thresholds would be more likely to speed than drivers in municipalities with a lower average proportion of younger drivers and drivers in municipalities with lower average speeding thresholds. Using roadway observational data of drivers' speeding behavior collected in 27 counties across the state of Pennsylvania, hierarchical Poisson and logistic models examined the empirical support for these hypotheses.

The Influence of Demographic Characteristics on Driver Offending Behavior

First, the findings showed that, contrary to expectations, driver gender was not a consistent or strong predictor of speeding behavior. The expected general relationship between gender and speeding behavior was very weak. In the model examining the most severe speeding behavior (25 mph over the limit), however, the hypothesis that males would be significantly more likely than females to speed more severely was supported. These findings are consistent with other research on the gender gap in crime, which has found that gender differences are smallest for mild forms of lawbreaking and greater for more serious offending (Steffensmeier & Allan, 1996). Similarly, studies of driving aggression and road rage have also shown that male and female drivers tend to be similarly aggressive in less serious types of mild aggression (e.g., horn honking, yelling, tailgating), while greater gender differences are evident for more serious verbally and physically aggressive actions (Harre, Field, & Kirkwood, 1996; Hennessy & Wiesenthal, 1997; 1999; 2001; Lawton and Nutter, 2002; Shinar & Compton, 2004; Wells-Parker et al., 2002). Corbett and Simon (1992) found that male drivers, more frequently than female drivers, indicated that several needs were met by speeding including: expressing individuality and rebelliousness, impressing and being accepted by peers, proving masculinity, and releasing frustration. Given that the gender differences in speeding are only evident at the most serious level of speeding examined in this study, perhaps it is only severe speeding that meets these needs.

It is also possible that the lack of significant gender differences in speeding behavior is a function of the study's research design. In order to maximize the observers' ability to identify driver and vehicle characteristics, observations were conducted only during daylight hours. If, as Lange et al. (2005) speculated, speeding is more likely to occur at night because of reduced traffic volume, it is possible that males and females might exhibit greater differences in speeding behavior at times of day that were unobserved in the present study.

That driver gender was not a strong predictor of speeding behavior in general is somewhat surprising, however, given that other research has shown male drivers are slightly more likely than female drivers to receive citations during traffic stops (Durose et al., 2007; Engel et al., 2009; Rowe, unpublished; Tillyer & Engel, forthcoming). Given that this study showed gender differences in law-violating speeding behavior only for the most serious speeding, it is possible that gender differences in citation rates reflect differential police treatment of male and female motorists. Specifically, previous research has suggested that male police officers may be reluctant to stop female drivers due to fears of being accused of misconduct (Rubinstein, 1973). Given that this study examined only differences in speeding behavior, however, it is also possible that differences in citation rates reflect gender differences in other law-violating and dangerous driving behaviors that are likely to produce citations such as accident involvement and driving under the influence (Abdel-Aty &

Abdelwahab, 2000; Boyle et al., 1998; Braver, 2003; Caetano & Clark, 2000; Everett et al., 2001; Harre et al., 1996; Massie et al., 1995; Miller et al., 1998; Voas et al., 1998; Zador et al., 2000).

Second, across all HLM models, the results indicated that age was one of the strongest and most consistent predictors of speeding behavior. Younger drivers were significantly more likely to exceed the posted speed limit than were their older driving counterparts. Furthermore, the age effects were stronger at more serious amounts over the limit. Therefore, both of these age-related hypotheses were well supported in these data. Furthermore, these findings are consistent with a considerable body of classic research that indicates youthfulness is a strong predictor of offending behavior (Farrington, 1986; Hirschi & Gottfredson, 1983; Sampson & Laub, 1992; Warr, 1993; 1998).

In trying to explicate the relationship between age, race, and speeding behavior, it was hypothesized that the influence of race on speeding behavior would be somewhat attenuated by the inclusion of age in the hierarchical models. The support for this hypothesis was weak. Although the degree to which the race effect was attenuated by the inclusion of age into the models varied by dependent variable, the race effect was only slightly weakened and often was essentially unchanged by the inclusion of age. Therefore, there is not much support for the proposition that the effect of race on speeding is actually due to the fact that minority drivers are, on average, younger than White drivers. It is possible that, if younger drivers of all races are more likely to drive at night, limiting the observation periods to daylight hours prohibited a true test of this relationship. It is important to note, however, that Lange et al. (2005) suggested that it is possible that a more precise, less subjective, measure of driver age like the one used in this study might show that the racial differences in speeding behavior to be further attenuated by driver age.

Third, the results showed significant racial differences in speeding behavior in the expected directions. Non-Whites, and specifically Blacks, were significantly more likely to exceed the posted speed limit than were their White driving counterparts. Furthermore, the race effects, particularly for Blacks, were stronger at more serious amounts over the limit (e.g., Blacks 1.4 times more likely than non-Blacks to exceed speed limit by 10 or more mph, but 2.0 times more likely to exceed limit by 25 mph). This latter finding is consistent with previous research that suggests that the racial gap in offending behavior is greatest for serious offending, but is smaller or even nonexistent for more minor offending (Elliot & Ageton, 1980). These racial differences in speeding behavior are also consistent with a handful of previous observational studies (summarized in Table 3.1) that differences in driving behavior as a possible explanation for racial disparity in police traffic stops. Specifically, the racial differences in speeding behavior reported in this study are consistent with the previous observational studies that go beyond a simple dichotomy of speeding or not speeding, and assess the true severity of speeding behavior (Engel et al., 2006; Lange et al., 2001, 2005; Smith et al., 2003). That is, the findings of the current study do not support Lamberth's (1994, 1996) findings in New Jersey and Maryland that Blacks and Whites drive indistinguishably. Rather, they mirror the findings of Lange et al. (2001, 2005) in New Jersey who discovered racial differences at the upper tail end of the speeding distribution that did not exist as the speeding criterion was lowered closer to the actual speed limit.

Felson, Deane, and Armstrong (2008) recently argued that it is theoretically important to understand if race is correlated with serious delinquency and violence or just violence; if race is associated with all types of crime then theories of crime apply, whereas if race correlates only with violent offending then theories of violence may be necessary. Their results suggested that Blacks were not generalists in their offending behavior and that race differences were evident only in violent offenses, not in non-violent but still serious offenses. The findings of the current study, however, seem to suggest that race does correlate with offense seriousness, not just violence, as the strength of the significant racial differences increases with the seriousness of speeding offenses. It is important to note, however, that Felson et al. compared racial differences in violent with minor and serious drug and property crime. It may be that there are components of illegal driving behavior that render it dissimilar, even at its most serious, to other types of non-violent crime. First, more opportunity for driving offenses exists for many more people because little effort is required, and the line distinguishing offending and non-offending behavior is much easier to cross. Second, the sanctions for driving behavior are often rare or nonexistent; when sanctions do exist, the majority of them bring relatively minimal harm to the offender (Clarke, 1996; Corbett, 2000; Corbett & Simon, 1992). Very little empirical research in criminology has examined unlawful driving behavior, but it could be fruitful for future research to examine whether general theories of crime can explain demographic differences in minor and serious speeding behavior. Indeed, Osgood et al. (1988) argued that although driving behavior is not a typical form of deviance studied by social scientists, it can be accurately included with other types of deviance because it is subject to social controls, recognized as an undesirable behavior and shares many traits with deviance, particularly excitement and risk.

Demographic differences in the severity of offending behavior may result from specific groups having different normative beliefs about acceptable degrees of speeding. Overall, the widespread lack of compliance with posted speed limits suggests that speeding is normative, rather than deviant, behavior (Clarke, 1996; Corbett, 2000; Corbett & Simon, 1991, 1992). Indeed, the perception exists that speeding is a behavior in which most people engage and for which there are minimal, if any, repercussions (Corbett, 2000). Survey research of drivers and police officers, however, suggests that there is a threshold past which more severe speeding is not tolerated as normative behavior (Corbett & Simon, 1991; Royal, 2003). Therefore, it is possible that social norms about "acceptable" speeding behavior may vary by speeding severity and males and females, young and old drivers, and White and minority drivers may differ in their perceptions of how acceptable it is to speed severely.

Both Sutherland (1947) and Akers (1999) argued that deviance is related to gender, age, and race, because these characteristics affect the likelihood of being exposed to crime-favorable messages. Akers (1999) specifically suggested that men, young people, and minorities would be more likely to receive messages that were favorable to crime. Therefore, extending the logic of differential association theory to driving behavior, it would be expected that due to their greater exposure to messages minimizing the illegality or dangerousness of speeding and messages that reinforce the rewards associated with speeding, minorities, younger people, and males would be more likely to speed.

The rational choice perspective developed by Cornish & Clarke (1986) can also be used to explain demographic differences in speeding behavior. The main proposition of this theory is that crime is purposively chosen in order to meet some need or bring some type of benefit to the offender (Clarke & Cornish, 2001; Cornish & Clarke, 1999). They argued that the initial decision to become involved in crime is affected by a much wider range of factors than the decision to participate in a criminal event, which is instead heavily influenced by characteristics of the immediate situation. The aspects of this theory that are most relevant for an analysis of illegal driving behavior are: the needs met by offending, the risks associated with offending, and the opportunities to offend. First, Clarke & Cornish (2001) explicitly argued that different crimes are associated with different needs of offenders, including the need for money or material goods, excitement, prestige, or face-saving. Second, offenders' decisions are made with limited or bounded rationality, as they cannot have perfect information about their risks of being caught. Offenders who decide to speed may be successful in doing so without being caught. The punishments for speeding, even if offenders are caught, do not appear to be particularly harmful and may be unlikely to make offenders reluctant to offend again (Clarke, 1986; Corbett, 2000). Third, the rational choice perspective makes little distinction between offenders & nonoffenders, emphasizing the role of situational opportunity in decisions to offend (Clarke & Cornish, 2001). This is particularly important for speeding behavior, as one simply needs to be driving in order to have the opportunity to speed. The rational choice perspective thus seems to suggest that speeding may be an attractive, relatively low-risk, type of offending for those seeking excitement, who are more likely to be young, male, and members of a minority group.

Finally, the general theory of crime can also be used to understand demographic differences in driving behavior. Gottfredson and Hirschi (1990) argued that deviance and other similar behaviors are more likely among people with low self-control (e.g., impulsive, risk-taking, focused on short-term thinking and simple tasks, and seeking immediate gratification). Gottfredson and Hirschi argued that low self-control results from ineffective or incomplete socialization, which they primarily attributed to poor parenting techniques. Applications of the general theory of crime to driving behaviors suggest that they are similarly rooted in the need for immediate gratification, thrill seeking, and the pursuit of risk and pleasure without regard for long-term consequences (Sorensen, 1994; Strand & Garr, 1994). Drivers with low self-control who consider speeding are unlikely to consider the possibilities or consequences of an accident or traffic citation that may result from such behavior (and if considered, risk is minimized). On the other hand, drivers with high self-control consider the consequences of driving illegally in that particular situation as well as the consequences of establishing a pattern of reckless driving (Sorensen, 1994). Because the opportunities for speeding are available to anyone who can drive, it is expected that those with low self-control, namely males, younger people, and minority group members, have many opportunities to offend.

Unfortunately, while each is a compelling theoretical possibility, the current study's data cannot speak to the observed drivers' normative beliefs about speeding or motivations for speeding. Nevertheless, it is one possible explanation for the demographic differences in speeding severity evident in this study's results and may be an avenue for future research to explore.

Beyond Driver Demographics

In addition to driver demographic variables, the hierarchical models also explored the influence of vehicle, situational, and municipality characteristics on speeding behavior. Several of these additional independent variables were significantly related to speeding behavior. Some of these statistical relationships were specifically predicted by the study's hypotheses. For example, drivers in municipalities with higher proportions of young drivers were significantly more likely to exceed the speed limit by 20 and 25 mph than drivers in municipalities with lower proportions of young drivers. This supports the hypothesis that drivers' speeding behavior may be influenced by the characteristics of other individuals driving in the same area. As discussed above, driver age is the strongest demographic predictor of speeding at the individual-level; therefore, it logically follows that the contextual effect of the proportion of young drivers would also be positively associated with drivers' speeding behavior.

A second municipality-level effect evident in each of the HLM models indicated that, as hypothesized, drivers in municipalities with higher average PSP speeding thresholds were significantly more likely to exceed the speed limit by 10, 15, 20, and 25 mph than drivers in municipalities with lower average speeding thresholds. This could be due to an overall faster traffic flow, a greater area-specific tolerance for speeding by PSP, and driver awareness of the local speeding thresholds. If one presumes that local drivers would be more likely to be familiar with specific locations or routes and know how much speeding the police will tolerate, then the finding that drivers with a Pennsylvania license plate were less likely than those with an out-of-state license plate to speed is entirely consistent with this line of reasoning. Local drivers, who learn what the informal social norms are about speed through their own experience or the experience of others, are more likely to drive accordingly.

Other significant effects were not specifically hypothesized but are consistent with what might be expected. For example, drivers traveling with passengers were less likely to be observed exceeding the speed limit, which is likely a function of increased concern for the safety of others in the vehicle. Similarly, drivers traveling in a 65 mph speed limit were less likely to speed than drivers traveling in all other lower speed limits. This is likely a function of concern for safety as well. That is, a driver traveling in a lower speed limit may be more willing to exceed the speed limit by a greater amount than drivers traveling in a 65 mph zone because that increased amount over the limit may push the limits of proportionately more drivers' assessments of safe or acceptable speeding. Finally, it is intuitive that drivers traveling in a sports car were significantly more likely to speed than all other vehicle types.

Contextual Effects

In addition to the influence of driver, vehicle, situational, and municipality characteristics on speeding behavior, this study also sought to explore whether contextual factors impacted how driver race influences driving behavior. The results of some of the hierarchical models indicated that at least some of the racial differences in speeding behavior were contextual. Specifically, the models for amount over the limit and exceeding the limit by 10 or more mph showed that there were statistically significant random effects for driver race. These multivariate findings confirmed the county-level bivariate examinations of race and speeding behavior reported in the first half of Chapter 6, where racial differences in speeding were statistically significant in some counties but not in others.

In order to further explore the interplay between municipality level variables and driver race on speeding behavior, two cross-level interactions were explored. The models with these interaction terms also supported the proposition that the influence of driver race on speeding behavior is contextual. Specifically, non-Whites were more likely to exceed the posted speed limit by 15, 20, and 25 mph in municipalities with higher proportions of young drivers, while Blacks were more likely to exceed the posted speed limit by 10 and 15 mph in municipalities with higher proportions of young drivers. Also, Nonwhites were more likely to exceed the posted speed limit by 10, 15, 20, and 25 mph in municipalities where the PSP has more strict speeding thresholds. Blacks were more likely to exceed the posted speed limit by 25 mph in municipalities with lower average amounts over the limit for PSP speeding stops. In order to further explore the significant cross-level interactions between driver race and PSP average amount over the limit for PSP speeding stops, a graphic display of the county-level average speeding thresholds was presented. This illustrated that the areas with above-average speeding thresholds occurred in many of the most populated counties in the state and the areas in which minorities are more likely to live. It is possible that minority drivers may be accustomed to a higher tolerance for speeding in the areas near which they live. If and when these same drivers travel in other parts of the state, with lower average speeding thresholds, but do not adjust their usual speeding behavior, then this may explain why the bi-level models indicated that minority drivers were more likely to exceed the posted speed limit in municipalities with stricter speeding thresholds.

If perceptions of acceptable speed vary by driver race, then this may account for these findings. Royal (2003) found that males and younger drivers perceived that they could travel at higher speeds without being ticketed than their female and older counterparts. While driver race was not examined in this survey research, it is plausible that perceptions of acceptable speeding also differ by race. Although Royal (2003) did not specify the thought process by which surveyed drivers arrived at their reported perceptions of acceptable miles per hour over the limit, it is possible that familiarity with speed thresholds near areas that drivers live is an important factor.

LEGAL, RESEARCH & POLICY IMPLICATIONS

This study's findings provide a plausible alternative explanation for demographic disparities in police outcomes that is not based on officer bias, but rather legitimate offending differences by driver age, race, and to a lesser degree, gender. In particular, racial differences in more serious speeding behavior were discovered that likely place minority drivers at increased risk of detection by police. These findings have a number of important implications for legal challenges of racially biased policing, traffic stop and benchmark research, and policy and training initiatives of police agencies across the country.

Legal Implications for Identifying Similarly Situated Persons

As described in Chapter 2, surveys of traffic violating behavior, and benchmark research more generally, grew out of a need to be able to identify "similarly situated individuals" in legal challenges to police behavior based on claims of selective enforcement. While not unanimous, growing numbers of both state and federal courts have concluded that population statistics do not provide reliable comparisons of similarly situated persons against which traffic stops can be compared. Furthermore, the opinions in these cases have suggested that, for the purposes of showing discriminatory effect, they would find statistical comparisons of stops and benchmark data most compelling when the comparison populations were based not on population baselines, but rather rates of drivers' actual roadway usage or, even more preferable, violating behavior (*Chavez v. Illinois State Police*, 2001; *State of New Jersey v. Kennedy*, 1991; *State of New Jersey v. Smith*, 1997; *U.S. v. Alcaraz-Arellano*, 2004; *U.S. v. Lindsey*, 2003; *U.S. v. Mesa-Roche*, 2003). As more research like the current study finds that demographic differences in driving behavior do exist, the courts will have to reconsider whether benchmarks that do not account for violating behavior (e.g., population estimates or observations of roadway usage) can ever be held up as legally appropriate evidence of similarly situated persons in future legal challenges.

Scholars argue that advancements in the case law surrounding racially biased policing are only as good as the social science research with which the courts are presented (Smith & Alpert, 2002). While traffic violator observations likely provide a more reliable and valid estimate of drivers eligible to be stopped than many other techniques, even strong benchmarks still are not without their limitations in their ability to provide estimates of similarly situated persons for selective enforcement litigation (Fridell, 2004). Although no study can directly measure the causes of racial/ethnic disparity in traffic stops, well-conceived studies that execute an examination of multiple alternative explanatory factors (other than police bias) can inform the courts about patterns of disparities and provide interpretation of statistical evidence that the courts can use in making a *legal* determination of discriminatory purpose and/or effect (Fridell et al., 2001; Smith & Alpert, 2002; Tillyer et al., 2008).

Implications for Traffic Stop Data Collection and Research

The research findings of this study have implications for future police traffic stop research. In order for police agencies to engage in a productive dialogue with the citizens they serve, analyses of their traffic stop data need to be based on appropriate comparison data. Furthermore, when a police agency is devoting considerable time and precious resources to a study of this kind, it is crucial that it be methodologically sound and well-executed (Smith & Alpert, 2002).

Research examining multiple types of popular benchmarks has shown that the findings of racial/ethnic disparity in stops by police can vary dramatically by benchmark (Engel et al, 2004). Unfortunately, since Census data are easily accessible and cost-effective, traffic stop research conducted internally by police agencies or by external research teams hired by police agencies has most commonly utilized these population-based statistics as benchmarks (Ridgeway & MacDonald, 2010). As reviewed earlier, Census benchmarks are based on the assumption that the offending behavior of drivers that come to the attention of police is equivalent across demographic groups. As is clear from the growing body of research on driving behavior, including this study, this assumption is not supported by empirical examinations.

The current study is the most comprehensive survey of traffic law violating behavior conducted at the state level, with observations conducted in 140 municipalities in approximately 40% of Pennsylvania counties over a 16-month period. Although time-intensive and cost-prohibitive, this study provides greater external reliability than previous surveys of speeding behavior in terms of geography, road types, seasonal variation, and day and time of the week. Given that studies in New Jersey, North Carolina, Ohio, and now Pennsylvania have all shown that behavioral differences do exist across racial groups (Engel et al., 2006; Lange et al., 2005; Smith et al., 2003), it becomes difficult to continue to defend the use of benchmarks based on residential population statistics and even surveys of roadway usage. Police agencies undertaking an analysis of their traffic stop data, therefore, should consider devoting the additional resources necessary to collect benchmark data that provide a more valid comparison group for traffic stops.

Nevertheless, it is crucial that data collection be viewed by police agencies and the public as only one step in the process of understanding disparities and combating inaccurate perceptions, not "the way" to respond to negative perceptions about police behavior (Fridell et al., 2001, 115). First, speeding is only one of many reasons that drivers are stopped. Although it is the most frequency reason for a traffic stop, it is possible that racial disparities in stop decisions might be evident in stops initiated for other reasons that are more difficult than speeding to objectively measure in a benchmark data collection effort (Lange et al., 2005). Furthermore, benchmark comparisons, regardless of the type of comparison data, are limited in that they can only account for potential disparity in the decision to initiate a traffic stop and cannot account for racial disparities reported in the analyses by many state police agencies in stop outcomes such as citations, searches & arrests even if the initial stop was legitimate (Anwar & Fang, 2006; Engel et al., 2004, 2005; Farrell et al., 2003; Lange et al., 2005, Lovrich et al., 2005).

This study's findings are also important for research examining driving behavior and travel patterns more generally. As background for the current study, a considerable body of research on demographic differences in travel patterns and various types of driving behavior was reviewed. The results of this review of mostly travel and transportation studies found that differences by driver age and gender are routinely examined, while race is often ignored. The findings of the current research indicate that speeding behavior is strongly predicted by both driver age and race. The current research also employed HLM, an analytical technique not previously used in research examining driver behavior. Bi-level modeling, used in order to account for the nesting of observations within municipalities, allowed for the ability to explore individual-level influences as well as contextual factors on speeding behavior, and to understand how municipality characteristics interacted with driver race to influence speeding behavior. The results of these bi-level models indicated that the influence of driver race did indeed vary based on contextual factors. Therefore, future studies of driving and travel behavior need to consider both the main effects of all three primary demographic characteristics (e.g., gender, age, and race) and also how the influence of these variables might potentially interact with community characteristics. Understanding these demographic differences might be helpful in targeting safer driving initiatives or public service announcements.

Policy and Practice

Demographic disparities in criminal justice outcomes, including traffic stops, do not necessarily mean that criminal justice officials have acted inappropriately. As noted throughout this study, an alternative explanation to discrimination is that demographic disparities in traffic stops, just as with many other outcomes of the criminal justice system, may reflect differences in legally relevant offending behavior by members of different demographic groups (Walker et al., 2000). Exploring the possible causes of disparities in traffic stops is important because the policy implications for police agencies vary with each of the explanations for disparity (Engel et al., 2002). For example, if members of a particular demographic group tend to be more serious driving offenders, then it would be irresponsible of police to ignore legally relevant offending behavior in order to eliminate the appearance of impropriety. On the other hand, if driving behavior and other race-neutral explanations of disparity are ruled out, then perhaps the appropriate policy response is for police officers to undergo racial sensitivity training or a review of appropriate stopping and searching procedures.

A thorough exploration of various explanations of disparity in traffic stops is crucial to understanding how police departments can best respond to such disparity and the public perceptions of those disparities. While understanding these disparities may seem a daunting task, as Engel et al. (2002, 270) argued, “It is only when we seek to explain officer behavior that we may then take steps to control it.” It is possible and perhaps even likely that there are multiple explanations for racial disparities in stops, which may be specific to individual police agencies. Furthermore, quantitative data analyses will likely never be able to definitively determine that racial/ethnic discrimination in traffic stops is occurring. Police departments whose quantitative data indicate potential issues with disparities, however, may be able to further understand the causes of these disparities by talking to their officers or the citizens they serve (Brunson, 2010; Tillyer et al., 2008). Focus group interviews have been conducted in a small number of state police agencies to better understand officers' decision making processes when initiating a traffic stop and have provided these agencies with more specific policy and training initiatives (Engel et al., 2007b, Engel et al., 2008a, 2008b. As a result, this may be a useful avenue for future research to explore.

Conclusion

Differences in the rate of stops of Non-White or Black drivers compared to White drivers may be based, in part, on legal considerations rather than inappropriate behavior by police officers. It is important to consider, however, that these two explanations for demographic disparity in stops are not mutually exclusive. That is, minority drivers can differentially offend, and at the same time, police can engage in discriminatory stop practices (Harris, 2003; Russell, 2001). The difficulty of this line of research is that no study can provide definitive conclusions about whether or not discrimination exists (Fridell et al., 2001; Fridell, 2004; Ridgeway & MacDonald, 2010; Tillyer et al., 2008). What the current study does show, however, is that racial differences in speeding behavior *do* exist. Therefore, this study echoes what Lange et al. (2005, 216, emphasis added) argued:

> The key conclusion that we can draw from this research is that the typical method of assessing racial profiling on the precinct or jurisdiction level is not adequate; the racial distribution in the population of driving nonviolators *cannot* be assumed to reflect the racial distribution in the population of driving violators, and it is from this latter population that police stops should be drawn.

Ultimately, although the findings of this study do not eliminate the possibility of inappropriate police behavior in traffic stop decision making, they do call into question the knee-jerk reaction to label any racial disparity in traffic stops as a product of police bias. Most previous research on police decision making has found offenders' legally relevant behavior and offense severity to be among the strongest and most consistent predictors of various types of police actions (Engel, Sobol, & Worden, 2000; Mastrofski, Worden, & Snipes, 1995; Mastrofski, Snipes, Parks, & Maxwell, 2000; National Research Council, 2004; Novak, Frank, Smith, & Engel, 2002; Riksheim & Chermak, 1993). Indeed, it is inconsistent with decades of police research for traffic stop studies to not consider the role of driving behavior in examining whether minorities are disproportionately stopped. Given the findings of this study and similar surveys of traffic law violating behavior that indicate minority drivers are more likely to speed than White drivers, it is incumbent upon future studies to consider this alternative, legitimate explanation for racial/ethnic disparity in traffic stops.

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REFERENCES

Abdel-Aty, M. A. & Abdelwahab, H.T. (2000). Exploring the relationship between alcohol and the driver characteristics in motor vehicle accidents. *Accident Analysis and Prevention, 32,* 473-482.

Akers, R. (1999). *Criminological Theories: Introduction and Evaluation.* Los Angeles: Roxbury.

Albrecht, S. L. & Green, M. (1977). Attitudes toward the police and the larger attitude complex: implications for police-community relationships. *Criminology, 15*, 67-86.

Allison, P.D. (1999). *Multiple Regression: A Primer.* Thousand Oaks, CA: Sage Publications.

Alpert Group. (2004). *Miami-Dade Police Department Racial Profiling Study*. Report to the Miami-Dade Police Department, Miami, FL. [On-line]. Available: http://www.aclufl.org/pdfs/Miami-Dade%20Police%20Department%20%20Racial%20Profiling%20Study%20-%20The%20Alpert%20Group.pdf

American Civil Liberties Union. (2000). *Plaintiff's Fifth Monitoring Report: Pedestrian and Car Stop Audit*. http://www.aclupa.org/report.htm.

Anwar, S., & Fang, H. (2006). An alternative test of racial prejudice in motor vehicles searches: Theory and evidence. *American Economic Review*, 127-151.

Baker, S. P., Braver, E. R., Chen, L., Pantula, J. F. & Massie, D. (1998). Motor vehicle occupant deaths among Hispanic and Black children and teenagers. *Archives of Pediatric & Adolescent Medicine, 152,* 1209-1212.

Bayley, D. H. & Mendelsohn, H. (1969). *Minorities and the Police*. New York: Free Press.

Beck, D. A. & Daly, A. (1999). State Constitutional Analysis of Pretext Stops: Racial Profiling and Public Policy Concerns. *Temple Law Review*, 72, 597-618.

Berger, D.E. & Snortum, J.R. (1986). A structural model of drinking and driving: Alcohol consumption, social norms, and moral commitments. *Criminology, 24,* 139-153.

Bernard, T.J., Calnon, J.M., Engel, R.S., & Hays, Z.R. (2005). Efficiency and the New Differential Processing. *Journal of Crime and Justice, 28.*

Biderman, A.D. & Lynch, J.P. (1991). *Understanding Crime Incidence Statistics: Why the UCR Diverges From the NCS.* New York: Springer-Verlag.

Boyle, J., Dienstfrey, S., & Sothoron, A. (1998). *National Survey of Speeding and Other Unsafe Driving Actions: Driver Attitudes and Behavior (vol 2.).* Washington, D.C.: National Highway Traffic Safety Administration.

Braver, E. R. (2003). Race, Hispanic origin, and socioeconomic status in relation to motor vehicle occupant death rates and risk factors among adults. *Accident Analysis & Prevention*, *35,* 295-309.

Browning, S., Cullen, F. T., Cao, L., Kopache, R., & Stevenson, T. J. (1994). Race and getting hassled by the police: a research note. *Police Studies, 17*, 1-11.

Brunson, R.K. (2010). Beyond stop rates: Using qualitative methods to examine racially biased policing. In S.K. Rice & M.D. White (Eds.), *Race, Ethnicity, and Policing: New and Essential Readings,* (pp. 221-238). New York: New York University Press.

Bureau of Transportation Statistics. (1997). *1995 American Travel Survey*. Washington, D.C.: U.S. Department of Transportation.

Burkhardt, J.E., McGavock, A.T., Nelson, C.A., & Mitchell, C.G.B. (2002). *Improving Public Transit Options for Older Persons, volume 2: Final Report.* Washington, D.C.: Transportation Research Board.

Caetano, R. & Clark, C. L. (2000). Hispanics, Blacks and Whites driving under the influence of alcohol: Results from the 1995 National Alcohol Survey. *Accident Analysis and Prevention*, *32,* 57-64.

Carter, D. L. (1983). Hispanic interaction with the criminal justice system in Texas: experiences, attitudes and perceptions. *Journal of Criminal Justice, 11,* 213-227.

Chu, X., Polzin, S. E., Rey, J. R. & Hill, E. T. (2000). Mode choice by people of color for non-work travel. In Federal Highway Administration (Ed.), *Travel Patterns of People of Color.* Washington, DC: U.S. Department of Transportation, pp. 137-162.

Clarke, R. (1996). The distribution of deviance and exceeding the speed limit. *British Journal of Criminology, 36*, 169-181.

Clarke, R.V. & Cornish, D.B. (2001). Rational choice. In R. Paternoster & R. Bachman, *Explaining Criminals and Crime,* pp. 23-42. Los Angeles, CA: Roxbury Publishing Company.

Cole, D. (1999). *No Equal Justice: Race and Class in the American Criminal Justice System.* New York: The New Press.

Corbett, C. (2000). The social construction of speeding as not "real" crime. *Crime Prevention and Community Safety: An International Journal, 2*, 33-46

Corbett, C. & Simon, F. (1992). Decisions to break or adhere to the rules of the road, viewed from the rational choice perspective. *British Journal of Criminology, 32*, 537-549.

Cordner, G., Williams, B., & Velasco, A. (2002). *Vehicle Stops in San Diego: 2001.* San Diego, CA: San Diego Police Department.

Cornish, D.B. & Clarke, R.V. (1999). Crime as a rational choice. In F.T. Cullen & R. Agnew, *Criminological Theory: Past to Present*, pp. 254-257. Los Angeles, CA: Roxbury Publishing Company.

Cornish, D.B. & Clarke, R.V. (1986). *The Reasoning Criminal.* New York: Springer-Verlag.

Cox, S. M., Pease S. E., Miller D. S., & Tyson C. B. (2001). *State of Connecticut 2000-2001 Report of Traffic Stops Statistics.* Rocky Hill, CT: Division of Criminal Justice.

Decker, S. H. (1981). Citizen attitudes toward the police: A review of past findings and suggestions for future policy. *Journal of Police Science and Administration, 9,* 80-87.

Donahue, J. (1999). "Trooper Boss: Race Plays Role in Drug Crimes." *Star-Ledger,* February 28 at News 01.

Dunham, R. C. & Alpert, G. P. (1988). Neighborhood differences in attitudes toward policing: Evidence for a mixed-strategy model of policing in a multi-ethnic setting. *Journal of Criminal Law and Criminology, 79*, 504-523.

Durose, M.R., Schmitt, E.L., Langan, P.A. (2007). *Contacts between police and the public, 2005.* Washington, D.C.: Bureau of Justice Statistics, U.S. Department of Justice.

Durose, M.R., Schmitt, E.L., Langan, P.A. (2005). *Contacts between police and the public: Findings from the 2002 national survey.* Washington, D.C.: Bureau of Justice Statistics, U.S. Department of Justice.

Eck, J., Liu, L., & Bostaph, L.G. (2003). *Police Vehicle Stops in Cincinnati.* Report submitted to the Cincinnati Collaborative Agreement. [On-line]. Available: http://www.uc.edu/criminaljustice/ResearchReports.html

Ekstrand, L.E. (2000). *Racial Profiling: Limited Data Available on Motorist Stops*. Washington, D.C.: United States General Accounting Office.

Elliott, D.S. & Ageton, S.S. (1980). Reconciling race and class differences in self-reported and official measures. *American Sociological Review, 44,* 95-110.

Engel, R.S. (2005). Citizens' perceptions of distributive and procedural injustice during traffic stops with police. *Journal of Research in Crime and Delinquency*.

Engel, R.S. & Calnon, J.M. (2004a). Examining the influence of drivers' characteristics during traffic stops with police: Results from a national survey. *Justice Quarterly, 21,* 49-90.

Engel, R. S. & Calnon, J. M. (2004b). Comparing benchmark methodologies for police-citizen contacts: Traffic stop data collection for the Pennsylvania State Police. *Police Quarterly, 7*, 97-125.

Engel, R. S., Calnon, J. M., & Bernard, T. J. (2002). Theory and racial profiling: Shortcomings and Future Directions in Research. *Justice Quarterly, 19*, 201-225.

Engel, R. S., Calnon, J. M., Liu, L., & Johnson, R. (2004). *Project on Police-Citizen Contacts: Year 1, Final Report.* Report submitted to the Pennsylvania State Police, Harrisburg, PA. Publicly available at: http://www.psp.state.pa.us/psp/lib/psp/pdf/psp_police_citizens_contact_final_report_2002-2003.pdf

Engel, R.S., Calnon, J.M., Tillyer, R., Johnson, R., Liu, L., & Wang, X. (2005). *Project on Police-Citizen Contacts: Year 2 Final Report (May 2003- April 2004).* University of Cincinnati: Cincinnati, OH. Submitted to the Commissioner of the Pennsylvania State Police, Harrisburg, PA.

Engel, R.S., Cherkauskas, J.C., Smith, M.R., Lytle, D., Moore, K. (2009). *Traffic Stop Data Analysis Study: Year 3 Final Report.* Submitted to the Arizona Department of Public Safety, Phoenix, AZ.

Engel, R.S., Cherkauskas, J.C., & Beck, S. (2008b). Identifying Best Practices in Criminal Interdiction Activities for the Nebraska State Patrol. Submitted to the Nebraska State Patrol, Lincoln, NE.

Engel, R.S., Cherkauskas, J.C., & Smith, M.R. (2008a). *Traffic Stop Data Analysis Study: Year 2 Final Report.* Submitted to the Arizona Department of Public Safety, Phoenix, AZ.

Engel, R.S., Frank, J., Tillyer, R., Klahm, R. (2006). *Cleveland Division of Police Traffic Stop Data Study: Final Report.* Report submitted to the Cleveland Division of Police. Publicly available at: http://www2.uc.edu/criminaljustice/ProjectReports/Cleveland_Traffic_Stop_Study.pdf

Engel, R.S., Sobol, J.J., & Worden, R.E. (2000). Further exploration of the demeanor hypothesis: The interaction effects of suspects' characteristics and demeanor on police behavior. *Justice Quarterly, 17,* 235-258.

Engel, R.S., Tillyer, R. & Cherkauskas, J.C. (2007b). *Understanding Best Search and Seizure Practices: Final Report*. University of Cincinnati, Submitted to the Ohio State Highway Patrol, Columbus, OH.

Everett, S. A., Shults, R. A., Barrios, L. C., Sacks, J. J., Lowry, R. & Oeltmann, J. (2001). Trends and subgroup differences in transportation-related risk and safety behaviors among high school students, 1991–1997. *Journal of Adolescent Health, 28,* 228–34.

Farrell, A., McDevitt, J., Cronin, S., Pierce, E. (2003). *Rhode Island Traffic Stop Statistics Act Final Report.* Boston, MA: Northeastern University Institute on Race and Justice.

Farrington, D.P. (1986). Age and Crime. Crime and Justice, 7, 189-250.

Federal Highway Administration. (1995). *Our nation's travel: 1995 Nationwide Personal Transportation Survey early results report.* Washington, D.C.: U.S. Department of Transportation.

Felson R.B., Deane, G., Armstrong, D.P. (2008). Do theories of crime or violence explain race differences in delinquency? Social Science Research, 37, 624-641.

Fridell, L., Lunney, R., Diamond, D. & Kubu, B. (2001). *Racially Biased Policing: A Principled Response.* Washington, D.C.: Police Executive Research Forum.

Fridell, L. (2004). *By the Numbers: A Guide for Analyzing Race Data from Vehicle Stops.* Washington, D.C.: Police Executive Research Forum.

Gabiddon, S.L., Marzette, L.N., & Peterson, S.A. (2007). Racial profiling and the courts: An empirical analysis of federal litigation, 1991-2006. *Journal of Contemporary Criminal Justice, 23,* 226-238.

Glassbrenner, D. (2003). *Safety Belt Use in 2002 – Demographic Characteristics.* Washington, DC: National Highway Traffic Safety Administration.

Gottfredson, M. & Hirschi, T. (1990). *A General Theory of Crime.* Stanford, CA: Stanford University Press.

Greenwald, H. P. (2001). *Final Report: Police Vehicle Stops in Sacramento, California* [On-line]. Available: http://www.sacpolice.com/report.pdf

Guo, G. & Zhao, H. (2000). Multilevel modeling for binary data. *Annual Review of Sociology, 26*, 441-462.

Harper, J. S., Marine, W. M., Garrett, C. J., Lezotte, D. & Lowenstein, S. R. (2000). Motor vehicle crash fatalities: a comparison of Hispanic and non-Hispanic motorists in Colorado. *Annals of Emergency Medicine, 36,* 589-596.

Harre, N., Field, J., & Kirkwood, B. (1996). Gender differences and areas of common concern in the driving behaviors and attitudes of adolescents. *Journal of Safety Research, 27,* 163-173.

Harris, D.A. (2003). The reality of racial disparity in criminal justice: The significance of data collection. Law and Contemporary Problems, 66, 71-97.

Harris, D. A. (2002). *Profiles in Injustice: Why Racial Profiling cannot work.* New York: The New Press.

Harris, D.A. (2001). Addressing racial profiling in the states: A case study of the "new federalism" in constitutional criminal procedure. *University of Pennsylvania Journal of Constitutional Law, 3,* 367-397.

Harris, D. A. (1999a). *Driving while Black: Racial profiling on our nation's highways*. Available: http://www.aclu.org/profiling/report/index.html

Harris, D. A. (1999b). The stories, the statistics, and the law: Why "driving while Black" matters. *Minnesota Law Review, 84*, 265-326.

Harris, D. A. (1997). "Driving while Black" and all other traffic offenses: The Supreme Court and pretextual traffic stops. *Journal of Criminal Law & Criminology*, *87,* 544-582.

Hennessy, D.A. & Wiesenthal, D.L. (2001). Gender, driver aggression, and driver violence: An applied evaluation. *Sex Roles, 44,* 661-676.

Hennessy, D.A. & Wiesenthal, D.L. (1999). Traffic congestion, driver stress, and driver aggression. *Aggressive Behavior, 25,* 409-423.

Hennessy, D.A. & Wiesenthal, D.L. (1997). The relationship between traffic congestion, driver stress, and direct versus indirect coping behaviors. *Ergonomics, 40,* 348-361.

Hickman, M.J. (2005). *Traffic Stop Data Collection Policies for State Police, 2004*. (NCJ 209156). Washington, D.C.: Bureau of Justice Statistics, U.S. Department of Justice.

Hindelang, M.J., Hirschi, T. & Weiss, J.G. (1979). Correlates of delinquency: The illusion of discrepancy between self-report and official measures. *American Sociological Review, 44*, 995-1014.

Hirschi, T. & Gottfredson, M. (1983). Age and the explanation of crime. AJS, 89, 552-583.

Hurst, Y., Frank, J., & Browning, S.L. (2000). The attitudes of juveniles toward police: A comparison of Black and White youth. *Policing: An International Journal of Police Strategies and Management, 23,* 37-53.

Institute on Race and Poverty (2001). *Saint Paul Traffic Stops Data Analysis.* Minneapolis, MN: University of Minnesota.

Ivers, R., Senserrick, T., Boufous, S., Stevenson, M., Chen, H., Woodward, M., & Norton, R. (2009). Novice drivers' risky driving behavior, risk perception, and crash risk: Findings from the DRIVE Study. American Journal of Public Health, 99, 1638-1644.

Jacob, H. (1971). Black and White perceptions of justice in the city. *Law and Society Review, 6*, 69-89.

Jones-Brown, D. & Maule, B.A. (2010). Racially biased policing: A review of the judicial and legislative literature. In S.K. Rice & M.D. White (Eds.), *Race, Ethnicity, and Policing: New and Essential Readings,* (pp. 140-173). New York: New York University Press.

Kennedy, R. (1997). *Race, Crime, and the Law*. New York: Vintage Books.

Kim, J. O. & Mueller, C. W. (1978). *Introduction to factor analysis.* Beverly Hills, CA: Sage Publications.

Klinger, D.A. (1996). Bringing crime back in: Toward a better understanding of police arrest decisions. *Journal of Research in Crime and Delinquency, 33,* 333-336.

Klinger, D.A. (1994). Demeanor or crime? Why 'hostile' citizens are more likely to be arrested. *Criminology, 32,* 475-493.

Kowalski, B.R. & Lundman, R.J. (2007). Vehicle stops by police for driving while Black: Common problems and some tentative solutions. *Journal of Criminal Justice, 35,* 165-181.

Krovi, R. & Barnes, C. (2000). Work-related travel patterns of people of color. In Federal Highway Administration (Ed.), *Travel Patterns of People of Color.* Washington, DC: U.S. Department of Transportation, pp. 45-66.

Lamberth, J. (2004). *Ann Arbor Police Department Traffic Stop Data Collection Methods and Analysis Study*. [On-line]. Available: http://www.ci.ann-arbor.mi.us/SafetyServices/Police/Racial%20Profiling%20Report%20A2_FinalReport_012204_v6co.pdf

Lamberth, J. (2003a). *Racial Profiling Study and Services: A Multijurisdictional Assessment of Traffic Enforcement and Data Collection in Kansas.* [On-line]. Available: http://www.racialprofilinganalysis.neu.edu/IRJ_docs/KS_2003.pdf

Lamberth, J. (2003b). *Racial Profiling Data Analysis Study - Final Report for the San Antonio Police Department.* [On-line]. Available: http://www.sanantonio.gov/sapd/pdf/LamberthSanAntonioRpt_2003.pdf

Lamberth, J. (1996). *A Report to the ACLU.* New York: American Civil Liberties Union.

Lamberth, J. (1994). Revised statistical analysis of the incidence of police stops and arrests of Black drivers/travelers on the New Jersey Turnpike between exits or interchanges 1 and 3 from the years 1988 through 1991. *Unpublished report*, Temple University.

Lamberth, J., Harris, D.A., McDevitt, J., & Ramirez, D. (2004). Making the case for measuring "who is driving" instead of "who is violating." Appendix D in L. Fridell, *By the Numbers: A Guide for Analyzing Race Data from Vehicle Stops.* Washington, D.C.: Police Executive Research Forum, pp. 411-416.

Langan, P. A., Greenfeld, L. A., Smith, S. K., Durose, M. R., & Levin, D. J. (2001). *Contacts between police and the public: Findings from the 1999 national survey*. Washington, DC: U.S. Department of Justice.

Lange, J.E., Johnson, M.B., & Voas, R.B. (2005). Testing the racial profiling hypothesis for seemingly disparate traffic stops on the New Jersey Turnpike. *Justice Quarterly, 22,* 193-223.

Lange, J. E., Blackman, K. O., & Johnson, M. B. (2001). *Speed Violation Survey of the New Jersey Turnpike: Final Report*. Trenton, NJ: Office of the Attorney General.

Lansdowne, W. M. (2000). *Vehicle stop demographic study.* San Jose, CA: San Jose Police Department.

Lasley, J. R. (1994). The impact of the Rodney King incident on citizen attitudes toward police. *Policing and Society, 3*, 245-255.

Lauritsen, J. & Sampson, R.J. (1998). Minorities, crime, and criminal justice. In M. Tonry (ed.), *The Handbook of Crime and Punishment*, (pp. 58-84). New York: Oxford University Press.

Lawton, R. & Nutter, A. (2002). A comparison of reported levels and expression of anger in everyday and driving situations. *British Journal of Psychology, 93*, 407-423.

Leiber, M.J., Nalla, M.K., & Farnworth, M. (1998). Explaining juveniles' attitudes toward the police. *Justice Quarterly, 15,* 151-174.

Lerner, E. B., Dietrich, V. K. J., Billittier, A. J., Moscati, R. M., Connery, C. M., & Stiller, G. (2001). The influence of demographic factors on seatbelt use by adults injured in motor vehicle crashes. *Accident Analysis and Prevention*, *33*, 659-662.

Liao, T.F. (1994). *Interpreting Probability Models: Logit, Probit, and Other Generalized Linear Models*. Thousand Oaks, CA: Sage.

Lovrich, N.P., Gaffney, M.J., Mosher, C.M., Pickerill, M., & Pratt, T.C. (2005). *Analysis of Traffic Stop Data Collected by the Washington State Patrol: Assessment of Racial and Ethnic Equity and Bias in Stops, Citations, and Searches Using Multivariate Quantitative and Multi-Method Qualitative Research Techniques.* University of Washington, Submitted to the Washington State Police, Olympia, WA.

Lundman, R.J. (2004). Driver race, ethnicity, and gender and citizen reports of vehicle searches by police and vehicle search hits: Toward a triangulated scholarly understanding. *Journal of Criminal Law & Criminology, 94,* 309-349.

Lundman, R. J., & Kaufman, R. L. (2003). Driving While Black: Effects of race, ethnicity, and gender on citizen self-reports of traffic stops and police actions. *Criminology*, *41*, 195-220.

Lundman, R.J. & Kowalski, B.R. (2009). Speeding While Black? Assessing the Generalizability of Lange et al.'s (2001, 2005) New Jersey Turnpike Speeding Survey Findings. *Justice Quarterly, 26,* 504-527.

Lyle, P.A. (2001). Racial profiling and the Fourth Amendment: Applying the minority perspective to ensure equal protection under the law. *Boston College Third World Law Journal, 21,* 243-277.

MacDonald, H. (2002). The racial profiling myth debunked. *City Journal, 12*, 63-73.

MacDonald, H. (2001). The myth of racial profiling. *City Journal, 11*, 14-27.

Massie, D.L., Campbell, K.L., and Williams, A.F. (1995). Traffic accident involvement rates by driver age and gender. *Accident Analysis and Prevention, 27*, 73-87.

Mastrofski, S.D., Snipes, J.B., Parks, R.B., & Maxwell, C.D. (2000). The helping hand of the law: Police control of citizens on request. *Criminology, 38,* 307-342.

Mastrofski, S.D., Worden, R.E. & Snipes, J.B. (1995). Law enforcement in a time of community policing. *Criminology, 33,* 539-563.

Miller, J.G. (1996). *Search and Destroy: African American Males in the Criminal Justice System.* New York: Cambridge University Press.

Miller, T.R., Spicer, R.S., and Lestina, D.C. (1998). Who is driving when unrestrained children and teenagers are hurt? *Accident Analysis and Prevention, 30*, 839-849.

Moon, B. & Cooley, C.J. (2007). Driving Across Campus: Assessing the impact of drivers' race and gender on police traffic enforcement actions. *Journal of Criminal Justice, 35*, 29-37.

Morgan, J. G. (2002). *Vehicle stops and race: A study and report in response to Public Chapter 910 of 2000.* Nashville, TN: State of Tennessee Comptroller of the Treasury.

Mustaine, E.E. & Tewksbury, R. (1999). Assessing the likelihood of drunk driving: Gender, context and lifestyle. *Journal of Crime and Justice, 22*, 57-93.

National Conference of State Legislatures. (2001). *State Laws Address "Racial Profiling."* Washington, DC: National Conference of State Legislatures.

National Highway Traffic Safety Administration. (2007a). *Traffic Safety Facts 2007 Data: Race and Ethnicity*. Washington, D.C.: U.S. Government Printing Office.

National Highway Traffic Safety Administration. (2007b). *Traffic Safety Facts 2007 Data: Children.* Washington, D.C.: U.S. Government Printing Office.

National Research Council. (2004). Fairness & Effectiveness in Policing: The evidence. Washington, DC: National Academies Press.

Newport, F. (1999). Racial profiling seen as widespread, particularly among young Black men. *The Gallup Poll*. Available: http://www.gallup.com/poll/releases/pr991209.asp

Novak, K. (2004). Disparity and racial profiling in traffic enforcement. *Police Quarterly, 7(1)*, 65-96.

Novak, K. J., Frank, J., Smith, B. W., & Engel, R. S. (2002). Revisiting the decision to arrest: Comparing beat and community officers. *Crime and Delinquency, 48*, 70-98.

Osgood, D.W., Johnston, L.D., O'Malley, P.M., & Bachman, J.G. (1988). The generality of deviance in late adolescence and early adulthood. *American Sociological Review, 53*, 81-93.

Paternoster, R., Brame, R., Mazerolle, P., & Piquero, A. (1998). Using the correct statistical test for the equality of regression coefficients. *Criminology, 36,* 859-866.

Pennsylvania Department of Transportation. (2001). 2001 Highway Statistics. Available: http://www.dot.state.pa.us

Pennsylvania Motor Vehicle Code, 75 Pa. C.S. § 3368.

Persico, N. & Todd, P. (2008). The hit rates test for racial bias in motor-vehicle searches. *Justice Quarterly, 25,* 37-53.

Police Foundation. (2005). *Racial Profiling: The State of the Law*. Washington, DC: Police Foundation.

Polzin, S. E., Chu, X., Rey, J. R. & Hill, E. T. (2000). Demographics of people of color: Findings from the Nationwide Personal Transportation Survey. In Federal Highway Administration (Ed.), *Travel Patterns of People of Color*. Washington, DC: U.S. Department of Transportation, pp. 27-44.

Ramirez, D., McDevitt, J. and Farrell, A. (2000). *A Resource Guide on Racial Profiling Data Collection Systems: Promising Practices and Lessons Learned*. Washington, D.C.: U.S. Department of Justice.

Raudenbush, S. W. & Bryk, A. S. (2002). *Hierarchical Linear Models, 2nd Edition*. Newbury Park, CA: Sage.

Reinfurt, D., Williams, A., Wells, J., & Rodgman, E. (1996). Characteristics of drivers not using seat belts in a high belt use state. *Journal of Safety Research, 27,* 209-215.

Reitzel, J.D., Rice, S.K., & Piquero, A.R. (2004). Lines and shadows: Perceptions of racial profiling and the Hispanic experience. *Journal of Criminal Justice, 32*, 607-616.

Rickabaugh, C.A. (2003). *A Study to Analyze Traffic Stop Data in Santa Cruz County.* [On-line]. Available: http://www.racialprofilinganalysis.neu.edu/IRJ_docs/SantaCruzFinalReport.pdf

Ridgeway, G. & MacDonald, J. (2010). Methods for Assessing Racially Biased Policing. In S.K. Rice & M.D. White (Eds.), *Race, Ethnicity, and Policing: New and Essential Readings,* (pp. 180-204). New York: New York University Press.

Riksheim, E. & Chermak, S.M. (1993). Causes of police behavior revisited. *Journal of Criminal Justice, 21,* 353-82.

Rojek, J., Rosenfeld, R., & Decker, S. (2004). The influence of driver's race on traffic stops in Missouri. *Police Quarterly, 7*, 126-147.

Rosenbloom, S. (1998). *Transit Markets of the Future: The Challenge of Change.* Washington, DC: National Academy Press.

Ross, C. L. & Dunning, A. E. (1997). *Land Use Transportation Interaction: An Examination of the 1995 NPTS Data.* Washington, DC: Federal Highway Administration.

Rowe, B. (Unpublished). Gender bias in the enforcement of traffic laws: Evidence based on a new empirical test. Available: http://www-personal.umich.edu/~rowebr/pdfs/rowe_policegenderbias_sep09.pdf

Royal, D. (2003). *National Survey of Distracted and Drowsy Driving Attitudes and Behavior: 2002.* Washington, D.C.: National Highway Traffic Safety Administration.

Royal, D. (2000). *Racial and ethnic group comparisons, National Surveys of Drinking and Driving Attitudes and Behavior – 1993, 1995, and 1997.* Washington, DC: National Highway Traffic Safety Administration.

Rubinstein, J. (1973). *City Police.* New York: Farrar, Straus and Giroux.

Russell, K.K. (2001). Racial profiling: A status report of the legal, legislative, and empirical literature. *Rutgers Race and the Law Review, 3,* 61-81.

Russell, K. K. (1999). "Driving while Black": Corollary phenomena and collateral consequences. *Boston College Law Review, 40, 717-731*

Sampson, R.J. & Laub, J.H. (1992). Crime and deviance in the life course. Annual Review of Sociology, 18, 63-84.

Scaglion, R., & Condon, R. G. (1980). The structure of Black and White attitudes toward police. *Human Organization, 39*, 280-283.

Shinar, D. & Compton, R. (2004). Aggressive driving: An observational study of driver, vehicle, and situational variables. *Accident Analysis & Prevention, 36,* 429-437.

Smith, M.R. & Alpert, G.P. (2002). Searching for direction: Courts, social science, and the adjudication of racial profiling claims. *Justice Quarterly, 19,* 673-703.

Smith, M. R. & Petrocelli, M. (2001). Racial profiling? A multivariate analysis of police traffic stop data. *Police Quarterly, 4*, 4-27.

Smith, S.K. & DeFrances, C.J. (2003). Assessing measurement techniques for identifying race, ethnicity, and gender: Observation-based data collection in airports and at immigration checkpoints. Washington, D.C.: U.S. Department of Justice.

Smith, W.R., Tomaskovic-Devey, D., Zingraff, M.T., Mason, H.M., Warren, P.Y., & Wright, C.P. (2003). *The North Carolina Highway Traffic Study*. Final Report to the National Institute of Justice, U.S. Department of Justice. [On-line]. Available: http://www.chass.ncsu.edu/justice/reports/hwy_traffic_study_03.htm

Sorensen, D.W.M. (1994). Motor vehicle accidents. In T. Hirschi & M.R. Gottfredson, *The Generality of Deviance*, pp.113-129.

Spitzer, E. (1999). *The New York City Police Department's "stop and frisk" practices: A Report to the people of the state of New York from the Office of the Attorney General*. Albany: New York Attorney General's Office.

Steffensmeier, D. & Allan, E. (1996). Gender and crime: Toward a gendered theory of female offending. *American Review of Sociology, 22,* 459-487.

Strand, G.C. & Garr, M.S. (1994). Driving under the influence. In T. Hirschi & M.R. Gottfredson, *The Generality of Deviance*, pp.131-147.

Strom, K.J., Brien, P., & Smith, S. (2001). *Traffic Stop Data Collection Policies for State Police, 2001* (NCJ 191158). Washington, D.C.: Bureau of Justice Statistics, U.S. Department of Justice.

Strom, K.J., & Durose, M.R. (2000). *Traffic Stop Data Collection Policies for State Police, 1999*. (NCJ 180776). Washington, D.C.: Bureau of Justice Statistics, U.S. Department of Justice.

Sutherland, E. M. (1947). *Criminology*. Philadelphia: J.B. Lippincott.

Taylor, J., & Whitney, G. (1999). Crime and racial profiling by U.S. police: Is there an empirical basis? *Journal of Social, Political and Economic Studies*, *24,* 485-510.

Taylor, T. J., Turner, K. B., Esbensen, F., & Winfree, L. T. (2001). Coppin' an attitude: Attitudinal differences among juveniles toward police. *Journal of Criminal Justice, 29*, 295-305.

Texas Department of Public Safety. (2000). *Traffic Stop Data Report.* [On-line]. Available: http://www.txdps.state.tx.us/director_staff/public_information/trafrep2q00.pdf.

Thomas, D. & Carlson, R. (2001). *Preliminary summary report Denver Police Department contact card data: June 1, 2001 through August 31, 2001* [On-line]. Available: http://www.denvergov.com/admin/template3/forms/DPD%20BP%20Preliminary%20Report.pdf

Tillyer, R. & Engel, R. S. (Forthcoming). The impact of drivers' race, gender, and age during traffic stops: Assessing interaction terms and the social conditioning model. *Crime & Delinquency.*

Tillyer, R., Engel, R. S., & Wooldredge, J. (2008). The intersection of racial profiling and the law. *Journal of Criminal Justice, 36,* 138-153.

Tonry, M. (1995). *Malign Neglect.* New York: Oxford University Press.

Tomaskovic-Devey, D., Wright, C.P., Czaja, R., Miller, K. (2006). Self-reports of speeding stops by race: Results from the North Carolina Reverse Record Check Survey. *Journal of Quantitative Criminology, 22,* 279-297.

Trende, S. P. (2000). Why Modest Proposals Offer the Best Solution for Combating Racial Profiling. *Duke Law Journal, 50,* 331-380.

Tuch, S. A. & Weitzer, R. (1997). The polls—trends: Racial differences in attitudes toward the police. *Public Opinion Quarterly, 61*, 642-663.

Tyler, T.R. (1990). *Why people obey the law*. New Haven: Yale University Press.

Tyler, T.R. & Wakslak, C. J. (2004). Profiling and police legitimacy: Procedural justice, attributions of motive, and acceptance of police authority. *Criminology, 42,* 253-281.

United States Census Bureau. (2002). *Census 2000 Data for the State of Pennsylvania*. Washington, D.C.: U.S. Census Bureau.

Verniero, P., & Zoubek, P. H. (1999). *Interim Report of the State Police Review Team Regarding Allegations of Racial Profiling*. Trenton, NJ: New Jersey Attorney General's Office.

Voas, R. B., Wells, J. K., Lestina, D. C., Williams, A. F. & Green, M. A. (1998). Drinking and driving in the United States: The 1996 National Roadside Survey. *Accident Analysis and Prevention*, *30,* 267-275.

Voas, R. B., Tippetts, A. S. & Fisher, D. A. (2000). *Ethnicity and Alcohol-Related Fatalities: 1990 to 1994.* Washington, DC: National Highway Traffic Safety Administration.

Walker, S. & Katz, C. (2002). *The Police in America, 4th Edition.* New York: McGraw-Hill.

Walker, S., Spohn, C., & DeLone, M. (2000). *The Color of Justice*. Belmont, CA: Wadsworth.

Warr, M. (1998). Life-course transitions and desistance from crime. Criminology, 36, 183-216.

Warr, M. (1993). Age, peers, and delinquency. Criminology, 31, 17-40.

Washington State Patrol. (2001). *Report to the Legislature on Routine Traffic Stop Data*. Washington State Patrol and Criminal Justice Training Commission.

Webb, V. J. & Marshall, C. E. (1995). The relative importance of race and ethnicity on citizen attitudes toward the police. *American Journal of Police, 14*, 45-66.

Weitzer, R. (2000). Racialized policing: Residents' perceptions in three neighborhoods. *Law and Society Review, 34*:129-155.

Weitzer, R. & Tuch, S.A. (2004a). Reforming the police: Racial differences in public support for change. *Criminology, 42,* 391-416.

Weitzer, R. & Tuch, S.A. (2004b). Race and perceptions of police misconduct. *Social Problems, 51,* 305-325.

Weitzer, R. & Tuch, S. A. (2002). Perceptions of racial profiling: Race, class, and personal experience. *Criminology, 40*, 435-456.

Weitzer, R. & Tuch, S. A. (1999). Race, class, and perceptions of discrimination by the police. *Crime and Delinquency, 45*, 494-507.

Wells, J. K., Williams, A. F., & Farmer, C. F. (2002). Seat belt use among African Americans, Hispanics and Whites. *Accident Analysis and Prevention, 34*, 523-529.

Wells-Parker, E., Ceminsky, J., Hallberg, V., Snow, R.W., Dunaway, G., Guiling, S., Williams, M. & Anderson, B. (2002). An exploratory study of the relationship between road rage and crash experience in a representative sample of U.S. drivers. *Accident Analysis and Prevention, 34*, 271-278.

Williams, H. & Murphy, P. V. (1990). The evolving strategies of police: A minority view. *Perspectives on Policing, 13*, Washington, D.C.: National Institute of Justice.

Williamson, L.W. (2003). Profiling, pretext, and equal protection: Protecting citizens from pretextual stops through the Fourteenth Amendment. *Washburn Law Journal, 42,* 657-685.

Wilson, G., Dunham, R., & Alpert, G. (2004). Prejudice in police profiling. *American Behavioral Scientist, 47,* 896-909.

Yu, J., Evans, P.C., & Perfetti, L. (2004). Road aggression among drinking drivers: Alcohol and non-alcohol effects on aggressive driving and road rage. *Journal of Criminal Justice, 32,* 421-430.

Zador, P.L., Krawchuk, S.A., & Voas, R.B. (2000). Alcohol-related relative risk of driver fatalities and driver involvement in fatal crashes in relation to driver age and gender: An update using 1996 data. *Journal of Studies on Alcohol, 61*, 387-395.

Zingraff, M. T., Mason, H. M., Smith, W. R., Tomaskovic-Devey, D., Warren, P., McMurray, L., & Fenlon, C.R. (2000). *Evaluating North Carolina State Highway Patrol data: Citations, warnings, and searches in 1998*. [On-line]. Available: http://www.nccrimecontrol.org/shp/ncshpreport.htm

Cases cited:

Castenada v. Partida, 430 U.S. 483 (1976)
Chavez v. Illinois State Police, 251 F.3d 612 (2001)
Commonwealth of Massachusetts v. Lora, 16 Mass L.Rep 715 (2003)
Harris v. City of Virginia Beach, 11 Fed. Appx. 212 (2001)
McClesky v. Kemp, 481 U.S. 279 (1987)
State of New Jersey v. Ballard, 752 A. 2d 735 (2000)
State of New Jersey v. Kennedy, 588 A. 2d 834 (1991)
State of New Jersey v. Smith, 703 A. 2d 954 (1997)
State of New Jersey v. Soto, 734 A. 2d 350 (1996)
Turner v. Fouche, 396 U.S. 346 (1970)
U.S. v. Alcaraz-Arellano, 302 F. Supp. 2d 1217 (2004)
U.S. v. Armstrong, 517 U.S. 456 (1996)
U.S. v. Bell, 86 F. 3d 820 (1996)
U.S. v. Duque Nava, 315 F. Supp. 2d 1144 (2004)
U.S. v. Hare, 308 F. Supp. 2d 955, (2004)
U.S. v. Lindsey, 288 F. Supp. 2d 1196 (2003)

U.S. v. Mesa-Roche, 288 F. Supp. 2d 1172 (2003)
U.S. v. Parada, 289 F. Supp. 2d 1291 (2003)
U.S. v. Stanley, #02-401-22-02 SAC (2003)
U.S. v. Williams, CR 03-95 JMR/FLN (2004)
Village of Arlington Heights et al. v. Metropolitan Housing Development Corp. et al., 429 U.S. 252 (1977)
Whren v. United States, 517 U.S. 806 (1996)
Wilkins v. Maryland State Patrol, Civil Action No. CCB-93-468 (D.Md. 1994)
Wo v. Hopkins, 118 U.S. 356 (1886)

APPENDIX A: DATA COLLECTION FORMS

Figure A-1. RADAR OBSERVATION FORM

NOTE: Any missing data should be indicated by a dash (--).

SPEED DETECTED	TYPE OF VEHICLE	COLOR OF VEHICLE	AGE OF VEHICLE	RACE OF DRIVER	GENDER OF DRIVER	AGE OF DRIVER	PASSENGERS	LICENSE PLATE
	S-Sedan **SC**-Sports Car/Coupe **SUV**-Sport Util. Veh. **MV**-Minivan, Wagon **T**-Pickup Truck **M**-Motorcycle	**R**-Red **BU**-Blue **G**-Green **S**-Silver/Gray **BK**-Black **W**-White **O**-Other	**N**-Less than 10 years old (newer) **O**-More than 10 years old (older)	**W**-White **B**-Black **H**-Hispanic **A**-Asian/Pac. Isl. **NA**-Native Amer. **ME**-Middle East. **O**-Other	**M**-Male **F**-Female	**Y**-25 & under **M**-26 to 65 **O**-Over 65	**Y**-Yes **N**-No	**P**-Pennsylvania **O**-Other

Figure A-2. Cover Sheet for Observation Forms (New Sheet Every Half Hour)

Observer Names:	
Date of Observation:	
Day of Week:	
Time of Observation (every half hour):	
Station and County:	
Location: (road name/number, direction of observed cards, intersection, etc.)	
Municipality Name and Numeric Code:	
Speed Limit of Road:	
Type of Road: (interstate, state highway, county/local road, other…specify)	
Visibility/Weather Conditions: VG=very good, G=good, F=fair, P=poor	

APPENDIX B: COUNTY OBSERVATION SESSIONS

Tables A.1 – A.21 document the observation data collected in each of the 27 sampled counties. Each county's table lists the following specific information for each of the municipalities that was observed:

- the municipality name,
- each municipality's percent of PSP stops (during Year 1 of stop data collection, May 2002-April 2003) in that county,
- the dates of each of the county's observation sessions,
- the road type on which observation was conducted,
- the speed limit in which observation was conducted,
- the total number of vehicles and hours observed during each day of observation,
- the average number of vehicles observed per hour,
- and the percentage of the total number of vehicles for which speeding behavior was measured with RADAR.

A brief summary of each county's collected data is provided.

Allegheny County

The first two columns of Table A.1 illustrate that the observed municipalities in Allegheny County reasonably mirror the municipalities with higher concentrations of PSP traffic stops. The major disjunction is that one observed municipality had less than 1% of all PSP stops (see West Deer Twp). In the same area of the county, Indiana Township, with 12.2% of the county's stops, there was not a suitably safe location for an observation team. Since West Deer Twp borders this municipality and presumably shares at least some of the same driving population, it was selected instead. The remainder of Table A.1 indicates that observations in Allegheny County were conducted only on interstate highways, but the speed limits in which observations occurred did vary. A large volume of vehicles was observed in Allegheny County, ranging from 76.5 vehicles to 144.1 vehicles observed per hour. The amount of RADAR conducted in the county (43.1%) was slightly higher than in the overall dataset (41.4%). Fortunately, there were no weather limitations in Allegheny County that prohibited observers from conducting RADAR.

Bucks County

The first two columns of Table A.2 illustrate that the observed municipalities in Bucks County directly parallel the municipalities with higher concentrations of PSP traffic stops. Table A.2 also indicates that observations in Bucks County were conducted on both interstate and state highways, but all observed municipalities had a posted speed limit of 55 mph. A large volume of vehicles was observed in Bucks County, ranging from 82.4 vehicles to 149.1 vehicles observed per hour. The amount of RADAR conducted in the county (47.8%) was somewhat higher than in the overall dataset (41.4%). Fortunately, the only day that there were weather limitations in Bucks County that prohibited observers from conducting RADAR was the last day of observation. Since the inclement weather was forecast, the observation team was able to compensate for the predicted lost RADAR time during the previous day.

Table A.1 Observations in Allegheny County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Harmar Twp	7.7	3/17/2002	Interstate	65	976	7.0	139.4	34.9
Monroeville Brgh	4.8	3/18/2002	Interstate	55	1,009	7.0	144.1	31.6
Ohio Twp	2.9	6/14/2002	Interstate	55	914	7.0	130.6	49.1
Robinson Twp	16.6	6/15/2002	Interstate	45	1,010	7.5	134.7	30.0
Monroeville Brgh	4.8	9/29/2002	Interstate	55	959	7.5	127.9	50.6
West Deer Twp	0.6	9/30/2002	Interstate	65	712	5.0	142.4	17.3
Harmar Twp	7.7	9/30/2002	Interstate	65	289	2.5	115.6	100.0
Marshall Twp	2.0	2/09/2003	Interstate	50	667	8.0	83.4	55.0
Robinson Twp	16.6	4/11/2003	Interstate	55	849	7.5	113.2	18.6
Robinson Twp	16.6	4/12/2003	Interstate	55	967	7.5	128.9	79.5
Franklin Park	5.5	4/15/2003	Interstate	55	574	7.5	76.5	42.9
County Total/Avg	---	------------	-----	---	8,926	74.0	120.6	43.1

* This column reflects the percent of PSP stops (n=10,811) in this county for each observed municipality.

Table A.2 Observations in Bucks County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Bensalem Twp	26.6	04/19/2002	Interstate	55	653	7.0	93.3	33.7
Lower Makefield Twp	5.6	04/20/2002	Interstate	55	618	7.5	82.4	49.0
Richland Twp	3.5	07/28/2002	State Hwy	55	858	7.5	114.4	38.5
Milford Twp	16.5	07/29/2002	State Hwy	55	800	7.5	106.7	39.6
Middletown Twp	8.2	10/25/2002	Interstate	55	698	7.5	93.1	98.9
Bensalem Twp	26.6	10/26/2002	Interstate	55	967	7.5	128.9	52.7
West Rockhill Twp	8.2	03/10/2003	State Hwy	55	963	7.5	128.4	40.3
Richland Twp	3.5	03/11/2003	Int & State Hwy	55	1,040	8.0	130.0	42.3
Bensalem Twp	26.6	04/25/2003	Interstate	55	865	8.0	108.1	100.0
Bensalem Twp	26.6	04/26/2003	Interstate	55	1,044	7.0	149.1	0.0
County Total/Avg	---	------------	-----	---	8,506	75.0	113.4	47.8

* This column reflects the percent of PSP stops (n=7,679) in this county for each observed municipality.

Centre County

The first two columns of Table A.3 illustrate that the observed municipalities in Centre County are directly comparable to the municipalities with higher concentrations of PSP traffic stops. Table A.3 also indicates that observations in Centre County were conducted on a combination of interstate and state highways, and in 50, 55, and 65 mph speed limits. A moderate volume of vehicles was observed in Centre County, ranging from 48.1 to 97.3 vehicles observed per hour. The amount of RADAR conducted in the county (48.2%) was somewhat higher than in the overall dataset (41.4%). Inclement weather prevented the completion of days of observation in December and January.

Chester County

The first two columns of Table A.4 illustrate that the observed municipalities in Chester County reasonably represent the municipalities with higher concentrations of PSP traffic stops. PSP traffic stops in Chester County, however, were evenly spread out and it was not possible to observe each of the municipalities with relatively high concentrations of PSP stops. Table A.4 also indicates that observations in Chester County were conducted on both interstate and state highways, and in 35, 40, and 55 mph speed limits. A large volume of vehicles was observed in Chester County, with a wide range from 67.1 vehicles to 173.1 vehicles observed per hour. The amount of RADAR conducted in the county (38.0%) was lower than in the overall dataset (41.4%). Unfortunately, two days of observation were marked by inclement weather, which prohibited the use of RADAR. In the case of New Garden Twp (2/16/03), the weather was severe enough that the normal 7-8 hour observation day had to be concluded after only four hours.

Table A.3 Observations in Centre County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Rush Twp	26.5	04/26/2002	State Hwy	55	361	7.5	48.1	100.0
Rush Twp	26.5	07/19/2003	State Hwy	55	435	7.5	58.0	55.9
Potter Twp	10.2	08/20/2002	State Hwy	55	406	7.5	54.1	53.2
Rush Twp	26.5	08/21/2002	Interstate	65	443	7.5	59.1	42.4
Worth Twp	5.6	12/13/2002	State Hwy	50	332	5.0	66.4	67.2
Snow Shoe Twp	2.6	01/31/2003	Interstate	65	326	6.0	54.3	0.0
Boggs Twp	7.7	03/07/2003	Interstate	65	730	7.5	97.3	37.7
Marion Twp	10.6	03/08/2003	Interstate	65	707	7.5	94.3	49.9
Spring Twp	10.2	04/28/2003	State Hwy	55	585	7.5	78.0	44.3
Benner Twp	5.9	04/30/2003	State Hwy	55	714	7.5	95.2	43.6
County Total/Avg	---	------------	-----	---	5,039	71.0	79.7	48.2

* This column reflects the percent of PSP stops (n=8,665) in this county for each observed municipality.

Table A.4 Observations in Chester County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Valley Twp	7.9	04/05/02	State Hwy	55	826	7.0	118.0	36.6
East Whiteland Twp	6.1	04/06/02	State Hwy	55	1,212	7.0	173.1	25.2
London Grove Twp	8.3	07/17/02	Interstate	55	716	7.5	95.5	42.7
Lower Oxford Twp	2.2	07/18/02	Interstate	55	546	7.5	72.8	42.3
South Coventry Twp	0.4	10/06/02	State Hwy	35	654	7.5	87.2	43.1
Charlestown Twp	5.1	10/07/02	State Hwy	40	729	7.5	97.2	40.9
New Garden Twp	6.5	02/14/03	State Hwy	55	647	7.5	86.3	50.2
New Garden Twp	6.5	02/16/03	State Hwy	55	288	4.0	72.0	0.0
West Nantmeal Twp	7.2	04/11/03	State Hwy	55	503	7.5	67.1	0.0
Valley Twp	7.9	04/12/03	State Hwy	55	814	7.5	108.5	72.1
County Total/Avg	---	------------	-----	---	6,935	70.5	86.2	38.0

* This column reflects the percent of PSP stops (n=8,658) in this county for each observed municipality.

Columbia County

The first two columns of Table A.5 illustrate that the observations are concentrated in the same four municipalities in Columbia County that PSP traffic stops are most prevalent. Table A.5 indicates that observations in Columbia County were conducted only on the major interstate highway (I 80) that runs through the county and only in 65 mph speed zones. A large volume of vehicles was observed in Columbia County, ranging from 86.5 vehicles to 148.6 vehicles observed per hour. The amount of RADAR conducted in the county (37.0%) was somewhat lower than in the overall dataset (41.4%). This lower percentage reflects two days of observation that were limited by inclement weather, which prohibited observers from conducting RADAR.

Dauphin County

The first two columns of Table A.6 illustrate that the observed municipalities in Dauphin County match well the municipalities with higher concentrations of PSP traffic stops. Table A.6 also indicates that observations in Dauphin County were conducted on both state and interstate highways, and in 45, 55, and 65 mph speed limits. A highly variable volume of vehicles was observed in Dauphin County, ranging from 39.6 vehicles to 142.0 vehicles observed per hour. The amount of RADAR conducted in the county (34.9%) was considerably lower than in the overall dataset (41.4%). Unfortunately, there were weather limitations in Dauphin County that prohibited observers from conducting RADAR for several partial or entire days.

Table A.5 Observations in Columbia County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Mifflin Twp	52.9	03/15/02	Interstate	65	770	7.0	110.0	22.1
Hemlock Twp	15.9	03/16/02	Interstate	65	1,040	7.0	148.6	36.9
Hemlock Twp	15.9	06/26/02	Interstate	65	692	8.0	86.5	35.4
Scott Twp	11.1	06/27/02	Interstate	65	694	7.0	99.1	46.1
South Centre Twp	10.8	11/10/02	Interstate	65	775	7.5	103.3	38.7
Mifflin Twp	52.9	11/11/02	Interstate	65	769	7.5	102.5	0.0
Mifflin Twp	52.9	03/01/03	Interstate	65	717	6.0	119.5	67.6
Scott Twp	11.1	03/03/03	Interstate	65	927	7.0	132.4	62.8
Hemlock Twp	15.9	04/11/03	Interstate	65	890	7.5	118.7	0.0
South Centre Twp	10.8	04/12/03	Interstate	65	720	7.0	102.9	65.6
County Total/Avg		---	------------	-----	7,994	71.5	111.8	37.0

* This column reflects the percent of PSP stops (n=2,736) in this county for each observed municipality.

Table A.6 Observations in Dauphin County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Middle Paxton Twp	2.7	04/07/02	State Hwy	55	923	6.5	142.0	43.2
Londonderry Twp	13.3	04/08/02	Interstate	65	948	7.0	135.4	37.8
Jackson Twp	1.1	06/06/02	State Hwy	55	717	7.5	95.6	36.0
Wiconisco Twp	1.4	06/07/02	State Hwy	55	761	7.5	101.5	34.8
Susquehanna Twp	23.7	10/04/03	State Hwy	55	800	7.5	106.7	0.0
Lower Paxton Twp	5.6	10/05/03	Interstate	55	857	8.0	107.1	66.2
Washington Twp	2.1	03/02/03	Interstate	45	380	7.5	50.7	55.0
Reed Twp	9.0	03/03/03	Interstate	45	277	7.0	39.6	39.4
Susquehanna Twp	23.7	04/11/03	Interstate	55	657	7.0	93.9	0.0
Lower Swatara Twp	6.7	04/12/03	Interstate	65	543	6.5	83.5	42.4
County Total/Avg	---	------------	-----	---	6,863	72.0	95.3	34.9

* This column reflects the percent of PSP stops (n=7,181) in this county for each observed municipality.

Delaware County

The first two columns of Table A.7 illustrate that the observations in Delaware County are concentrated in the same municipalities that have the highest concentrations of PSP traffic stops. Table A.7 also indicates that observations in Delaware County took place on local, state, and interstate highways, and in 35, 45, and 55 mph speed limits. A large volume of vehicles was observed in Delaware County, ranging from 69.3 vehicles to 148.7 vehicles observed per hour. The amount of RADAR conducted in the county (41.0%) was approximately the same as in the overall dataset (41.4%). Fortunately, there were no weather limitations in that prohibited observers from conducting RADAR.

Erie County

The first two columns of Table A.8 illustrate that the observed municipalities in Erie County reasonably correspond to the municipalities with higher concentrations of PSP traffic stops. One municipality that accounted for about 10% of the county's stops (the City of Erie) was not observed because the PSP personnel in this jurisdiction indicated that they did not have primary jurisdiction in the area. Table A.8 also indicates that observations in Erie County were conducted on local, state, and interstate highways, and in several speed limits: 40, 45, 55, and 65 mph. A highly variable volume of vehicles was observed in Erie County, ranging from 55.8 vehicles to 193.4 vehicles observed per hour. The amount of RADAR conducted in the county (38.7%) was somewhat lower than in the overall dataset (41.4%). Unfortunately, this area of the state was frequently prone to severe weather. Many observation sessions in Erie County had to be rescheduled due to inclement weather, and one day of observation (2/1/03) had to be concluded early because of an impending winter storm. The ability to conduct RADAR was also prohibited during that observation session.

Table A.7 Observations in Delaware County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Radnor Twp	15.6	04/05/02	Interstate	55	552	6.0	92.0	24.8
Tinicum Twp	18.2	04/06/02	Interstate	55	485	7.0	69.3	46.0
Middletown Twp	16.8	07/31/02	State Hwy	45	659	7.5	87.9	40.7
Tinicum Twp	18.2	08/01/02	Interstate	55	742	8.0	92.8	33.7
Middletown Twp	16.8	10/27/02	State Hwy	45	898	8.5	105.7	42.0
Radnor Twp	15.6	10/28/02	Interstate	55	1,115	7.5	148.7	33.8
Concord Twp	11.0	03/07/03	State Hwy	45	858	7.5	114.4	33.2
Middletown Twp	16.8	03/08/03	Inter/Local	35 & 45	865	7.5	115.3	49.7
Chadds Ford Twp	8.5	05/25/03	Local	55	660	8.5	77.7	48.5
Tinicum Twp	18.2	06/11/03	Interstate	55	918	8.0	114.8	56.0
County Total/Avg	---	------------	-----	---	7,752	76.0	102.0	41.0

* This column reflects the percent of PSP stops (n=6,063) in this county for each observed municipality.

Table A.8 Observations in Erie County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Franklin Twp	2.9	04/05/02	County/local	45	1,539	8.0	193.4	22.5
Fairview Twp	8.6	04/06/02	Interstate	65	1,450	7.5	193.3	42.7
Summit Twp	20.5	07/09/02	Interstate	55	693	6.5	106.6	7.8
Summit Twp	20.5	07/10/02	State Hwy	55	530	8.0	66.3	100.0
Amity Twp	1.3	01/31/03	State Hwy	55	446	8.0	55.8	44.4
Union Twp	1.5	02/01/03	State Hwy	55	315	3.5	90.0	0.0
Girard Twp	6.3	03/30/03	State Hwy	55	666	7.5	88.8	52.0
McKean Twp	12.2	03/31/03	State Hwy	55	555	7.5	74.0	41.6
McKean Twp	12.2	05/14/03	State Hwy	40	600	7.5	80.0	41.8
Harborcreek Twp	7.5	05/15/03	State Hwy	55	884	7.5	117.9	45.1
County Total/Avg	---	------------	-----	---	7,678	71.5	107.4	38.7

* This column reflects the percent of PSP stops (n=8,182) in this county for each observed municipality.

Franklin County

The first two columns of Table A.9 illustrate that the observed municipalities and municipalities with higher concentrations of PSP traffic stops in Franklin County match well. Table A.9 also indicates that observations in Franklin County were conducted on state and interstate highways, and in 45, 55, and 65 mph zones. A highly variable volume of vehicles was observed in Franklin County, ranging from 36.7 vehicles to 159.0 vehicles observed per hour. The amount of RADAR conducted in the county (50.4%) was considerably higher than in the overall dataset (41.4%). This high percentage is the result of two different factors. First, the observation sessions conducted in February 2002 involved two observation teams, one conducting all RADAR, the other doing only observation. Second, there were three locations where traffic volume was low enough that the use of RADAR was possible for entire days.

Indiana County

The first two columns of Table A.10 illustrate that the observed municipalities in Indiana County are consistent with the municipalities with higher concentrations of PSP traffic stops. Table A.10 also indicates that observations in Indiana County were conducted only on state highways, as there are no interstates that pass through this county. Observed municipalities included 35, 45, 50, 55, and 65 mph speed limits. A moderate volume of vehicles was observed in Indiana County, ranging from 59.2 vehicles to 112.3 vehicles observed per hour. The amount of RADAR conducted in the county (42.9%) was slightly higher than in the overall dataset (41.4%). Fortunately, there were no weather limitations in Indiana County that prohibited observers from conducting RADAR.

Table A.9 Observations in Franklin County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Guilford Twp	10.6	02/24/2002	Int/St Hwy	55 & 65	897	9.0	99.7	30.9
Antrim Twp	17.2	02/24/2002	Interstate	65	216	2.0	108.0	0.0
Greene Twp	17.6	02/25/2002	State Hwy	55	353	6.0	58.8	100.0
Hamilton Twp	2.8	02/25/2002	State Hwy	55	477	3.0	159.0	0.0
St. Thomas Twp	2.3	05/28/2002	State Hwy	55	343	7.5	45.7	100.0
Peters Twp	1.4	05/29/2002	State Hwy	55	432	7.5	57.6	100.0
Greene Twp	17.6	09/20/2002	State Hwy	55 & 65	542	7.5	72.3	47.8
Antrim Twp	17.2	09/21/2002	Interstate	65	843	7.5	112.4	51.5
Fannett Twp	28.8	03/30/2003	State Hwy	45	220	6.0	36.7	0.0
Guilford Twp	10.6	03/31/2003	State Hwy	45	333	6.5	51.2	100.0
Fannett Twp	28.8	06/05/2003	State Hwy	45	403	7.5	53.7	42.2
Southampton Twp	5.7	06/06/2003	State Hwy	55	637	7.5	84.9	42.4
County Total/Avg	---	------------	-----	---	5,696	77.5	73.5	50.4

* This column reflects the percent of PSP stops (n=5,913) in this county for each observed municipality.

Table A.10 Observations in Indiana County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Cherryhill Twp	10.3	05/30/2002	State Hwy	65	815	8.0	101.9	35.0
White Twp	26.1	05/31/2002	State Hwy	65	757	8.0	94.6	48.7
White Twp	26.1	08/04/2002	State Hwy	35	684	7.5	91.2	45.8
White Twp	26.1	08/05/2002	State Hwy	45	842	7.5	112.3	48.8
Blairsville Brgh	1.1	01/17/2003	State Hwy	50	482	7.0	68.9	56.6
East Wheatfield Twp	8.5	01/18/2003	State Hwy	55	393	5.5	71.5	53.2
Armstrong Twp	6.1	03/21/2003	State Hwy	55	636	7.0	90.9	36.3
Pine Twp	9.7	03/22/2003	State Hwy	45	701	9.0	77.9	29.7
Burrell Twp	17.6	04/27/2003	State Hwy	50	633	7.5	84.4	41.4
Pine Twp	9.7	04/28/2003	State Hwy	55	444	7.5	59.2	40.8
County Total/Avg	---	------------	-----	---	6,387	74.5	85.7	42.9

* This column reflects the percent of PSP stops (n=3,129) in this county for each observed municipality.

Juniata County

The first two columns of Table A.11 illustrate that the observation sessions in Juniata County were focused on the few municipalities in which PSP traffic stops are also highly concentrated. Observations in Juniata County were conducted only on state highways, as there are no interstates that pass through this county. Observed municipalities included 40, 55, 60, and 65 mph speed limits. The remainder of Table A.11 indicates that a rather variable volume of vehicles was observed in Juniata County, ranging from 45.5 vehicles to 130.6 vehicles observed per hour. The amount of RADAR conducted in the county (40.7%) was slightly lower than in the overall dataset (41.4%). Fortunately, there were no weather limitations in Juniata County that prohibited observers from conducting RADAR.

Lackawanna County

The first two columns of Table A.12 illustrate that the observed municipalities in Lackawanna County reasonably match the municipalities with higher concentrations of PSP traffic stops. One observed municipality (Abington Twp), however, accounted for less than 1% of the county's stops, but was selected for observation because Interstate 81 runs directly through it. In addition, although 12.4% of the county's stops occurred there, another municipality (the Borough of Moosic) was not observed because there was not a suitably safe location for an observation team. The majority of observations were conducted on interstate highways, and in either 55 or 65 mph speed limits. A very large volume of vehicles was observed in Lackawanna County, ranging from 105.3 vehicles to 213.3 vehicles observed per hour. The amount of RADAR conducted in the county (44.2%) was somewhat higher than in the overall dataset (41.4%), which is at least partially due to the fact that there were no weather limitations during any observation sessions in Lackawanna County.

Table A.11 Observations in Juniata County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Walker Twp	57.1	04/26/2002	State Hwy	65	914	7.0	130.6	18.9
Walker Twp	57.1	04/27/2002	State Hwy	65	861	7.5	114.8	50.3
Fermanagh Twp	19.2	08/11/2002	State Hwy	60	693	7.5	92.4	54.4
Walker Twp	57.1	08/12/2002	State Hwy	40	463	7.0	66.1	55.7
Delaware Twp	9.5	11/05/2002	State Hwy	65	469	7.5	62.5	47.3
Delaware Twp	9.5	11/06/2002	State Hwy	65	601	7.5	80.1	43.4
Beale Twp	1.9	02/08/2003	State Hwy	55	550	6.5	84.6	42.5
Walker Twp	57.1	02/24/2003	State Hwy	65	341	7.5	45.5	5.8
Fermanagh Twp	19.2	04/06/2003	State Hwy	65	700	7.5	93.3	49.0
Delaware Twp	9.5	04/09/2003	State Hwy	65	653	7.5	87.1	45.9
County Total/Avg	---	------------	-----	---	6,245	73.0	85.6	40.7

*This column reflects the percent of PSP stops (n=2,000) in this county for each observed municipality.

Table A.12 Observations in Lackawanna County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Dunmore Brgh	31.7	05/05/2002	Interstate	65	1,706	8.0	213.3	42.8
Throop Brgh	1.7	05/06/2002	State Hwy	65	1,579	8.0	197.4	43.0
Clifton Twp	4.9	07/26/2002	Interstate	65	1,042	6.5	160.3	50.2
Roaring Brook Twp	14.0	07/27/2002	Interstate	65	989	7.5	131.9	49.5
City of Scranton	10.3	10/15/2002	Interstate	55	807	7.5	107.6	45.1
Roaring Brook Twp	14.0	03/07/2003	Interstate	65	790	7.5	105.3	42.0
Abington Twp	0.1	03/08/2003	Interstate	55	919	7.5	122.5	44.2
City of Scranton	10.3	04/17/2003	Interstate	55	887	7.5	118.3	39.0
Dunmore Brgh	31.7	04/18/2003	Interstate	55	831	7.5	110.8	40.2
Scott Twp	3.7	04/19/2003	Interstate	65	854	7.5	113.9	45.7
County Total/Avg	---	------------	-----	---	10,404	75.0	138.7	44.2

* This column reflects the percent of PSP stops (n=4,484) in this county for each observed municipality.

Lehigh County

The first two columns of Table A.13 illustrate that the observations were concentrated in the same municipalities in Lehigh County that PSP traffic stop activity is highest. Observations in Lehigh County were conducted on local, state, and interstate highways. Despite the variation in road type, all observed locations were within 55 mph zones. The remainder of Table A.13 indicates that at a majority of the observed locations, a large volume of vehicles was observed in Lehigh County, ranging from 65.7 vehicles to 172.4 vehicles observed per hour. The amount of RADAR conducted in the county (35.7%) was lower than in the overall dataset (41.4%), largely due to rainy weather in several of the early observation sessions that limited observers' ability to conduct RADAR.

McKean County

The first two columns of Table A.14 illustrate that the observed municipalities in McKean County are a good representation of the municipalities with higher concentrations of PSP traffic stops. Observations in McKean County were conducted only on local and state highways, as no interstate highways run through the county. Observations occurred in 45 or 55 mph speed zones. The remainder of Table A.14 indicates that a fairly low volume of vehicles was observed in McKean County, ranging from 32.7 vehicles to 77.9 vehicles observed per hour. The amount of RADAR conducted in the county (56.3%) was considerably higher than in the overall dataset (41.4%) because traffic volume was so low that the use of RADAR was possible for entire days. There were also no significant weather limitations in McKean County that prohibited observers from conducting RADAR.

Table A.13 Observations in Lehigh County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
City of Bethlehem	2.1	04/07/2002	State Hwy	55	1,293	7.5	172.4	48.1
South Whitehall Twp	13.3	04/08/2002	State Hwy	55	887	7.5	118.3	25.5
Upper Macungie Twp	22.2	06/20/2002	Interstate	55	1,017	7.5	135.6	38.8
City of Allentown	2.7	06/21/2002	Interstate	55	1,452	7.5	193.6	0.0
North Whitehall Twp	14.4	11/08/2002	State Hwy	55	729	6.5	112.2	53.6
North Whitehall Twp	14.4	11/09/2002	County/local	35	803	7.0	114.7	34.4
Weisenberg Twp	13.7	04/04/2003	Interstate	55	649	7.5	86.5	48.5
Upper Macungie Twp	22.2	04/05/2003	Interstate	55	810	7.5	108.0	47.9
Weisenberg Twp	13.7	06/12/2003	Interstate	55	493	7.5	65.7	47.5
Lower Macungie Twp	6.4	06/13/2003	Interstate	55	674	7.5	89.9	44.5
County Total/Avg	---	------------	-----	---	8,807	73.5	119.8	35.7

* This column reflects the percent of PSP stops (n=7,797) in this county for each observed municipality.

Table A.14 Observations in McKean County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Sergeant Twp	7.7	05/21/2002	State Hwy	55	281	7.5	37.5	52.7
Wetmore Twp	5.2	05/22/2002	State Hwy	55	431	7.5	57.5	49.2
Corydon Twp	7.1	08/11/2002	State Hwy	55	357	7.5	47.6	100.0
Lafayette Twp	3.8	08/12/2002	State Hwy	55	377	7.5	50.3	100.0
Hamlin Twp	36.0	12/18/2002	State Hwy	45	229	7.0	32.7	95.6
Hamlin Twp	36.0	12/19/2002	State Hwy	45	275	7.5	36.7	100.0
Keating Twp	9.2	03/21/2003	County/local	45	509	7.5	67.9	27.1
Eldred Twp	6.1	03/22/2003	State Hwy	55	584	7.5	77.9	34.4
Hamlin Twp	36.0	04/25/2003	County/local	55	289	7.5	38.5	53.3
Keating Twp	9.2	04/26/2003	County/local	55	422	7.5	56.3	7.8
County Total/Avg	---	------------	-----	---	3,753	74.5	50.4	56.3

* This column reflects the percent of PSP stops (n=1,989) in this county for each observed municipality.

Mercer County

The first two columns of Table A.15 illustrate that the observed municipalities in Mercer County are reasonably similar to the municipalities with higher concentrations of PSP traffic stops. Observations in Mercer County were conducted only on interstate highways and only in 65 mph zones. The remainder of Table A.15 indicates that a moderately large volume of vehicles was observed in Mercer County, ranging from 67.6 vehicles to 132.7 vehicles observed per hour. The amount of RADAR conducted in the county (49.3%) was higher than in the overall dataset (41.4%). Fortunately, there were no weather limitations in Mercer County that prohibited observers from conducting RADAR.

Montgomery County

The first two columns of Table A.16 illustrate that the observed municipalities in Montgomery County correspond well to the municipalities with higher concentrations of PSP traffic stops. Observations in Montgomery County were conducted on local, state, and interstate highways, and in 35, 45, and 55 mph zones. The remainder of Table A.16 indicates that a large volume of vehicles was observed in Montgomery County, ranging from 76.7 vehicles to 153.9 vehicles observed per hour. The amount of RADAR conducted in the county (36.4%) was lower than in the overall dataset (41.4%), due largely to inclement weather and very heavy traffic volume. Observations in those municipalities that were observed for less than 7.5 hours per day were cut short due to darkness or weather hazards.

Table A.15 Observations in Mercer County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Lackawannock Twp	8.3	04/19/2002	Interstate	65	734	7.5	97.9	35.6
Springfield Twp	5.7	04/20/2002	Interstate	65	983	7.5	131.1	35.9
Wolf Creek Twp	13.6	07/28/2002	Interstate	65	995	7.5	132.7	47.8
Deer Creek Twp	3.2	07/29/2002	Interstate	65	946	7.5	126.1	92.6
Jackson Twp	11.0	01/09/2003	Interstate	65	517	7.0	73.9	48.0
Findley Twp	30.5	01/10/2003	Interstate	65	562	7.5	74.9	35.4
East Lackawannock Twp	4.8	03/23/2003	Interstate	65	600	7.0	85.7	40.8
Findley Twp	30.5	03/24/2003	Interstate	65	507	7.5	67.6	34.1
Wolf Creek Twp	13.6	05/23/2003	Interstate	65	586	7.5	78.1	52.2
Jackson Twp	11.0	05/24/2003	Interstate	65	653	7.0	93.3	54.7
County Total/Avg	---	------------	-----	---	7,083	73.5	96.4	49.3

* This column reflects the percent of PSP stops (n=2,517) in this county for each observed municipality.

Table A.16 Observations in Montgomery County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Whitemarsh Twp	12.9	03/15/2002	Interstate	55	702	6.0	117.0	24.5
Whitemarsh Twp	12.9	03/16/2002	County/local	45	1,000	6.5	153.9	28.0
Upper Salford Twp	0.9	07/01/2002	County/local	35	840	7.5	112.0	39.9
Worcester Twp	5.0	07/02/2002	Interstate	55	791	7.5	105.5	32.5
Upper Merion Twp	16.2	12/08/2002	Interstate	55	345	4.5	76.7	47.2
Upper Merion Twp	16.2	12/09/2002	Interstate	55	414	4.0	103.5	40.6
Limerick Twp	2.9	03/14/2003	State Hwy	55	954	7.5	127.2	45.4
Lower Providence Twp	3.6	03/15/2003	Interstate	55	974	7.5	129.9	50.3
Lower Merion Twp	10.2	04/27/2003	Interstate	55	807	7.5	107.6	34.6
Plymouth Twp	6.2	04/28/2003	Interstate	55	988	7.5	131.7	27.3
County Total/Avg	---	------------	-----	---	7,815	66.0	118.4	36.4

* This column reflects the percent of PSP stops (n=11,008) in this county for each observed municipality.

Tioga County

The first two columns of Table A.17 illustrate that the observations in Tioga County were focused on three municipalities in which the majority of PSP traffic stops were concentrated, in addition to a few others with moderate percentages of PSP traffic stops. Observations in Tioga County were conducted primarily on state highways, as no interstate highways run through this county's borders. Observed locations included 45, 55, and 65 mph zones. The remainder of Table A.17 indicates that a moderate volume of vehicles was observed in Tioga County, ranging from 41.6 vehicles to 110.0 vehicles observed per hour. The amount of RADAR conducted in the county (27.4%) was considerably lower than in the overall dataset (41.4%), due to several partial or entire days when the weather prohibited observers from conducting RADAR.

Washington County

The first two columns of Table A.18 illustrate that the observed municipalities in Washington County match up well with the municipalities with higher concentrations of PSP traffic stops. Observations in Washington County were conducted only on interstate highways, in both 55 and 65 mph zones. The remainder of Table A.18 indicates that a relatively large volume of vehicles was observed in Washington County, ranging from 63.7 vehicles to 158.8 vehicles observed per hour. The amount of RADAR conducted in the county (32.4%) was much lower than in the overall dataset (41.4%), due to both inclement weather and very heavy traffic that limited observers' ability to conduct RADAR.

Table A.17 Observations in Tioga County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Liberty Twp	8.5	04/12/2002	State Hwy	65	770	7.0	110.0	46.4
Mansfield Brgh	17.7	04/13/2002	State Hwy	55	768	7.0	109.7	6.5
Delmar Twp	4.9	07/14/2002	County/local	55	382	7.5	50.9	49.2
Tioga Twp	18.7	07/15/2002	State Hwy	55	490	7.5	65.3	35.3
Richmond Twp	20.4	01/31/2003	State Hwy	55	699	7.5	93.2	0.0
Richmond Twp	20.4	02/01/2003	State Hwy	45	704	7.5	93.9	0.0
Tioga Twp	18.7	03/04/2003	State Hwy	45	291	7.0	41.6	100.0
Charleston Twp	6.7	03/05/2003	State Hwy	55	476	7.5	63.5	24.6
Richmond Twp	20.4	05/19/2003	State Hwy	55	324	6.5	49.9	42.0
Tioga Twp	18.7	05/20/2003	State Hwy	55	375	7.5	50.0	36.3
County Total/Avg	---	------------	-----	---	5,279	72.5	72.8	27.4

* This column reflects the percent of PSP stops (n=1,320) in this county for each observed municipality.

Table A.18 Observations in Washington County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Cecil Twp	7.4	06/02/2002	Interstate	55	890	7.5	118.7	35.4
South Strabane Twp	6.8	06/03/2002	Interstate	55	1,191	7.5	158.8	37.1
Chartiers Twp	16.1	08/21/2002	Interstate	55	1,050	7.5	140.0	22.9
Somerset Twp	8.4	08/22/2002	Interstate	55	870	7.5	116.0	36.8
Cecil Twp	7.4	01/31/2003	Interstate	55	1,012	7.5	134.9	38.0
Donegal Twp	1.3	02/01/2003	Interstate	65	796	6.5	122.5	0.0
Chartiers Twp	16.1	03/21/2003	Interstate	55	865	7.5	115.3	26.8
North Strabane Twp	6.2	03/22/2003	Interstate	55	848	7.5	113.1	49.8
Fallowfield Twp	10.9	05/04/2003	Interstate	55	605	9.5	63.7	33.2
Amwell Twp	4.9	06/02/2003	Interstate	65	653	7.5	87.1	44.1
County Total/Avg	---	------------	-----	---	8,780	76.0	115.5	32.4

* This column reflects the percent of PSP stops (n=11,083) in this county for each observed municipality.

Westmoreland County

The first two columns of Table A.19 illustrate that the observed municipalities in Westmoreland County reasonably mirror the municipalities with higher concentrations of PSP traffic stops. Table A.19 also indicates that observations in Westmoreland County were conducted on local, state, and interstate highways. Observed speed limits included 35, 45, 50, 55, and 65 mph zones. A rather variable volume of vehicles was observed in Westmoreland County, ranging from 68.4 vehicles to 172.7 vehicles observed per hour. The amount of RADAR conducted in the county (38.9%) was lower than in the overall dataset (41.4%), mainly due to inclement weather that prohibited observers from conducting RADAR for an entire day.

York County

The first two columns of Table A.20 illustrate that the observed municipalities in York County correspond well to the municipalities with higher concentrations of PSP traffic stops. Observations in York County were conducted on state and interstate highways, and in both 55 and 65 mph speed limits. The remainder of Table A.20 indicates that a generally large volume of vehicles was observed in York County, ranging from 62.9 vehicles to 157.5 vehicles observed per hour. The amount of RADAR conducted in the county (42.8%) was very similar to the percentage in the overall dataset (41.4%). Fortunately, there were no weather limitations in York County that prohibited observers from conducting RADAR.

Table A.19 Observations in Westmoreland County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Derry Twp	4.4	04/12/2002	State Hwy	50	499	7.0	71.3	38.7
Salem Twp	4.9	04/13/2002	State Hwy	55	458	5.0	91.6	0.0
Penn Twp	7.1	06/26/2002	Interstate	65	1,295	7.5	172.7	42.8
Hempfield Twp	22.3	06/27/2002	Interstate	65	796	6.5	122.5	32.8
Derry Twp	4.4	09/22/2002	State Hwy	45	757	7.5	100.9	35.1
East Huntingdon Twp	1.6	09/23/2002	State Hwy	55	871	7.5	116.1	43.3
Mount Pleasant Twp	13.9	04/13/2003	State Hwy	50	903	7.5	120.4	53.7
Donegal Twp	15.7	04/14/2003	County/local	35	578	7.5	77.1	35.5
Mount Pleasant Twp	13.9	05/14/2003	State Hwy	45	513	7.5	68.4	43.5
Hempfield Twp	22.3	05/15/2003	State Hwy	45	617	7.5	82.3	43.9
County Total/Avg	---	------------	-----	---	7,217	71.0	101.7	38.9

*This column reflects the percent of PSP stops (n=17,440) in this county for each observed municipality.

Table A.20 Observations in York County

Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# of Vehicles Observed	# of Hours Observed	Avg. Number vehicles/hour	% RADAR
Newberry Twp	8.0	03/24/2002	Interstate	65	993	7.5	132.4	38.1
Springfield Twp	14.5	03/25/2002	Interstate	55	1,093	7.5	145.7	35.4
Shrewsbury Twp	10.1	06/06/2002	Interstate	65	710	7.0	101.4	46.5
Warrington Twp	1.7	06/07/2002	State Hwy	55	535	8.5	62.9	43.9
Fairview Twp	15.8	10/25/2002	State Hwy	55	782	7.0	111.7	11.8
Manchester Brgh	4.7	10/26/2002	State Hwy	65	756	7.5	100.8	64.8
Shrewsbury Twp	10.1	03/02/2003	Interstate	65	900	7.0	128.6	53.2
Newberry Twp	8.0	03/03/2003	Interstate	55	1,260	8.0	157.5	48.6
Fairview Twp	15.8	04/13/2003	Interstate	55	757	7.5	100.9	43.5
York Twp	11.8	04/14/2003	Interstate	65	649	7.5	86.5	41.9
County Total/Avg	---	------------	-----	---	8,435	75.0	112.5	42.8

*This column reflects the percent of PSP stops (n=5,441) in this county for each observed municipality.

Table A.21 shows that in all of the observed municipalities in the additional seven sampled counties, at least 20 percent of the county's stops occurred in those municipalities. This reflects the selection criteria for these extra observation sessions. Table A.21 also indicates that observations were conducted only on interstate highways (e.g., I-81, I-80, and I-76), and primarily in 65 mph speed limits. Large volumes of vehicles were observed in each of these municipalities, ranging from 81.0 vehicles to 197.4 vehicles observed per hour. The amount of RADAR conducted in these municipalities was slightly higher than in the overall dataset (41.4%), with the exception of two days. Fortunately, these observation sessions were not marked by prolonged weather limitations that prohibited observers from conducting RADAR.

Table A.21 Observations in Additional Counties

County Observed	Municipality Observed	% of PSP Stops*	Date	Road Type	Speed Limit	# Vehicles Observed	# Hours Observed	Avg # vehicles/hour	% RADAR
Susquehanna	New Milford Twp	33.0	6/08/2003	Interstate	65	648	8.0	81.0	47.1
Susquehanna	Lenox Twp	23.9	6/09/2003	Interstate	65	689	8.0	86.1	43.8
Montour	Liberty Twp	45.0	6/22/2003	Interstate	65	752	8.0	94.0	45.3
Montour	Valley Twp	36.4	6/23/2003	Interstate	65	829	8.0	103.6	47.8
Clarion	Clarion Twp	33.7	6/19/2003	Interstate	65	996	8.0	124.5	38.4
Clarion	Clarion Twp	33.7	6/20/2003	Interstate	65	1,228	8.0	153.5	47.5
Jefferson	Washington Twp	46.2	6/22/2003	Interstate	65	1,126	8.0	140.8	52.6
Jefferson	Washington Twp	46.2	6/23/2003	Interstate	65	1,325	8.0	165.6	41.4
Clinton	Lamar Twp	72.4	6/24/2003	Interstate	65	1,264	8.0	158.0	41.1
Clinton	Lamar Twp	72.4	6/25/2003	Interstate	65	1,149	8.0	143.6	45.3
Fulton	Brush Creek Twp	28.2	6/27/2003	Interstate	55	1,256	8.0	157.0	51.6
Fulton	Wells Twp	40.9	6/28/2003	Interstate	65	1,340	8.0	167.5	50.4
Bedford	East Providence Twp	39.8	6/29/2003	Interstate	55	1,579	8.0	197.4	45.1
Bedford	East Providence Twp	39.8	6/30/2003	Interstate	55	1,293	8.0	161.6	48.5

* This column reflects the percent of each county's PSP stops that occurred in the observed municipality.

Table A.22. Correlation Matrix for Dependent and Independent Variables*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 Male	1.000																		
2 Black	.007	1.000																	
3 Nonwhite	.032**	.720**	1.000																
4 Young	-.099**	.027**	.043**	1.000															
5 Passengers	.081**	-.002	.014**	-.053**	1.000														
6 PA Plate	-.052**	-.084**	-.113**	.000	-.137**	1.000													
7 Red vehicle	.002	-.007	-.009*	.022**	-.005	.028**	1.000												
8 Sports Car	-.046**	-.001	-.001	.159**	-.059**	.036**	.066**	1.000											
9 Rush Hour	-.003	-.005	-.013**	-.006	-.045**	.029**	.004	-.008*	1.000										
10 Weekday	-.020**	-.007	-.015**	-.024**	-.207**	.060**	.002	.012**	-.032**	1.000									
11 Interstate	.038**	.078**	.101**	.019**	.077**	-.308**	-.021**	-.019**	-.008*	-.125**	1.000								
12 65 mph limit	.038**	-.011**	.002	.016**	.087**	-.186**	.000	-.028**	.048**	-.102**	.359**	1.000							
13 Munic avg for stops	-.011**	.100**	.104**	.013**	-.059**	.027**	-.026**	.035**	-.026**	-.052**	.177**	-.425	1.000						
14 Amt over limit	.008*	.082**	.092**	.108**	-.014**	-.086**	-.018**	.045**	-.033**	-.065**	.155**	-.280**	.281**	1.000					
15 5 mph over	.004	.059**	.068**	.073**	-.012**	-.071**	-.013**	.028**	-.028**	-.044**	.123**	-.232**	.250**	.770**	1.000				
16 10 mph over	.000	.071**	.081**	.093**	-.007	-.059**	-.014**	.040**	-.037**	-.055**	.088**	-.250**	.256**	.748**	.545**	1.000			
17 15 mph over	.007	.064**	.068**	.094**	-.004	-.047**	-.012**	.041**	-.032**	-.063**	.070**	-.177**	.180**	.614**	.305**	.559**	1.000		
18 20 mph over	.006	.052**	.056**	.079**	-.009*	-.030**	-.003	.034**	-.021**	-.034**	.041**	-.094**	.093**	.424**	.155**	.285**	.509**	1.000	
19 25 mph over	.010*	.030**	.035**	.060**	-.006	-.009*	-.003	.022**	-.010*	-.011**	.017**	-.045**	.039*	.259**	.073**	.134**	.240**	.472**	1.000

*Note: *Correlation is significant at the .05 level (2-tailed). ** Correlation is significant at the .01 level (2-tailed)

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B.A. Sociology and Political Science, State University of New York at Geneseo May 1999

Professional Experience

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Project Director, Project on Police Citizen Contacts, Dr. Robin Engel Jan 2002-Aug 2003

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Selected Peer Reviewed & Technical Publications

Tillyer, Rob, Engel, Robin S. & **Cherkauskas, Jennifer C.** (2010). Best Practices in Vehicle Stop Data Collection and Analysis. *Policing*, *33*, 69-92.

Engel, Robin S., **Cherkauskas, Jennifer C.**, & Smith, Michael R. (2009). *Traffic Stop Data Analysis Study: Year 3 Final Report.* Submitted to the Arizona Department of Public Safety, Phoenix, AZ.

Engel, Robin S., **Cherkauskas, Jennifer C.**, & Smith, Michael R. (2008). *Identifying Best Practices in Criminal Interdiction Activities for the Arizona Department of Public Safety.* Submitted to the Arizona Department of Public Safety, Phoenix, AZ.

Engel, R.S., Tillyer, R., & **Cherkauskas, Jennifer C.** (2007). *Understanding best search and seizure practices: Final report.* Submitted to the Ohio State Highway Patrol, Office of the Superintendent, Columbus, OH.

Bernard, Thomas J., **Calnon, Jennifer M.**, Engel, Robin S., & Hays, Zachary R. (2005). Efficiency and the New Differential Processing. *Journal of Crime and Justice, 28*, 79-105.

Engel, Robin S. & **Calnon, Jennifer M.** (2004). Examining the influence of race during traffic stops with police: Results from a national survey. *Justice Quarterly, 21*, 49-90.

Engel, Robin S. & **Calnon, Jennifer M.** (2004). Comparing baseline methodologies for police-citizen contacts: Traffic stop data collection for the Pennsylvania State Police. *Police Quarterly, 7*, 97-125.

Engel, Robin S., **Calnon, Jennifer M**, Liu, Lin, & Johnson, Richard. (2004). *Project on Police-Citizen Contacts: Year 1 Final Report.* Report submitted to the Pennsylvania State Police Department, Harrisburg, PA.

Engel, Robin S., **Calnon**, **Jennifer M.** & Bernard, Thomas J. (2002). Theory and racial profiling: Shortcomings and directions for future research. *Justice Quarterly¸19*, 249-273.