



**CLEVELAND DIVISION OF POLICE
TRAFFIC STOP DATA STUDY:
FINAL REPORT**

JULY 7, 2006

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EXECUTIVE SUMMARY

The perception that officers make discretionary decisions to stop, cite, search and arrest citizens based solely or partially on their race/ethnicity has led to widespread concern at the local, state and national levels. In response to these concerns, the National Institute of Justice (NIJ) and the Community Oriented Policing Services (COPS) Office have made federal grant monies available to local law enforcement agencies to research their officers' behaviors during traffic and pedestrian stops. The Cleveland Division of Police (CDP) applied for and received a grant from the COPS Office to study officer decision making during traffic stops. Specifically, this grant provided for an independent, external evaluation of policing practices during traffic stops conducted by the CDP. A research team from the University of Cincinnati (UC), Criminal Justice Research Center (CJRC) applied for, and was awarded, the contract to perform this evaluation. This document represents the final report for this traffic stop study.

The initial purpose of this study was to aid CDP administrators in determining if racial and/or ethnic disparities in traffic stops and post-stop outcomes existed, and if evident, the possible sources of these disparities. Traffic stop studies, though prevalent across the country, often involve complicated methodological and statistical issues that limit the ability of researchers to fully address certain research questions. For example, the research methodology of using officer-collected data during traffic stops that is currently used by many academics and internal police research units (and used in the current study) does not allow for a determination of whether or not "racial profiling" exists. Although racial profiling has several different definitions, the common components of these definitions are that police officers make decisions to exercise their authority (in the form of stopping, questioning, citing, arresting, searching, etc.) based solely or partially on citizens' race/ethnicity. Unfortunately, the type of data collection and statistical analyses of those data presented in this report cannot determine whether or not officers make decisions to stop motorists based solely or partially on their race/ethnicity. Rather, this type of study can determine only whether or not racial/ethnic disparities in police actions exist, and speculate at the causes of these disparities. Findings of racial/ethnic disparities in police actions should serve as a warning for police administrators that more in-depth examination of officers' actions is needed in particular areas, units, shifts, etc.

The efforts of the UC research team to address the complicated research issues surrounding the collection, analyses, and interpretation of traffic stop data are documented throughout this report. A brief overview of the data collection procedures, analyses, and findings are presented in this Executive Summary. Please refer to the report in its entirety for a more thorough discussion of the processes and procedures used to produce the findings and conclusions reported below.

Four different types of data were collected as part of this project: 1) traffic stop data collected by the CDP officers, 2) observations of traffic patterns collected at ten locations in the city by UC undergraduate and graduate students, 3) Census data for the City of Cleveland collected by the U.S. Census Bureau, and 4) geographic information systems (GIS) data for the City of Cleveland, collected by the CDP. Of these four data sources, the UC research team were directly involved in the collection of the first two (traffic stop data and traffic observation data). A description of these data are provided below.

TRAFFIC STOP DATA

A traffic stop form was developed to collect information for *all* officer-initiated traffic stops conducted by the CDP, regardless of the disposition of the traffic stop. Specifically, the traffic stop form collected information on the following: 1) the stop (e.g., date/time, location, type of roadway, reasons for the stop, and the duration of the stop), 2) the driver (e.g., gender, age, race/ethnicity, zip code of residency, demeanor), 3) the vehicle (e.g., condition of the vehicle, modifications, state of registration, number of passengers), 4) the outcome of the stop (e.g., citation, written warning, arrest, search, property seized during the search), and 5) identification information (e.g., location of the stop by zone, and officers' badge number, unit number, and district number).

Data analyzed in this report represents information recorded on the traffic stop forms from July 1st, 2005 to February 28th, 2006. During the 8-month study period, the CDP reported traffic stops of 43,707 drivers. One of the most important findings of this study is that in 96.7% of the traffic stops reported, at least one citation was issued to the driver. In the remaining 3.3% of traffic stops, nearly all involved some other form of official action taken by the police, including a written warning, search or arrest of the driver, or one or more passengers in the vehicle. This finding is important because it suggests that the purpose and design of the research study (to capture information on all traffic stops, regardless of formal dispositions) may have been compromised. Therefore, this study is better described as a study of citation and arrest data, rather than all traffic stop data. This has a number of important implications for the analyses, findings, and conclusions generated in this report. Most importantly, the analyses comparing traffic stops to benchmarking data are of questionable validity, as the purpose of these types of analyses is to compare the racial/ethnic composition of all motorists stopped to the expected racial/ethnic composition of motorists at risk of being stopped by the police. Since 96.7% of the traffic stops resulted in a citation, it is unlikely that information was collected on all traffic stops initiated by CDP officers during the 8-month study period. Specifically, no information is available for those motorists who were stopped but were not officially sanctioned.

Of the 43,707 traffic stops that were recorded on the traffic stop forms, over half of the stopped drivers were characterized by police officers as Black (61.5%), compared to a little under a third of the drivers who were characterized as Caucasian (30.5%), and less than five percent characterized as Hispanic (4.6%). The average age of drivers was 36.3 years, and 66.6% of the drivers stopped by officers were males. Almost all drivers were Ohio residents (97.8%), while many were also Cleveland residents (62.3%). Yet the data also indicated that some drivers' characteristics, particularly race/ethnicity and Cleveland residency, varied considerably by district, zone, and traffic or patrol assignment. This dramatic variation is likely due to a combination of residential and commuter traffic patterns, along with CDP deployment practices.

For the entire department, the most frequent violation observed prior to a traffic stop was moving misdemeanor violations (53.8%), followed by speeding violations (25.4%). The average speed over the limit was recorded at 16.8 miles per hour, but ranged widely across districts (13.7 m.p.h. to 18.5 m.p.h.) and across zones (13.3 m.p.h. to 19.1 m.p.h.). The majority of traffic stops

occurred on a weekday (80.5%), during the daylight hours (55.3%), on a main city roadway (71.6%) or local neighborhood street (19.8%), and lasted between 1-15 minutes (80.2%). Officers described 46.4% of the vehicles they stopped as being in good condition, 45.7% in fair condition, and 7.8% in poor condition.

TRAFFIC OBSERVATION DATA

As part of the data collection process, the UC research team conducted observations of the roadways in an effort to observe and record traffic flow patterns and driving behavior. In addition, observations allowed for the collection of driver characteristics (e.g., race/ethnicity) that were used as a benchmark against which the traffic stop data was compared. Traffic observation data were also compared to residential Census data to determine if residential Census data could be used as a proxy measure for roadway usage in the locations throughout the city where there were no traffic observations.

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. UC students were trained to conduct traffic observations and assess law violating behaviors, including speeding. These observers conducted over 557 hours of traffic observations between May 5th and November 19th, 2005 at the selected locations. A total of 37,926 vehicles were observed and a speed detection device (i.e., RADAR or LASER) was used during 78.5% of the observation hours.

TRAFFIC STOP BENCHMARK COMPARISONS

Information gathered by officers on traffic stop forms, regarding the percentage of motorists stopped by police of different racial/ethnic origins, is relatively meaningless until compared to other data. For example, information gathered on the traffic stop forms indicates that 61.5% of the traffic stops made by CDP officers were of Black motorists. The information collected on the traffic stop forms, however, does not indicate whether or not this percentage represents a racial/ethnic disparity in traffic stops. Until this percentage is compared to the *expected* percentage of Black motorists stopped, the information is of little value. While researchers have employed a number of methodological strategies for examining traffic stop data, one of the most popular techniques is the use of benchmarks. Essentially benchmarking provides a comparison of the percentage of minorities stopped by the police to the percentage of *expected* stops of minorities, assuming no police bias. That is, if 61.5% of traffic stops in a particular area are of minority motorists, benchmarking analyses compare this 61.5% to the percentage of stops expected if police decision making was based on factors other than the motorists' race/ethnicity. While the concept of benchmarking is intuitively appealing, it is somewhat complicated in design because measuring the expected rate of minority stops (assuming no police bias) is a difficult task for researchers. There are no data that are readily available that measure roadway usage by racial/ethnic groups. Therefore, to perform benchmarking analyses either new benchmarking data must be collected, or data that currently exists that measures something

different (e.g., residential Census data) must be used as a proxy to estimate the percentage of minority motorists expected to be stopped assuming no police bias.

To further complicate the collection of benchmark data, the data must provide an estimate of the motorists using the roadway who are *at risk* of being stopped for a traffic offense. Motorists' risk of being stopped for a traffic offense varies based on a number of factors. For example, an accurate benchmark must take into consideration driving location, time of travel, driving quantity, vehicle types and conditions, driving behavior, and drivers' characteristics. All of these factors are believed to have the potential to influence motorists' likelihood of being stopped for traffic offenses, and therefore must be measured to assess motorists who are eligible for a police stop. Unfortunately, none of the data generated by the benchmarking techniques currently available can adequately address all of the risk factors associated with the likelihood of motorists being stopped by police.

Traffic benchmarking data vary dramatically in their validity and reliability, and therefore results of traffic stop studies involving the use of benchmark data must be viewed with caution. The current study is no exception. In fact, the benchmark data collected and used for comparisons to traffic stop data within this report have numerous limitations and produced somewhat inconsistent findings. In this study, four benchmark comparisons were conducted:

- Comparison #1: All traffic stop data were compared to residential Census data (in 42 police zones).
- Comparison #2: Only stops of drivers who lived in the zone of interest were compared to residential Census data (in 17 police zones).
- Comparison #3: Motorists stopped during daylight hours were compared to daytime observations of motorists (in 9 police zones).
- Comparison #4: Motorists stopped during daylight hours for speeding offenses were compared to daytime observations of speeding motorists (in 5 police zones).

The results of these comparisons varied dramatically. First, comparisons between residential Census data and traffic observation data showed much inconsistency. That is, the findings demonstrated that residential Census data cannot be used as a reliable proxy for traffic observation data in the zones where observations data is unavailable. While this report shows that residential Census data are not good proxies for traffic observation data, the amount of error associated with the use of Census data as a benchmark comparison to traffic stops is unknown. That is, while it is likely that the disproportionality indices created with residential Census data are inaccurate, it is unknown how much error is introduced by using this type of benchmark data.

Once benchmark data are collected, they are compared with traffic stop data to provide a disproportionality ratio. Most simply described, disproportionality ratios can be interpreted as the likelihood of minorities being stopped compared to Caucasians. Disproportionality ratios that are higher than 1.0 indicate that minorities are more likely to be stopped by police compared to Caucasians, while disproportionality ratios that are less than 1.0 indicate that Caucasians are more likely to be stopped compared to minority motorists. For example, a disproportionality ratio of 2.5 indicates that minority motorists are 2.5 times more likely than Caucasians to be stopped by police in a given police zone.

In this study, the comparisons across the four different benchmarking techniques resulted in a wide range of disproportionality ratios. That is, there was little consistency in the results. While there is reason to have more confidence in the accuracy of the traffic observation data (compared to the residential Census data), these data also have limitations and therefore can only provide an estimate of minority motorists at risk for traffic stops in particular locations.

Results from comparisons of traffic stop data to traffic observation data (the benchmark data in which we have the most confidence) suggest that there are racial and ethnic disparities in stopping patterns. Black motorists were more than 1.5 times more likely to be stopped compared to Caucasians in six of nine police zones observed. In two of these zones, Blacks were over 4 times more likely to be stopped compared to Caucasians. While there may be legitimate explanations for these disparities, their existence suggests that a follow-up study is needed. That is, these results suggest that in some areas, there are racial/ethnic disparities in traffic stop patterns that should be further examined by CDP officials.

Additional analyses were conducted to identify any racial/ethnic differences in the initial reasons for traffic stops. The results showed significant variation across racial/ethnic groups for the initial reasons for traffic stops. Caucasians were significantly more likely than other racial/ethnic groups to be stopped for speeding. In contrast, Black motorists were significantly more likely than Caucasians to be stopped for moving felony violations, equipment violations, registration violations, license violations, as the result of special traffic enforcement programs, and for other/unknown reasons. Hispanic motorists were significantly more likely than Caucasians to be stopped for equipment violations, preexisting information, registration violations, license violations, and other/unknown reasons.

Of the motorists who were stopped for speeding, Blacks were stopped for lower levels of speeding severity compared to motorists of all other racial/ethnic groups. That is, for speeding stops conducted by CDP officers, Black motorists were stopped for more minor offenses compared to all other racial/ethnic groups.

ANALYSES OF TRAFFIC STOP OUTCOMES

In addition to the initial decision to stop motorists, this report examines the outcomes that motorists receive at the conclusion of the traffic stop. Specifically, racial and ethnic differences in searches and arrests during traffic stops were explored. During the 8-month study period, CDP reported traffic stops of 43,707 drivers. As previously noted, in 96.7% of these traffic stops, at least one citation was issued to the driver. In addition, 8.8% of traffic stops resulted in a search of the motorists and/or the vehicle, and 4.8% of traffic stops resulted in a custodial arrest of the motorist.

Of the Caucasian motorists stopped by CDP officers, 3.3% were arrested, compared to 5.7% of Black motorists and 4.7% of Hispanic motorists. That is, Black and Hispanic motorists were statistically significantly *more* likely than Caucasian motorists to be arrested. Likewise, of the Caucasian motorists stopped by CDP officers, 5.9% were searched, compared to 10.5% of Black motorists and 9.0% of Hispanic motorists. Again, Black and Hispanic motorists were

statistically significantly *more* likely than Caucasian motorists to be searched during a traffic stop.

Interpretation of the above findings, however, must be couched with additional information. The racial/ethnic differences detected in post-stop outcomes may exist due to legal and extralegal factors other than motorists' race/ethnicity. To explore this possibility, multivariate statistical modeling was performed to statistically control for other factors that might influence officers' decisions to arrest and search motorists. Findings from the multivariate statistical models estimating arrest indicated that Black and Hispanic motorists are *not* significantly more likely than Caucasians to be arrested during traffic stops when other legal and extralegal factors are considered. Instead, these analyses suggests that a number of situational and officer-level factors accounted for the variance in arrest rates across racial/ethnic groups (e.g., being male, disrespectful, driving a vehicle in poor working condition, being stopped at night, etc.). In conclusion, the findings suggest that **Black and Hispanic motorists are *not* significantly more likely than Caucasians to be arrested during traffic stops when other legal and extralegal factors are considered.**

A similar multivariate statistical analysis was performed focusing on searches. The findings showed that after controlling for other relevant legal and extra legal factors that could be measured with these data, drivers' race/ethnicity did demonstrate a significant influence over whether or not vehicle and person searches were conducted. The odds of being searched were 1.3 times higher for Black drivers stopped by CDP officers compared to Caucasian drivers. As with the arrest model, a number of situational and officer-level variables were also significant when searches were examined – yet, unlike the arrest model, even after statistically controlling for other legal and extralegal factors that might influence officers' decisions to conduct a vehicle or person search, Black motorists are still significantly more likely to be searched compared to Caucasians. In conclusion, the findings show that **even after controlling for other relevant legal and extra legal factors, drivers' race/ethnicity has a significant influence over whether or not searches are conducted. The odds of being searched are 1.3 times higher for Black drivers compared to Caucasian drivers.**

To further explore the observed racial disparities in search rates, additional statistical analyses were performed. It was determined that a majority of the searches conducted by CDP officers (71.2%) were mandatory (i.e., required by departmental policy). In contrast, 23.7% of the searches conducted were discretionary, while only 4.7% of the searches were based solely on motorists' consent. The most common reason for a search was administrative inventory (52.0%), followed by incident to an arrest (31.6% of searches). Hispanic motorists were more likely to be searched for mandatory reasons, compared to other racial groups, while Black motorists were more likely to be searched for discretionary reasons. Caucasian motorists were more likely to be searched based solely on consent, compared to other racial ethnic groups. Thus, there is no consistent evidence to suggest that minority motorists were singled out for the most discretionary types of searches (i.e., consent).

Department-wide, 55.2% of all searches resulted in the seizure of contraband. Discretionary searches were the most likely to result in the discovery of contraband. Department wide, 55.2% of all searches resulted in the seizure of contraband. This is a very high search success rate, and

likely is an artifact of the data collection effort that counted vehicles as “seizures” during administrative inventory “searches.” Finally, discretionary searches of Black motorists were the *most productive* in the seizure of contraband, followed by Hispanics and then Caucasians. Combining these results, **although Black motorists were significantly more likely than Caucasians to be searched by CDP officers, searches of Black motorists were more likely than searches of Caucasians to result in the seizure of contraband.**

SUMMARY

The following is a list of the major findings of this traffic stop study:

- The data collected by CDP officers during traffic stops likely reflects the most serious traffic stops, as information for traffic stops that did not result in a citation, search, or arrest did not appear to be collected by CDP officers.
- The benchmarking data collected has significant limitations, and the comparisons between benchmarking data and traffic stop data show inconsistent results across methods, analyses, and locations.
- The benchmarking approach believed to be the most reliable (but not without limitations) demonstrates racial/ethnic disparities in traffic stops in some locations that should be further examined by CDP officials.
- Racial/ethnic differences in the initial reasons for traffic stops were apparent. Caucasians were more likely to be stopped for speeding, while Blacks and Hispanics were more likely to be stopped for other moving violations, license and registration violations, etc.
- Of the motorists who were stopped for speeding, the average speed over the limit was higher for Caucasians compared to Black motorists. That is, when stopped for speeding, Black motorists were more likely than Caucasians to be stopped for more minor speeding infractions.
- Although Black and Hispanic motorists were more likely than Caucasians to be arrested during traffic stops, the reasons for the arrests were more likely due to legal and extralegal reasons, and not solely due to their race/ethnicity.
- Black and Hispanic motorists were more likely than Caucasians to be searched during traffic stops. For Black motorists, these disparities remained even after statistically controlling for other possible legal and extralegal reasons to conduct searches. Black motorists were 1.3 times more likely to be searched compared to Caucasian motorists.
- Although Black motorists were more likely to be searched, searches of these motorists were more likely to result in the seizure of contraband, compared to searches of Caucasians. That is, while Blacks are searched more often by CDP officials, these searches are more productive in terms of seizure of contraband compared to searches of Caucasians.

RECOMMENDATIONS

To promote equitable treatment across racial/ethnic groups during traffic stops, it is strongly recommended that a systematic data collection of both traffic and pedestrian stops be incorporated into the daily practices and procedures of the CDP. This type of data collection is becoming routine in police agencies across the country. Currently, 19 states legislatively mandate the collection of traffic stop data for all agencies in their state, while an additional 11 states have legislation pending. Numerous municipal and state law enforcement agencies voluntarily collect traffic and pedestrian stop data. This trend is likely to continue, as an increasing number of states collect information on all officer initiated traffic stops.

Many of the problems associated with this data collection effort (documented throughout this report) could be eliminated with a systematic, long-term data collection strategy that would best benefit the CDP and Cleveland residents. The routine collection and analyses of traffic stop data could aid CDP administrators regarding potential problem areas, and increase citizens' perceptions of the department's legitimacy. A data collection system that is immersed within CDP's current practices may be a cost-effective solution for information gathering during all officer initiated traffic stops, including those that do not result in an official disposition.

It is further recommended that any long-term data collection system or follow-up study be developed in a working partnership between CDP management and union officials. Many of the problems associated with this research study were the result of poor working relationships among CDP officials, City of Cleveland officials, and police union officials. The result was a study that likely produced more questions than answers. A long-term strategy for equitable treatment toward citizens and progressive leadership to implement this strategy is necessary for the CDP to prosper and regain its reputation as an innovative and professional police department.

1. INTRODUCTION

OVERVIEW

This report documents the findings from statistical analyses of data collected during traffic stops by the Cleveland Division of Police¹ from July 1, 2005 – February 28, 2006. In June 2004², the CDP contracted with the University of Cincinnati, Center for Criminal Justice Research to design, collect, and analyze data for the “Cleveland Division of Police Traffic Stop Data Study.” Dr. Robin Engel and Dr. James Frank were the Principal Investigators for this research project, which was approved by the Institutional Review Board (IRB) at the University of Cincinnati as adhering to the protections of human subjects and principles of social scientific research. The research team worked with the CDP in an effort to design and collect information on every traffic stop conducted by CDP officers during a designed time period. There were, however, numerous complications regarding the collection of these data that somewhat limit the findings and conclusions produced in this report. These limitations are fully documented.

In September 2003, the CDP disseminated a Request for Proposals (RFP) to which the UC research team responded. After review of this proposal, revisions to the scope of work and budget, and numerous contractual delays, the Cleveland Division of Police Traffic Stop Data Study (here after, Traffic Stop Study) was initiated in February, 2005

It should be noted that the CDP *voluntarily* implemented a data collection effort designed to examine traffic stop patterns and post-stop outcomes for citizens stopped by CDP officers. This agency sought external monies to support this research effort, receiving a federal grant from COPS within the Department of Justice.

ISSUES INVOLVED IN POLICE STOP DATA COLLECTION

There are generally five core areas of concern in all traffic stop data collection efforts: 1) data collection of traffic stop data by police (i.e., the numerator), 2) comparison of traffic stop data to benchmarks (i.e., the denominator), 3) the creation and interpretation of disproportionality indices and ratios (i.e., the numerator divided by the denominator), 4) examinations of post-stop outcomes (i.e., disposition data), and 5) appropriate interpretations of traffic stop data. Each of these four areas has special considerations and research issues that must be addressed to provide data and analyses that are accurate and valid. These issues, and the responses of the CDP, are documented throughout this report.

DATA COLLECTION OF TRAFFIC STOP DATA (i.e., “The Numerator”)

One of the most consistent problems with racial profiling data is the questionable validity of the actual stop data that is collected by individual officers. The importance of maintaining reliable and valid traffic stop data cannot be understated. Regardless of the sophistication of the

¹ Throughout this report, the Cleveland Division of Police is referred to by the acronym “CDP”.

² On June 4, 2004 the University of Cincinnati was advised that they would be awarded the contract. The actual contract was not signed by both parties until November, 2004 due to issues that had to be resolved by each party’s legal departments.

statistical analyses and benchmark comparisons utilized by researchers, the research study is virtually meaningless if the traffic stop data itself is not valid. It is imperative that police departments initiate data collection efforts that incorporate considerable forethought and planning. The following factors are among the most important to consider: 1) selecting the mechanism for data collection, 2) developing the data collection instrument, 3) conducting a pilot test, 4) training officers to use the data collection instrument(s), 5) minimizing officer disengagement, and 6) developing a data auditing system. Each of these factors is necessary for an effective data collection project.

Selection of the data collection mechanism is a key component to ensure that there is an accurate and reliable collection of data on all traffic stops that occur within the police jurisdiction. Failing to select a mechanism that collects all relevant information can lead to an ineffective and misleading final analysis. Related, the selection of an appropriate data collection instrument is a fundamental component to collecting information that will inform the analysis and allow the police department to be provided with the most accurate information available. While these two components are crucial to an effective data collection effort, often unforeseen issues arise when pilot testing the data collection instrument.

Data collection pilot tests are simply a “dry run” for the data collection effort. They ensure that the research design is feasible, and the data collected is both reliable and valid. Pilot tests are typically conducted by a selected group of officers in a more limited geographic area. Based on findings from the pilot test, the data collection instrument is changed and officer training is modified (if needed). Once the pilot test provides feedback regarding any potential problems with the data collection process, a comprehensive training curriculum is important to ensure that all officers understand the goal of the data collection effort and how to accurately complete the data collection form. This helps to eliminate potential problems in later stages of the research project.

Effective training that outlines the importance of the data collection can also minimize officer disengagement. The importance of the previous components can be mitigated if the officers, who are in essence the data collectors, disengage from the process. This disengagement is crucial to avoid; thus, comprehensive training and a clear explanation to the officers of the importance of the data collection effort is a useful mechanism to avoid this concern. Finally, maintaining data quality ensures reliable and valid results. It is essential for any data collection effort, but particularly important for data collected through official sources (i.e., the police). There are five general ways that traffic stop data may be inaccurate: 1) the information is incorrectly recorded, 2) some stops are not recorded, 3) data is missing due to random and non-random errors, 4) data is intentionally missing, and 5) data contains misstatements of facts (Fridell, 2003). Data “auditing” can be used to check for these types of inaccuracies and to maintain quality control. Each of these five factors is central to the collection of traffic stop data.

DATA COLLECTION OF BENCHMARKS (i.e., “The Denominator”)

The second important issue facing researchers examining police traffic stops is determining how often minorities are stopped by police; however, this is not particularly meaningful until those percentages are compared to some “expected probability” of these actions toward minorities

(Rojek, Rosenfeld, and Decker, 2004). These expected probabilities are often referred to as “benchmarks,” “base rates,” “baselines,” or “denominators.” Studies examining racial disparities compare police stop data with the “expected” rate of stops of minorities assuming that no racial discrimination or prejudice exists by police.

The most frequent type of data used to determine expected probabilities is Census population figures. Though readily available, comparisons based on Census data are limited. First, several researchers have suggested that there is ample reason to suspect that residential populations do not necessarily represent the driving population in those areas. Second, the Census does not include measures of driving behavior that may account for racial disparity in stops. That is, merely demonstrating a difference between the percent of minorities stopped and the percent living in a particular area does not necessarily mean police officers have acted inappropriately. Indeed, an alternative explanation is that disparities may reflect differences in legally relevant behavior by members of particular demographic groups (Walker, Spohn, and DeLone, 2000).

Some researchers have defended the use of population figures as an appropriate comparison group, suggesting that no research has indicated that there are racial differences in traffic violations or travel routines (ACLU; 2000; Lamberth, 1996, Verniero & Zoubek, 1999). Research in the travel, transportation, and accident analysis literatures, however, does show considerable racial and ethnic differences in a variety of driving-related behaviors. In addition, some traffic stop studies have reported that drivers’ behavior may at least partially account for racial disparity in police stops and stop outcomes (e.g., Engel et al., 2003; Lange et al., 2005; Smith et al., 2003).

Relying solely on Census data as a benchmark comparison for traffic stops means that it is reasonable to assume that people drive where they live and that different demographic groups do not drive differently. The evidence for these assumptions, however, is lacking. Therefore, although collecting data on driving behavior is more costly—in terms of expenditures and time—than relying on demographic proxies, the acknowledged weaknesses of Census data have caused some researchers to initiate observational studies of roadway usage and driving behavior in order to determine both who is driving where and how they are driving. Indeed, many researchers involved in traffic stop data collection efforts have become more cautious in their conclusions based on population benchmarks. They note that further research needs to measure differences in driving behavior as an alternative explanation for racial disparity (Cordner et al., 2001; Cox, Pease, Miller, & Tyson, 2001; Lansdowne, 2000; Zingraff et al., 2000; Rojek et al., 2004).

This study supplements comparisons based on Census data with observations of roadway usage and driver violating behavior. Although a number of different driving behaviors are illegal, this study focuses primarily on one particular violating behavior—speeding. The research team focused on speeding for several reasons. First, a national survey revealed that people reported speeding was the most frequent reason (64%) for being stopped by police (Boyle et al., 1998). Second, in terms of methodological considerations, speeding is easier to measure than many other illegal driving behaviors; furthermore, with RADAR technology, it can be measured reliably and objectively. Third, for many police agencies, the majority of traffic stops are for

speeding. At the initiation of this research project, it was simply unknown what percentage of traffic stops conducted by the CDP was for speeding infractions.

In an effort to better examine and interpret the police-citizen contact data, this study utilized several different benchmark measures. Specifically, the traffic stop data were compared to four related benchmarks: 1) Census data of residential driving-age populations (i.e., individuals 18 years or older) where the traffic stops occurred, 2) Census data of residential driving-age populations for only stops of motorists who resided in the zone where the traffic stop occurred, 3) systematic observations of roadway usage (i.e., traffic observation data), and 4) systematic observations of traffic violating behavior (i.e., speeding). An attempt was made by the research team to develop a “traffic flow model” from residential Census populations and traffic stop data similar to those developed for other jurisdictions, however due to the limited number of cases in some zones, the development of this benchmark was problematic. **Section 5** describes each of these benchmark measures in more detail. Comparisons of traffic stops to the benchmarks are also reported.

THE CREATION AND INTERPRETATION OF DISPROPORTIONALITY INDICES AND RATIOS

Using traffic stop data as the numerator and benchmarks as the denominator, “disproportionality” or “disparity” indices can be created. These indices are used to estimate the differences between the “actual” and “expected” rates of traffic stops for different racial, ethnic, gender, and age groups. Disproportionality indices greater than one indicate that the rate of stops for particular groups are *greater than expected* based on the benchmark. Disproportionality indices less than one indicate that the rates of traffic stops for particular groups are *less than expected* based on the benchmark. The larger the absolute size of the disproportionality index, the larger the disparity between the actual and expected rate of stops.

While the disproportionality index provides a general comparison between minority and majority groups, it is not easily interpretable. Alternatively, a disproportionality ratio can be created, which provides a clear interpretation of the likelihood of a minority driver receiving an outcome when compared to a majority driver. As with the disproportionality index, a ratio of one indicates no disparity, while values above one suggest a disproportionate outcome for the minority group. The larger the absolute size of the disproportionality ratio, the larger the disparity between the actual and expected rate of stops.

There are several issues involved with the use of disproportionality indices and ratios. First, there is an obvious connection between the validity of disproportionality indices and ratios and the type of benchmark used to make the comparison. As described above, not all benchmarks are of equal validity. Therefore, disproportionality indices and ratios based on Census data, for example, must be interpreted with extreme caution.

Second, the stability of the disproportionality indices and ratios is based in part on the size of the denominator. This is especially a concern when Census figures are used to estimate the expected rate of stops. Fortunately, in Cleveland, there are no police zones in which the percentage of Black residents is below 1.0%. There are a couple of police zones that have less than 5.0% Black

population; likewise, there are several police zones in which the Hispanic population is less than 5.0%. Thus, a small number of traffic stops of Blacks and Hispanics in these zones would dramatically raise the disproportionality indices and ratios because the denominator is so small.

Third, there is no scientifically accepted standard for the interpretation of the size of disproportionality indices and ratios. That is, there is no generally accepted statistical test that can be performed to determine if disproportionality indices and ratios are “too big” or “too small.” Likewise, there is no generally accepted “rule of thumb” used by researchers regarding the appropriate size of disproportionality indices and ratios. For this study, the research team examined the size of the disproportionality indices and ratios created for each zone in relationship to other zones, particularly adjacent zones. That is, researchers looked for outliers, or zones that had unexplainably high disproportionality indices and ratios. In addition, the team compared disproportionality indices and ratios for the same zones created through different benchmarks. Specific findings and more information related to disproportionality indices and ratios are provided in **Section 5**.

EXAMINATIONS OF POST-STOP OUTCOMES (i.e., disposition data)

Concerns of biased-based policing do not end with the initial traffic stop. Indeed, post-stop outcomes are an important consideration of any profiling data collection effort because the potential exists for differential treatment based on the drivers’ race, ethnicity, gender, and/or age after the initial stop has been made. Therefore, in addition to benchmark comparisons of traffic stop data, analyses of post-stop outcomes (e.g., warnings, citations, arrest, searches, and seizures) must be conducted. These analyses should examine differences in outcomes for different types of drivers.

Those who believe that officers target minority drivers suggest that there is a perception among law enforcement officials that minority drivers – and more specifically, young Black and Hispanic males – are more likely to be transporting drugs, unregistered weapons, or other contraband (Harris, 2002; Ramirez et al., 2000). Some crime statistics support this proposition. For example, the National Crime Victimization Survey consistently finds that Blacks have higher rates of violent offending compared to Caucasians (Lauritsen & Sampson, 1998). In addition, research based on official arrest statistics consistently shows that young minority males are significantly more likely to be arrested for drug offenses and violent crime (for review, see LaFree, 1995; Lockwood, Pottieger, & Inciardi, 1995). It has been argued, however, that minorities are disproportionately represented in official crime statistics because these data are measured through arrests. If officers are more likely to stop, question, and search young minority males, then arrest statistics may become what Harris (1999, 2002) has described as a “self-fulfilling prophecy.” Thus, it is important to examine all individuals stopped by police to determine the proportion of those individuals who are searched, and subsequently the proportion of those searched individuals who were discovered to be carrying or transporting contraband. If drivers were searched strictly based on legal factors and suspicions unrelated to race, one would expect similar percentages of searches resulting in seizures across racial groups. This has been described as the “outcome test” (Ayres, 2001). The outcome test is a simple comparison across groups of the percentage of searches that result in seizures. This is also referred to as the “search

success rate” or “hit rate.” Statistically assessing search success rates of discretionary searches will allow CDP administrators to identify potential problems and institute policy interventions.

It is also important to consider multiple factors that might simultaneously influence officer decision-making. A multivariate statistical model takes many different factors into account when attempting to explain a particular behavior. Unlike a bivariate model, it does not simply assess the relationship between two variables. Rather, a multivariate model examines many variables simultaneously, and therefore provides a more thorough and accurate interpretation of the data. For example, without controlling for the behavior of drivers, it is impossible to say whether higher rates of citations issued to particular drivers are justified based on legal considerations. A multivariate model can provide this information because it statistically controls for the existence of other variables in the model.

The multivariate statistical analyses conducted, however, can only statistically control for those variables that we can measure. Unmeasured factors that might influence the model are called “specification error” or the error in a statistical model due to the inability to specify all of the factors that might have an influence over the outcome (in this case, officers’ behavior). Due to issues associated with specification error, the results from the multivariate models must be interpreted with caution.

Furthermore, caution is also warranted due to the extremely large samples of roadway observations and traffic stops. Sample size has direct implications for the finding of statistically significant results. Significance testing used with multivariate regression techniques determines the likelihood that observed relationships between variables are not due to chance; i.e., that they are true relationships. Typically, a 5% threshold is used, indicating that in only 5 times in 100 an observed relationship is due to chance. Significance testing in large samples, however, can be more sensitive to very small or artificial relationships between variables, thus detecting statistically significant differences that are not substantively or practically significant (Allison, 1999). It is for this reason that we have increased the significance threshold to 0.1% for our analyses that rely on large sample sizes (i.e., only 1 time in 1000 is relationship due to chance). Furthermore, we focus on the magnitude of the regression coefficients (which indicates the strength of the relationship), rather than just their statistical significance. A further description of the multivariate analyses and associated caveats are described in **Section 6**.

In summary, this report examines the outcomes drivers receive after traffic stops are made (e.g., warnings, citations, searches and arrests), and whether these outcomes differ significantly across racial, ethnic, and gender groups. Based on these initial findings, additional analyses that focus specifically on searches and seizures are included in **Section 7**.

APPROPRIATE INTERPRETATIONS OF TRAFFIC STOP DATA

The final, and perhaps most important, issue involved in traffic stop data analyses is the interpretation of the analyses and conclusions offered by the analyst. Current research examining racial profiling suggests that in many jurisdictions, police officers disproportionately stop non-Caucasian drivers compared to some benchmark. Some studies have inappropriately characterized these disparities as “proof” of discrimination, while other studies correctly

acknowledge that a disparity exists and that inferences as to the cause of the disparities cannot be adequately made with the data available (for review, see Engel et al., 2002). That is, even when racial/ethnic disparities are demonstrated in traffic stops, the cause of these disparities is not often known (and can never be known) based on the current data available. Without examining alternative explanations of racial disparities in traffic stops, one cannot claim that officers have made stopping decisions based on the drivers' race/ethnicity. The term racial profiling implies racial bias or discrimination demonstrated by police. Traffic stop studies, however, cannot measure these concepts. As noted by Engel, Calnon & Bernard (2002: 250), "the problem with interpreting these findings is that the mere presence of disparity in the aggregate rate of stops does not in itself demonstrate racial prejudice, any more than racial disparity in prison populations demonstrates racial prejudice by sentencing judges." Fridell (2004: 2) has addressed the concern over how to interpret findings from traffic stop data analyses by documenting what police administrators and other stakeholders can expect from traffic stop studies. As she notes, "because the data will never 'prove' or 'disprove' racially biased policing, we contend that vehicle stop data collection and analysis should never be viewed – either by police or resident stakeholders – as a 'pass-fail test'. Rather, she argues that "it should be viewed as a diagnostic tool to help pinpoint the decisions, geographic areas, and procedures that should get priority attention when the agency, in concert with concerned residents, identifies its next steps for addressing the problem or perception of racial profiling" (Fridell, 2004).

Most of the current traffic stop studies now appropriately acknowledge that it cannot be determined with traffic stop data if disparities are due to discrimination because of the inability to measure alternative factors that might account for these disparities. Scholars have noted that measuring alternative, race-neutral factors, including racial differences in driving patterns, location, frequency, and/or degree of law-violating behavior, as well as spatial characteristics such as high police presence, might explain racial/ethnic disparities (e.g., Cordner et al., 2001; Cox et al., 2001; Criminal Justice Training Commission, 2001; Engel et al., 2004; Farrell et al., 2004; Fridell, 2004; Lansdowne, 2000; Rojek et al., 2004; Smith et al., 2003; TDPS, 2000; Zingraff et al., 2000). The majority of current social scientific opinion clearly indicates that traffic stop data alone cannot be used to directly measure racial profiling.

In addition, studies measuring disparity have not established a threshold value above which the racial/ethnic disproportionality is considered illegitimate or unjustified (Cox et al., 2001; Decker et al., 2002, Farrell et al., 2003). That is, there is no scientifically accepted standard for the interpretation of the size of the disparity, or a generally accepted statistical test that can be performed to determine if the disparity is "too big" or "too small."

Given these limitations, the statistical findings in this report must be cautiously interpreted. Analyses of traffic stop data can only report patterns and trends in racial/ethnic disparities. These analyses cannot determine if individual police officers are engaging in the behavior commonly referred to as "racial profiling." Any such conclusion would be based on the analyst's opinion and not the data themselves.

REPORT OUTLINE

The following Traffic Stop Study Report is divided into eight sections, including this introduction. The following sections detail: 2) traffic stop project timeline, 3) description of Traffic Stop Form data methods and descriptive statistics, 4) description of observation methods and descriptive statistics (i.e., traffic observation data), 5) discussion of benchmarking and results of the traffic stop data analyses, 6) reporting of post-stop outcomes, 7) focus on searches and seizures, and 8) conclusions and policy recommendations. The general content and summary of findings for **Sections II - VII** are described below.

SECTION 2

This section details the timeline of the Traffic Stop Study from the initial request for proposals through the completed data collection effort. This discussion provides an overview of the tasks involved with this project and the dates of both the original timeline and the actual completion dates.

SECTION 3

Section 3 provides an overview of the methodology for collection of the traffic stop data and the associated descriptive statistics for the data collected during the entire 8-month period (July 1st, 2005 – February 28th, 2006). This description includes the development of the Traffic Stop Form, the training of CDP officers, and the pilot test of the form. In addition, this section provides a description of the traffic stop data including: the number of stops, characteristics of the stops (e.g., time, day, month, reason for the stop, roadway type, vehicle registration, number of passengers, length of the stop), the reason for the stop (e.g., speeding, moving violation, equipment or inspection violation, etc.), the characteristics of the drivers (e.g., sex, race, age, residency) and several stop outcome measures (e.g., whether a driver or passenger was warned, cited or arrested and whether a search was conducted). The averages for this information are reported in tables at the department, district, and zone levels where appropriate.

SECTION 4

This section provides an overview of the methodology for the collection of the traffic observation data and the associated descriptive statistics for the data collected from May through November, 2005. This section begins with a discussion of the recruitment, selection and training of the observers. Next, the process used to select observation locations is addressed. The section concludes with a description of each of the observation periods, the observed traffic patterns (motor vehicles observed, hours of observations, use of speed detection devices) and the characteristics of observed drivers.

SECTION 5

Section 5 compares the rate of stops of racial groups to available benchmark information, including: 1) residential driving-age population based on Census data, 2) residential driving-age population Census data for stops of motorists who reside in the police zone where the stop occurred, 3) observations of roadway usage, and 4) observations of drivers' speeding behaviors. Based on these data, comparisons are made at the police zone level. Disproportionality indices and ratios are created to examine the differences in the percentage of minority drivers stopped by CDP officers compared to their expected rate of stops as determined through the four different benchmarks.

SECTION 6

The post-stop outcomes (e.g., arrest, search, and seizure of contraband) are documented in **Section 6**. Information examining all of the post-stop outcomes is presented for different drivers by racial, gender, and age groups. In addition, CDP officer differences in stop outcomes are examined in detail. At the conclusion of **Section 6**, several hierarchical multivariate analyses are presented that predict officer decision making after the traffic stop has been made. The primary purpose of these analyses is to examine the predictors of arrests and searches, while controlling for all variables prior research has determined may influence officer decision making in these situations. This allows an examination of the independent effects of driver race/ethnicity on arrest and search behavior. That is, **Section 6** documents the outcomes drivers receive after traffic stops are made (e.g., searches and arrests), and whether these outcomes differ significantly across racial, ethnic, and gender groups.

SECTION 7

Section 7 focuses specifically on the post-stop outcomes of searches and seizures. This focus is conducted due, in part, to the importance of search and seizure practices. **Section 7** documents the search rates for minority motorists compared to Caucasians, and further describes the racial/ethnic disparities in searches and seizures at multiple geographic and organization levels. Comparisons of search success rates are made, followed by analyses specifically of consent searches.

SECTION 8

Section 8 summarizes the information presented, and provides policy recommendations based on interpretations of collected data. Note that the findings reported in this document must be interpreted cautiously. The data collected and presented in this report cannot be used to determine whether or not the CDP officers have individually or collectively engaged in "racial profiling." In addition, the legality of prior or future individual traffic stops cannot be assessed with these data. This report is designed to give feedback to the CDP administrators regarding the results of the data collection process, and the general trends and patterns observed in the traffic stop data over the 8-month period of the study.

APPENDICES

Appendix A contains the University of Cincinnati research team proposal. Of special importance is the timeline submitted with the initial proposal application. **Appendix B** contains the coding instructions developed by the University of Cincinnati for the Traffic Stop Form. **Appendix C** contains the Observation Data Collection Coversheet Form and the Observation Data Collection Form. **Appendix D** contains the observation data logistic regression analysis results and explanations. **Appendix E** contains a detailed discussion regarding the benchmarking analyses.

2. PROJECT TIMELINE

PROJECT PROPOSAL AND PROJECT INITIATION

On September 25th, 2003 the City of Cleveland, Department of Public Safety, Division of Police (DOP) issued a “Request for Proposals, Traffic Stop Data Collection Project.” The University of Cincinnati research team submitted a grant proposal in response to this request on October 10th, 2003. Based on a request from the City of Cleveland, the University of Cincinnati research team submitted an amended proposal modifying the research tasks and reducing the budget from \$119,862 to \$95,679 and submitted the proposal for reconsideration in December 2003. In April 2004, the research team met at the District 3 Headquarters with several CDP officials and the Citizen Contact Committee to discuss the proposed study. On July 7th, 2004, the University of Cincinnati research team was notified that it was awarded the contract.

Upon being notified that the University of Cincinnati was awarded the contract, a research protocol was submitted to the University of Cincinnati’s Institutional Review Board (IRB) requesting human subjects’ approval of the project. On June 28th, 2004, the research team was contacted by IRB requesting additional clarification regarding the collection of project data that may identify specific individuals (i.e., how will location of the stop be recorded, will specific license numbers be recorded). On July 6th, 2004, the requested information was forwarded to the IRB and on July 9th, 2004, the project was approved by the IRB at the University of Cincinnati.

Unfortunately, the official contract between the City of Cleveland and the University of Cincinnati was not signed until November 4th, 2004. This was in large part due to negotiations between each party’s legal departments concerning acceptable contract language. The lengthy contractual process was problematic in that the initial timeline for research tasks was continually modified in anticipation of a project start date.

RESEARCH PROPOSAL TIMELINE

The proposal submitted to the City of Cleveland included a detailed timeline identifying important target dates for project objectives. Please refer to **Appendix A** for the actual timeline that was submitted with the amended proposal. The timeline indicates five important objectives and the corresponding time periods for which the research team anticipated completing the tasks. It was the intent of the research team to begin project initiation on January 1st, 2004. Traffic stop data form development and officer training was scheduled to occur between February 1st and February 28th, 2004. The next major task was initiating the pilot test. The pilot test data was initially scheduled to occur between March 1st, 2004 and April 30th, 2004. The department-wide data collection process was intended to begin between May 1 and May 31, 2004 and continue until May 31, 2005 ensuring a full year of data collection. Lastly, the research team anticipated compiling and analyzing the data and writing the final report between June 1st and August 31st, 2005.

RESEARCH TASKS AND ACTUAL PROJECT TIMELINE

Unfortunately due to the need to submit an amended contract, combined with delays in the awarding of the contract and subsequent contract negotiations, actual research tasks did not begin on the dates in the proposed timeline. According to University policy the research team was unable to begin actual research tasks until there was notification that the study was awarded to the University of Cincinnati. When notification was received, the research team immediately contacted Chief Lohn. The principal investigators stressed the necessity of having a meeting with all parties involved in the project to discuss the research plan and begin development of the traffic stop forms. **Table 2.1** identifies seven major tasks and the months during which related tasks were undertaken.

Table 2.1: Project Timeline

Research Task	Jul 04	Aug 04	Sep 04	Oct 04	Nov 04	Dec 04	Jan 05	Feb 05	Mar 05	Apr 05	May 05	Jun 05
Project Initiation	X											
TSDF Preliminary Tasks		X								X		
Pilot Test								X			X	X
Traffic Stop Data Collection												
Roadway Observation Data									X		X	X
Data Analysis									X			X
Final Report												

Table 2.1: Project Timeline (Continued)

Research Task	Jul 05	Aug 05	Sep 05	Oct 05	Nov 05	Dec 05	Jan 06	Feb 06	Mar 06	Apr 06	May 06	Jun 06
Project Initiation												
TSDF Preliminary Tasks												
Pilot Test												
Traffic Stop Data Collection	X	X	X	X	X	X	X	X				
Roadway Observation Data	X	X	X	X	X							
Data Analysis	X	X	X	X	X	X	X		X	X		
Final Report											X	X

TRAFFIC STOP DATA FORMS: DEVELOPMENT AND EQUIPMENT PURCHASES

The project proposal required the purchase of a customizable scanner and customizable traffic stop data collection forms. Any purchase made by the CDP in excess of \$100.00 required the approval of city counsel. In addition, because the project was funded by federal monies, any equipment that needed to be purchased for the study had to be put up for bid. Pursuant to the City of Cleveland's guidelines, the CDP opened up the bidding process to any company that provided the desired services and/or products. On July 28th, 2004, CDP officials notified the research team that Scantron, Inc. had won the bid for the traffic stop study and would provide the scanner, forms, and form definition files necessary for reading the data collection forms.

Shortly thereafter, on August 18th, 2004 the research team requested a meeting with all involved parties to begin development of the Traffic Stop Data Form. It was determined by Chief Lohn that a meeting was not necessary at that time. Deputy Chief Green notified the research team that a working group had been established to determine the information for inclusion on the traffic stop form. The group was comprised of Commander Cuevas, Commander Morrow, and Commissioner Bungo. On September 28th, 2004 an email was sent by the research team to the working group outlining the importance of the traffic stop form, providing suggestions for the type of information that should be captured on the form, and asking if a meeting between the working group and research team was necessary. On October 11th, 2004, in response to this email, Deputy Chief Green indicated that the working group had not yet begun constructing the traffic stop form. On October 20th, 2004 the working group forwarded their recommendations to Deputy Chief Green who then relayed the information to the research team.

During November and until mid-December 2004, emails were exchanged between the University of Cincinnati research team and the CDP concerning data fields to be included on the Traffic Stop Data Form. On December 16th, 2004, after several revisions, an order was placed with Scantron. Scantron advised the research team that they could not fit all the requested fields on the form. Another draft of the form was forwarded to CDP officials for proofing on January 26th, 2005 before being forwarded to Scantron. On February 17th, 2005 the forms for the pilot test were reordered.

Throughout December 2004 and January 2005, the research team worked closely with Scantron representatives to produce the software that the scanner would use to read the traffic stop forms. During February 2005 the research team customized the statistical software to be used to read the data files produced by the scanner software.

PILOT TEST: TRAFFIC STOP DATA FORM AND DATA COLLECTION

Prior to testing the data collection form in the field, the research team created detailed instructions concerning each of the traffic form data fields (see **Appendix B**). In January 2005, the coding instructions were forwarded to Deputy Chief Green. At that time, it was suggested that the research team meet with officers at the Training Academy to introduce them to the project and discuss the data collection process. It was determined by the CDP that instead of the

research team introducing the project during officer training, a video would be produced concerning the traffic stop data collection project. This video would presumably be shown to officers throughout the department during roll calls or at other times the police department deemed most appropriate. In February 2005, a training video was made regarding the data collection effort and was reportedly disseminated to all CDP officers through the spring of 2005.

A pilot test of the officer data collection procedures was conducted during February 2005. Officers from the Traffic Unit participated in the Pilot Test and were presumably trained using the data collection instructions developed by the research team. On March 30th, 2005 a report documenting the data collected for the pilot test was submitted to the CDP command staff.

On March 10th, 2005, after conclusion of the pilot test, members of the research team met with the Chief Lohn, Deputy Chief Green, Safety Director Watson, Robert Beck of the Cleveland Police Patrolmen's Association (CPPA), the Fraternal Order of Police, and the Black Shield Association, to discuss issues relating to data collection procedures. As a result of this meeting the University of Cincinnati research team reiterated its commitment to protect the confidentiality of officers involved in the study and to report all findings in such a manner that individual officers will not be able to be identified by the CDP. The CDP agreed to mail Traffic Stop Data Forms to the research team on a daily basis and to provide the research team with a limited amount of officer data (badge numbers, age, race, years of service, etc).

Using information secured from the Pilot Test, final changes were made to the Traffic Stop Data Form. On April 11th, 2005 forms were sent to Scantron and Cleveland Safety Director Watson was notified that the forms were ready for printing. The next day the research team was advised that the CPPA had not formally agreed to the project terms and that forms would not be printed until the CPPA acted. A final draft of the Traffic Stop Data Form was sent to Scantron on April 27th, 2005.

ROADWAY OBSERVATIONS

Three tasks were involved in conducting the roadway observations designed to collect traffic observation data. Specifically, observation locations were selected, observers were trained, and observations were conducted.

On April 12th, 2005 an email was sent to Deputy Chief Green and each of the District Commanders requesting possible roadway observation locations within each District. The email requested commanders to select high traffic areas that would allow for observation of traffic roadway patterns, driving behavior and, at the same time, would provide for the safety of observers. In addition, each District Commander was asked to designate a contact person who could act as a liaison with the research team. Between April 15th and 17th, each commander forwarded at least four potential observation locations to the research team. On April 20th and 21st, three members of the research team visually inspected each of the provided locations and the locations were ranked within each district. In addition, members of the research team met with several of the District Commanders to explain the procedures for conducting the observations.

Beginning in March 2005, the UC research team began recruiting and training student observers. Roadway observations began on May 1st, 2005 and concluded on November 19th, 2005. During this period a total of 33 observation trips (three consecutive observation days per trip) were conducted at 15 different locations³. During the week before an observation was to be conducted, the research team contacted the District Commander or designated representative and provided the person with the selected observation location, the times during which the observations would be carried out, and the times when the observers would be at each district to secure and return speed detection devices.

DEPARTMENT-WIDE TRAFFIC STOP DATA COLLECTION PROCESS

Department-wide data collection on the Traffic Stop Data Form began on approximately May 18th, 2005 and continued through February 28th, 2006. During this time period, 50,721 traffic stop forms were received and properly scanned by the UC research team.

In early June 2005, preliminary analyses of the data indicated that there were some misunderstandings among officers regarding the collection of the data and the specific coding instructions. On June 10th, 2005 a communication was emailed to Deputy Chief Green containing the previously distributed coding rules asking that they again be forwarded to each of the District Commanders. Shortly thereafter, on June 22nd, 2005 the first bi-weekly report was submitted to the CDP. This report documented rejection rates (the rate at which Traffic Stop Data Forms were rejected by the scanner due to various human generated errors such as double entries, not fully marking a bubble, stray marks, and not filling in any information) and missing data rates (the rate at which forms contained missing data by data field). These rates were provided for the entire department and also by District. This first report also contained an explanation of how each rate was computed and the data collection fields that were especially problematic. The bi-weekly report also emphasized the need for officers to follow the coding rules and for supervisors to closely review the forms prior to their being placed in the mail.

The bi-weekly written reports described above were emailed to the command staff throughout the project. Several District Commanders were able to correct the data collection problems within their districts almost immediately after being notified. Other districts, however, took longer to meet the project team's recommended 5% missing data rate. After the first six weeks of data collection, the errors on the data collection forms dramatically decreased across all districts, and thus only the information collected after July 1st, 2006 is included in the analyses within this report. The University of Cincinnati research team also delivered two presentations to the command staff with updates regarding the status of the research project and preliminary data findings (Sep 21st, 2005 and Dec 15th, 2005).

The initial contract specified a one-year data collection effort. On July 19th, 2004, the project was extended until Dec 31st, 2005. Due to the continual delays documented above, the University of

³ Not all of these observation trips resulted in the collection of data that could be used for the traffic stop analysis. For a more detailed explanation, please see **Section 4**.

Cincinnati research team advised CDP officials that only six months of data could be collected with a data collection start date of May 1st 2005 and end date of Dec. 31st 2005. The research team had simply run short of time and funding. As noted above, however, data was not collected during the first two weeks in May, and the subsequent six weeks of data collected (May 18th – June 30th, 2005) could not be used in any analyses because of the poor quality and questionable validity. Because of these data quality issues, a decision was made to consider this six week period a department-wide pilot test. Therefore, in November 2005, there were only five months of valid data available for analyses. It was recommended by the research team that the CDP continue the data collection effort for a longer time period in order to ensure an accurate and reliable traffic stop study. Chief McGrath indicated his interest in continuing the data collection effort, and a budget of \$9,911 was submitted for consideration of an additional three months of data collection, and two additional months for data analyses and report writing. Due again to contractual delays between the City of Cleveland and the University of Cincinnati, this contract extension was actually signed after the additional three months of data were collected. This contractual delay, however, forced the research team to suspend work on the analyses, and as a result the issuance of the final report has been delayed.

SUMMARY

While the intention of all parties was to begin the project in January 2004 when the proposal was submitted, numerous unexpected delays prevented the University of Cincinnati research team from initiating project activities until July 2004. Additional hurdles were also encountered that caused project delays. For instance, contractual issues had to be resolved between the University of Cincinnati and the City of Cleveland. In addition, existing issues between the CPPA and the city had to be resolved and CPPA concerns with the project had to be mediated by the Cleveland Safety Director.

- The University of Cincinnati research team was asked to submit an amended proposal that included a reduced budget.
- Issues needed to be resolved between the legal departments of the City of Cleveland and the University of Cincinnati.
- Approval from the University of Cincinnati Institutional Review Board was requested in June 2004 and secured in July 2004.
- The primary task of the University of Cincinnati research team was to collect data that would permit them to address concerns that decisions of officers to stop motorists were based on citizens' race or ethnicity. As such, research team efforts were primarily directed at developing procedures to allow for the collection of valid and reliable data that would allow for an assessment of these concerns.
- In August 2004, the University of Cincinnati research team suggested the data fields that should be included on the Traffic Stop Data Form. In negotiation with a working group formed by Deputy Chief Green, a form was developed in October 2004.
- The research team worked with Scantron to develop the form and software needed to read the traffic forms and convert the information into a usable database.

- Detailed coding instructions were provided to the CDP concerning how to code each officer initiated traffic stop.
- An initial Pilot Test was conducted with officers from the Traffic Unit, after which feedback was provided and changes were made to the Traffic Stop Data Form.
- The research team suggested introducing the project during officer training. Instead, the CDP decided to produce a video containing project information that was to be viewed by all officers.
- Department-wide data collection began on May 18th. Bi-weekly summaries of the traffic stop data were sent via email to the command staff throughout the project.
- Sites were selected to perform the roadway observations of traffic patterns and driving behavior to collect the traffic observation data. These observations occurred between May 2005 and November 2005.

3. TRAFFIC STOP DATA METHODS AND DESCRIPTIVE STATISTICS

OVERVIEW

This section first addresses the methodology used in the collection of the traffic stop data during the course of this research project. The method for the traffic stop study included the development of a traffic stop form to be completed in every police-initiated traffic stop encounter, the procedures implemented for the completion of a pilot test of the traffic stop form, and the department-wide training on the Traffic Stop Data Form for the 8-month period of data collection. Based on this data collection, this section next reports the descriptive statistics for the traffic stop forms. That is, the information collected on the Traffic Stop Data Forms is summarized in a descriptive manner at the department, district and the zone level. **These initial statistics are not meant to provide any conclusions as to the behavior of the CDP; rather, they are descriptive in nature to provide an overview of the data collected during the 8-month study.**

TRAFFIC STOP DATA COLLECTION METHOD

As discussed in **Section 1**, one of the primary issues with biased-based profiling data is the validity of the actual stop data that is collected by individual officers. The importance of maintaining reliable and valid traffic stop data cannot be understated. It is imperative that police departments initiate data collection efforts that incorporate considerable forethought and planning. The following factors are among the most important to consider: 1) selecting the mechanism for data collection, 2) developing the data collection instrument, 3) conducting a pilot test, 4) training officers to use the data collection instrument, 5) minimizing officer disengagement, and 6) developing a data auditing system. Each of these factors, and the efforts of the research team and the CDP to resolve these issues, is discussed in the first portion of this section.

SELECTING THE MECHANISM FOR DATA COLLECTION

A group of approximately 5-10 community group members and officials from the police department routinely gather every third Thursday of the month to discuss the traffic stop research project and other police-community related issues. This group initially served as a loosely formed “committee” to guide the data collection effort. Members of the University of Cincinnati research team presented different data collection mechanisms to this group, including the use of MDTs, palm pilots, hand written forms, and scannable forms, and suggested the use of a Scantron data collection system as a cost-effective and reliable alternative to handwritten forms. Scannable forms were preferred because of the time-intensive and costly nature of using hand-entered forms and the lack of computer technology to allow for direct data entry by all officers. Thus, recognizing the size and complexity of the data collection task, the research team recommended and the committee approved the use of scannable forms. A scanner (i.e., the Scanmark ES 2800) and data collection forms were purchased by the CDP from Scantron, Inc. The data scanner reads each individual form and enters the information into a compiled data file.

DEVELOPING THE DATA COLLECTION INSTRUMENT

The specific data collection instrument utilized by the CDP was developed over the course of several months (December 2004- February 2005) through a series of discussions involving the University of Cincinnati research team and CDP officials. Initially, a proposed form was forwarded to the CDP by the research team and three commanders (Commander Morrow, Commander Cuevas and Commissioner Bungo) met and responded with their proposal. Committee members sought to develop a form that would include the relevant data items while limiting officer disengagement due to the possible cumbersome task of actually collecting the data.

The committee was guided in their decisions by examining data collection forms used in other departments and data collection guidelines developed for the National Institute of Justice. The specific elements included on the form represent a compromise between what is needed to assess patterns of officer decision-making, and the logistical issues associated with collecting information. The form was devised to capture the most possible information without interfering with officers' duties and/or lengthening traffic stops for citizens.

CDP officers were instructed to fill out these forms after *every officer-initiated* traffic stop. Traffic stops based on citizens' initiation or as the result of police check-points (e.g., registration, DUI, seat belts, etc.) were not included in the data. In addition, contact with citizens resulting from traffic accidents was also excluded from the data collection effort.

The traffic stop form ultimately utilized by officers gathered information regarding: 1) the stop (e.g., date/time, location, type of roadway, reasons for the stop, and the duration of the stop), 2) the driver (e.g., gender, age, race/ethnicity, zip code of residency), 3) the vehicle (e.g., condition of the vehicle, modifications, state of registration, number of passengers), 4) the outcome of the stop (e.g., citation, written warning, arrest, search, property seized during the search), and 5) identification information (e.g., location of the stop by zone, and officers' badge number, unit number, and district number).

The gender and racial/ethnic characteristics of drivers stopped were determined through officers' perceptions. That is, drivers were not asked to identify their gender, race, or ethnicity. The use of officers' perceptions of drivers' race/ethnicity is an acceptable method for examining racially based policing. Officers may incorrectly perceive drivers' actual race and/or ethnicity. This possible misperception, however, is irrelevant for data collection analyses that seek to explain officer decision making. Accusations of racial profiling are based on the presumption that officers treat minority citizens differently. Therefore, proper data collection efforts must identify officers' *perceptions* of the race/ethnicity of the driver, not the driver's actual race/ethnicity. Other information about the driver (year of birth and residential zip code) was gathered from drivers' licenses.

CONDUCTING A PILOT TEST

The University of Cincinnati research team developed an initial data collection instrument that was pilot tested by the Traffic Unit from February 1st to February 28th 2005. Prior to the initial pilot test conducted by the Traffic Unit, a brief training package was sent to Deputy Chief Green so all Traffic officers would be familiar with the traffic stop form and how to properly complete the form. Based on data results and informal feedback from the officers involved in the pilot test, the data collection form was slightly modified and the data collection effort was expanded department-wide in May 2005. Initial data analyses indicated that officers were not accurately completing the data collection forms. Therefore, the first two months of data collected department-wide (May and June, 2005) are *not* included in the data analyses and findings described throughout this report. A decision was made to consider this period a department-wide pilot test.

TRAINING OFFICERS TO USE THE DATA COLLECTION INSTRUMENT

Once the pilot test data was analyzed and the traffic stop form modified to address some problems with the form, a video was made describing the data collection effort and was disseminated across the department. Several members of the CDP introduced the project and then a research team member, Dr. James Frank, explained the data collection process, the types of data (stop forms, observations of traffic patterns) that would be collected during the project, the procedures to be employed to protect the confidentiality of project participants, and the importance of collecting reliable and valid data.

As is described in more detail in other sections of this report, this training method was apparently insufficient for producing a reliable and valid data collection effort. For instance, once data collection began department-wide in May 2005, it was clear that officers were not properly completing the traffic stop forms. This was likely due, in part, to the poor training received regarding the data collection effort, and the lack of details provided regarding when and how to properly complete the forms. Also, the proportion of stops that resulted in formal police action (citations and/or arrests) far exceeds the national average and raises questions about whether a traffic form was completed for every stop. Finally, we are still unsure of how the information in the project video was transferred to officers.

MINIMIZING OFFICER DISENGAGEMENT

As briefly described in **Section 1**, officer disengagement refers to a reduction in officers' activities due to changes in work conditions. Officer disengagement is a potential problem accompanying any change in reporting procedures. The extent and severity of officer disengagement after officer-citizen contact data collection efforts have been implemented, however, have not been adequately assessed in previous studies. It has been generally acknowledged that officer disengagement likely accompanies most data collection efforts initially; however, it is substantially reduced within four to six months, as the data collection becomes part of the officers' daily routines.

Officer disengagement can likely be minimized through a number of mechanisms. First, it is essential that rank-and-file officers are involved in the initial decision-making regarding the data collection effort. Second, issues of confidentiality of the data must be addressed. Third, there must be support (or at least partial “buy-in”) from the police union. Fourth, continual supervisory oversight and holding officers accountable for their activities is essential. Finally, there must be a commitment from department administrators for the data collection effort itself.

It is unfortunate that the Traffic Stop Study initially had few of these critical components necessary to minimize officer disengagement and produce an accurate data collection effort. Although lower ranked officers were initially consulted through the community group sessions regarding the use of the forms, their input was not continually sought throughout the research process. While issues of confidentiality were addressed by the research team, it was never clear if these assurances were properly communicated to field officers. The largest police union, the Cleveland Police Patrolmen’s Association (CPPA), was a source of opposition to this study. The relationships among the University of Cincinnati research team, the CDP Chief, and the President of the CPPA, Bob Beck, were strained, and negotiations involving the Safety Director were required to continue the planned research. Although union officials agreed not to challenge the data collection effort, they did not openly support it either, which likely limited research project credibility among the rank and file.

With a change in the Chief of Police on March 30th 2005 came better working relations between the research team and CDP. In addition, this administrative change signified that the data collection effort would be taken more seriously by the CDP command staff. After initial bi-weekly reports were distributed documenting officer failure to properly complete the traffic stop forms during the first two months, the command staff actively worked with the University of Cincinnati research team to collect reliable and valid data for the remaining months of data collection.

In order to get accurate information, officers were promised confidentiality. The identity of CDP officers was protected in the following ways. The forms filled out by individual officers were collected at the district level and mailed daily to a post office box rented by the research team. Once the individual forms were received and scanned by project personnel, they were stored in a locked file cabinet, within a locked project office at the University of Cincinnati until the electronic datasets were corrected for errors and considered ready for analysis. At that point, the actual data collection forms containing officers’ badge numbers were destroyed.

After the information was scanned into a database, officers’ badge numbers were used to combine the traffic stop data with officer demographic information (e.g., officers’ sex, race, length of service, age, rank, and current assignment). After the data was scanned and the files were merged, the badge numbers were deleted from the new data file. The original data with badge numbers was destroyed.

Using this procedure, individual officers’ identities cannot be disclosed. In this report, only aggregate comparisons are produced (e.g., differences in behavior patterns between male and female officers, majority and minority officers, particular units, etc.) and reported for the department as a whole. Officers were made aware of these procedures through the training

video. It is believed that the promise of confidentiality and adherence to confidentiality procedures could increase the validity of the data collection effort and reduce officer disengagement, although the precise impact cannot be measured.

Officer disengagement was also likely reduced due to supervisory oversight of the data collection effort after the initial months of data were collected by CDP officers. Field supervisors were required to review and sign every data collection card.

Despite these efforts, some officer disengagement is to be expected. The extent of officer disengagement can be estimated with measures of officer productivity. Assuming that officers continue their ratio of the number of stops to the number of citations issued, the extent of officer disengagement can be estimated by comparing the number of citations issued before and after the data collection effort. These analyses should be conducted at aggregate levels (e.g., district, shift, etc.) to determine if officer disengagement is concentrated in particular areas of the organization. Unfortunately, these data are not currently available to the University of Cincinnati research team.

DEVELOPING A DATA AUDITING SYSTEM

Maintaining data quality ensures reliable and valid results. There are five general ways that traffic stop data may be inaccurate: 1) the information is incorrectly recorded, 2) some stops are not recorded, 3) data is missing due to random and non-random errors, 4) data is intentionally missing, and 5) data contains misstatements of facts (Fridell, 2003). Data “auditing” can be used to check for these types of inaccuracies and to maintain quality control.

One typical method of data auditing – conducting cross-checks of traffic stop data with other data sources – was not possible. The traffic stop data could not be directly linked to any other existing data because the Traffic Stop Data Form did not include unique identifiers. For example, the traffic stop form could not be connected to a citation form, arrest report, etc., that may have resulted from that stop, to check for the accuracy of the data. There were attempts to check the traffic stop data by comparing it to UTT data (citation data) collected by CDP, though as is discussed later in this section, these efforts were not successful.

The data auditing procedures used by the research team included: 1) rejection of improperly completed forms by the scanner, 2) routine identification and correction of data errors and inconsistencies in the compiled data sets, 3) continual feedback to CDP administrators regarding the levels of errors and missing data, and 4) comparisons of UTT (citation data) compiled by CDP to the number of citations recorded on the traffic stop form. These procedures are described in more detail below.

DATA COLLECTION PROCESS

Several specific tasks were associated with receipt and processing of the traffic stop forms. The forms were collected at each district and mailed nightly to the research team. The research team purchased a Post Office Box in Cincinnati specifically for the receipt of the forms. The forms

were then logged in by the research team and scanned for purposes of transferring the data from the paper forms into electronic data. This process also allowed a determination of any missing data. Every two weeks, a brief report was then forwarded back to the CDP containing general information about the collected traffic stop data.

BIWEEKLY DATA REPORTS

One method of data auditing was the creation of bi-weekly reports, which were emailed to the command staff of the CDP throughout the traffic stop data collection effort. Each report included data that was received during the prior two week period. The bi-weekly reports were in a format that resembled **Table 3.1**. After each table highlights were provided that often focused on data collection areas that needed attention.

Table 3.1 provides a summary of data received and provided in the bi-weekly reports, for the 8-month study. The first table column indicates the number of forms received department-wide and from each District (including the Traffic Unit). The next table columns report number of traffic stop forms initially rejected by the scanner, the percentage of forms rejected by the scanner, and the percentage of forms with missing data. The missing data and inconsistencies column reflects traffic stop forms that either had missing information or information that was not logically consistent. For example, if a traffic stop form indicated that property was seized, but no search occurred, this would be considered an inconsistency. The next three columns report the percentage of traffic stop forms that were missing race of the driver, a valid badge number or a valid unit number. The final column reflects the number of traffic stop forms that were included in the data set for analysis. These results of all analyses are discussed in **Sections V, VI and VII**.

Table 3.1: Scan Form Report for Jul, 2005 - Feb, 2006

Zone	Total # Received	# Reject Initially	% Reject Initially	% Missing Any Data	% Missing Any Data and Inconsist.	% Missing Race	% Missing Valid Badge #	% Missing Valid Unit #	Total # in Dataset*
CDP	44,796	1,942	4.34	5.6	6.7	1.7	0.3	1.9	43,707
Traffic	11,352	286	2.52	4.4	5.3	2.1	0.1	1.5	11,283
District 1	4,518	203	4.49	8.0	8.9	0.7	0.3	4.7	4,370
District 2	3,831	165	4.31	4.9	5.7	0.7	0.1	1.0	3,702
District 3	5,203	190	3.65	4.4	5.4	1.9	0.2	1.1	5,126
District 4	7,934	344	4.34	5.6	6.9	2.3	0.3	1.5	7,736
District 5	4,251	180	4.23	4.8	6.5	1.2	0.6	2.8	4,099
District 6	7,653	566	7.40	7.3	8.6	1.8	0.3	1.7	7,385

* The total number of stops included in the data set do not equal the total number of cards received because the total number of cards received are based on two-week periods beginning July 2005. Therefore, cards from May and June 2005 were submitted in July 2005 but were discarded from the data set.

With this information, the CDP command staff was able to provide continuous feedback to their supervisors regarding officer compliance with departmental directives. Bi-weekly report comments varied depending on the quality of the collected data, though each report emphasized the need to reduce each rate (rejection and missing) to less than 5 percent. Over time, this goal was achieved by most of the Districts and the Traffic Unit.

UTT DATA

An alternative method to ensure that a data collection effort is producing accurate and reliable data is to compare it against another dataset. In August, 2005, as a means to check the reliability of the collected data, the research team requested and received UTT data from the CDP. UTT data contains counts of the number of citations issued by each District. In September, 2005, preliminary analysis comparing the UTT data and the number of citations issued as reported on the traffic stop form was conducted. A report was then sent to the CDP in an effort to reconcile the observed data differences. It was determined at this point that citations issued to citizens from non-traffic related behaviors were included in the UTT data. An attempt was then made to determine if these citations could be removed from the UTT data. In October 2005, a request was forwarded to Deputy Chief Green asking for two more months of UTT data. Unfortunately, upon examination of the updated dataset, it was determined that the non-traffic citations could not be specifically identified and removed from the UTT data; thereby, making the two data sets irreconcilable. Therefore, this reliability check of the traffic stop data could not be performed.

TRAFFIC STOP DATA DESCRIPTIVE STATISTICS

The next portion of this section describes the traffic stop data that was collected between July 1st, 2005 and February 28th, 2006. The findings address the characteristics of the stops, the drivers and, to a limited extent with stop outcomes, the behavior of officers. **Tables 3.2 – 3.7** report the specific data segments presented by category across the department, each district, and the Traffic Unit. Data for these aggregate levels are presented for comparison purposes only. While the data tables vary slightly depending on the issue addressed, the findings allow for an examination of the overall city levels, comparison across districts and comparison across zones.

This section describes the findings based on a compilation of eight months of data (July 1st, 2005 – February 28th, 2006) received from the Traffic Stop Data Forms. The characteristics of traffic stops and the characteristics of drivers are reported in a strictly descriptive nature based upon forms submitted by CDP officers. **This summary does not suggest any causal influences, as those are discussed in subsequent sections of this report.**

TRAFFIC STOP CHARACTERISTICS

Based on the valid data available, 43,707 traffic stops were initiated by CDP officers between July 1st, 2005 and February 28th, 2006. As noted previously, the first 6 weeks of data were considered the pilot test phase and are not included in the analyses. The Traffic Unit accounted for slightly more than one-fourth (25.8%) of the total stops (11,283). **Table 3.2** documents the

specific details of the traffic stops including: day, time, shift, roadway type, number of passengers, and duration of the stops by department, district and zone level. Across the department, the majority of the stops were initiated on a weekday (80.5%) and occurred during the daytime (55.3%). A substantial majority of the stops occurred on a main city roadway (71.6%), while an additional 19.8% occurred on a local neighborhood street. The vehicles stopped had on average 0.7 passengers. Slightly more than 80% of the stops lasted between 1-15 minutes in duration, while over 94% of the stops were completed within 30 minutes. Please refer to **Table 3.2** for specific variation across areas of the city and districts.

Table 3.2: Traffic Stop Characteristics By Department, District & Zone (p. 1 of 2)

Zone	Total # of Stops	Day of Stop % Weekday	Time of Stop % Daytime	% Inter.	Roadway Type			# of Passengers Avg/vehicle	Duration of Stop (minutes)			
					% Main	% Local	% Other		% 1-15	% 16-30	% 31-60	% 61+
CDP Dept	43,707	80.5	55.3	7.7	71.6	19.8	0.9	0.7	80.2	14.6	4.2	1.1
Traffic Unit	11,283	77.1	85.6	22.3	66.9	10.5	0.4	0.7	88.6	9.2	1.7	0.6
District 1	4,370	84.6	49.1	1.7	82.5	15.2	0.6	0.6	81.4	13.4	4.1	1.1
District 2	3,702	74.8	21.5	3.4	73.6	21.1	1.9	0.8	79.3	13.3	5.6	1.8
District 3	5,126	78.3	33.7	8.4	75.6	15.7	0.8	0.8	68.8	21.7	8.0	1.5
District 4	7,736	83.4	51.4	0.5	73.3	25.7	0.5	0.8	72.3	20.9	5.7	1.2
District 5	4,099	84.8	57.0	0.5	70.3	28.9	0.3	0.6	79.0	15.7	4.0	1.3
District 6	7,385	82.5	47.8	2.0	68.1	27.9	2.1	0.7	84.1	11.9	3.1	0.9
Zone Level												
Zone 111	849	85.2	64.7	11.7	72.1	15.6	0.6	0.6	87.4	9.1	2.2	1.3
Zone 112	1,994	82.2	46.8	5.7	79.9	14.3	0.2	0.6	87.7	9.2	2.8	0.4
Zone 113	788	80.0	47.0	15.8	67.8	16.2	0.3	0.6	77.4	14.6	5.6	2.4
Zone 121	717	83.1	72.3	16.6	72.2	10.5	0.7	0.6	81.0	14.3	3.9	0.8
Zone 122	940	88.9	85.2	13.2	73.8	8.2	4.8	0.5	88.6	7.6	3.2	0.6
Zone 123	1,186	78.4	77.5	26.6	61.6	10.9	0.8	0.6	83.7	13.1	2.5	0.8
Zone 211	901	78.7	60.5	15.5	69.4	14.9	0.2	0.6	85.8	9.4	2.3	2.4
Zone 212	863	71.0	32.8	9.9	76.4	12.2	1.6	0.7	81.0	12.1	6.0	0.9
Zone 213	929	68.1	25.0	16.5	45.9	37.7	0.0	0.6	92.3	5.3	1.8	0.7
Zone 221	953	74.9	37.3	7.1	78.4	14.0	0.5	0.8	78.8	13.8	6.0	1.5
Zone 222	2,057	82.6	69.2	10.7	80.0	7.2	2.2	0.7	87.9	8.4	3.1	0.7
Zone 223	434	79.7	38.3	9.0	77.7	12.4	0.9	0.7	77.7	14.3	5.5	2.5
Zone 224	561	84.9	79.0	41.8	52.7	5.4	0.2	0.5	84.5	10.5	3.9	1.1
Zone 311	2,956	59.4	46.1	10.5	77.4	11.9	0.2	0.8	80.5	14.7	3.7	1.2
Zone 312	1,187	78.0	65.1	22.6	70.6	6.2	0.5	0.7	79.6	14.0	4.5	1.9
Zone 313	791	82.2	62.3	20.4	68.2	11.1	0.3	0.7	67.7	23.7	7.6	1.0
Zone 321	653	81.8	43.8	10.9	74.7	12.6	1.8	0.7	66.2	21.6	10.4	1.8
Zone 322	847	83.7	42.9	16.4	70.5	12.6	0.5	0.7	80.6	13.7	4.7	0.9
Zone 323	1,216	79.8	36.0	1.4	83.8	14.6	0.3	0.7	71.5	20.1	7.1	1.4
Zone 324	606	78.9	47.0	2.6	78.7	17.3	1.3	0.8	63.6	25.5	9.9	1.0

Table 3.2: Traffic Stop Characteristics By Department, District & Zone (p. 2 of 2)

Zone	Total # of Stops	Day of Stop % Weekday	Time of Stop % Daytime	% Inter.	Roadway Type			# of Passengers Avg/vehicle	Duration of Stop (minutes)			
					% Main	% Local	% Other		% 1-15	% 16-30	% 31-60	% 61+
CDP Dept	43,707	80.5	55.3	7.7	71.6	19.8	0.9	0.7	80.2	14.6	4.2	1.1
Zone Level												
Zone 411	1,817	86.6	52.0	0.3	89.4	10.3	0.1	0.9	89.2	8.8	1.7	0.4
Zone 412	590	83.7	51.0	0.9	72.3	25.3	1.5	0.8	58.7	29.5	9.9	1.9
Zone 413	1,199	77.6	63.1	0.3	44.6	54.7	0.4	0.7	68.1	23.2	7.3	1.5
Zone 414	517	78.9	41.9	0.2	74.9	24.8	0.2	0.8	73.1	20.3	6.2	0.4
Zone 421	580	81.2	51.0	0.2	68.1	30.7	1.0	0.8	63.6	27.8	6.6	2.1
Zone 422	1,575	83.0	62.1	0.4	76.4	22.7	0.4	0.8	74.2	20.6	4.2	1.0
Zone 423	1,087	85.0	63.1	0.6	66.1	32.9	0.4	0.7	67.3	24.6	6.8	1.3
Zone 424	951	85.7	39.9	1.1	80.7	17.9	0.4	0.8	79.6	15.0	4.3	1.1
Zone 425	274	84.3	74.8	0.4	88.7	10.6	0.4	0.7	63.5	27.4	8.0	1.1
Zone 511	977	83.1	57.5	7.4	72.3	20.1	0.2	0.7	71.8	21.4	5.9	0.9
Zone 512	713	85.8	72.1	1.1	78.4	19.5	1.0	0.7	82.2	14.5	2.5	0.8
Zone 513	1,023	85.2	61.6	0.2	71.4	28.3	0.2	0.6	83.1	12.1	3.7	1.1
Zone 514	684	89.2	61.7	0.2	75.9	24.0	0.0	0.6	79.8	13.5	5.1	1.6
Zone 521	554	89.4	77.0	0.4	68.4	30.9	0.4	0.6	85.2	11.6	2.5	0.7
Zone 522	374	86.6	69.8	0.8	61.5	37.4	0.3	0.9	89.0	8.0	2.1	0.8
Zone 523	952	86.8	70.4	1.2	71.2	27.4	0.2	0.6	78.1	19.8	1.4	0.8
Zone 611	959	84.2	42.4	1.9	76.1	21.0	1.0	0.9	80.9	14.3	3.2	1.6
Zone 612	2,006	84.3	45.0	1.0	70.3	23.1	5.5	0.8	83.3	12.5	3.0	1.2
Zone 613	1,704	86.4	58.1	1.0	65.2	32.8	1.1	0.7	78.4	17.9	2.7	1.0
Zone 621	562	81.0	52.9	4.5	76.8	18.5	0.2	0.7	80.4	17.3	2.1	0.2
Zone 622	1,450	81.9	62.0	4.0	62.6	32.7	0.7	0.7	87.5	9.7	2.3	0.5
Zone 623	1,596	75.8	51.1	12.4	55.7	31.6	0.3	0.6	88.6	7.2	3.5	0.8

Table 3.3 provides additional information concerning the vehicle that was stopped. Only a small percentage of stopped vehicles department-wide (1.8%) had some form of after-market modification (i.e., tinted windows, etc.). Officers described 46.4% of the vehicles they stopped as being in good condition, 45.7% in fair condition, and 7.8% in poor condition. Over 90% of the vehicles stopped across the department were registered in Ohio (93.0%).

There was some variation across districts in officer perceptions of the condition of stopped vehicles. Specifically, the district percentages for “good condition” vehicles varied from a low of 27.8% in District 4 to a high of 56.0% in District 1. In addition, there was considerable variation across zones as far as stops involving good condition cars. Only 14.4% of the cars stopped in Zone 413 were reported as being in “good condition”, compared to 68.7% of the cars stopped in Zone 122.

The percentage of cars registered in Ohio also varied across the city. This is most apparent in **Table 3.3** when the figures are compared across zones. Zones with Ohio registration percentages below 90% generally had substantial numbers of stopped vehicles that were “not registered” versus registered in another state. This is most obvious with vehicles stopped in Zone 413 (41.1% were reported as not registered).

Table 3.3: Characteristics of Vehicles Stopped By Department, District, and Zone (p. 1 of 2)

Zone	Total # of Stops	% Vehicle Modified	Vehicle Condition			% Ohio Registered	% Other State	% No Registration
			% Good	% Fair	% Poor			
CDP Dept	43,707	1.8	46.4	45.7	7.8	93.0	1.9	4.7
Traffic	11,283	0.8	55.4	37.8	6.7	96.6	2.2	1.0
District 1	4,370	1.7	56.0	40.0	6.9	95.2	2.4	2.2
District 2	3,702	1.8	51.2	39.4	9.4	96.0	1.3	2.1
District 3	5,126	2.2	40.6	48.6	10.7	91.4	1.6	6.5
District 4	7,736	1.7	27.8	64.4	7.6	86.8	2.5	10.2
District 5	4,099	2.1	44.9	46.7	8.4	84.9	1.6	13.3
District 6	7,385	2.9	48.7	44.1	7.1	96.8	1.2	1.3
Zone Level								
Zone 111	849	1.1	57.4	33.3	9.0	94.5	4.8	0.2
Zone 112	1,994	1.3	58.0	35.9	6.1	94.7	2.3	2.9
Zone 113	788	1.0	50.9	38.3	10.8	95.7	2.7	1.5
Zone 121	717	1.4	56.8	36.5	6.6	96.7	2.2	1.0
Zone 122	940	1.6	68.7	25.6	5.6	96.6	1.8	1.4
Zone 123	1,186	3.4	64.2	32.8	3.0	96.1	2.4	1.2
Zone 211	901	0.7	57.5	35.1	7.3	95.0	1.9	2.8
Zone 212	863	3.0	54.7	37.0	8.3	96.4	1.5	1.6
Zone 213	929	0.7	57.6	35.1	7.3	98.2	0.9	0.5
Zone 221	953	1.6	46.5	42.6	10.8	97.3	1.5	0.9
Zone 222	2,057	1.1	58.1	34.3	7.5	95.6	1.7	2.1
Zone 223	434	1.4	44.2	50.2	5.5	97.2	1.6	1.2
Zone 224	561	0.9	51.2	38.9	10.0	97.2	2.3	0.4
Zone 311	2,956	1.7	57.7	36.4	5.9	95.6	2.3	1.9
Zone 312	1,187	2.7	39.8	49.7	10.3	93.9	3.0	2.5
Zone 313	791	1.0	38.3	46.3	15.3	81.5	1.5	16.3
Zone 321	653	2.1	36.1	50.2	13.6	92.3	1.4	6.3
Zone 322	847	0.7	35.2	54.4	10.4	96.5	1.4	2.1
Zone 323	1,216	1.7	34.7	53.6	11.7	95.2	1.1	3.5
Zone 324	606	2.3	33.7	52.8	13.2	88.9	1.5	9.6

Table 3.3: Characteristics of Vehicles Stopped By Department, District, and Zone (p. 2 of 2)

Zone	Total # of Stops	% Vehicle Modified	Vehicle Condition			% Ohio Registered	% Other State	% No Registration
			% Good	% Fair	% Poor			
CDP Dept	43,707	1.8	46.4	45.7	7.8	93.0	1.0	4.7
Zone Level								
Zone 411	1,817	0.7	34.2	60.2	5.6	96.5	1.5	1.2
Zone 412	590	2.0	31.0	56.4	12.2	93.1	1.0	5.1
Zone 413	1,199	1.0	14.4	77.7	7.8	57.7	0.8	41.1
Zone 414	517	1.9	24.0	68.3	7.5	78.5	1.4	20.1
Zone 421	580	2.4	30.9	57.8	11.2	94.7	2.8	2.6
Zone 422	1,575	1.1	44.3	48.4	7.2	94.2	2.9	2.7
Zone 423	1,087	3.4	36.2	55.0	8.7	89.7	5.2	4.7
Zone 424	951	1.2	34.1	60.8	4.9	94.5	3.1	2.1
Zone 425	274	2.2	28.8	62.0	9.1	94.5	0.7	4.4
Zone 511	977	2.2	41.7	50.3	8.0	87.1	1.8	10.9
Zone 512	713	2.0	40.7	51.2	8.1	90.5	2.0	7.0
Zone 513	1,023	1.8	44.5	48.1	7.4	73.2	2.4	24.3
Zone 514	684	2.6	43.4	49.3	7.3	97.4	1.6	0.9
Zone 521	554	2.0	52.7	39.9	7.4	95.9	1.4	2.5
Zone 522	374	1.3	29.4	65.2	5.4	93.6	1.1	4.8
Zone 523	952	0.8	41.7	48.8	9.5	83.2	2.1	14.6
Zone 611	959	2.0	45.2	45.3	9.5	97.6	1.2	0.6
Zone 612	2,006	2.8	43.0	48.1	8.8	96.8	1.1	1.5
Zone 613	1,704	1.9	42.7	49.5	7.5	96.5	1.1	1.6
Zone 621	562	1.8	50.5	45.4	3.9	97.3	1.3	1.1
Zone 622	1,450	3.0	45.9	48.1	5.9	97.3	1.5	0.8
Zone 623	1,596	3.5	65.2	30.5	4.3	96.8	1.4	1.3

Table 3.4 reports the reasons for the stop, both preceding the stop (P) and subsequent to the stop (S) initiated by DOP officers. The reasons include speeding, moving violations, vehicle inspections and traffic enforcement. This table also includes the average speed over the limit observed for speeding traffic stops. All categories are summarized at the department, district and zone level.

Across the department, *misdemeanor moving violations* were the most frequent violation observed prior to the stop (53.8%). There is some variation across areas in the frequency of misdemeanor moving violations, with District 6 reporting misdemeanor violations as the reason preceding the stop of 63.1% of their drivers, compared to the Traffic Unit's 48.0% of drivers stopped. For each District and the Traffic Unit, this reason was the most likely one reported for the stop.

Speeding violations were the second most common reason (25.4%) preceding the traffic stop across the department. The Districts varied in the proportion of stops for speeding from a high of 37.8% in District 1 to a low of 12.5% in District 6. The *average speed over the limit* across the department was 16.8 miles per hour. At the district level, the average speed over the limit ranged from a high of 18.5 miles per hour over the limit in Districts 2 and 3, to a low of 13.7 miles per hour over the limit in District 6.

At the department level, the third ranking reason for stops was *equipment inspections* (6.8%) and *vehicle registration* (6.8%). When examined at the district and unit level, 4 districts (Districts 1, 4, 5 and 6) all ranked *vehicle inspections* as the third most common reason for stopping a vehicle, while District 2, District 3 and the Traffic Unit reported *equipment inspection* as the third most frequent reason.

Two of the traffic stop reasons were much more likely to have been observed subsequent to the stop, in contrast to reasons preceding the traffic stop. Specifically, across the department *equipment inspection* was noted as a reason preceding the stop in 6.8% of the situations and 16.0% of the reasons subsequent to the stop. Likewise, the percent of stops for *license violations* increased from 1.2% to 14.7% when preceding and subsequent reasons are compared.

Table 3.4: Reason for Stop By Department, District, & Zone (1 of 2)

	Total # of Stops	% Speeding		Average Amount Over Limit	% Moving Misdemeanor		% Moving Felony		% Equip. Inspection		% Preexisting Information		% Regis.		% License		% Special Traf. Enforcement		% Other	
		P	S		P	S	P	S	P	S	P	S	P	S	P	S	P	S		
CDP Dept.	43,707	25.4	0.6	16.8	53.8	5.3	0.3	0.1	6.8	16.0	0.5	0.2	6.8	4.0	1.2	14.7	1.0	0.3	5.8	11.0
Traffic Unit	11,283	35.4	0.5	18.1	48.0	5.7	0.1	0.1	8.4	18.7	0.1	0.1	7.9	4.8	0.8	12.6	0.3	0.1	2.6	12.2
District 1	4,370	37.8	0.2	17.4	49.0	4.4	0.2	0.0	3.1	10.8	0.5	0.2	4.1	2.2	0.9	9.6	0.2	0.0	4.9	3.7
District 2	3,702	8.5	1.5	18.5	62.9	4.9	0.4	0.2	6.9	15.0	2.1	0.2	5.2	3.1	1.2	15.1	0.3	0.0	15.0	15.2
District 3	5,126	21.0	0.7	18.5	45.7	6.4	0.4	0.1	15.2	28.6	0.7	0.3	8.6	6.1	1.4	18.3	0.2	0.0	8.0	10.5
District 4	7,736	29.7	0.2	14.4	54.3	6.6	0.6	0.1	4.1	21.1	0.3	0.1	5.8	4.3	1.0	21.2	0.2	1.1	5.0	13.1
District 5	4,099	20.0	1.0	16.8	59.6	2.5	0.5	0.2	5.5	7.0	0.3	0.0	7.4	3.2	1.1	12.3	0.7	0.2	4.4	3.4
District 6	7,385	12.5	0.6	13.7	63.1	4.6	0.4	0.1	4.3	6.1	0.5	0.3	6.8	3.3	1.6	12.7	4.6	0.1	6.5	13.5
Zone Level																				
Zone 111	849	34.9	0.5	17.5	53.2	5.5	0.1	0.0	4.5	14.7	0.4	0.1	4.6	2.4	0.5	8.6	0.6	0.4	2.1	3.4
Zone 112	1,994	41.3	0.5	18.2	51.8	5.6	0.2	0.1	2.8	13.6	0.1	0.2	2.2	2.1	0.5	9.6	0.3	0.0	2.1	3.4
Zone 113	788	37.4	0.8	19.1	39.7	5.6	0.8	0.0	5.1	8.6	0.6	0.3	7.1	2.9	1.7	8.8	1.1	0.0	6.9	6.6
Zone 121	717	47.3	0.1	16.4	35.7	3.1	0.0	0.0	6.4	17.3	0.1	0.1	6.4	4.2	1.3	12.6	0.0	0.0	5.7	2.2
Zone 122	940	32.9	2.9	16.0	53.2	10.2	0.0	0.1	4.9	21.2	0.7	0.0	2.3	1.9	0.5	9.4	0.1	0.0	7.0	7.2
Zone 123	1,186	47.1	0.1	16.6	41.2	9.3	0.0	0.0	2.0	18.5	0.6	0.1	3.8	3.5	0.8	8.7	0.1	0.3	5.4	4.7
Zone 211	901	37.5	1.1	18.8	43.5	4.8	0.1	0.1	9.9	14.4	1.0	0.0	6.6	2.9	0.7	10.9	0.0	0.0	4.0	11.2
Zone 212	863	17.3	1.6	17.6	57.6	5.3	0.5	0.6	6.8	14.1	0.1	0.0	6.8	3.1	0.5	11.8	0.8	0.1	10.7	14.5
Zone 213	929	16.2	2.1	19.4	76.4	7.8	0.3	0.0	2.4	21.1	0.2	0.3	1.8	2.9	0.5	5.7	0.0	0.0	3.7	19.1
Zone 221	953	13.8	0.1	17.9	51.6	4.7	0.2	0.0	10.0	13.5	2.5	0.3	5.5	4.4	1.3	21.3	0.0	0.3	19.5	18.4
Zone 222	2,057	18.1	0.5	17.9	59.2	2.4	0.1	0.2	5.2	9.5	1.6	0.1	6.7	4.2	1.1	12.1	0.2	0.0	9.9	15.6
Zone 223	434	23.0	1.4	17.9	51.4	7.1	0.2	0.0	9.9	13.4	2.3	0.0	5.5	4.8	0.5	18.2	0.2	0.0	9.5	17.7
Zone 224	561	37.4	0.0	19.5	42.1	10.5	0.0	0.4	10.2	26.9	0.2	0.0	4.8	3.9	0.4	8.2	0.0	0.0	6.4	7.7
Zone 311	2,956	27.2	0.2	19.2	52.7	5.5	0.3	0.0	9.0	20.6	0.1	0.2	7.2	4.5	1.1	11.7	0.0	0.1	4.5	8.5
Zone 312	1,187	32.8	0.3	19.7	39.4	6.8	0.2	0.0	13.0	22.3	0.3	0.1	9.8	7.8	1.9	19.1	0.0	0.0	6.2	9.6
Zone 313	791	21.5	0.5	17.9	44.9	5.8	0.3	0.0	17.2	25.7	1.0	0.0	10.4	8.1	1.5	20.0	0.0	0.0	6.1	9.5
Zone 321	653	13.0	1.5	19.4	49.5	7.4	0.0	0.0	15.3	28.2	0.8	0.5	10.6	8.9	2.1	25.3	0.8	0.2	10.0	11.0
Zone 322	847	30.6	0.4	18.7	39.6	4.8	0.5	0.1	16.3	30.2	0.7	0.1	7.8	4.8	0.9	13.7	0.8	0.0	3.7	10.6
Zone 323	1,216	26.6	1.1	18.5	44.4	4.9	0.8	0.1	12.5	29.1	1.0	0.4	7.7	6.7	1.0	18.1	0.0	0.0	7.3	14.6
Zone 324	606	11.2	0.8	17.7	51.3	5.0	0.2	0.2	17.8	26.2	0.0	0.5	12.4	4.5	1.5	19.5	0.2	0.0	6.8	7.8

P – Prior to the Stop; **S** – Subsequent to the Stop

Table 3.4: Reason for Stop By Department, District, & Zone (2 of 2)

	Total # of Stops	% Speeding		Average Amount Over Limit	% Moving Misdemeanor		% Moving Felony		% Equip. Inspection		% Preexisting Information		% Regis.		% License		% Special Traf. Enforcement		% Other	
		P	S		P	S	P	S	P	S	P	S	P	S	P	S	P	S	P	S
CDP Dept.	43,707	25.4	0.6	16.8	53.8	5.3	0.3	0.1	6.8	16.0	0.5	0.2	6.8	4.0	1.2	14.7	1.0	0.3	5.8	11.0
Zone Level																				
Zone 411	1,817	73.1	0.2	14.4	18.9	5.8	0.1	0.1	1.8	18.1	0.1	0.1	2.9	3.1	0.5	16.0	1.3	1.3	2.9	17.6
Zone 412	590	18.3	0.0	14.7	53.6	6.1	1.4	0.2	6.4	23.7	0.7	0.2	11.9	9.2	3.1	32.2	0.3	0.3	6.3	15.6
Zone 413	1,199	6.8	0.1	14.6	72.4	6.1	1.1	0.3	6.5	26.9	0.3	0.3	8.8	4.6	2.1	23.7	0.0	0.9	4.1	5.8
Zone 414	517	14.7	0.4	13.3	60.9	7.7	1.2	0.0	6.0	18.6	0.2	0.2	10.6	7.7	3.1	23.4	0.0	0.0	5.2	9.5
Zone 421	580	12.9	0.2	14.2	64.0	6.7	1.0	0.0	6.2	17.4	0.2	0.2	8.5	4.1	2.4	26.0	0.2	1.7	6.7	16.6
Zone 422	1,575	24.6	0.1	15.1	59.6	4.8	0.4	0.2	5.4	24.1	0.0	0.1	7.7	4.8	1.2	25.1	0.1	1.3	4.1	19.9
Zone 423	1,087	5.2	0.4	15.1	73.3	9.1	0.4	0.2	6.9	17.3	0.4	0.1	7.1	3.6	2.1	21.4	0.2	0.4	5.9	13.6
Zone 424	951	43.4	0.2	14.2	46.1	7.4	0.1	0.1	1.9	17.6	0.3	0.0	3.4	2.3	0.5	18.1	0.0	1.2	5.6	16.9
Zone 425	274	13.5	0.0	14.1	76.3	4.7	0.0	0.0	2.2	35.8	1.5	0.0	2.9	6.2	0.7	17.9	0.0	0.0	4.7	10.2
Zone 511	977	13.7	0.8	17.4	65.5	1.8	0.5	0.0	6.2	5.4	0.4	0.1	9.7	3.1	1.3	10.2	0.0	0.0	4.0	6.7
Zone 512	713	18.0	0.3	16.3	57.5	2.0	0.0	0.0	8.0	8.6	0.4	0.0	9.1	2.7	1.5	11.1	0.6	0.7	4.5	4.2
Zone 513	1,023	41.9	2.4	16.9	41.3	1.9	0.3	0.2	4.4	6.2	0.0	0.0	6.6	3.4	1.0	11.0	0.0	0.1	3.5	3.1
Zone 514	684	20.5	0.3	17.2	58.2	1.2	1.0	0.6	7.9	15.2	0.0	0.0	8.0	2.2	1.6	16.1	0.0	0.0	4.4	5.1
Zone 521	554	9.6	0.4	16.9	70.0	5.1	0.4	0.0	4.9	10.7	0.5	0.0	7.9	3.1	1.4	11.2	0.0	0.4	5.1	4.7
Zone 522	374	25.7	0.3	16.0	47.3	2.7	0.0	0.3	12.8	7.8	0.5	0.0	11.2	3.7	0.8	11.2	0.0	0.0	3.2	2.9
Zone 523	952	8.9	0.2	16.2	75.5	2.1	0.4	0.2	5.6	10.7	0.2	0.0	4.4	3.4	0.2	13.0	2.4	0.1	2.3	5.4
Zone 611	959	14.6	0.5	13.9	64.0	3.8	0.3	0.3	4.3	4.0	0.9	0.0	8.3	2.8	0.8	15.3	0.2	0.0	6.8	12.5
Zone 612	2,006	7.7	0.1	14.0	52.6	3.3	0.6	0.1	4.6	6.7	0.7	0.4	7.2	3.4	1.4	12.5	16.7	0.2	8.4	11.9
Zone 613	1,704	16.5	0.4	14.4	61.9	5.5	0.5	0.2	4.7	7.8	0.2	0.2	8.1	3.8	2.6	12.1	0.0	0.0	5.5	17.6
Zone 621	562	7.5	0.7	15.2	78.5	5.0	0.5	0.0	6.1	17.3	0.0	0.7	5.3	5.2	0.2	17.1	0.0	0.0	3.2	8.0
Zone 622	1,450	9.7	1.3	13.4	71.3	5.5	0.1	0.1	6.2	6.7	0.3	0.3	7.2	3.2	1.5	10.9	0.0	0.0	4.8	10.8
Zone 623	1,596	28.6	0.8	15.3	51.9	4.5	0.3	0.0	7.1	8.6	0.3	0.3	9.0	3.5	1.5	14.3	0.0	0.1	5.6	16.2

P – Prior to the Stop; **S** – Subsequent to the Stop

DRIVERS' CHARACTERISTICS

Table 3.5 provides the synopsis of drivers' characteristics across the department, districts, and zone levels. Department-wide, the average age of drivers was 36.3, and 66.6% of the drivers stopped by officers were males. At the zone and district levels, the average age of drivers stopped was quite similar with the largest difference in average age occurring at the district level. For example, the average age of drivers stopped in District 2 was 32.9, compared to 37.9 by Traffic Unit officers. While males were consistently more likely than females to be stopped at all levels within the department, the greatest differences occurred when zone levels are compared. The highest percentage of male drivers stopped occurred in Zone 113 (74.1%), while the lowest percentage of male drivers were stopped in Zone 522 (58.7%).

The racial/ethnic background of drivers was also recorded by officers on the Traffic Stop Form. The racial and ethnic composition of drivers was visually determined by the officers. That is, no motorists were asked for their racial or ethnic category. These determinations were based solely on officer's perceptions. For data collected directly by police, the reliability and validity of citizens' race involves two related concerns. First, police may be reluctant to indicate drivers' race, or may simply report inaccurately. Second, officers may "disengage," or initiate fewer traffic stops overall. Both of these behaviors represent an effort by officers to protect themselves from criticism, departmental discipline, and potential lawsuits. From the officer's perspective, this is a reasonable response to data collection efforts that are specifically designed to identify officers who "racially profile" and engage in bias-based policing. Unfortunately, the validity of the data collected by police often cannot be directly assessed. There are strategies, however, to increase validity and reliability of this type of data collection. For the data collection effort with the CDP, for example, confidentiality was contractually promised by the research team. Although officers' badge numbers are initially reported on the data collection forms, the research team is required to strip this information from all data files after the demographic information has been successfully merged with the traffic stop data. Through the procedures included in the contract and approved by the University Institutional Review Board, CPPA officials and the City of Cleveland, individual officers cannot be identified in data analyses and the findings from the study may not be used for disciplinary purposes. Information about these protections was presented on the training video by a research team member and CPPA union officials agreed to these terms specifically.

Table 3.5: Characteristics of Drivers Stopped By Department, District, and Zone (p. 1 of 2)

Zone	Total # of Stops	Average Age	% Male	% White	% Black	% Hispanic	Race of Driver			% Unknown	% In-Zone Resident	% Cleveland Resident	% Ohio Resident
							% Native American	% Asian/Pac. Isl.	% Middle Eastern				
CDP Dept	43,707	36.3	66.6	30.5	61.5	4.6	0.1	0.5	1.1	1.6	29.1	62.3	97.8
Traffic	11,283	37.9	63.7	48.9	43.6	5.9	0.0	0.6	1.1	1.6	18.9	51.5	96.4
District 1	4,370	34.6	71.3	56.3	25.8	12.2	0.1	1.2	4.5	5.8	37.2	65.9	98.4
District 2	3,702	32.9	72.6	52.4	27.0	18.4	0.1	0.6	1.5	2.2	31.1	64.2	98.2
District 3	5,126	33.7	73.8	26.7	69.7	2.1	0.1	0.6	0.9	1.6	28.4	67.8	98.3
District 4	7,736	37.1	65.3	7.0	92.4	0.2	0.1	0.1	0.3	0.4	34.9	70.1	98.6
District 5	4,099	37.8	64.6	18.4	79.9	0.5	0.0	0.6	0.6	1.2	24.1	65.9	98.2
District 6	7,385	36.9	63.1	13.3	85.9	0.3	0.0	0.2	0.3	0.5	36.8	62.9	98.5
Zone Level													
Zone 111	849	36.5	66.6	61.5	26.2	9.6	0.0	0.6	2.1	2.7	26.4	59.2	98.1
Zone 112	1,994	34.4	69.7	54.8	25.2	14.8	0.0	1.1	4.0	5.1	38.4	66.2	98.0
Zone 113	788	34.3	74.1	58.7	23.9	12.8	0.1	0.8	3.7	4.6	40.0	66.0	97.3
Zone 121	717	34.8	71.6	66.7	17.6	7.3	0.3	1.4	6.6	8.3	32.1	53.9	96.5
Zone 122	940	37.7	65.0	71.7	18.1	6.2	0.0	0.8	3.2	3.9	38.6	52.7	96.4
Zone 123	1,186	36.1	65.5	66.4	23.9	4.7	0.2	1.5	3.3	5.0	20.1	45.9	96.0
Zone 211	901	37.3	71.3	53.0	30.9	14.4	0.1	0.8	0.9	1.8	25.7	59.7	97.2
Zone 212	863	33.5	73.2	47.5	38.0	11.2	0.0	0.5	2.8	3.3	7.9	54.8	97.8
Zone 213	929	33.7	68.9	60.5	27.8	8.7	0.0	0.9	2.2	3.0	13.8	53.1	98.2
Zone 221	953	33.4	70.8	48.1	23.2	26.8	0.1	0.4	1.3	1.8	45.5	69.8	97.6
Zone 222	2,057	35.9	66.3	54.7	21.3	23.1	0.1	0.4	0.5	0.9	24.6	65.3	97.2
Zone 223	434	34.2	69.1	72.1	11.1	15.4	0.0	1.0	0.5	1.4	52.1	63.7	98.2
Zone 224	561	37.8	64.3	74.5	16.6	7.2	0.0	0.5	1.1	1.6	26.6	45.7	97.3
Zone 311	2,956	34.8	73.7	48.5	46.6	2.9	0.0	0.7	1.4	2.1	5.8	42.4	95.8
Zone 312	1,187	35.9	68.8	38.4	57.4	1.9	0.1	1.1	1.1	2.3	4.6	52.8	97.2
Zone 313	791	36.8	75.1	33.1	61.4	3.4	0.0	1.3	0.9	2.2	20.0	62.3	97.6
Zone 321	653	34.1	71.7	18.0	80.0	1.1	0.0	0.2	0.8	0.9	22.6	74.0	98.8
Zone 322	847	35.7	70.3	27.9	68.8	1.7	0.0	0.5	1.1	1.6	42.3	69.9	98.5
Zone 323	1,216	33.9	69.9	19.5	78.5	1.5	0.3	0.1	0.2	0.5	50.1	80.1	99.3
Zone 324	606	35.4	71.8	30.4	67.1	2.0	0.0	0.2	0.3	0.5	41.0	77.1	97.9

Table 3.5: Characteristics of Drivers Stopped By Department, District, and Zone (p. 2 of 2)

Zone	Total # of Stops	Average Age	% Male	Race of Driver							% In-Zone Resident	% Cleveland Resident	% Ohio Resident
				% White	% Black	% Hispanic	% Native American	% Asian/Pac. Isl.	% Middle Eastern	% Unknown			
CDP Dept	43,707	36.3	66.6	30.5	61.5	4.6	0.1	0.5	1.1	1.6	29.1	62.3	97.8
Zone Level													
Zone 411	1,817	37.7	61.0	6.2	92.9	0.5	0.1	0.1	0.3	0.5	21.1	75.1	98.3
Zone 412	590	37.3	68.4	7.4	91.8	0.3	0.2	0.0	0.3	0.5	37.4	74.2	99.3
Zone 413	1,199	37.5	68.6	6.4	93.0	0.2	0.0	0.0	0.4	0.4	46.8	77.1	98.8
Zone 414	517	36.1	69.0	20.2	78.5	0.7	0.0	0.2	0.4	0.7	35.9	70.0	99.4
Zone 421	580	36.7	66.9	5.4	94.4	0.2	0.0	0.0	0.0	0.0	30.2	77.2	98.6
Zone 422	1,575	37.5	61.5	4.2	95.3	0.1	0.1	0.0	0.3	0.3	42.5	71.6	98.8
Zone 423	1,087	36.8	65.3	2.5	97.3	0.0	0.0	0.2	0.0	0.2	42.1	69.1	98.7
Zone 424	951	37.1	59.7	7.1	92.2	0.0	0.1	0.3	0.2	0.6	25.7	56.5	97.9
Zone 425	274	36.7	66.1	8.9	90.7	0.0	0.0	0.4	0.0	0.4	31.5	44.9	99.3
Zone 511	977	36.9	64.8	16.8	81.9	0.6	0.0	0.5	0.2	0.7	24.2	69.8	97.0
Zone 512	713	38.7	63.5	26.0	70.3	1.6	0.0	1.3	0.9	2.1	16.9	60.3	98.2
Zone 513	1,023	38.7	62.9	19.7	78.6	0.6	0.0	0.6	0.5	1.1	21.3	64.0	98.3
Zone 514	684	37.6	65.2	20.4	78.7	0.2	0.0	0.3	0.4	0.7	21.3	58.8	96.9
Zone 521	554	40.2	65.3	32.9	66.2	0.0	0.0	0.0	0.9	0.9	18.6	58.9	98.2
Zone 522	374	36.8	58.7	13.4	85.0	1.1	0.0	0.3	0.3	0.5	30.5	69.5	97.9
Zone 523	952	38.9	60.8	15.7	82.7	0.4	0.0	0.7	0.4	1.2	24.8	64.3	98.2
Zone 611	959	36.4	60.0	7.1	91.8	0.3	0.1	0.2	0.4	0.7	42.7	73.3	98.0
Zone 612	2,006	36.5	62.5	6.5	92.7	0.3	0.0	0.2	0.4	0.6	35.1	72.7	99.1
Zone 613	1,704	37.2	63.4	8.5	90.8	0.4	0.0	0.1	0.3	0.4	39.2	60.9	98.7
Zone 621	562	37.2	60.4	13.8	85.5	0.4	0.0	0.0	0.4	0.4	42.4	45.2	98.0
Zone 622	1,450	38.4	63.8	19.4	79.7	0.5	0.1	0.2	0.1	0.4	27.2	55.5	97.9
Zone 623	1,596	36.2	65.1	29.9	68.8	0.5	0.1	0.4	0.4	0.9	34.6	53.7	98.4

The racial and ethnic descriptions of drivers stopped by officers are recorded at the department, district and zone level in **Table 3.5**. The Traffic Stop Form captures officers' perceptions of drivers' race/ethnicity in one of seven categories, with the percentages across the department indicated in brackets:

- Caucasian (30.5%)
- Black (61.5%)
- Hispanic (4.6%)
- Native American (0.1%)
- Asian/Pacific Islander (0.5%)
- Middle Eastern (1.1%)
- Unknown race/ethnicity or missing data (1.6%)

In **Table 3.5**, the missing data is collapsed with the category "unknown race." It is important to note that the percentages of unknown or missing drivers' race/ethnicity are extremely low, with only District 1 reporting greater than 5% of traffic stops with unknown or missing drivers' race/ethnicity. The District 1 rate (5.8%) is primarily attributable to missing or unknown race/ethnicity reported in Zone 121 (8.3%), Zone 112 (5.1%) and Zone 123 (5.0%).

It should also be noted that variation in the racial and ethnic background of drivers stopped across the city is to be expected due to differences in the demographic makeup of residents and travelers, along with differences in traffic flow patterns in these locations. These issues and their implications for determining discrimination in stopping patterns will be more fully explored in **Sections 6 and 7** of this report.

As shown in **Table 3.5**, at the District level, variations in the racial/ethnic background of drivers was evident. For example, over half of the drivers stopped in District 1 and District 2 were Caucasian (56.3% and 52.4% respectively). These two Districts also stopped the highest percent of Hispanic drivers (12.2% and 18.4% respectively). In contrast, only 7.0% of the drivers in District 4 and 13.3% of the drivers in District 6 were Caucasian. As would be expected, differences in racial composition of drivers stopped across Districts are also pronounced for Black drivers. For example, Black drivers accounted for 92.4% of drivers stopped in District 4, compared to 25.8% of drivers in District 1.

Similar fluctuations can be seen at the zone level (**Table 3.5**). The percentage of White drivers stopped ranged from 2.5% in Zone 423 to 74.5% in Zone 224. Black drivers represented 97.3% of the stops in Zone 423, while only 11.1% of the stops in Zone 223. Finally, the city rate for Hispanics stopped was the result of officer behavior in District 1 and District 2 zones.

Table 3.5 also reports drivers' residency. For every traffic stop, officers were to record drivers' zip code to determine the percentage of stops which occur in locations where the drivers actually reside and whether they are Ohio residents. This is important information to collect because benchmarks based on Census data assume that the driving population is similar to the residential population of an area. As shown in **Table 3.5**, however, this is an inaccurate assumption. Specifically, department-wide, only 29.1% of the drivers stopped by Division of Police officers resided in the zone where they were stopped. Over half (62.3%) of the drivers stopped were

residents of Cleveland and 97.8% resided in Ohio. It should be noted that Traffic Unit officers were generally much *less* likely to stop drivers who resided in the zone where they were stopped (18.9%) and Cleveland residents (51.5%) than were other officers.

When aggregated to the district and zone levels, it becomes obvious that the percentages of stops of drivers who reside where they were stopped and were Cleveland residents varied dramatically by location. For example, when comparing across Districts, residents who resided in the zones where they were stopped ranged from a high of 37.2% of District 1 stops to a low of 24.1% of District 5 stops. A comparison across zones also evidenced substantial variation within Districts. Specifically, the percentages of stopped motorists in District 2 who resided in the zones where they were stopped ranged from a low of 7.9% (Zone 212) to a high of 52.1% (Zone 223). Similarly, in District 3, the percentage of drivers stopped who resided in the zone where the stop occurred ranged from a low of 4.6% in Zone 312 to a high of 50.1% in Zone 323.

Less dramatic differences in the percentages of Cleveland residents stopped by officers were apparent across Districts, though there was some variation again at the zone level within two districts. For example, District percentages of Cleveland residents ranged from 70.1% of stops in District 4 to 62.9% of stops in District 6. The most substantial differences in zone totals within a District occurred in District 3, with 42.4% of stops in Zone 312 involving Cleveland residents compared to 80.1% of stops in Zone 323.

Finally, District 5 exhibited the most overall consistency across zones for both stops of people who resided in the zone where the stop occurred, and Cleveland residents. Stops of motorists who resided in the zone where they were stopped ranged from 16.9% to 30.5% in District 5, while the percentage of stops involving city residents ranged from 58.8% to 69.8%.

Citizen demeanor is a characteristic that has received considerable attention by researchers examining officer decision making. The CDP officers were asked to indicate on the Traffic Stop Form whether the driver was civil, disrespectful, non-compliant, verbally resistant and/or physically resistant. This was the first traffic stop study to contain this driver information.

Table 3.6 displays the driver demeanor findings for the department, districts and zones. Across the department a substantial majority (93.0%) of drivers were reported to be civil, 4.3% disrespectful, 1.8% non-compliant, 1.8% verbally resistant and only 0.3% of the drivers physically resisted.

The percentage of drivers perceived to be civil was fairly consistent across the districts and zones. The lowest district percentage of civil drivers (89.0%) was in District 4 and this was the only district with a percentage below 90%. Only five zone level percentages were below 90% and three of these zones were in District 4. The percentage of drivers who were perceived to be disrespectful evidenced more variation, especially across zones. For instance, zone percentages varied from a low of 1.3% in Zone 513 to a high of 14.9% in Zone 414. Also within district variation across zones ranged from 1.8% to 14.9% in District 4.

There is considerably more consistency in officer perceptions of driver demeanor when more highly disrespectful categories (non-compliant, verbally resistant and physically resistant) are

examined. For example, five of the district level percentages of non-compliant drivers were below 1.5%, with the percent of non-compliant drivers in District 4 was 6.04%. The percent of drivers who were verbally resistant was quite low across zones except for Zone 112 (6.0%). Across districts, District 1 had the highest percent of verbally resistant drivers at 3.6%. There were very few physically resistant drivers and only Zone 321, with 1.8% was above one percent.

Table 3.6: Characteristics of Driver’s Demeanor By Department, District, and Zone (p. 1 of 2)

Zone	Total # of Stops	% Civil	% Disrespectful	% Non-Compliant	% Verbally Resistant	% Physically Resistant
CDP Dept	43,707	93.0	4.3	1.8	1.8	0.3
Traffic	11,283	95.7	3.6	0.6	1.1	0.1
District 1	4,370	93.0	3.6	0.9	3.6	0.4
District 2	3,702	94.3	4.1	1.2	1.7	0.2
District 3	5,126	92.5	4.9	1.4	2.4	0.5
District 4	7,736	89.0	4.8	6.0	1.5	0.3
District 5	4,099	95.0	3.1	0.9	1.8	0.4
District 6	7,385	91.9	5.5	1.0	2.0	0.3
Zone Level						
Zone 111	849	95.1	3.4	0.7	1.5	0.0
Zone 112	1,994	91.5	3.6	0.8	6.0	0.4
Zone 113	788	94.9	3.2	1.1	1.5	0.4
Zone 121	717	96.1	2.8	0.3	1.1	0.4
Zone 122	940	94.6	3.7	1.4	1.7	0.2
Zone 123	1,186	94.9	3.3	0.9	1.4	0.3
Zone 211	901	95.5	3.2	0.7	1.6	0.2
Zone 212	863	93.3	4.3	1.5	2.6	0.1
Zone 213	929	96.1	2.5	1.1	1.7	0.1
Zone 221	953	96.9	2.4	0.1	0.7	0.0
Zone 222	2,057	93.7	5.4	0.7	1.0	0.2
Zone 223	434	93.3	4.8	0.9	1.8	0.2
Zone 224	561	94.7	4.5	0.9	0.7	0.2
Zone 311	2,956	91.8	7.0	1.0	1.7	0.2
Zone 312	1,187	94.4	3.6	1.2	1.8	0.3
Zone 313	791	94.3	4.1	1.1	1.5	0.5
Zone 321	653	92.5	4.8	1.5	2.0	1.8
Zone 322	847	95.8	2.6	0.7	1.9	0.1
Zone 323	1,216	94.3	3.2	1.3	2.3	0.6
Zone 324	606	91.6	4.1	2.8	3.3	0.3

* Totals do not equal 100% because officers could mark more than one category.

Table 3.6: Characteristics of Driver’s Demeanor By Department, District, and Zone (p. 2 of 2)

Zone	Total # of Stops	% Civil	% Disrespectful	% Non-Compliant	% Verbally Resistant	% Physically Resistant
CDP Dept	43,707	93.0	4.3	1.8	1.8	0.3
Zone Level						
Zone 411	1,817	91.5	1.8	6.4	0.8	0.1
Zone 412	590	93.7	4.1	2.4	1.2	0.2
Zone 413	1,199	88.2	6.8	5.8	1.3	0.3
Zone 414	517	84.0	14.9	1.7	0.6	0.4
Zone 421	580	85.2	7.1	6.9	2.9	0.9
Zone 422	1,575	89.4	4.8	5.9	1.4	0.3
Zone 423	1,087	95.6	2.9	0.6	1.6	0.2
Zone 424	951	93.5	2.7	3.9	1.9	0.5
Zone 425	274	96.0	2.9	0.4	1.8	0.0
Zone 511	977	90.7	4.6	4.0	1.9	0.1
Zone 512	713	95.8	3.0	0.3	1.1	0.4
Zone 513	1,023	96.7	1.3	0.7	1.8	0.5
Zone 514	684	93.7	3.8	1.5	2.1	0.2
Zone 521	554	86.5	2.4	10.7	1.6	0.5
Zone 522	374	96.8	1.3	0.8	0.8	0.0
Zone 523	952	95.6	2.7	0.4	1.2	0.2
Zone 611	959	91.0	5.8	1.3	2.8	0.5
Zone 612	2,006	92.6	4.7	1.4	2.4	0.4
Zone 613	1,704	86.9	9.9	0.8	2.3	0.4
Zone 621	562	95.2	2.5	1.1	0.5	0.4
Zone 622	1,450	96.5	2.3	0.6	1.0	0.2
Zone 623	1,596	94.6	3.9	0.8	1.4	0.0

* Totals do not equal 100% because officers could mark more than one category.

STOP OUTCOMES

Table 3.7 displays the stop outcomes by department and district. Across the department, 96.7% of the stops resulted in the driver being cited, in 4.0% of the stops the driver was warned and in 4.8% the driver was arrested. The findings for passengers indicate that in 2.1% of the stops a passenger was cited, a passenger was warned in 0.4% of the stops and arrested in 0.6% of these situations. There were also 3,847 searches conducted subsequent to the stop, or in other words, in 8.8% of the stops a person or the vehicle was searched.

Table 3.7 also indicates that there are differences between the outcomes of stops involving the Traffic Unit and the districts as to the percentages of drivers and passengers arrested and the proportion of stops that included searches. For example, the Traffic Unit stops were *less likely* to result in an arrest for both drivers (1.4%) and passengers (0.0%). Further, only 2.3% of the Traffic Unit stops involved a search of the vehicle or a person.

When the stop outcomes are compared across districts there is the greatest variation in the proportion of searches conducted. For instance, in three districts the percentage is above 12%

with the highest proportion in District 3 (15.1%) followed by District 2 (13.1%) and then District 4 (12.2%). District 5 was the most likely to issue a warning to a driver (7.0%) while the least likely district to issue a warning to the driver was District 3 (2.2%).

Table 3.7: Stop Outcomes for Drivers and Passengers by Department and District

Zone	Total # of Stops	% Driver Warned	% Driver Cited	% Driver Arrested	% Passenger Warned	% Passenger Cited	% Passenger Arrested	Total # of Searches	% Person or Vehicle Searched
CDP Dept	43,707	4.0	96.7	4.8	0.4	2.1	0.6	3,847	8.8
Traffic Unit	11,283	3.4	99.4	1.4	0.0	0.4	0.0	262	2.3
District 1	4,370	4.1	96.6	6.0	0.3	2.6	1.2	393	9.0
District 2	3,702	3.2	97.6	6.9	0.5	2.1	0.5	484	13.1
District 3	5,126	2.2	98.9	7.7	0.6	3.7	1.4	775	15.1
District 4	7,736	3.4	96.8	6.2	0.6	2.1	0.6	945	12.2
District 5	4,099	7.0	94.7	5.1	0.5	2.0	0.8	339	8.3
District 6	7,385	5.5	91.4	4.5	0.6	3.3	0.7	649	8.8

SUMMARY

Section 3 describes the characteristics of traffic stops and stopped drivers at the department, district and zone levels, based on data collected from July 1st, 2005 through February 28th, 2006. The trends in these descriptive findings are summarized below.

- At all jurisdictional levels, the majority of traffic stops had the following characteristics:
 - Occurred on a weekday (80.5%)
 - Occurred during the daytime (55.3%)
 - Occurred on an main city roadway (71.6%) or local neighborhood street (19.8%)
 - Involved vehicles with an average of 0.7 passengers
 - Lasted between 1-15 minutes (80.2%)
- At the department level, the most frequent violation observed prior to traffic stops was moving misdemeanor violations (53.8%), followed by speeding violations (25.4%), equipment inspections (6.8%), and registration issues (6.8%).
- The departmental average speed over the limit was recorded at 16.8, but the range varies across districts (13.7 to 18.5) and across zones (13.3 to 19.1).

- Department-wide, officers recorded the following drivers' characteristics:
 - Average age of 36.3 years
 - 66.6% were male
 - White (30.5%), Black (61.5%), Hispanic (4.6%), Middle Eastern (1.1%), Asian/Pacific Islander (0.5%), unknown race/ethnicity or missing data (1.6%)
 - Ohio residents accounted for 97.8% of the stops and Cleveland residents were stopped 62.3% of the time.
 - Only 29.1% of the stops were in zones where the driver resided.

- Drivers' characteristics, particularly race and city of Cleveland residency, varied considerably by district and zone and whether the Traffic Unit was involved.

- 96.7% of the drivers stopped were cited, 4.8% were arrested, and 8.8% of the stops included a search of a person or the vehicle.

4. OBSERVATION DATA METHODS AND DESCRIPTIVE STATISTICS

OVERVIEW

In order to determine if certain groups are disproportionately represented in the traffic stop data collected by CDP officers, it is necessary to have benchmarks or comparison rates. Benchmarks are discussed in detail in **Section 5**, but the most basic explanation regarding benchmarks is that they measure the percentage of minorities one would expect to be stopped by police, given no officer bias. The collection of traffic observation data involves locating an individual (preferably in pairs – to be discussed below) on roadways and collecting information on passing vehicles. This information is used as a benchmark against which the traffic stop data can be measured.

Traffic observation data (or surveys) represent one of several benchmarks used in this study to determine the expected percentage of minority drivers on particular roadways. The goal of conducting stationary roadway observations is to obtain an accurate depiction of the population using the roadways in specific locations within the city. In addition, stationary roadway observations allow for observation of driving violations which may heighten the risk of being stopped. In this study, observers collected information on traffic patterns and violating behavior through the use of RADAR and LASER equipment.

This section is divided into two sub-sections. First, a description of the method involved in collecting the observation data is presented, which includes the selection of observers, their training, and the selection of locations for observation. Second, the descriptive statistics from the observation data are presented. These include a description of the locations where the observations occurred. Specifically, **Tables 4.1 and 4.2** provide the descriptive statistics from the observation data. **Tables 4.3 – 4.22** provide information about each specific observation location and the drivers observed at each location.

OBSERVATION DATA COLLECTION METHOD

To collect observation information, several undergraduate and graduate students were selected from the University of Cincinnati. These students were recruited by posting flyers, informing the Director of the Division of Criminal Justice's Field Placement program, and asking professors to make announcements to students in their courses. Interested students filled out an application and were selected based on the following criteria: grade point average, class rank, and recommendations from professors and past employers.

TRAINING OF OBSERVERS

The selected students attended an eight-hour training session that covered six substantive areas including: 1) data collection purpose and techniques, 2) identification of stop sign and red light violations, 3) RADAR usage, 4) LASER usage, 5) data entry requirements, and 6) confidentiality issues. Training on the data collection purpose, procedures and data entry was conducted by the University of Cincinnati research team in conjunction with two law enforcement officers, one a former Indiana State Police Officer and the other presently a Trooper with the Ohio State Highway Patrol. These individuals provided specific instruction on the identification of stop sign

and red light violations, RADAR usage, and LASER usage. RADAR and LASER equipment was provided by the Ohio State Highway Patrol to facilitate the training of all observers.

In addition to the training the observers received on RADAR and LASER equipment, they completed training on how to accurately collect information on passing vehicles. Observers were instructed that only information on personal vehicles was to be collected. For example, public transportation vehicles such as buses, city, state or federal cars and trucks, emergency response vehicles, and taxi cabs were not included in the observations because they likely have a different probability of being stopped compared to private passenger vehicles. The collection of information on passing vehicles was completed using two forms: a) Observation Data Collection Cover Sheet, and b) Observation Data Collection Form (**Appendix C**).

The Observation Data Collection Cover Sheet collected information on the actual location of the observations, including: date of the observation, day of the week, time of the day, violations observed, location of the observation, type of area, speed limit on the road, type of road, number of lanes, lane being observed, weather conditions, and vehicle sampling technique. Violations observed recorded the actual speed of the passing vehicle (if RADAR or LASER was available). Location of the observation was identified by the closest street address to where the observers' vehicle was parked. Type of area was either: residential, commercial, industrial, or mixed. Areas coded as commercial primarily consisted of service-oriented establishments such as restaurants, gas stations, or any other non-residential building. Areas primarily comprising single or multi-family dwellings were classified as residential, while areas consisting of industry type buildings such as warehouses or power plants were coded as industrial. Type of road was coded as either an Interstate, County/Local road, or Other. Lane being observed refers to the driving, center (on a six lane road) or passing lane. Weather condition (visibility conditions) was recorded as very good, good, fair, and poor. If observers indicated the conditions were fair or poor they also described the actual conditions and it was later determined if these observations could be retained for analyses. Sampling technique indicates how the vehicle was chosen for inclusion into the data set and varied from every passing vehicle, every second vehicle or every third vehicle. The flow of traffic dictated which sampling technique was used.

This information was important to ensure that the observations were conducted in a systematic fashion and any environmental factors that may have affected the ability of the observers to accurately collect information would be recorded. Pursuant to coding guidelines, a new coversheet was filled out every one half hour throughout the day or if any conditions related to the observations changed. Observers were instructed to fill out a new coversheet every one-half hour because of the possibility that conditions relating to weather, traffic, or vision may change quickly and necessitate a change in the data collection procedure. For example, during non-rush hour traffic it was possible for observers to record information on every vehicle using the roadway in the direction they were observing. However, their sampling technique may have changed to every other vehicle or every third vehicle during rush hour traffic due to the increased volume of vehicles traveling on the roadways during those times. Again, any change in the sampling technique was captured on the coversheet.

The Observation Data Collection Form recorded information on passing vehicles including: the driving behavior, the characteristics of the vehicle, and the characteristics of the occupants. The

driving behavior of the vehicle was recorded by the speed of the vehicle to allow an assessment of whether or not the vehicle was speeding, and if the vehicle demonstrated a non-speeding moving violation. Vehicle characteristics include: type, color, and condition of the vehicle, if the vehicle was modified, and if the vehicle was registered in Ohio. Occupants' characteristics include: race, gender, and age of driver, and whether or not there were any passengers in the vehicle.

More specifically, driving violations were captured through the use of RADAR or LASER equipment which recorded the speed of the vehicle. Observers also noted (when possible) any other moving violations (i.e., red light or stop sign infractions) that occurred. The type of vehicle was recorded as sedan, SUV, mini-van, station wagon, sport coupe, motorcycle, pickup truck, or van. Type and color of the vehicle were recorded to ensure that the two observers were collecting information about the same vehicle. Vehicle condition was also collected and classified as "good" if there were no visible blemishes or cosmetic defects to the exterior of the vehicle, "fair" if there were visible blemishes (dents) or the vehicle was older, and "poor" if there were visible cosmetic defects to the exterior of the vehicle, such as broken head or taillight(s), mirror(s), muffler, window(s), or severe body damage. In addition, this data collection instrument captured whether the vehicle had customizable, after-market features which would draw attention to the vehicle while on the roadway, including tinted windows, high performance exhaust systems, or spinners (aftermarket rims). The final vehicle characteristic captured whether or not the vehicle was registered in Ohio.

Demographic information regarding the driver of the vehicle was also gathered, including drivers' race/ethnicity, sex, and approximate age. Race and ethnicity were captured using the following categories: Caucasian, Black, Hispanic, Asian, Native American, Middle Eastern, Non-Caucasian, and Other. Non-Caucasian is comprised of anyone who is not Caucasian; thereby including the following race/ethnicity groups: Black, Hispanic, Asian, Native American, and Middle Eastern. The Other category was used only in the case where the observers could not agree on the race of the driver. If both observers agreed that the driver was a member of a minority group, but could not agree on a specific minority group, they were trained to record the race as simply "non-Caucasian." If the observers could not agree on the more general Caucasian / non-Caucasian 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.

Observers also collected information on the gender of the driver and the driver's age. This field/variable had three categories reflecting different age ranges. Due to the fact that it would be impossible to exactly determine a driver's age from observations on a roadway, three categories were chosen which offered a more reliable classification of the driver's age. The categories for driver's age were: 25 or younger, 26 to 65, and 65 and over. **Observations were restricted to daylight hours to ensure that observers were collecting data under conditions that allowed them the most opportunity to accurately distinguish between race categories.**

Observer training emphasized the importance of collecting data that was accurate and valid. One method to enhance reliability and validity was to establish inter-rater reliability. Inter-rater reliability refers to the degree to which different raters (i.e., observers) record the same information (i.e., observer agreement on the characteristics of the vehicle and its operator). Two

observers were required to record information on the same passing vehicle and ensure that it matched. If the observers disagreed about any aspect of the coded information recorded on the Observation Data Collection Form, it was recorded as missing.

To ensure the confidential nature of the data collected, observers were instructed that they were not permitted to discuss details of the project with anyone outside of the University of Cincinnati research team. Observers were directed to distribute prepared statements written by research staff explaining the research project if they were approached by citizens during observation sessions. Student observers were further required to sign paperwork indicating that they understood the data collection procedures concerning the confidential protections of data. Observers were not allowed to retain any of the data (written or electronic) that was collected as part of this project. It was emphasized to the observers that failure to comply with data collection procedures could result in expulsion from the University.

SELECTION OF LOCATIONS FOR OBSERVATIONS

As previously mentioned, field observations are intended to identify the actual driving population using the roadways across the city. Therefore, it was necessary to observe traffic flow patterns across each of the six policing districts within Cleveland's city limits. To achieve a representative sample of drivers across all districts, the research team requested that the Commander from each district provide several locations that met the following criteria. First, it was imperative that each observation location contained a major thoroughfare that served as a conduit into and out of the city. This would lead to observation data being collected on a sufficiently large proportion of drivers using the roadways within the city. Furthermore, it is likely that areas with major thoroughfares have driving demographic populations that differ dramatically from residential populations (one alternative method of benchmarking). For the second criteria, Commanders were asked to identify locations where a high volume of traffic infractions and enforcement occurred. This was intended to would allow a thorough assessment of possible driving violations in selected areas. Third, it was necessary that the locations allowed observers to have an unobstructed view of traffic patterns. Fourth, it was imperative that the roadways did not contain major construction or any other problems that may disrupt the regular traffic patterns on that road. Finally, it was necessary that the locations did not pose a safety threat to observers. In summary, the first two criteria for roadway selection focused on ensuring that observers would have the opportunity to collect a sufficient quantity of data concerning the driving behavior of people using the roadways in the city of Cleveland, while the remaining criteria were intended to maximize the likelihood that observers would be able to collect valid and accurate data.

Each of the six district commanders submitted lists containing four to six locations that they believed fit the aforementioned criteria. The research team traveled to each location and evaluated them based on (1) flow of traffic, (2) unobstructed view of traffic, (3) whether there was construction in the immediate areas surrounding the location and (4) safety. The research team was unable to evaluate the locations in terms of frequency of traffic violations. After evaluating each location, the research team selected two locations in each district where observers would monitor traffic patterns. The Commander from each District appointed a liaison that served as the primary contact for the research team throughout the course of the observation

data collection. In addition, the research team met with the contact person from District 1, 2, and 3 after evaluating the locations to ensure that the selected areas were the most appropriate for the purposes of the study. In Districts 4, 5 and 6, the liaison was unavailable for consultation and therefore the research team was unable to confirm the appropriateness of the selected locations with the representatives from these districts.

Two locations in each district were chosen to allow for flexibility if there was a problem with the primary location. At any given time, issues could arise which effect traffic patterns and therefore may influence who uses the roadway. For example, construction and/or accidents may cause drivers to seek out alternative routes. In such cases, the observers would not be capturing the true demographics of drivers who use the roadway under normal conditions. Therefore, two locations were chosen so the research team could direct observers to an already established alternative location if any issues were encountered. The selected locations are discussed in detail below.

SAMPLING METHOD

Next, the research team had to determine the number of hours that must be observed at each location in order for the results to be generalizable to times that were not observed. Based on the recommendations of Wilson (2000), between 2% and 3% of the possible time that could be observed should be sampled in order to be confident that the results are generalizable to times when no information was recorded. More specifically, it was necessary to determine the total number of hours of observations that needed to be conducted at one location in order for the observed findings to be generalizable to driving patterns on the observed roadways for times when no observations were conducted. Based on Wilson's 2% to 3% figure the research team concluded that 58.8 hours should be observed at each location in order for the results to be representative of the entire population. That figure is based on the following information:

- 12 daylight hours in a day that could be observed
- 7 days a week that could be observed
- 7 months is the actual length of time traffic patterns were observed

Based on those figures, the following calculation was used to derive the 58.8 hours estimate:

$$\begin{aligned} 12 \text{ Hours} \times 7 \text{ Days} &= 84 \text{ Hours} \\ 84 \text{ Hours} \times 28 \text{ Weeks} &= 2,352 \text{ Hours} \\ 2,352 \text{ Hours} \times 0.025 \text{ (time to be sampled)} &= 58.8 \text{ Hours} \end{aligned}$$

OBSERVATION DATA COLLECTION PROCESS

Observations were scheduled for the spring, summer, and fall in 2005. Spring observations were conducted from May 5th to June 4th, 2005. Summer observations took place from July 10th to August 23rd, 2005, while fall observations were performed between October 16th and November 19th, 2005. The research team conducted observations over three seasons to account for possible seasonal effects in traffic patterns. The research team did not schedule observations during the winter months due to potential poor visibility and safety concerns as a result of traveling during bad weather conditions.

Observation “trips” consisted of three eight-hour days of recording traffic flow patterns at the selected locations. Trips were scheduled from Thursday – Saturday or Sunday – Tuesday to maximize weekday and weekend observations. In addition, starting and ending times varied across observation days to capture both morning and evening rush hour time periods. After accounting for set-up time, lunch and regularly scheduled breaks, the average time recording traffic data was approximately 6.5 hours per day. Thus, to meet the targeted 58.8 hours of observation time at each location, it was necessary to conduct a minimum of nine days of observations at each location. **Tables 4.1 and 4.2** report on the descriptive statistics for all of the information gathered during the observations from the Observation Data Collection Cover Sheet and Observation Data Collection Form.

As demonstrated in **Table 4.1**, a total of 41,257 observations were made of drivers/vehicles using the roadways across all six policing districts. The number of vehicles observed were similar across Thursday, Friday and Saturday, while Monday, Tuesday and especially Sunday involved fewer observed vehicles. (Wednesday is the only day of the week for which data was not collected; however, this is not a concern because there is no reason to believe that traffic patterns on Wednesdays would be different from Tuesdays or Thursdays.) A majority of the observations were conducted in the afternoon between 12:00 P.M. and 7:00 P.M. (63.0%) and rush-hour traffic accounted for 27% of all observations. Observers were located in commercial areas for a majority of the observations.

While in the field, observers recorded speeding using RADAR or LASER provided by the CDP. Approximately 87.0% of the observations were preformed with RADAR or LASER equipment. In addition, observers noted non-speeding moving violating behaviors, such as, failing to stop at a traffic light or sign and making illegal right-hand turns while at a stoplight. Observers only recorded non-speeding moving violations in 12.4% of the observations due to lack of RADAR or LASER equipment being provided to the research team.

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. Almost one-third (31.7%) of the observations were of vehicles traveling on four lane roads and cars operating in the driving lane (66.9%) were most likely to be included in the data. Most of the observations (71.4%) occurred on roadways with a speed limit of 35 MPH, and were conducted under good or very good conditions. In regard to the sampling technique, every car passing the stationary observers was included in the data set for 37.1% of observations, while a similar percentage of observations (37.4%) involved recording information on every other car. For the remaining observations, every third car passing the observers was included in the data set.

Table 4.1: Summary of Observation Data From Coversheets (p. 1 of 2)

Variable (N = 41,257 Vehicles Observed)	N	%
Day of the Week		
Monday	6,265	15.2
Tuesday	6,298	15.3
Wednesday	0	0.0
Thursday	7,906	19.2
Friday	8,147	19.7
Saturday	7,508	18.2
Sunday	5,133	12.4
Time of Observations		
Morning (7:00 A.M. – 11:59 A.M.)	15,269	37.0
Afternoon (12:00 P.M. – 7:00 P.M.)	25,988	63.0
Rush Hour Observations		
Morning Rush Hour (7:00 A.M. – 9:30 A.M.)	5,437	13.2
Afternoon Rush Hour (4:00 P.M. – 6:30 P.M.)	5,682	13.8
Non Rush Hour	30,138	73.0
Type of Area		
Residential	5,604	13.6
Commercial	16,462	39.9
Industrial	967	2.3
Residential & Commercial	12,596	30.5
Residential & Industrial	1,665	4.0
Commercial & Industrial	3,963	9.6
Violations Observed		
Any Speed Detection Device	35,936	87.1
RADAR	31,058	75.3
LASER	94	0.2
RADAR & Moving Violations	4,784	11.6
Moving Violations	5,104	12.4
Observations Only	217	0.5

Table 4.1: Summary of Observation Data From Coversheets (p. 2 of 2)

Variable (N = 41,257 Vehicles Observed)	N	%
Number of Lanes on Road Observed		
Two Lanes	7,521	18.2
Three Lanes	2,130	5.2
Four Lanes	13,070	31.7
Five Lanes	2,900	7.0
Six Lanes	12,203	29.6
Seven Lanes	3,433	8.3
Lane Observed		
Driving Lane	27,607	66.9
Passing Lane	5,519	13.4
Middle Lane	2,819	6.8
All Lanes	9	0.0
Driving & Passing	5,290	12.8
Missing	13	0.0
Speed Limit on Road		
20 m.p.h.	274	0.7
25 m.p.h.	11,527	27.9
35 m.p.h.	29,456	71.4
Visibility During Observations		
Very Good	25,740	62.4
Good	10,504	25.5
Fair	3,267	7.9
Poor	1,746	4.2
Sampling Technique		
Every Car	15,302	37.1
Every Other Car	15,445	37.4
Every Third Car	10,510	25.5

The results from the Observation Data Collection Form are reported in **Table 4.2**. A non-speeding moving violation was observed in less than 1% of the observations. The majority of violating behavior 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 mile per hour over the limit. As a result, the research team determined that eight miles per hour over the posted speed limit would be defined as speeding for the subsequent analyses. To arrive at this standard, the research team examined the traffic stop form data to assess the “normal” speed at which the CDP officers stop vehicles over the speed limit. The traffic stop data indicated that the mean amount over the limit was 16.8 miles

per hour, with a standard deviation of 4.5. Ninety-six percent of the vehicles cited for speeding fell within 2 standard deviations of the mean. Therefore, we defined speeding as traveling 8 MPH or more over the legal limit based on the stopping practices of CDP officers. This represents the lowest bound for speeding. 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 the definition of speeding for this report, forty-five 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 race group (see **Appendix D** for the logistic regression analysis and explanation).

As **Table 4.2** demonstrates, four door sedans were the most commonly observed vehicle (52%) on the roadways and silver was the most frequently observed vehicle color (18.4%). Seventy-five percent of the vehicles observed were considered to be in good condition. A majority of the vehicles observed had no visible aftermarket modifications. Nearly 96% of the vehicles had an Ohio license plate and a majority of drivers had no passengers (69%) in the vehicle.

Caucasian citizens were the most commonly observed drivers (47.3%). African American drivers (37.5%) were the next most frequently observed vehicle operators during the study period. Hispanic, Asian, Native American, Middle Eastern, and Non-Caucasian drivers accounted for the remaining 15.2% of the sample (see **Table 4.2**). With regard to driver gender, a majority of the drivers observed were male (59.7%). Observers were unable to obtain or did not agree on the driver's gender in 2.7% of the observations and thus were coded as missing. Drivers believed to be between the ages of 26 and 65 accounted for a majority of the observations.

Table 4.2: Summary of Observation Data (p. 1 of 2)

Variable	N	%
Moving Violation Observed (non-speeding)		
Red Light Violation	255	0.6
Stop Sign Violation	1	0.0
Right Turn on Red	5	0.0
None	40,996	99.4
Speeding 8 MPH or More Over Limit		
Yes	3,038	7.4
No	31,943	77.4
Missing (speed detection unit not available for use)	6,276	15.2
Type of Vehicle		
Sedan	21,465	52.0
Sports Car/Coupe	3,768	9.1
Sport Utility Vehicle	6,368	15.4
Mini Van	4,412	10.7
Truck	3,256	7.9
Motorcycle	132	0.3
Station Wagon	935	2.3
Van	714	1.7
Missing	207	0.5
Vehicle Color		
Red	6,253	15.2
Blue	5,097	12.4
Green	4,387	10.6
Silver/Gray	7,571	18.4
Black	5,782	14.0
White	5,272	12.8
Gold	3,928	9.5
Other	2,421	5.9
Missing	546	1.3
Vehicle Condition		
Good	30,944	75.0
Fair	8,202	19.9
Poor	1,945	4.7
Missing	166	0.4

Table 4.2: Summary of Observation Data (p. 2 of 2)

Variable	N	%
Vehicle Modified		
Yes	2,954	7.2
No	38,113	92.4
Missing	190	.5
Ohio License Plate		
Yes	39,406	95.5
No	890	2.2
Missing	961	2.3
Passengers		
Yes	12,167	29.5
No	28,479	69.0
Missing	611	1.5
Driver Race		
Caucasian	19,508	47.3
Black	15,488	37.5
Hispanic	2,694	6.5
Asian	646	1.6
Native American	9	.0
Middle Eastern	301	.7
Non-Caucasian	714	1.7
Missing	1,897	4.6
Driver Gender		
Male	24,613	59.7
Female	15,528	37.6
Missing	1,116	2.7
Driver Age		
25 and Under	6,084	14.7
26 to 65	30,067	72.9
Over 65	3,872	9.4
Missing	1,234	3.0

OBSERVATION LOCATION DESCRIPTIONS

Although there were 41,257 vehicles included in the observation data, only 37,926 of those were used in the benchmarking calculations described in **Section 5**. 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. For example, in District 6 one of the selected locations was the intersection of Euclid Avenue and London Road. Observers collected information for three days, but were unable to return due to major construction. In addition, the intersection of Eddy Road and St. Clair Avenue was also initially observed in District 6 but eliminated from the benchmarking analyses. Project observers were harassed by citizens at this location, and the location was eliminated as a return observation site due to safety concerns. Another 1,182 observations were discarded due to data collection errors and were treated as a pilot test. The research team discovered an error in the first set of observations conducted in early May 2005. Upon discovering the errors made by one observation team, research staff quickly held a mandatory meeting to ensure that all observers understood the protocol. Specifically, the observers had coded taxi cabs as sedans in this set of observations, which was inconsistent with the data collection procedures. The error associated with this set of observations required us to discard these observation data from benchmark analyses.

LOCATION DESCRIPTIONS

A location was defined as an intersection or a range of adjacent blocks on either side of an intersection. For example, the intersection of 73rd Street and Lorain Avenue was initially one location. However, after visiting this location it was determined that 73rd Street was a major thoroughfare and traffic patterns west of 73rd Street may be different from those east of 73rd Street. The rationale was that traffic turning onto Lorain Avenue from 73rd Street would not be captured in observations on the West side of 73rd and therefore this location was divided into two observation locations (six adjacent blocks west of 73rd and five adjacent blocks east of 73rd Street on Lorain Avenue).

These two locations and the remaining eight are described in further detail below. For each location two tables are provided. The first table provides descriptive information about the observation location (number of vehicles observed, number of hours of observations, number of observation hours during which RADAR was used, and the average number of vehicles observed per hour). The second table reports the characteristics of the observed drivers (drive gender, race and age).

Location 1: West of 73rd Street on Lorain Avenue

Location 1 is located in District 1 and consists of six adjacent blocks west of 73rd Street on Lorain Avenue. **Table 4.3** indicates the dates that observations were conducted at this location, as well as other characteristics of the location. There were a total of 3,980 vehicles observed, 65 hours of observations were conducted at this location, and only 39.2% of the observations were conducted with RADAR. Observers recorded information on approximately 61 vehicles per hour across all observation dates.

Table 4.3: General Descriptives for Observation Location 1

Dates	# of Observations	# of Hours	# of Radar Hours	% Radar	Average # of Vehicles Per Hour
Location Total	3,980	65	25.5	39.2	61
May 12 th	448	6.5	6.5	100.0	69
May 13 th	213	2.75	2.75	100.0	77
May 14 th	149	2.75	2.75	100.0	54
Jun 12 th	418	6.5	0	0.0	64
Jun 13 th	375	6	0	0.0	63
Jun 14 th	420	6	0	0.0	70
Jul 28 th	288	4.5	4.5	100.0	64
Jul 29 th	368	6.25	6.25	100.0	59
Jul 30 th	185	2.75	2.75	100.0	67
Sep 15 th	392	6.5	0	0.0	60
Sep 16 th	324	6.5	0	0.0	50
Sep 17 th	281	6	0	0.0	47
Oct 16 th	119	2	1	50.0	60

Table 4.4 summarizes the demographics of drivers observed at Location 1. Of the 3,980 drivers, 71.5% were male, and 57.4% of the drivers were Caucasian, while 37.1% were recorded as Non-Caucasian drivers. In 5.5% of the observations driver race was not recorded. With regard to driver age, 16.5% of the vehicle operators were considered to be under the age of 25, while just over 80% appeared to be 26 years of age or older.

Table 4.4: Driver Characteristics for Observation Location 1

	# of Drivers	% of Drivers	% Missing
Male	2,844	71.5%	2.2%
Female	1,050	26.4%	
Caucasian	2,286	57.4%	5.5%
Non-Caucasian	1,475	37.1%	
25 Years of Age and Younger	658	16.5%	3.4%
26 Years of Age and Over	3,845	80.1%	

Location 2: East of 73rd Street on Lorain Avenue

Location 2 is also located in District 1 and consisted of five adjacent blocks east of 73rd Street on Lorain Avenue. **Table 4.5** indicates that 46.25 hours of observations were conducted at this location and a total of 2,683 vehicles were observed for an average of 58 vehicles per hour. Observers used RADAR during all of the observation periods.

Table 4.5: General Descriptives for Observation Location 2

Dates	# of Observations	# of Hours	# of Radar Hours	% Radar	Average # of Vehicles Per Hour
Location Total	2,683	46.25	46.25	100.0	58
May 13 th	242	3.75	3.75	100.0	65
May 14 th	214	3.75	3.75	100.0	57
Jul 28 th	81	1.75	1.75	100.0	46
Jul 29 th	10	0.25	0.25	100.0	40
Jul 30 th	174	3.75	3.75	100.0	46
Oct 16 th	256	3.5	3.5	100.0	73
Oct 17 th	408	6.25	6.25	100.0	65
Oct 18 th	563	6.5	6.5	100.0	87
Nov 3 rd	194	3.75	3.75	100.0	52
Nov 4 th	314	6.5	6.5	100.0	48
Nov 5 th	227	6.5	6.5	100.0	35

Table 4.6 summarizes the demographics of drivers observed at Location 2. Of the 2,683 drivers observed, nearly 71.0% were male, while 27.9% were female. Observers classified the vehicle's operator as Caucasian in 59.3% of the observations, while 36.5% of the drivers were considered to be Non-Caucasian. Observers were unable to record driver race/ethnicity in 4.2% of the observations. With regard to driver age, 12.8% of the vehicle operators were under the age of 25 and 84.5% appeared to be 26 years of age or older

Table 4.6: Driver Characteristics for Observation Location 2

	# of Drivers	% of Drivers	% Missing
Male	1,903	70.9%	1.2%
Female	748	27.9%	
Caucasian	1,591	59.3%	4.2%
Non-Caucasian	978	36.5%	
25 Years of Age and Younger	344	12.8%	2.6%
26 Years of Age and Over	2,268	84.5%	

Location 3: Fulton Road between the 2,800 and 3,100 blocks

Location 3 is located in District 2 on Fulton Road between the 2800 and 3100 blocks. At this location there were a total of 4,936 vehicles observed using the roadway (see **Table 4.7**). On average observers collected information on 65 vehicles per hour. There were a total of 75.5 hours of observation conducted at this location and almost all of the observation time (98.3%) included the use of RADAR.

Table 4.7: General Descriptives for Observation Location 3

Dates	# of Observations	# of Hours	# of Radar Hours	% Radar	Average # of Vehicles Per Hour
Location Total	4,936	75.5	74.25	98.3	65
May 5 th	381	6.5	5.25	80.8	59
Jul 10 th	226	3.5	3.5	100.0	65
Jul 11 th	568	6	6	100.0	95
Jul 12 th	384	4.75	4.75	100.0	81
Aug 11 th	467	6.5	6.5	100.0	72
Aug 12 th	412	6.5	6.5	100.0	63
Aug 13 th	366	6.5	6.5	100.0	56
Oct 16 th	510	5.5	5.5	100.0	93
Oct 17 th	576	6	6	100.0	96
Oct 18 th	456	6	6	100.0	76
Nov 17 th	184	4.75	4.75	100.0	39
Nov 18 th	202	6.5	6.5	100.0	31
Nov 19 th	204	6.5	6.5	100.0	31

Table 4.8 summarizes the demographics of drivers observed at Location 3. Of the 4,936 drivers observed, 59% were male. Fifty-one percent of the drivers observed were Caucasian, while 44.7% were Non-Caucasian drivers. Slightly over three-fourths (76.6%) of the observed drivers were believed to be 26 years of age or older.

Table 4.8: Driver Characteristics for Observation Location 3

	# of Drivers	% of Drivers	% Missing
Male	2,913	59.0%	1.7%
Female	1,939	39.3%	
Caucasian	2,515	51.0%	4.3%
Non-Caucasian	2,208	44.7%	
25 Years of Age and Younger	1,053	21.3%	2.0%
26 Years of Age and Over	3,782	76.6%	

Location 4: Fulton Road and Clark Avenue Intersection

Location 4 is also located in District 2. Location 4 observations were conducted on Fulton Road within one block of either side of Clark Avenue. **Table 4.9** reports that there were a total of 1,949 vehicles observed during the 34.5 hours of observations. As such, an average of 56 vehicles per hour were observed. Approximately 68% of the observations were carried out with RADAR.

Table 4.9: General Descriptives for Observation Location 4

Dates	# of Observations	# of Hours	# of Radar Hours	% Radar	Average # of Vehicles Per Hour
Location Total	1,949	34.5	23.5	67.6	56
May 6 th	507	6.5	1	15.4	78
May 7 th	466	6.5	0.75	11.5	72
Jul 10 th	142	2	2	100.0	71
Jul 12 th	115	2	2	100.0	58
Nov 3 rd	179	4.75	4.75	100.0	38
Nov 4 th	262	6.5	6.5	100.0	40
Nov 5 th	278	6.5	6.5	100.0	43

Table 4.10 summarizes the demographics of drivers observed at Location 4. Sixty-three percent of the 1,949 drivers were male, while 35.4 were female. Caucasian drivers were observed in 42.0% of the vehicles, 52.6% of the drivers were considered to be Non-Caucasian, and observers were unable to record this information for 4.3% of the observed drivers. In 82.3% of the observed vehicles the driver appeared to be 26 years of age or older.

Table 4.10: Driver Characteristics for Observation Location 4

	# of Drivers	% of Drivers	% Missing
Male	1,229	63.1%	1.5%
Female	690	35.4%	
Caucasian	819	42.0%	5.4%
Non-Caucasian	1,025	52.6%	
25 Years of Age and Younger	307	15.8%	1.9%
26 Years of Age and Over	1,605	82.3%	

Location 5: Chester Avenue between the 3100 and 4500 blocks

Location 5 is located in District 3 on Chester Avenue between the 3100 and 4500 blocks. **Table 4.11** indicates the dates that observations were conducted at this location. A total of 3,634 vehicles observed using the roadway. Observers conducted observations for 49.25 hours for an average of 74 vehicles per hour. RADAR equipment was available during all of the observation hours.

Table 4.11: General Descriptives for Observation Location 5

Dates	# of Observations	# of Hours	# of Radar Hours	% Radar	Average # of Vehicles Per Hour
Location Total	3634	49.25	49.25	100.0	74
May 15 th	378	6.5	6.5	100.0	58
May 16 th	401	6	6	100.0	67
May 17 th	477	6.5	6.5	100.0	73
Aug 8 th	29	0.5	0.5	100.0	--
Oct 21 st	284	5.25	5.25	100.0	54
Oct 22 nd	234	6.5	6.5	100.0	36
Nov 6 th	460	5	5	100.0	92
Nov 7 th	740	6.5	6.5	100.0	114
Nov 8 th	631	6.5	6.5	100.0	97

Table 4.12 summarizes the driver characteristics at this location. More than half of the drivers were males (57.4%). For observations where driver race was discernible, a majority (52.4%) of the drivers were Caucasian and 84.1% were believed to be 26 years old or older.

Table 4.12: Driver Characteristics for Observation Location 5

	# of Drivers	% of Drivers	% Missing
Male	2,086	57.4%	4.1%
Female	1,398	38.5%	
Caucasian	1,905	52.4%	5.2%
Non-Caucasian	1,540	42.4%	
25 Years of Age and Younger	438	12.1%	3.8%
26 Years of Age and Over	3,057	84.1%	

Location 6: Chester Avenue and East 55th Street Intersection

Location 6 is located in Districts 3 and 5 at the intersection of Chester Avenue and East 55th Street. Observations were conducted on Chester Avenue within one block of the intersection on either side of East 55th Street. For benchmarking purposes, observations conducted west of East 55th Street were counted towards District 3 totals, while those conducted east of East 55th Street were allocated to District 5.

Table 4.13 provides summaries of the Location 6 observations. At this location, a total of 4,018 vehicles were observed over 58.5 hours of observations for an average of approximately 69 vehicles per hour. RADAR was only available during 65.8% of the observer hours.

Table 4.13: General Descriptives for Observation Location 6

Dates	# of Observations	# of Hours	# of Radar Hours	% Radar	Average # of Vehicles Per Hour
Location Total	4018	58.5	38.5	65.8	69
Jun 2 nd	143	3.5	0	0.0	41
Jun 3 rd	209	3.25	0	0.0	64
Jun 4 th	195	3.5	0	0.0	56
Jul 21 st	581	6.5	6.5	100.0	89
Jul 22 nd	671	6.5	6.5	100.0	103
Jul 23 rd	575	6.5	6.5	100.0	88
Aug 18 th	384	6.5	6.5	100.0	59
Aug 19 th	378	6.5	6.5	100.0	58
Aug 20 th	367	6	6	100.0	61
Oct 20 th	277	4.5	0	0.0	62
Nov 13 th	238	5.25	0	0.0	45

Table 4.14 indicates that 40.0% of the cars were operated by females. Observers classified the vehicle’s operator as Caucasian in 50.5% of the observations, while 43.8% of the drivers were considered to be Non-Caucasian. Observers did not record this information for 5.7% of the vehicles. Again, most of the drivers (83.9%) appeared to be 26 years of age or older.

Table 4.14: Driver Characteristics for Observation Location 6

	# of Drivers	% of Drivers	% Missing
Male	2,298	57.2%	2.8%
Female	1,607	40.0%	
Caucasian	2,031	50.5%	5.7%
Non-Caucasian	1,759	43.8%	
25 Years of Age and Younger	507	12.6%	3.5%
26 Years of Age and Over	3,370	83.9%	

Location 7: East 55th Street between the 1600 and 2000 blocks

Location 7 is also located in Districts 3 and 5 on East 55th Street. For benchmarking purposes the vehicles were placed in one of these two districts depending on their direction of travel. Specifically, vehicles traveling south on East 55th Street were counted towards District 3 totals, while north bound vehicles were considered in the totals for District 5.

Table 4.15 indicates that information was recorded on approximately 59 vehicles per hour across all observations. There were a total of 58 hours of observations and during 80.6% of these hours RADAR equipment was used. A total of 3,426 vehicles were observed.

Table 4.15: General Descriptives for Observation Location 7

Dates	# of Observations	# of Hours	# of Radar Hours	% Radar	Average # of Vehicles Per Hour
Location Total	3426	58	46.75	80.6	59
Jun 2 nd	196	2.75	0	0.0	71
Jun 3 rd	217	2.75	0	0.0	79
Jun 4 th	157	2.75	0	0.0	57
Jul 28 th	466	5.5	4.5	81.8	85
Jul 29 th	458	6.5	6.5	100.0	70
Jul 30 th	359	5.25	5.25	100.0	68
Oct 27 th	364	5.75	5.75	100.0	63
Oct 28 th	352	6.5	6.5	100.0	54
Oct 29 th	323	6.25	6.25	100.0	52
Nov 14 th	293	7.5	5.5	73.3	39
Nov 15 th	241	6.5	6.5	100.0	37

Table 4.16 summarizes the demographics of drivers observed at Location 7. Of the 3,426 drivers observed, 62.0% were male, while 34.6% were female. Only 27.4% of the drivers observed were Caucasian, while 69.1% were Non-Caucasian drivers. In 3.5% of the observations driver race was recorded as missing. Similar to the other locations, 85.0% appeared to be over 25 years of age.

Table 4.16: Driver Characteristics for Observation Location 7

	# of Drivers	% of Drivers	% Missing
Male	2,125	62.0%	3.4%
Female	1,184	34.6%	
Caucasian	938	27.4%	3.5%
Non-Caucasian	2,367	69.1%	
25 Years of Age and Younger	391	11.4%	3.6%
26 Years of Age and Over	2,913	85.0%	

Location 8: Carnegie Avenue between the 8200 and 9000 blocks

Location 8 is located in District 5. A total of 6,189 vehicles were observed using the roadway during the 58.5 hours of observations for an average of 106 vehicles per hour (see **Table 4.17**). Eight-four percent of the observations were carried out with RADAR.

Table 4.17: General Descriptives for Observation Location 8

Dates	# of Observations	# of Hours	# of Radar Hours	% Radar	Average # of Vehicles Per Hour
Location Total	6,189	58.5	49.25	84.2	106
May 22 nd	494	6.5	0	0.0	76
May 23 rd	511	6.5	6.5	100.0	79
May 24 th	473	6.5	6.5	100.0	73
Jul 24 th	486	6.5	6.5	100.0	75
Jul 25 th	753	6.5	4.5	69.2	116
Jul 26 th	875	6.5	6.5	100.0	135
Aug 28 th	781	6.5	6.5	100.0	120
Aug 29 th	844	6.5	5.75	88.5	130
Aug 30 th	972	6.5	6.5	100.0	150

Table 4.18 summarizes the demographics of drivers observed at Location 8. Fifty-six percent of the drivers were male and observers classified the vehicle’s operator as Caucasian in 58.4% of the observations, while 37.9% of the drivers were considered to be Non-Caucasian. Observers did not record this information for 3.7% of the observations. Consistent with most locations, a majority of the drivers (86.9%) appeared to be 26 years of age or older.

Table 4.18: Driver Characteristics for Observation Location 8

	# of Drivers	% of Drivers	% Missing
Male	3,488	56.3%	2.8%
Female	2,529	40.9%	
Caucasian	3,583	57.9	3.3
Non-Caucasian	2,402	38.8	
25 Years of Age and Younger	772	12.5	1.9
26 Years of Age and Over	5,300	85.6	

Location 9: Lee Road between the 3800 and 4000 blocks

Location 9 is located in District 4 on Lee Road between the 3800 and 4000 blocks. There were a total of 3,510 vehicles observed using the roadway and observers recorded information on approximately 63 vehicles per hour (see **Table 4.19**). RADAR was used during 70.7% of the observation hours.

Table 4.19: General Descriptives for Observation Location 9

Dates	# of Observations	# of Hours	# of Radar Hours	% Radar	Average # of Vehicles Per Hour
Location Total	3,510	55.5	39.25	70.7	63
May 19 th	388	6	5.25	87.5	65
May 20 th	488	6.25	0	0.0	78
May 21 st	498	6.25	0	0.0	80
Jul 24 th	415	6.5	6.5	100.0	64
Jul 25 th	446	6.5	6.5	100.0	69
Jul 26 th	453	6.5	6.5	100.0	70
Oct 20 th	265	5.75	5.75	100.0	46
Oct 21 st	337	6.5	6.5	100.0	52
Oct 22 nd	220	5.25	2.25	42.9	42

Table 4.20 summarizes the demographics of drivers observed at this location. Of the 3,510 drivers observed, 54.7% were male. Only 14.5% of the drivers observed were Caucasian, while 82.8% were classified as Non- Caucasian. In 2.6% of the observations driver race was recorded as missing. Once again, drivers considered to be 26 years old or older accounted for a majority of the observations.

Table 4.20: Driver Characteristics for Observation Location 9

	# of Drivers	% of Drivers	% Missing
Male	1,919	54.7%	3.4%
Female	1,470	41.9%	
Caucasian	510	14.5%	2.6%
Non-Caucasian	2,907	82.8%	
25 Years of Age and Younger	646	18.4%	3.5%
26 Years of Age and Over	2,740	78.1%	

Location 10: Lakeshore Boulevard (18000 block)

Location 10 is located in District 6 on Lakeshore Boulevard. At Location 10 there were a total of 3,601 vehicles observed during 55.75 hours of observations for an average of approximately 65 vehicles per hour (see **Table 4.21**). In 79.8% of the observation hours, the observers were equipped with a speed detection device.

Table 4.21: General Descriptives for Observation Location 10

Dates	# of Observations	# of Hours	# of Radar Hours	% Radar	Average # of Vehicles Per Hour
Location Total	3601	55.75	44.5	79.8	65
May 22 nd	138	4	4	100.0	35
May 23 rd	291	6.25	6.25	100.0	47
May 24 th	272	6.5	4.75	73.1	42
Jul 28 th	417	6.5	0	0.0	64
Oct 20 th	438	5.5	3.5	63.6	80
Oct 21 st	540	6	6	100.0	90
Oct 22 nd	583	5.5	4.5	81.8	106
Nov 3 rd	146	2.5	2.5	100.0	58
Nov 4 th	377	6.5	6.5	100.0	58
Nov 5 th	399	6.5	6.5	100.0	61

Table 4.22 summarizes the demographic characteristics of drivers observed at Location 10. Fifty-four percent of the drivers were male, while 43.2% were female. The vehicle’s operator was classified as Caucasian in 63.6% of the observations, while 33.5% of the drivers were considered to be Non-Caucasian. Nearly 82.5 of drivers were 26 years old or older.

Table 4.22: Driver Characteristics for Observation Location 10

	# of Drivers	% of Drivers	% Missing
Male	1,942	53.9%	2.8%
Female	1,557	43.2%	
Caucasian	2,292	63.6%	2.9%
Non-Caucasian	1,205	33.5%	
25 Years of Age and Younger	543	15.1%	3.3%
26 Years of Age and Over	2,939	81.6%	

SUMMARY

- The purpose of observations is to identify the actual driving population using the roadways across the city. This information is used as a benchmark against which the traffic stop data can be measured.
- One way to collect data on actual roadway usage and driving behavior is to conduct stationary roadway observations. This involves locating an individual (preferably in pairs) on roadways and collecting information on passing vehicles.

- Observers were recruited, selected and trained on the proper use of speed detection devices, identification of non-speeding moving violations and data coding and entry methods. Information relating to the observation location and period (date, time, type of area, violations observed, number of lanes on the roadway, lane observed, speed limit of roadway, visibility/weather conditions, and sampling technique), vehicle (type, color, condition, whether any aftermarket modifications were visible, whether there were any passengers in the vehicle, and whether the vehicle had an Ohio license plate), and driver of the vehicle (race, age, gender) was collected.
- Suggested observation locations were provided by the commanders from each district. Based on these recommendations, a primary and secondary location in each district were selected for observations.
- Observations were conducted between May 5 and November 19, 2005. There were a total of 37,926 used for benchmarking purposes. These observations were collected over the course of 557 hours. A speed detection device was used in 437 of the observation hours (78.5%).
- In general, while there were slight differences in observations by observer location most of the observed drivers were male, Caucasian, and 26 years of age or older. A majority of Non-Caucasian drivers was observed in only three locations (Locations 4, 7, and 9). Most of the observations were conducted with the use of a speed detection device. The average number of vehicles observed per hour at each location ranged from a low of 56 to a high of 106.

5. TRAFFIC STOP DATA ANALYSIS USING BENCHMARKS

OVERVIEW

This section details the analysis of the traffic stop data collected by the CDP between July 1st, 2005 and February 28th, 2006. In order to analyze the traffic stop data, it is necessary to compare this data against a benchmark(s) value. The following sub-sections detail the strengths and limitations of various reporting methods for the benchmarks, present several different benchmark techniques, and provide the results of traffic stop comparisons to four benchmarks. This section concludes with an overview of the results across the various benchmarks and the interpretation of these results based on the traffic stop data.

BENCHMARKING

The key issue facing researchers examining police traffic stops is that simply determining how often minorities are stopped, searched, cited, or arrested by police is not particularly meaningful until those percentages are compared to some “expected probability” of these actions toward minorities; this comparison is referred to as a benchmark (Rojek et al., 2004; Engel et al., 2002). That is, a group’s representation in traffic stops is only meaningful when compared to the same group’s “expected” representation in traffic stops, based on alternative data (i.e., the benchmark). For traffic stop studies, the key is to compare those motorists who are stopped by police with those motorists who were eligible to be stopped. In this manner, it can be determined if the percentage of minority motorists stopped by police is equivalent to the percentage expected to be stopped, absent officer bias. Accurately measuring the percentage of minority motorists eligible for a stop, however, has proven to be a difficult task for researchers.

Traffic stops studies have historically used several different types of benchmark, including: 1) Census data, 2) adjusted Census data, 3) observations of roadway usage, 4) official accident data, 5) assessments of traffic violating behavior, 6) citizen surveys of roadway usage and driving patterns, and 7) internal departmental comparisons. Each of these benchmarks has associated strengths and weaknesses (for a more thorough review of these techniques, see Engel & Calnon, 2004b). The best approach for comparisons to traffic stop data is to measure several benchmarks and compare the results to one another. While none of the benchmark methodologies are without flaws, some are inherently stronger than others, and those benchmarks should be given more weight when comparing the results from different benchmarks. For example, Census data are widely regarded as the weakest benchmark measure, while observations that are based on methodologically sound data collection efforts are considered more valid indicators of actual roadway usage. This study employs four different benchmarks to analyze the stop data in order to identify trends and/or patterns across the forty-two police zones. Each of these benchmarks and their results will be discussed in detail after a brief discussion of the limitations of benchmarking in general.

LIMITATIONS OF BENCHMARKING

The key consideration for assessing the validity of benchmarks is the accuracy with which these benchmarks reflect motorists’ *risk* of being stopped by police. As a motorist, the risk of being

stopped can be affected by at least six factors: 1) where they drive, 2) when they drive, 3) how often they drive, 4) what they drive, 5) how they drive, and 6) who they are. That is, an accurate benchmark must take into consideration driving location, time of travel, driving quantity, vehicle types and conditions, driving behavior, and drivers' characteristics (Engel et al., 2004). All of these factors are believed to have the potential to influence motorists' likelihood of being stopped for traffic offenses, and therefore must be measured to assess motorists who are eligible for a police stop. Unfortunately, none of the available data generated by the benchmarking techniques identified above has adequately addressed all of the risk factors associated with the likelihood of motorists being stopped by police.

In addition, there are several different statistical methods used to compare traffic stop data to benchmark data (see Fridell, 2004). Most traffic stop studies use one of two methods: a disproportionality index and/or a disproportionality ratio⁴. Both of these methods are utilized in this report and further described below.

Disproportionality Index (DI)

Using traffic stop data as the numerator and a benchmark as the denominator, a "disproportionality" or "disparity" index can be created. These indices are used to estimate the differences between the "actual" and "expected" rates of traffic stops for different racial, ethnic, gender, and age groups (e.g., Cox et al., 2001, Rojek et al., 2004). Disproportionality indices greater than one indicate that the rate of stops for particular groups are *greater than expected* in comparison to the benchmark. A disproportionality index of less than one indicates that the rates of traffic stops for particular groups are *less than expected* based on the benchmark. The larger the size of the disproportionality index, the larger the disparity between the actual and expected rate of stops.

$$DI = \frac{\text{the proportion of a group's actual rates of police actions}}{\text{the proportion of the group's expected rates of the same actions}}$$

The numerator—the actual proportion of the group—is typically based on all traffic stops, but it can be limited to only daylight stops, stops of just county residents (this presumably should mirror population statistics more closely than stops of everyone), or stops made for speeding violations only. More frequently, however, benchmark comparisons have focused on changing the denominator based on the group's representation in one of the several types of comparison populations listed above. Indices greater than 1.0 indicate that a group is stopped *more* often than would be expected based on its percentage in the benchmark population; indices less than 1.0 indicate that a group is stopped *less* often than would be expected by their representation in the benchmark population. As previously mentioned, the larger the size of the disproportionality index, the larger the disparity between the actual and expected rate of stops.

There are several issues involved with the use of disproportionality indices. First, while a disproportionality index is relatively simple to create, it is not easily interpretable. That is, the creation of a disproportionality index is simply a matter of dividing the rate of stops for a

⁴ Disproportionality indices and ratios are also referred to as Disparity Indices or Ratios and are abbreviated by DI and DR.

particular group by the benchmark for that group to produce a value. The difficulty becomes how to interpret this value because it is not in relation to the other group. That is, if a particular zone has a DI of 3.5 for Hispanic drivers, the value has no anchor or reference point. Due to the manner in which the DI is created, the value for Hispanic drivers is not in relation to Caucasian drivers or Black drivers; therefore, the value is not interpretable. A DI of 3.5 does suggest that there is disparity between the rate of Hispanic drivers stopped and what is expected to be stopped based on the benchmark, but it is not in relation to any other group.

Second, there is an obvious connection between the perceived validity of disproportionality indices and the type of benchmark used to make the comparison. A benchmark with a higher degree of validity will produce disproportionality indices with more validity. As described above, not all benchmarks are of equal validity. Therefore, disproportionality indices based on Census data, for example, must be interpreted with extreme caution.

Third, the stability of the disproportionality indices is based in part on the size of the denominator. This is especially a concern when Census figures are used to estimate the expected rate of stops. For example, as will be shown below, the racial composition of the police zones across the City of Cleveland vary considerably and have a substantial impact on the resulting disproportionality index. For example, on the east side of the city, the Census reports the racial composition as predominately Black, with few Caucasian residents. Thus, a small number of traffic stops of Caucasian drivers in these zones would dramatically raise the disproportionality indices because the denominator is very small. In other words, in jurisdictions with unstable or small denominators (benchmarks), the numerator has a larger influence on the resulting disproportionality index.

Finally, there is no scientifically accepted standard for the interpretation of the size of disproportionality indices. That is, there is no generally accepted statistical test that can be performed to determine if disproportionality indices are “too big” or “too small.” Likewise, there is no generally accepted “rule of thumb” used by researchers regarding the appropriate size of disproportionality indices. Consequently, one of the shortcomings of the disproportionality index is the difficulty in interpreting the level of disproportionality based on the method described above.

As noted above, studies expressing disproportionality in terms of all of these indices have not established a threshold value above which the disproportionality is considered illegitimate or unjustified (Cox et al., 2001; Decker et al., 2002, Farrell et al., 2003). The main reason for this is that the sources of disparity are numerous—officer bias, institutional/organizational norms, legally relevant offending behavior, etc. (Engel & Calnon, 2004a; Farrell et al., 2003; Walker et al., 2000). To date, it has not been possible for researchers to measure the legitimacy of all possible explanations for disparity. One recent study of traffic stops singled out jurisdictions with disproportionality indices above the statewide average for further analysis (Farrell et al., 2003). Often, researchers have further analyzed traffic patterns (e.g., commuters, tourists, etc.) to try to explain why particular jurisdictions have disproportionality indices that appear to be outliers in comparison to other jurisdictions (Cox et al., 2001; Decker et al., 2002). In an attempt to address the shortcomings of the disproportionality index, creation of a disproportionality ratio (described below) is the preferred method.

Disproportionality Ratio (DR)

As described above, one of the primary difficulties associated with the disproportionality index is the difficulty interpreting its value. In order to address this shortcoming, a more effective method of reporting the results is to calculate a disproportionality ratio.⁵ To calculate this value, the disproportionality index must be available for both the minority population of interest and the majority population of interest. Once those values are determined, the disproportionality ratio is calculated as follows:

$$\mathbf{DR} = \frac{\text{the minority disproportionality index}}{\text{the majority disproportionality index}}$$

The resulting value is the disproportionality ratio and is interpreted as the likelihood of being stopped if you are part of the racial group of interest in comparison to the majority group. For example, if the disproportionality ratio is 3.0, this indicates that the group of interest is three times more likely to be stopped in comparison to the majority group. While the disproportionality index is strictly calculated through the use of one racial group, (i.e., Black drivers stopped divided by what is predicted by the benchmark), the disproportionality ratio actually compares the difference between the disproportionality index of the minority group against the majority group.⁶

As with the disproportionality index, the validity of the benchmark, which underlies the analysis, remains a concern. This is due to the fact that the disproportionality ratio is based on the disproportionality index and so while the disproportionality ratio is preferred to the disproportionality index for reasons of interpretability, the validity of the benchmark is still unresolved. Furthermore, the statistical instability of the denominator is not rectified, and jurisdictions with small values may be unduly affected by a small change in the number of stops. Finally, there is no agreed upon value that unequivocally provides a threshold for a determination of disparity. Notwithstanding these concerns, the disproportionality ratio is a superior measure to the disproportionality index due to its clearer interpretative value. Both disproportionality indices and disproportionality ratios are calculated and included in the analyses reported below.

TYPES OF BENCHMARKS & RESULTS OF ANALYSIS

Traffic stop data collected by CDP officers are compared to four types of benchmarks. Each of these comparisons uses various forms of the stop data and modifies the benchmark (denominator) to produce a series of findings that should be considered as a whole to examine

⁵ We use the term disproportionality ratio in place of the often mentioned ‘odds ratio’ because the ratios may be greater than one.

⁶ Consequently, if the disproportionality index for Caucasian drivers is less than one, indicating they are less likely to be stopped than expected, it will increase the disproportionality ratio for minority drivers. Conversely, if the Caucasian disproportionality index is greater than one, showing an overrepresentation in stops of Caucasian drivers, then the disproportionality ratio for Black drivers would be lower than the Black disproportionality index. In other words, due to the fact that the Caucasian disproportionality index is above one, it pushes the Black disproportionality ratio lower in comparison to the Black disproportionality index.

patterns and trends within locations. Analyzing the data using more than one benchmark allows for a greater understanding of the data and provides multiple viewpoints in order to assess the general stopping trends and patterns displayed by the CDP. Each of the four benchmark comparisons are detailed below, complete with a discussion of their creation, the strengths and limitations of each and a summary of the results from these analyses. Disproportionality indices and disproportionality ratios are calculated for each of the benchmarks across the policing zones in order to facilitate easier comparison across geographic areas.

For the first two benchmark comparisons, residential demographic data drawn from the 2000 Census was used. It provides the benchmark for a comparison with all of the traffic stops that occurred within the City of Cleveland during the study period. It will also provide the benchmark for an analysis of within police zone stops. That is, only the stops of residents who live in the police zone where they were stopped will be compared against the residential Census values of that police zone. The third benchmark comparison uses daylight traffic stops in comparison to the daytime traffic observations. Only daylight stops are used in order to maintain temporal consistency between the observations and the traffic stops. The final benchmark comparison uses violating behavior recorded by the observers in comparison to traffic stops of speeders at eight miles per hour over the legal limit. To ensure that the analyses are computed with enough statistical variation, benchmarks were only created when there were a minimum of fifty traffic stops and a minimum of thirty traffic stops within any race/ethnicity group. That is, if any of the police zones did not meet the fifty traffic stop minimum or the thirty traffic stop minimum within a race/ethnicity group, the analysis was not completed for those geographic areas.

Due to the design of the traffic stop form, the smallest geographic unit for any traffic stop was the police zone. As a result, all analyses of the traffic stop data is conducted at the police zone level, and as such, all other sources of information must be adjusted to provide consistency with this geographic unit. The procedure for adjusting the various data sources to ensure that they are compatible with the police zone is described within each benchmark comparison.

For all comparisons, four race/ethnicity groups were identified: Caucasians, Blacks, Hispanics, and Non-Caucasians across all data sources. These categories were based on the criteria used by the Census Bureau when collecting demographic information for the Census. Using this as a framework, the CDP officers were trained on the Traffic Stop Data Form (please see **Section 3** for more information on the officer training), and the student observers were trained to record the race/ethnicity of observed drivers (please see **Section 4** for more information on the training of observers). Non-Caucasian is a category that reflects any individual determined to not be Caucasian and includes: Black, Hispanic, Asian, Native American, Middle Eastern, and Other. On the Traffic Stop Data Form one option was “Unknown”. Since the race/ethnicity of these individuals could not be determined by the officer, they are not included in the analyses provided in **Sections 5, 6, and 7**.

In order to develop the four benchmark comparisons, multiple data sources were tapped to provide information beyond that which was gathered on the Traffic Stop Data Forms. In addition, various software packages were used to receive and store the traffic stop data, and manipulate the data from the other sources. For example, a Geographic Information System

(GIS) was used to spatially locate the traffic stops (by police zone) and exact locations of the observations conducted by the research team.

COMPARISON #1 – ALL STOPS VS. CENSUS VARIABLES

Census variables are collected once every ten years to provide a measure of the demographic, social and economic characteristics of an area. This information is made available to the public and is often used by researchers to assist in understanding the varying characteristics of different geographic neighborhoods. This study uses information from the 2000 Census to develop spatial characteristics for the police zones within the City of Cleveland, which in turn are used to provide a benchmark for comparison to traffic stopping patterns by the CDP. In addition, Census variables will be used in the analyses of post-stop outcomes discussed in **Sections 6 and 7**.

Census variables are used in analyses of traffic stops as the denominator when creating disproportionality indices and disproportionality ratios. Specifically, Census data are used as a proxy for the driving population or those that are “expected” to be stopped within a particular geographic area (i.e., police zone). The Census data are used to develop rates of racial groups within a geographic area that become the benchmark against which traffic stops are compared. For example, the Census provides a percentage of Caucasian individuals living in a geographical area. This value is subsequently used as a proxy for the driving population at risk of being stopped for a violation. For the purposes of developing the disproportionality index and the disproportionality ratio, the Census variables provide the denominator or the “expected” rate of motorists who are using the roadways.

Comparison #1 Limitations

Census data have numerous limitations that need to be highlighted to ensure that the results of any analyses conducted using Census variables are tempered with a consideration of such limitations. First, using the Census data as a proxy for the driving population assumes that everyone in the Census drives a vehicle. This assumption is questionable at best, even when only the driving aged population is used. It would be preferable to use licensed drivers within the geographic area of interest, but these data were not available with racial/ethnic identifiers. As a result, the use of Census data relies on the assumption that everyone counted in the Census drives a vehicle.

A second significant limitation to this benchmark is the underlying assumption that the residents who live in a particular area are the only ones who drive in that area. Unfortunately, this assumption is particularly tenuous in areas that contain thoroughfares used by commuters to reach major business areas, such as the downtown core. In Cleveland, streets such as Carnegie and Chester are major traffic corridors for commuters entering and leaving the downtown business area. The accuracy of Census variables as a proxy for driving populations in these areas may be particularly questionable as the traffic on the streets may not be represented by the individuals who live in those neighborhoods. As described this assumption is particularly questionable in commuter zones.

Third, the use of Census variables as a proxy for the driving population does not include any measures of risk of being stopped. As previously mentioned, there are at least six types of risk that affect the likelihood of being stopped (e.g., when you drive, how you drive, condition of vehicle, etc.). Unfortunately, the Census data do not measure any of these types of risk.

As a result of these limitations, the Census data represent the driving population only with the assumptions that all residents in the Census drive, citizens only drive within their own home zone, and none of the risk factors associated with the likelihood of being pulled over make any difference. Clearly, these limitations raise considerable concern about the interpretation of the results derived from this method and the analyses conducted with Census data need to be considered with caution. Another difficulty arising from the use of Census variables when analyzing traffic stops is the spatial incongruence of the police zones and the Census geographic areas. Both this problem and its solution are described in greater detail in **Appendix E**.

Results of Comparison # 1

Once the 42 police zones received the appropriate Census values as calculated using the apportionment method (discussed in **Appendix E**), disproportionality indices and ratios were created for all the police zones. Comparisons are made between all traffic stops by race as reported on the Traffic Stop Data Forms (i.e., the numerator of the disproportionality index) to the expected values based on the Census information (i.e., the denominator of the disproportionality index).

Table 5.1 reports the final calculation of disproportionality ratios. Specifically, the first set of columns reports the following information by police zone: the total population over eighteen according to the Census, the total number of police stops that occurred, and the Caucasian disproportionality index. Thereafter, the following information is reported for Blacks, Hispanics and Non-Caucasians: the percent of the population eighteen and over as reported in the Census, the percent of stops by the CDP, the disproportionality index, and the disproportionality ratio. For purposes of interpretation, the most pertinent values are the disproportionality ratios for Blacks, Hispanics and Non-Caucasians. Recall that these values should be interpreted as the number of times drivers are more likely to be stopped in comparison to Caucasian drivers within each police zone.

For Black drivers, the disproportionality ratios ranged from a low of 0.03 to a high of 14.89. Recall that a disproportionality ratio of 1.0 indicates no differences in stopping patterns across racial groups. Ratios greater than one indicate the number of times more likely the minority group is stopped compared to Caucasians, while ratios less than one indicate the number of times less likely the minority group is stopped compared to Caucasians. Across forty police zones⁷, fifteen zones (38%) had disproportionality ratios at or below 1.00, which indicates no disparity. Another seven zones (18%) had disproportionality ratios between 1.01 and 2.00. The remaining eighteen stations (45%) had disproportionality ratios that ranged between 2.01 to a high of 14.89 in Zone 324. Specifically, there were six zones that had disproportionality ratios above 5.00, indicating a substantial pattern of racial disparity in traffic stops compared to residential Census.

⁷ Disproportionality ratios were calculated for forty police zones, as two police zones did not have enough traffic stops to calculate Caucasian disproportionality indices.

For Hispanic drivers, the disproportionality ratios ranged from a low of 0.51 to a high of 3.80. Across fourteen police zones⁸, five police zones had disproportionality ratios at or below 1.00 (36%), six police zones (43%) had a disproportionality ratio between 1.01 and 2.00, while the remaining three Zones had a disproportionality ratio above 2.01.

The pattern of disproportionality ratios for Non-Caucasian drivers is similar to the Black drivers and range from a low of 0.03 to a high of 11.95. Across forty police zones⁹, fifteen zones (38%) had disproportionality ratios at or below 1.00 and fourteen zones (35%) were between 1.01 and 2.00. The remaining eleven zones (28%) had disproportionality ratios between 2.01 and 11.95. Due to the fact that Black drivers comprise a large percentage of the Non-Caucasian population both in the Census and in the stop data, it is not surprising that the same pattern of results for Blacks and Non-Caucasians is seen across zones.

Based on their raw value, some of these disproportionality ratios may raise a caution flag as to the behavior of officers within those zones. Importantly, however, the limitations of this comparison must be recognized. The use of Census data is imbued with significant limitations due to the underlying assumptions that must accompany using such data. As a result, it is inappropriate to draw any substantive conclusions from only this one comparison. Again, it is important to analyze the pattern of results across the various benchmarks and in combination with the post-stop outcomes (see **Sections 6 and 7**) prior to forming any conclusions regarding the activities of the CDP.

⁸ Disproportionality ratios were calculated for fourteen police zones, as twenty-eight police zones did not have enough traffic stops to calculate Hispanic disproportionality indices or ratios.

⁹ Disproportionality ratios were calculated for forty police zones, as two police zones did not have enough traffic stops to calculate Caucasian disproportionality indices.

Table 5.1: Zone Disproportionality Ratios Based on Census Data for Population 18 & Over (p. 1 of 2)

Zone	Total Pop > 18	Total # CDP Stops	Caucasian DI	<u>Blacks</u>				<u>Hispanics</u>				<u>Non - Caucasian</u>			
				% Pop > 18	% CDP Stops	Pop > 18 DI	Disparity Ratio	% Pop > 18	% CDP Stops	Pop > 18 DI	Disparity Ratio	% Pop > 18	% CDP Stops	Pop > 18 DI	Disparity Ratio
111	15,102	831	0.83	12.60	26.23	2.08	2.51	8.12	9.63	1.18	1.43	26.10	38.51	1.48	1.78
112	8,383	1,970	0.83	13.54	25.23	1.86	2.24	15.46	14.82	0.96	1.16	33.97	45.18	1.33	1.60
113	14,705	780	0.82	8.63	23.85	2.76	3.37	14.76	12.82	0.87	1.06	28.37	41.28	1.46	1.77
121	21,712	709	0.77	5.77	17.63	3.06	3.97	5.20	7.33	1.41	1.83	13.34	33.29	2.49	3.24
122	21,020	913	0.81	5.58	18.07	3.24	4.00	3.64	6.24	1.71	2.12	11.84	28.26	2.39	2.95
123	13,114	1,168	0.89	16.91	23.89	1.41	1.58	4.98	4.71	0.95	1.06	24.95	33.56	1.35	1.51
211	5,772	891	0.91	16.22	30.86	1.90	2.09	23.72	14.37	0.61	0.67	41.94	47.03	1.12	1.23
212	6,672	857	0.92	24.47	38.04	1.55	1.68	23.15	11.20	0.48	0.53	48.28	52.51	1.09	1.18
213	4,772	921	0.98	18.56	27.80	1.50	1.53	17.25	8.69	0.50	0.51	38.37	39.52	1.03	1.05
221	12,161	943	0.74	7.67	23.22	3.03	4.09	25.64	26.83	1.05	1.41	35.07	51.86	1.48	2.00
222	10,961	2,013	0.93	10.49	21.31	2.03	2.18	28.91	23.05	0.80	0.86	40.93	45.26	1.11	1.19
223	18,963	423	0.79	1.75	11.11	6.35	8.04	5.12	15.37	3.00	3.80	9.25	27.90	3.02	3.82
224	13,788	553	0.82	2.95	16.64	5.64	6.88	4.13	7.23	1.75	2.13	9.27	25.50	2.75	3.35
311	3,088	2,871	1.20	54.57	46.57	0.85	0.71	3.96	2.93	0.74	0.62	59.65	51.55	0.86	0.72
312	4,744	1,169	1.45	63.10	57.40	0.91	0.63	2.30	--	--	--	73.46	61.59	0.84	0.58
313	3,375	774	0.77	23.24	61.37	2.64	3.43	9.28	--	--	--	57.26	66.93	1.17	1.52
321	3,517	645	3.61	93.98	80.00	0.85	0.24	1.08	--	--	--	95.02	82.02	0.86	0.24
322	4,501	827	0.40	22.81	68.80	3.02	7.55	5.82	--	--	--	30.31	72.07	2.38	5.94
323	6,685	1,199	0.31	30.32	78.48	2.59	8.35	4.21	--	--	--	36.08	80.48	2.23	7.20
324	8,142	592	0.36	12.52	67.06	5.36	14.89	2.26	--	--	--	16.18	69.59	4.30	11.95

-- indicates that there was either no data to compute the Disparity Ratio or there were less than 30 cases which may cause the Disparity Ratio to be unstable.

Disparity Ratios may vary slightly at the hundredth decimal place due to rounding during the calculations.

Table 5.1: Zone Disproportionality Ratios Based on Census Data for Population 18 & Over (p. 2 of 2)

Zone	Total Pop > 18	Total # CDP Stops	Caucasian DI	Blacks				Hispanics				Non - Caucasian			
				% Pop > 18	% CDP Stops	Pop > 18 DI	Disparity Ratio	% Pop > 18	% CDP Stops	Pop > 18 DI	Disparity Ratio	% Pop > 18	% CDP Stops	Pop > 18 DI	Disparity Ratio
411	3,162	1,782	2.11	96.32	92.93	0.96	0.45	0.51	--	--	--	97.07	93.83	0.97	0.46
412	7,408	582	3.13	96.88	91.75	0.95	0.30	0.37	--	--	--	97.64	92.61	0.95	0.30
413	8,365	1,176	2.66	97.15	93.03	0.96	0.36	0.50	--	--	--	97.60	93.62	0.96	0.36
414	10,943	465	0.33	36.93	78.49	2.13	6.45	1.83	--	--	--	39.45	79.78	2.02	6.13
421	10,879	570	2.08	96.67	94.39	0.98	0.47	0.62	--	--	--	97.39	94.56	0.97	0.47
422	8,917	1,564	3.84	98.34	95.33	0.97	0.25	0.69	--	--	--	98.90	95.78	0.97	0.25
423	7,736	1,068	--	98.44	97.28	0.99	--	0.58	--	--	--	98.90	97.47	0.99	--
424	11,396	939	1.08	92.25	92.23	1.00	0.93	0.50	--	--	--	93.38	92.86	0.99	0.92
425	5,844	270	--	90.13	90.74	1.01	--	0.72	--	--	--	91.65	91.11	0.99	--
511	7,119	955	0.78	72.40	81.88	1.13	1.45	5.35	--	--	--	78.62	83.25	1.06	1.36
512	4,935	701	5.20	93.69	70.33	0.75	0.14	1.59	--	--	--	95.01	74.04	0.78	0.15
513	7,390	1,008	5.64	95.65	78.57	0.82	0.15	0.79	--	--	--	96.50	80.26	0.83	0.15
514	11,098	676	0.50	47.06	78.70	1.67	3.34	1.48	--	--	--	58.84	79.59	1.35	2.71
521	2,219	550	19.94	97.40	66.18	0.68	0.03	0.94	--	--	--	98.35	67.09	0.68	0.03
522	6,217	373	1.19	86.85	84.99	0.98	0.82	0.82	--	--	--	88.73	86.60	0.98	0.82
523	13,872	944	0.72	73.12	82.73	1.13	1.57	1.25	--	--	--	78.24	84.32	1.08	1.50
611	10,452	944	0.79	90.28	91.84	1.02	1.29	0.58	--	--	--	91.04	92.90	1.02	1.29
612	12,742	1,969	6.45	98.49	92.74	0.94	0.15	0.58	--	--	--	99.00	93.55	0.94	0.15
613	7,184	1,691	2.14	95.43	90.83	0.95	0.44	0.53	--	--	--	96.05	91.54	0.95	0.45
621	10,175	552	0.66	77.38	85.51	1.11	1.68	0.67	--	--	--	78.98	86.23	1.09	1.65
622	5,723	1,403	0.46	55.36	79.69	1.44	3.13	1.31	--	--	--	57.82	80.61	1.39	3.03
623	14,863	1,584	0.60	48.03	68.75	1.43	2.38	0.89	--	--	--	49.95	70.14	1.40	2.34

-- indicates that there was either no data to compute the Disparity Ratio or there were less than 30 cases which may cause the Disparity Ratio to be unstable.

Disparity Ratios may vary slightly at the hundredth decimal place due to rounding during the calculations.

COMPARISON #2 – IN-ZONE STOPS VS. CENSUS VARIABLES

The second comparison examines only stops that occurred within the home zone of the driver in comparison to the Census values for that police zone. That is, only traffic stops of motorists who reside in the zone where they were stopped are included in the analyses. The primary difference between Comparison #1 and this comparison is that the numerator of this comparison is a closer match to the denominator. That is, by only including drivers who live in the police zone of interest, these stops should match the denominator more closely.

Comparison #2 Limitations

The limitations that are associated with the creation of the denominator in Comparison #1 still exist with this comparison as a result of using Census variables. In addition to these limitations, there is an additional assumption related to identifying the home zone of the drivers. In brief, due to the spatial incongruence between the zip code boundaries and the police zones, one zip code crosses multiple police zones. As a result, the traffic stop was assigned to more than one police zone depending on the driver's home zip code (for details, see **Appendix E**).

Results of Comparison # 2

Once the 42 police zones received the appropriate Census values as calculated using the apportionment method and the stops were assigned to the appropriate police zones (see **Appendix E**), disproportionality indices and ratios were created for all the police zones. This comparison is based on the use of only within police zone traffic stops by race (the numerator of the disproportionality index) in comparison to the expected values based on the Census information. **Table 5.2** reports disproportionality ratios (in addition to the Caucasian disproportionality index) for all 42 zones. In some cases, disproportionality ratios were not able to be calculated because no stops occurred for that racial/ethnic group of citizens, and are represented in **Table 5.2** with a dash.

The first set of columns reports the following information by police zone: the total number of stops that were of within zone residents (motorists who lived in the police zone where they were stopped), the percent of stops within that zone that were of within zone residents, and the Caucasian disproportionality index. The next columns include the following information for Blacks, Hispanics and Non-Caucasians: the percent of the population eighteen and over as reported in the Census, the percent of CDP stops, the disproportionality index, and the disproportionality ratio. For purposes of interpretation, the most pertinent values are the disproportionality ratios for Blacks, Hispanics and Non-Caucasians. Recall that these values should be interpreted as the number of times drivers are more likely to be stopped in comparison to Caucasian drivers within each police zone.

For Black drivers, the disproportionality ratios ranged from a low of 0.75 to a high of 12.07. Across the seventeen police zones¹⁰, only one police zone (6%) had a disproportionality ratio at or below 1.00, which indicates no disparity (values below 1.00 indicate that Blacks are less likely to be stopped in comparison to their Caucasian counterparts). Another three zones (18%) had disproportionality ratios between 1.01 and 2.00. The remaining thirteen zones (76%) had disproportionality ratios that ranged between 2.01 to a high of 12.07 in Zone 324. Specifically, five zones (36%) had disproportionality ratios above 5.00, indicating a substantial pattern of disparity in stopping behavior.

For Hispanic drivers, the disproportionality ratios ranged from a low of 1.40 to a high of 4.10. Across the seven zones¹¹, three zones (43%) had disproportionality ratios between 1.01 and 2.00, and four zones (57%) had disproportionality ratios above 2.01 with the highest ratio in Zone 223 at 4.10.

The pattern of disproportionality ratios for Non-Caucasian drivers is again similar to the Black drivers and ranges from a low of 0.81 to a high of 9.52 across the 20 zones that had disproportionality ratios calculated¹². Two of the zones (10%) had disproportionality ratios at or below 1.00, whereas three zones (15%) had disproportionality ratios between 1.01 and 2.00. The remaining fifteen zones (75%) had disproportionality ratios over 2.01. Due to the fact that Black drivers comprise a large percentage of the Non-Caucasian population both in the Census and in the stop data, it is not surprising that the same pattern of results for Blacks and Non-Caucasians is seen across zones.

¹⁰ Disproportionality ratios were calculated for seventeen police zones, as twenty-one police zones did not have enough traffic stops to calculate Caucasian disproportionality indices and four police zones did not have enough traffic stops to calculate Black disproportionality indices.

¹¹ Disproportionality ratios were calculated for seven police zones, as thirty-five police zones did not have enough traffic stops to calculate Hispanic disproportionality indices and ratios.

¹² Disproportionality ratios were calculated for twenty police zones, as twenty-one police zones did not have enough traffic stops to calculate Caucasian disproportionality indices and one police zone did not have enough traffic stops to calculate a Non-Caucasian disproportionality index or ratio.

Table 5.2: Disproportionality Ratios for Blacks, Hispanics, and Non-Caucasians for Within Zone Residents Only (p. 1 of 2)

Zone	# Stops In-Zone Residents	% of Stops In-Zone Residents	Caucasian DI	Blacks				Hispanics				Non - Caucasian			
				% Pop > 18	% CDP Stops	Pop > 18 DI	Disparity Ratio	% Pop > 18	% CDP Stops	Pop > 18 DI	Disparity Ratio	% Pop > 18	% CDP Stops	Pop > 18 DI	Disparity Ratio
111	220	26.47	0.71	12.60	25.91	2.06	2.90	8.12	19.09	2.35	3.31	26.10	47.27	1.81	2.55
112	760	38.58	0.72	13.54	25.26	1.87	2.60	15.46	22.63	1.46	2.03	33.97	52.24	1.54	2.14
113	313	40.13	0.74	8.63	20.77	2.41	3.26	14.76	21.41	1.45	1.96	28.37	46.65	1.64	2.22
121	226	31.88	0.81	5.77	--	--	--	5.20	--	--	--	13.34	29.65	2.22	2.74
122	356	38.99	0.78	5.58	19.94	3.57	4.58	3.64	--	--	--	11.84	31.46	2.66	3.41
123	234	20.03	0.76	16.91	34.19	2.02	2.66	4.98	--	--	--	24.95	42.74	1.71	2.25
211	229	25.70	0.79	16.22	24.45	1.51	1.91	23.72	28.38	1.20	1.52	41.94	54.15	1.29	1.63
212	68	7.93	0.97	24.47	--	--	--	23.15	--	--	--	48.28	50.00	1.04	1.07
213	128	13.90	1.08	18.56	22.7*	1.22*	1.13*	17.25	--	--	--	38.37	33.59	0.88	0.81
221	427	45.28	0.65	7.67	18.03	2.35	3.62	25.64	39.34	1.53	2.35	35.07	57.61	1.64	2.52
222	501	24.89	0.84	10.49	15.77	1.50	1.79	28.91	34.13	1.18	1.40	40.93	50.10	1.22	1.45
223	221	52.25	0.82	1.75	--	--	--	5.12	17.19	3.36	4.10	9.25	25.34	2.74	3.34
224	147	26.58	0.91	2.95	--	--	--	4.13	--	--	--	9.27	--	--	--
311	169	5.89	1.10	54.57	45.56	0.83	0.75	3.96	--	--	--	59.65	55.62	0.93	0.85
312	53	4.53	--	63.10	60.38	0.96	--	2.30	--	--	--	73.46	81.13	1.10	--
313	155	20.03	0.59	23.24	63.87	2.75	4.66	9.28	--	--	--	57.26	74.84	1.31	2.22
321	145	22.48	--	93.98	97.93	1.04	--	1.08	--	--	--	95.02	98.62	1.04	--
322	343	41.48	0.32	22.81	76.09	3.34	10.44	5.82	--	--	--	30.31	77.55	2.56	8.00
323	599	49.96	0.32	30.32	77.80	2.57	8.03	4.21	--	--	--	36.08	79.80	2.21	6.91
324	241	40.71	0.42	12.52	63.49	5.07	12.07	2.26	--	--	--	16.18	64.73	4.00	9.52

-- indicates that there was either no data to compute the Disparity Ratio or there were less than 30 cases which may cause the Disparity Ratio to be unstable.

* These values were created with a low number of cases which may make their values unstable.

Disparity Ratios may vary slightly at the hundredth decimal place due to rounding during the calculations.

Table 5.2: Disproportionality Ratios for Blacks, Hispanics, and Non-Caucasians for Within Zone Residents Only (p. 2 of 2)

Zone	# Stops In-Zone Residents	% of Stops In-Zone Residents	Caucasian DI	Blacks				Hispanics				Non - Caucasian			
				% Pop > 18	% CDP Stops	Pop > 18 DI	Disparity Ratio	% Pop > 18	% CDP Stops	Pop > 18 DI	Disparity Ratio	% Pop > 18	% CDP Stops	Pop > 18 DI	Disparity Ratio
411	374	20.99	--	96.32	98.40	1.02	--	0.51	--	--	--	97.07	98.40	1.01	--
412	216	37.11	--	96.88	97.69	1.01	--	0.37	--	--	--	97.64	97.69	1.00	--
413	549	46.68	--	97.15	96.54	0.99	--	0.50	--	--	--	97.60	96.72	0.99	--
414	157	33.76	0.33	36.93	80.25	2.17	6.58	1.83	--	--	--	39.45	80.25	2.03	6.15
421	174	30.53	--	96.67	98.28	1.02	--	0.62	--	--	--	97.39	98.28	1.01	--
422	668	42.71	--	98.34	98.05	1.00	--	0.69	--	--	--	98.90	98.20	0.99	--
423	448	41.95	--	98.44	99.33	1.01	--	0.58	--	--	--	98.90	99.33	1.00	--
424	240	25.56	--	92.25	100.0	1.08	--	0.50	--	--	--	93.38	100.0	1.07	--
425	85	31.48	--	90.13	98.82	1.10	--	0.72	--	--	--	91.65	98.82	1.08	--
511	231	24.19	--	72.40	93.51	1.29	--	5.35	--	--	--	78.62	93.94	1.19	--
512	120	17.12	--	93.69	96.67	1.03	--	1.59	--	--	--	95.01	99.17	1.04	--
513	214	21.23	--	95.65	95.33	1.00	--	0.79	--	--	--	96.50	95.79	0.99	--
514	142	21.01	--	47.06	91.55	1.95	--	1.48	--	--	--	58.84	91.55	1.56	--
521	103	18.73	--	97.40	95.15	0.98	--	0.94	--	--	--	98.35	95.15	0.97	--
522	114	30.56	--	86.85	98.25	1.13	--	0.82	--	--	--	88.73	99.12	1.12	--
523	234	24.79	--	73.12	90.17	1.23	--	1.25	--	--	--	78.24	91.88	1.17	--
611	403	42.69	--	90.28	98.01	1.09	--	0.58	--	--	--	91.04	98.26	1.08	--
612	691	35.09	--	98.49	98.70	1.00	--	0.58	--	--	--	99.00	98.84	1.00	--
613	661	39.09	--	95.43	98.49	1.03	--	0.53	--	--	--	96.05	98.49	1.03	--
621	236	42.75	--	77.38	91.10	1.18	--	0.67	--	--	--	78.98	91.53	1.16	--
622	377	26.87	0.25	55.36	89.12	1.61	6.44	1.31	--	--	--	57.82	89.39	1.55	6.20
623	547	34.53	0.46	48.03	76.97	1.60	3.48	0.89	--	--	--	49.95	77.15	1.54	3.35

-- indicates that there was either no data to compute the Disparity Ratio or there were less than 30 cases which may cause the Disparity Ratio to be unstable.

Disparity Ratios may vary slightly at the hundredth decimal place due to rounding during the calculations.

COMPARISON # 3 – DAYTIME STOPS VS. OBSERVATIONS

Similar to the Census variables used in Comparisons #1 and #2, the data collected from the roadway observations are used as a proxy for the actual driving population. Student observers were placed in nine police zones to collect information on the vehicles within those locations (for a more complete discussion of the observation process, including training, selection of the locations, and amount of time spent observing, please see **Sections 2 and 4**). The observations in the nine police zones provide the benchmark for comparison to the traffic stop data collected by the CDP. Due to the fact that the observations were conducted only during daylight hours, the traffic stop data used in this analysis only include daylight stops by officers. As a result, Comparison #3 uses daylight traffic stops in the numerator and observation data in the denominator across the nine police zones in which observations were conducted.

Comparison #3 Limitations

Similar to the previous benchmarks, the use of observation data has limitations that must be considered when interpreting the results. One of the most obvious and potentially limiting concerns is the spatial dispersion of the observation locations. Some police zones cover several square miles; however, the majority of the observations occurred on one street and only varied a few blocks in radius. These locations were selected due to methodological and budgetary considerations. As a result of these concerns, the observation data collected at these locations are used as a proxy for the driving population throughout the entire police zone. Most often these observation locations were on major thoroughfares that carry a significant commuter population. It is possible that the results from this comparison could be reflective of only the drivers who use the commuter routes and not of the driving population of the entire police zone. While this limitation is a concern, the majority of police stops recorded on the Traffic Stop Data Forms are also on those major thoroughfares. Thus, for purposes of comparing the observations to police stop data, this limitation is less problematic.

A second limitation of this benchmark is its inability to measure all factors associated with a drivers' risk of being stopped. In other words, while it does collect information on where drivers drive, when they drive, what they drive, and who they are, it does not collect information on how they drive. Arguably, one of the most important risk factors for drivers is the manner in which they drive. That is, if they violate driving rules and regulations, they run an increased risk of being stopped by police.

A third limitation of the observation data is its inability to measure and record driving behavior in non-daylight hours. For example, the observations conducted for this research were only conducted during daylight hours; thus, it is not possible to compare the observation data with the traffic stop data for non-daylight hours. Therefore, comparison for benchmark purposes can only be conducted for traffic stops that occur in the daylight hours.

Results of Comparison # 3

Comparison #3 is limited to the nine police zones in which observations were conducted. In addition, Comparison #3 uses only daytime stops on the Traffic Stop Data Form and compares that value to the rate of drivers according to the observation data. Only the daytime stops were used to ensure that the values being compared correspond in time, as the observations were only conducted during daylight hours (7AM till 7PM).

The first column in **Table 5.3** identifies the police zone of the comparison. The second column provides the Caucasian disproportionality index. The following column sections represent Blacks, Hispanics and Non-Caucasians. Each race/ethnic group category contains: the percent of drivers observed in each of the police zones during daylight hours, the percent of drivers stopped in those police zones during daylight hours, the race/ethnicity group disproportionality index and disproportionality ratio.

The results of Comparison #3 indicate a range of disproportionality ratios for Black drivers from a low of 0.67 to a high of 4.73. Only one police zone (11%) had a disproportionality ratio at or below 1.00, which indicates no disparity in stopping Black drivers in comparison to Caucasian drivers. Four of the nine police zones (44%) had disproportionality ratios between 1.01 and 2.00. The remaining four zones had disproportionality ratios above 2.01.

For Hispanic drivers, the disproportionality ratios range from a low of 0.47 to a high of 1.23. Disproportionality ratios were calculated for only four police zones due to a low number of traffic stops involving Hispanics in the remaining police zones. A low number of traffic stops produces unstable and unreliable disproportionality indices and ratios and are not used in this analysis. Three of the four police zones (75%) had disproportionality ratios below 1.00 and the one remaining police zone had a disproportionality ratio slightly above that level (1.42).

For Non-Caucasian drivers, the pattern of findings is similar to that of Black drivers with disproportionality ratios ranging from a low of 0.66 to a high of 4.52. Three of the nine police zones (33%) had disproportionality ratios below 1.00, while another three police zones (33%) had disproportionality ratios between 1.00 and 2.00. The remaining three police zones had disproportionality ratios above 2.01, with Zones 513 and Zone 623 recording the highest values for Non-Caucasian drivers at 3.90 and 4.52, respectively.

While there were only nine police zones analyzed using the observation data, the zones in Districts 1, 2, and 3 generally had lower disproportionality ratios than the ratios reported in the previous two comparisons. The police zones in Districts 4, 5, and 6 (except Zone 512) reported slightly higher disproportionality ratios than those in the other comparisons. In general, the pattern of results based on the observation data do not suggest a significant pattern of disparity although the ratios in Zone 513 and Zone 623 are of some concern. As previously mentioned, it is best to interpret these values in combination with the disproportionality ratios generated from the other comparisons.

Table 5.3: Disproportionality Ratios for Blacks, Hispanics, and Non-Caucasians Based on Observation Data Only

Zone	Caucasian DI	<u>Blacks</u>				<u>Hispanics</u>				<u>Non - Caucasian</u>			
		% Obs.	% CDP Stops	Disparity Index	Disparity Ratio	% Obs.	% CDP Stops	Disparity Index	Disparity Ratio	% Obs.	% CDP Stops	Disparity Index	Disparity Ratio
112	0.87	21.88	27.70	1.27	1.46	12.76	15.70	1.23	1.42	38.63	46.78	1.21	1.39
212	1.01	18.03	30.96	1.72	1.70	24.81	11.74	0.47	0.47	46.72	46.26	0.99	0.98
221	1.12	8.57	25.51	2.98	2.66	39.74	28.12	0.71	0.63	60.00	55.36	0.92	0.82
222	1.22	23.82	19.52	0.82	0.67	27.15	22.48	0.83	0.68	52.80	42.58	0.81	0.66
313	0.78	38.22	53.29	1.39	1.78	0.54	--	--	--	47.20	59.02	1.25	1.60
424	0.44	83.29	92.58	1.11	2.52	--	--	--	--	85.05	93.41	1.10	2.49
512	0.86	60.88	66.87	1.10	1.28	--	--	--	--	65.93	70.68	1.07	1.24
513	0.45	34.26	69.89	2.04	4.39	--	--	--	--	38.14	72.34	1.90	3.90
623	0.45	32.11	68.28	2.13	4.73	--	--	--	--	34.29	70.40	2.05	4.52

-- indicates that there was either no data to compute the Disparity Ratio or there were less than 30 cases which may cause the Disparity Ratio to be unstable.

Disparity Ratios may vary slightly at the hundredth decimal place due to rounding during the calculations.

COMPARISON #4 – DAYTIME STOPS VS. VIOLATING BEHAVIOR (SPEEDING 8+)

Comparison #4 is also based on the observations conducted by student observers across nine police zones. The primary difference in this analysis compared to the previous one is that only violating behavior is included in an attempt to assess the risk of being stopped. One of the six factors affecting the risk of being stopped is how citizens drive and examining violating behavior allows some measurement of this risk. For Comparison #4, only speeding behavior is considered as one of the factors that places a vehicle at risk of being stopped.

To create these comparisons, only daylight traffic stops that occurred for speeding violations were considered (to match the daylight observations of speeders). In Comparison #4, any stops of vehicles for speeding eight or more miles per hour over the legal speed limit in the area of the stop were included in the numerator. The choice of speeding at eight miles per hour or more was chosen based on the statistical mean of speeders (i.e., 17 miles per hour) and then reduced by two standard deviations (i.e., one standard deviation is equal to slightly less than 5 miles per hour). The benchmark (denominator) is based on the traffic observation data collected by the student observers. As outlined in **Section 4**, the observers were equipped with RADAR/LASER and captured the speed of the passing motorists to gather a sample of the risk associated with being stopped. As with Comparison #3, the data from the Traffic Stop Data Form comprised the numerator and the observation data represented the denominator.

Comparison # 4 Limitations

As with all of the benchmarks, Comparison #4 has a set of limitations that must be considered when evaluating the results of the analysis. This comparison has the same set of limitations as Comparison #3 due to the fact that the data used in this comparison analysis are a subset of the data used in Comparison #3. Consequently, one limitation is the assumption that the observations accurately reflect driving patterns across the entire police zone. In addition to that limitation, the use of speeding violations is only one type of violating behavior which could increase the risk of being stopped by the police. That is, other driving violations were not captured by the observers, and as such, while speeding is one of the most common types of violations, there are other violations that were not included in this analysis. This benchmark limitation is less important, however, when the data are only compared to traffic stops for speeding.

Another limitation that arises when examining these speeding violations is that the number of stops and observations included is quite low. While this does not directly bias the analysis, it is important to recognize the significant reduction in the quantity of stops included in the analysis in comparison to some of the other analyses (e.g., Comparison #1 using all traffic stops). Despite these limitations, Comparison #4 provides an alternative picture of the stopping patterns engaged in by CDP officers.

Results of Comparison # 4

As described previously, Comparison #4 is limited to the nine police zones in which observations were conducted. Comparison #4 uses daytime stops that occurred as a result of speeding eight or more miles per hour over the legal speed limit as reported on the Traffic Stop Data Form. This value is compared to drivers that were recorded speeding eight miles per hour or more according to the observation data. Only the daytime stops were used to ensure that the values being compared correspond in time, as the observations were only conducted during daylight hours (7:00 am – 7:00 pm).

The first column in **Table 5.4** identifies the police zone of the comparison. The second column provides the Caucasian disproportionality index. The following columns include the following information for Blacks, Hispanics and Non-Caucasians: the percent of drivers observed in each of the police zones during daylight hours, the percent of drivers stopped in those police zones during daylight hours, the race/ethnic group disproportionality index and disproportionality ratio.

As **Table 5.4** demonstrates, the results of this analysis were only calculated for five police zones¹³. For Black drivers across these five remaining police zones, the disproportionality ratios ranged from a low of 0.58 to a high of 3.14. In Zones 112 and 512, Black drivers were actually less likely to be stopped in comparison to Caucasian drivers, whereas in the remaining three police zones, disproportionality ratios were above 1.00, with two of these zones having ratios above 2.01.

For Hispanic drivers, it was not possible to calculate disproportionality ratios for any of the police zones in which observations of speeders occurred. Either there were not enough observations of Hispanic drivers speeding at eight miles per hour or more over the speed limit or there were not enough traffic stops for speeding.

For Non-Caucasian drivers, the disproportionality ratios ranged from a low of 0.68 to a high of 3.01 across the five police zones¹⁴. Two of the police zones had disproportionality ratios below 1.00, indicating that Non-Caucasian drivers were less likely than Caucasian drivers to be stopped during daylight hours for speeding eight miles per hour or more over the legal speed limit. There was one police zone with a disproportionality ratio slightly above 1.00 (1.02). The remaining two police zones had disproportionality ratios above 2.01 and these ratios suggest slight disparity in stopping patterns.

¹³ Disproportionality ratios were calculated for five police zones, as four police zones did not have enough traffic stops to calculate Caucasian disproportionality indices and the subsequent Black disparity ratio.

¹⁴ Disproportionality ratios were calculated for five police zones, as four police zones did not have enough traffic stops to calculate Caucasian disproportionality indices and the subsequent Non-Caucasian disparity ratio.

Table 5.4: Disproportionality Ratios for Blacks, Hispanics, and Non-Caucasians Based on Observation Data of Speeding 8+

Zone	Caucasian DI	<u>Blacks</u>				<u>Hispanics</u>				<u>Non - Caucasian</u>			
		% Obs.	% CDP Stops	Disparity Index	Disparity Ratio	% Obs.	% CDP Stops	Disparity Index	Disparity Ratio	% Obs.	% CDP Stops	Disparity Index	Disparity Ratio
112	1.15	26.11	17.41	0.67	0.58	9.29	--	--	--	41.30	32.34	0.78	0.68
212	--	--	--	--	--	--	--	--	--	--	33.33	--	--
221	--	--	--	--	--	--	--	--	--	--	39.47	--	--
222	--	--	14.80	--	--	--	27.20	--	--	56.36	42.00	0.75	--
313	1.01	31.07	38.24	1.23	1.21	--	--	--	--	42.01	41.18	0.98	0.97
424	--	83.38	94.12	1.13	--	--	--	--	--	85.93	95.29	1.11	--
512	0.99	52.00	47.83	0.92	0.93	--	--	--	--	56.00	56.52	1.01	1.02
513	0.64	33.84	59.39	1.75	2.83	--	--	--	--	41.44	62.80	1.52	2.47
623	0.62	26.80	52.07	1.94	3.14	--	--	--	--	30.72	57.14	1.86	3.01

-- indicates that there was either no data to compute the Disparity Ratio or there were less than 30 cases which may cause the Disparity Ratio to be unstable.

Disparity Ratios may vary slightly at the hundredth decimal place due to rounding during the calculations.

COMPARISON OF CENSUS VARIABLES TO OBSERVATION VARIABLES

One of the on-going difficulties with the issue of benchmarking is comparing the accuracy of one benchmark in relation to another benchmark. This research project enabled an examination of this issue by comparing the Census benchmarks to the observation benchmark in nine police zones.

Due to the limited number of police zones that contained observation data (observations were limited due to budgetary considerations), the research team wanted to explore the possibility of using Census data as a proxy for observations in those areas in which no observations were performed. The best method to assess if there is a difference between the benchmarks is to compare them using a single sample t-test for difference. The t-test examines the percentage of a group within both the Census and the observation data to determine if the values are significantly different from one another. For example, in the case of Caucasian drivers, the percentage of Caucasian drivers observed in a police zone would be compared to the percentage of Caucasian drivers who live in the police zone according to the Census. The t-test statistically examines if there is a difference between the two rates, and if there is a difference, this indicates a discrepancy between the two data sources. If a discrepancy exists, it would be problematic to use the Census data as a proxy in areas that do not have observations. That is, the Census variables associated with the police zones without observations would have to be assessed with all the aforementioned limitations of the Census data.

Results of Census Variables vs. Observation Variables

Table 5.5 reports the results of the t-test comparison between the Census data and the observation data. The comparison was conducted at the lowest geographic unit provided by the Census – the block group. In **Table 5.5**, each of the observation locations were separated into the corresponding block groups and are identified in the first column of the table. In other words, since some of the ten observation locations described in **Section 4** crossed block group boundaries of the Census, additional observation “locations” were created (the number now exceeds nine). The comparison was conducted on Caucasian and Black drivers due to the fact that these were the only two racial/ethnic groups that were frequently recorded driving using the observation method. The second column reports the number of observations that occurred at that location. The next set of columns is divided into the results for the Caucasian and Black drivers. For each of these groups, the percent of drivers observed and the percent according to the proxy Census measure are reported. The final column in each section provides the actual t-test value.

Table 5.5: T-Test Comparison of Observation Data vs. Census Data by Block Group

Block Group Location	# of Observations	Caucasian Drivers			Black Drivers		
		% Obs.	% Census	T Value	% Obs.	% Census	T Value
1	2,801	.61	.57	4.32	.22	.16	7.61
2	3,529	.61	.56	6.67	.22	.15	9.70
3	1,844	.44	.52	-6.56	.18	.08	11.18
4	3,135	.54	.43	12.18	.17	.12	7.41
5	1,588	.52	.31	16.81	.20	.14	6.05
6	1,616	.62	.41	17.45	.27	.16	9.99
7	5,281	.50	.38	17.18	.42	.59	-25.74
8	1,356	.25	.04	18.12	.70	.95	-19.87
9	1,226	.31	.02	21.81	.67	.97	-22.44
10	1,061	.49	.03	29.85	.42	.95	-35.15
11	6,577	.49	.12	80.97	.34	.88	-93.57
12	55	.55	.79	-3.61	.33	.15	2.78
13	461	.60	.01	25.88	.35	.98	-28.52
14	3,497	.66	.81	-19.23	.32	.17	19.04
15	244	.16	.01	6.48	.82	.99	-6.91
16	1,891	.13	.01	15.60	.85	.99	-17.18
17	169	.13	.01	4.63	.86	.99	-4.77
18	1,112	.18	.01	14.74	.80	.99	-15.81

All values were significant at the .001 level.

As **Table 5.5** demonstrates, all of the t-tests indicate that there is a statistically significant difference between the data from the observations and the data gathered from the Census. The value of the t-test is interpreted as whether or not there is equivalence between the two values. The same procedure is used for Black drivers. The results of this analysis suggest that across all 18 block group locations, the rate of Caucasian and Black drivers observed did *not* match the corresponding values gathered from the Census. Substantively, these results do *not* support using the Census variables as a proxy for observations, or in other words, census data and observation data do not provide the same estimates of the driving population. As a result, Census data should *not* be considered a valid proxy for observations in the police zones that did not have roadway observations.

COMPARISON OF BENCHMARKING RESULTS

Table 5.6 provides a summary of the four benchmarks across Black, Hispanic and Non-Caucasian drivers used in this analysis and **Figures 5.1 – 5.4** provide a visual representation of Black and Non-Caucasian drivers across Comparison #1 and Comparison #3. Keeping in mind the litany of limitations associated with each benchmark, several general trends appear in the results when examining the benchmarks. First, the results suggest that Districts 1, 2, and 3 are distinct from Districts 4, 5, and 6 across all the benchmark comparisons. For example, using the Census model, Districts 1, 2, and 3 demonstrate some concerning disproportionality ratios, whereas the same model shows much lower ratios for Districts 4, 5, and 6. Within each group

(Districts 1, 2, and 3 versus Districts 4, 5, and 6), there are police zones that do not support the general trend (e.g., Zone 311, 312, 414, and 514), but overall, this pattern seems to be consistent. The results from the In-Zone, Observations, and Speed 8+ models are more difficult to interpret individually due to various data collection limitations, and as a result, disproportionality ratios were calculated for only a few police zones. Due to this difficulty, interpretation of the In-Zone, Observation, and Speed 8+ model are only provided in relation to one another and the Census model.

A second general trend arising from the results of this analysis is the similarity between the Black disproportionality ratios and the Non-Caucasian disproportionality ratios. As previously discussed, this is primarily due to the large percentage of Non-Caucasians that are Black. In general, the disproportionality ratios for the Non-Caucasians are slightly lower than those for Black drivers, likely due to the inclusion of Hispanic drivers.

Third, and related to the first general trend, when comparing across the benchmarks, Districts 1, 2, and 3 show a distinct pattern of results in comparison to Districts 4, 5, and 6. Specifically, in Districts 1, 2, and 3, the Census model does produce some slightly concerning disproportionality ratios; however, these disproportionality ratios decrease in many police zones when examining the In-Zone model. Conversely, Districts 4, 5, and 6 demonstrate a substantial increase in disproportionality ratios when comparing the In-Zone model to the Census model. This pattern is consistent across Black, Hispanic, and Non-Caucasian drivers. Districts 1, 2, and 3 demonstrate lower In-Zone disproportionality ratios when compared to the Census model, as would be expected when comparing these two benchmarks. When using Census as the denominator in both calculations, the change in the In-Zone model to only traffic stops of within zone residents should reduce the disproportionality ratio, as it restricts the analysis to only those drivers who more closely mirror the Census values.

This trend is reversed in Districts 4, 5, and 6, which are predominately Black neighborhoods with commuter traffic traveling through towards other destinations. The In-Zone model increases in these districts when compared to the Census model. The different race/ethnicity makeup of these geographic areas may explain this different trend. The manner in which the In-Zone disproportionality ratio was created should increase the ratio in areas that have a lot of out of zone traffic of a different race/ethnicity background because more drivers from other areas are being stopped in this geographic area. Unfortunately, there were not enough observations conducted with traffic stops or traffic stops of Hispanic drivers in Districts 4, 5, and 6 to examine the patterns for that race/ethnicity group. To more fully understand the dynamics of the changing benchmarks, it is important to examine the observation models.

In comparison to the Census-based models, the disproportionality ratios for the observation models for Districts 4, 5, and 6 show an increase, while the disproportionality ratios for the observation models decrease for Districts 1, 2, and 3. Consistent with the explanation provided for the changing In-Zone disproportionality ratios, the increase in disproportionality ratios in Districts 4, 5, and 6 for the observation model does reflect the inaccuracy of the Census based models as a proxy for the driving population. The high concentration of Black residents is reduced by the non-Black commuter traffic; consequently, the actual observations show a more

accurate picture of the driving population. For Hispanic drivers, the use of the observation data as a benchmark reduces the disproportionality ratios, particularly in primarily Hispanic zones.

The Speed 8+ model generally follows the same trend as the Observation model in Districts 1, 2, and 3 by reducing the disproportionality ratio in comparison to the Census model. In Districts 4, 5, and 6, the same pattern is demonstrated in which the disproportionality ratio is reduced when compared to the Observation model in all police zones except for one; however, it does show higher disproportionality ratios when compared with the Census model. Similar to the results observed in the Observation model, the Speed 8+ model is likely higher than the Census model due to the race/ethnicity composition of the area and the commuter traffic in those areas.

Table 5.6: Comparison of Disproportionality Ratios for the Four Methods by Zone (p. 1 of 2)

Zone	<u>Black</u>				<u>Hispanic</u>				<u>Non-Caucasian</u>			
	Census Model	In-Zone Model	Observation Model	Speed Model 8 MPH+	Census Model	In-Zone Model	Observation Model	Speed Model 8 MPH+	Census Model	In-Zone Model	Observation Model	Speed Model 8 MPH+
111	2.51	2.90	--	--	1.43	3.31	--	--	1.78	2.55	--	--
112	2.24	2.60	1.46	0.58	1.16	2.03	1.23	--	1.60	2.14	1.39	0.68
113	3.37	3.26	--	--	1.06	1.96	--	--	1.77	2.22	--	--
121	3.97	--	--	--	1.83	--	--	--	3.24	2.74	--	--
122	4.00	4.58	--	--	2.12	--	--	--	2.95	3.41	--	--
123	1.58	2.66	--	--	1.06	--	--	--	1.51	2.25	--	--
211	2.09	1.91	--	--	0.67	1.52	--	--	1.23	1.63	--	--
212	1.68	--	1.70	--	0.53	--	0.47	--	1.18	1.07	0.98	--
213	1.53	1.13*	--	--	0.51	--	--	--	1.05	0.81	--	--
221	4.09	3.62	2.66	--	1.41	2.35	0.71	--	2.00	2.52	0.82	--
222	2.18	1.79	0.67	--	0.86	1.40	0.83	--	1.19	1.45	0.66	--
223	8.04	--	--	--	3.80	4.10	--	--	3.82	3.34	--	--
224	6.88	--	--	--	2.13	--	--	--	3.35	--	--	--
311	0.71	0.75	--	--	0.62	--	--	--	0.72	0.85	--	--
312	0.63	--	--	--	--	--	--	--	0.58	--	--	--
313	3.43	4.66	1.78	1.21	--	--	--	--	1.52	2.22	1.60	0.97
321	0.24	--	--	--	--	--	--	--	0.24	--	--	--
322	7.55	10.44	--	--	--	--	--	--	5.94	8.00	--	--
323	8.35	8.03	--	--	--	--	--	--	7.20	6.91	--	--
324	14.89	12.07	--	--	--	--	--	--	11.95	9.52	--	--

-- indicates that there was either no data to compute the Disparity Ratio or there were less than 30 cases which may cause the Disparity Ratio to be unstable.

* These values were created with a low number of cases which may make their values unstable.

N/A – Values for these police zones were not able to be computed due to a lack of observations in these areas.

Disparity Ratios may vary slightly at the hundredth decimal place due to rounding during the calculations.

Table 5.6: Comparison of Disproportionality Ratios for the Four Methods by Zone (p. 2 of 2)

Zone	<u>Black</u>				<u>Hispanic</u>				<u>Non-Caucasian</u>			
	Census Model	In-Zone Model	Observation Model	Speed Model 8 MPH+	Census Model	In-Zone Model	Observation Model	Speed Model 8 MPH+	Census Model	In-Zone Model	Observation Model	Speed Model 8 MPH+
411	0.45	--	--	--	--	--	--	--	0.46	--	--	--
412	0.30	--	--	--	--	--	--	--	0.30	--	--	--
413	0.36	--	--	--	--	--	--	--	0.36	--	--	--
414	6.45	6.58	--	--	--	--	--	--	6.13	6.15	--	--
421	0.47	--	--	--	--	--	--	--	0.47	--	--	--
422	0.25	--	--	--	--	--	--	--	0.25	--	--	--
423	--	--	--	--	--	--	--	--	--	--	--	--
424	0.93	--	2.52	--	--	--	--	--	0.92	--	2.49	--
425	--	--	--	--	--	--	--	--	--	--	--	--
511	1.45	--	--	--	--	--	--	--	1.36	--	--	--
512	0.14	--	1.28	0.93	--	--	--	--	0.15	--	1.24	1.02
513	0.15	--	4.39	2.83	--	--	--	--	0.15	--	3.90	2.47
514	3.34	--	--	--	--	--	--	--	2.71	--	--	--
521	0.03	--	--	--	--	--	--	--	0.03	--	--	--
522	0.82	--	--	--	--	--	--	--	0.82	--	--	--
523	1.57	--	--	--	--	--	--	--	1.50	--	--	--
611	1.29	--	--	--	--	--	--	--	1.29	--	--	--
612	0.15	--	--	--	--	--	--	--	0.15	--	--	--
613	0.44	--	--	--	--	--	--	--	0.45	--	--	--
621	1.68	--	--	--	--	--	--	--	1.65	--	--	--
622	3.13	6.44	--	--	--	--	--	--	3.03	6.20	--	--
623	2.38	3.48	4.73	3.14	--	--	--	--	2.34	3.35	4.52	3.01

-- indicates that there was either no data to compute the Disparity Ratio or there were less than 30 cases which may cause the Disparity Ratio to be unstable.

N/A – Values for these police zones were not able to be computed due to a lack of observations in these areas.

Disparity Ratios may vary slightly at the hundredth decimal place due to rounding during the calculations.

Figure 5.1: DR for Black Census Model

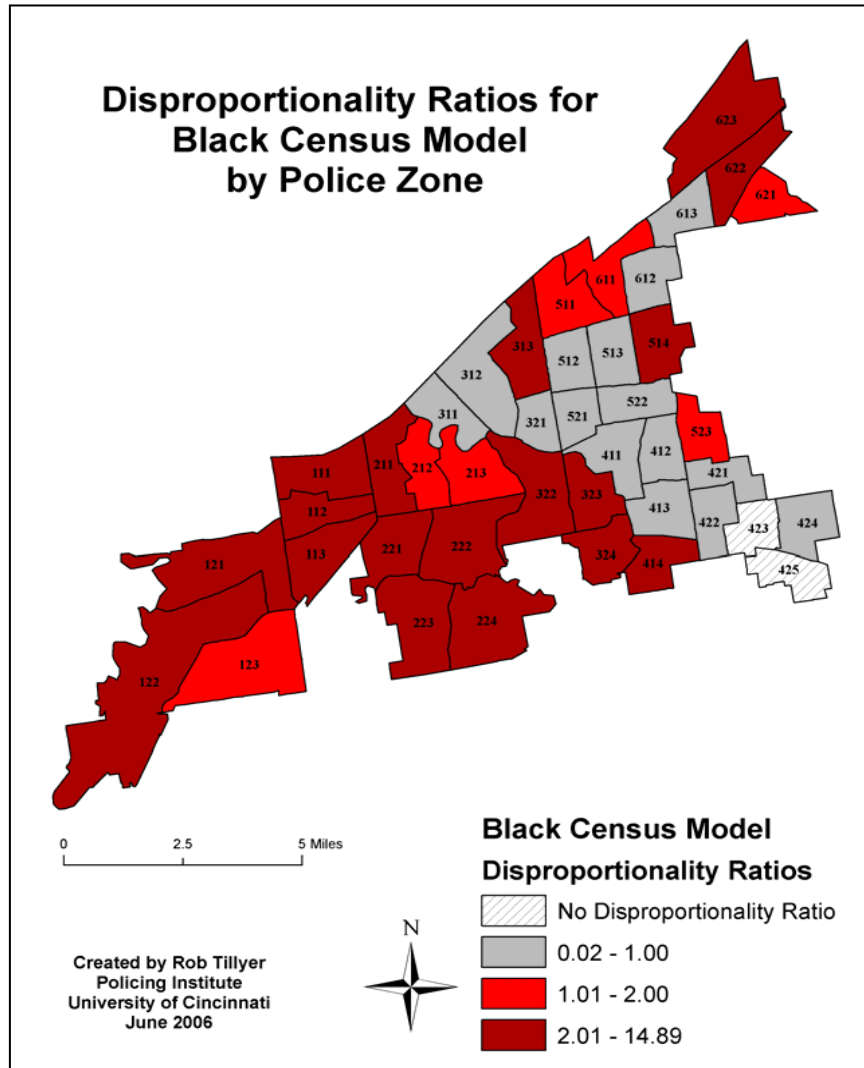


Figure 5.2: DR Model for Black Observation Model

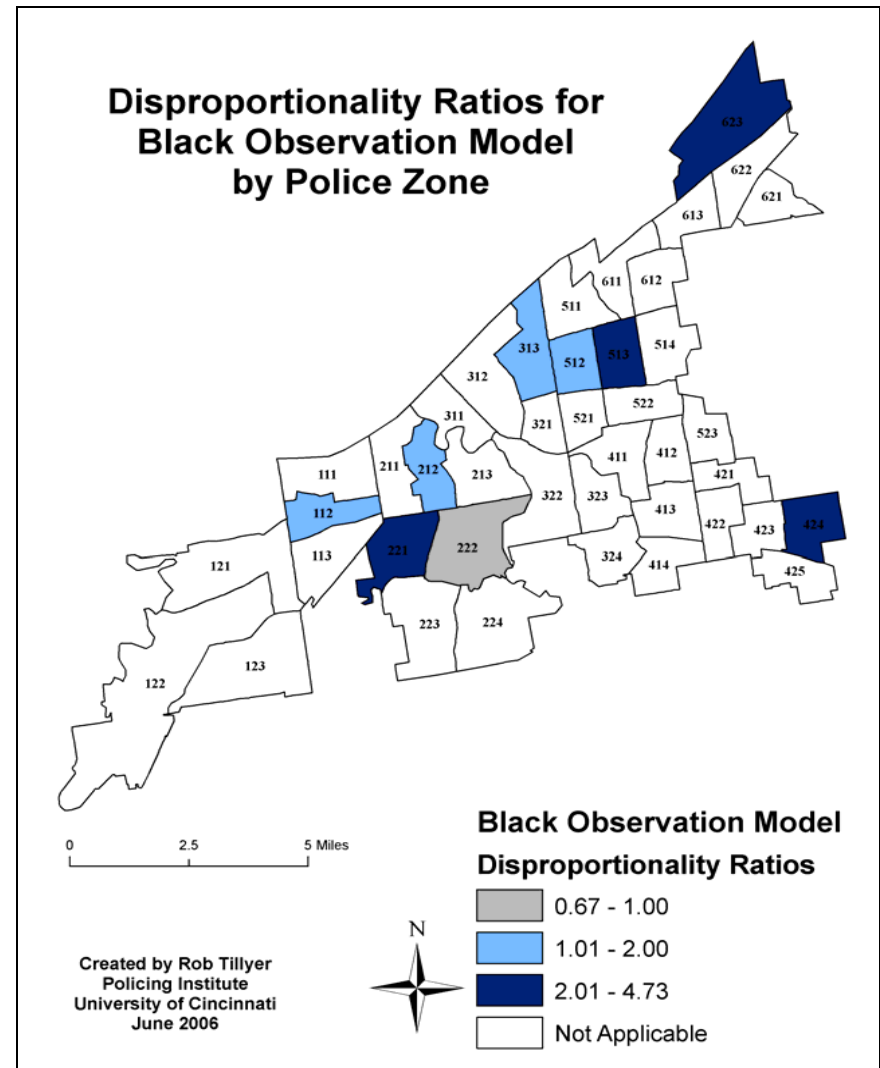


Figure 5.3: DR for Non-Caucasian Census Model

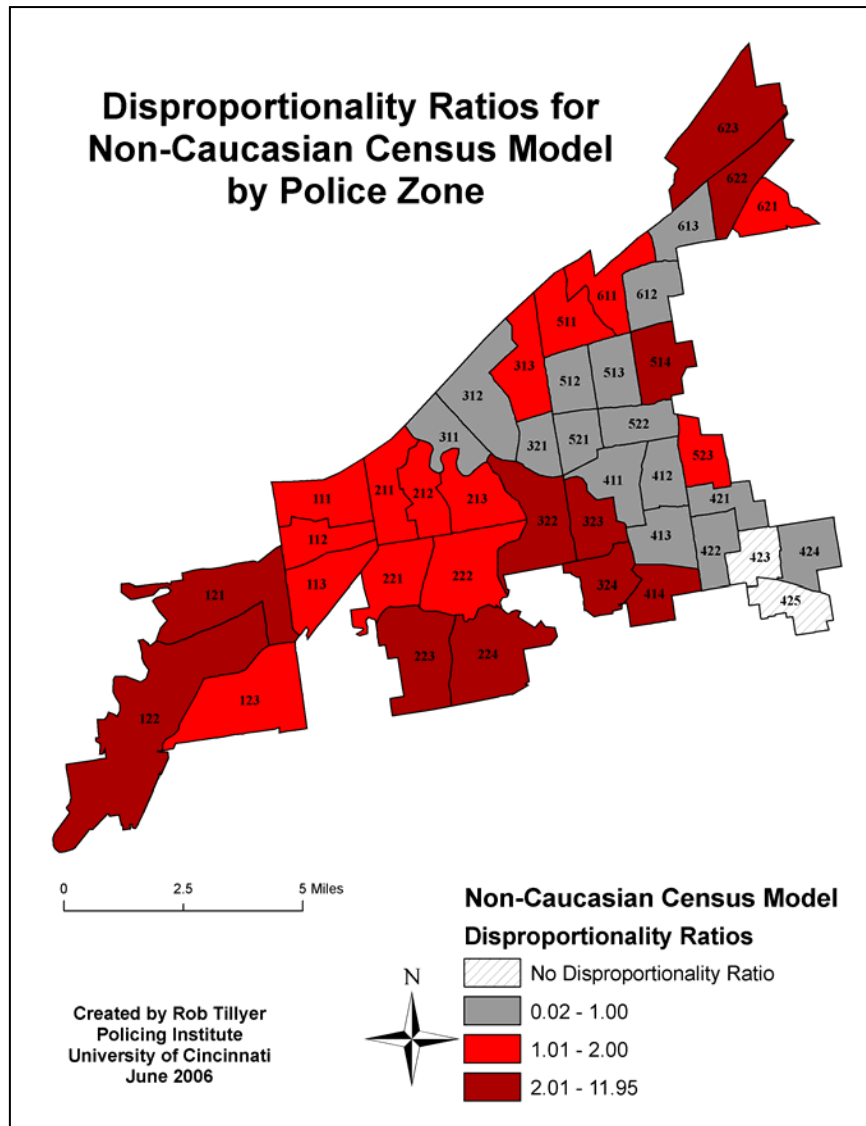
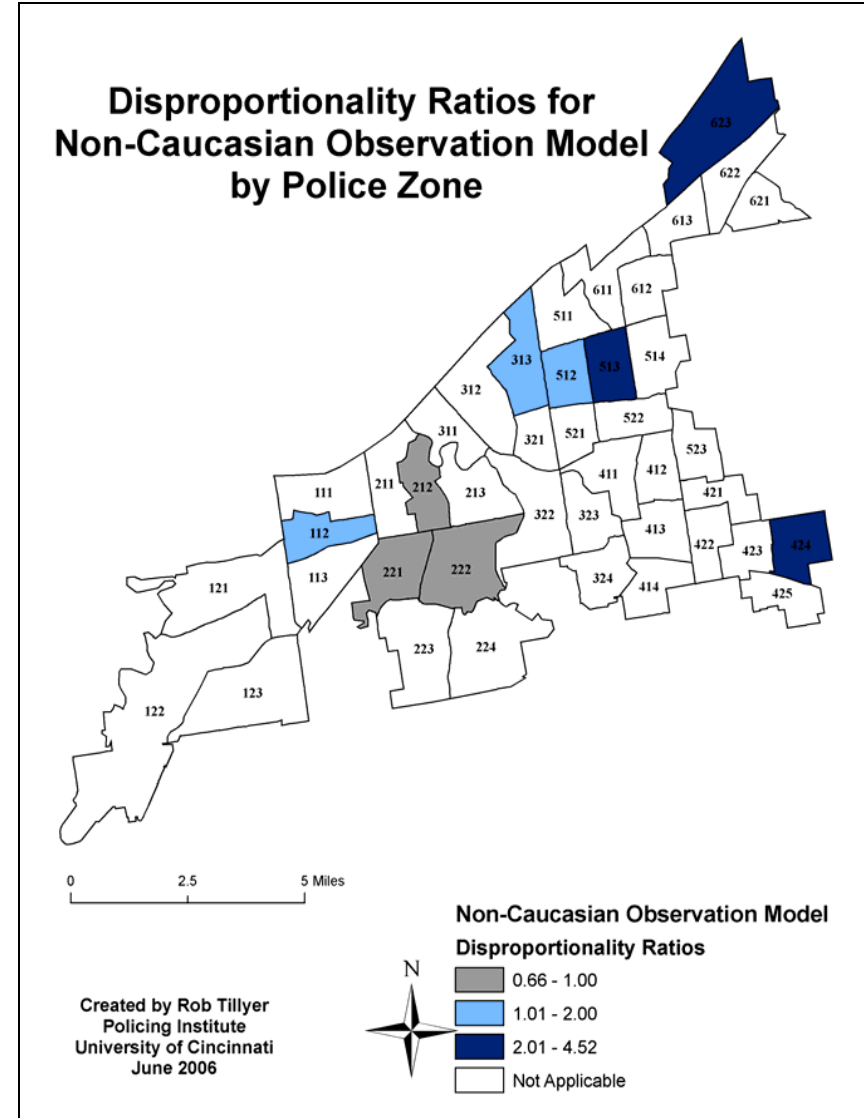


Figure 5.4: DR for Non-Caucasian Observation Model



ALTERNATIVE ANALYSES OF TRAFFIC STOP DATA

Given the numerous limitations associated with the benchmarking method to analyze traffic stop data, additional data analyses are reported below. These analyses demonstrate the differential stopping patterns by the CDP for different racial and ethnic groups.

The first consideration is to examine any racial/ethnic differences in the reason for the traffic stop initially and violations identified after the initial stop. Analyses of these data consistently indicate that Caucasian motorists are significantly more likely to be stopped for speeding compared to Black and Hispanic motorists. For example, 34.0% of Caucasian motorists were stopped for speeding, compared to only 21.8% of Black motorists and 24.8% of Hispanic motorists. In contrast, Black motorists were significantly more likely than Caucasians to be stopped for moving felony violations, equipment violations, registration violations, license violation, as the result of special traffic enforcement programs, and for other / unknown reasons. Likewise, Hispanic motorists were significantly more likely than Caucasians to be stopped for equipment violations, preexisting information, registration violations, license violations, and other / unknown reasons.

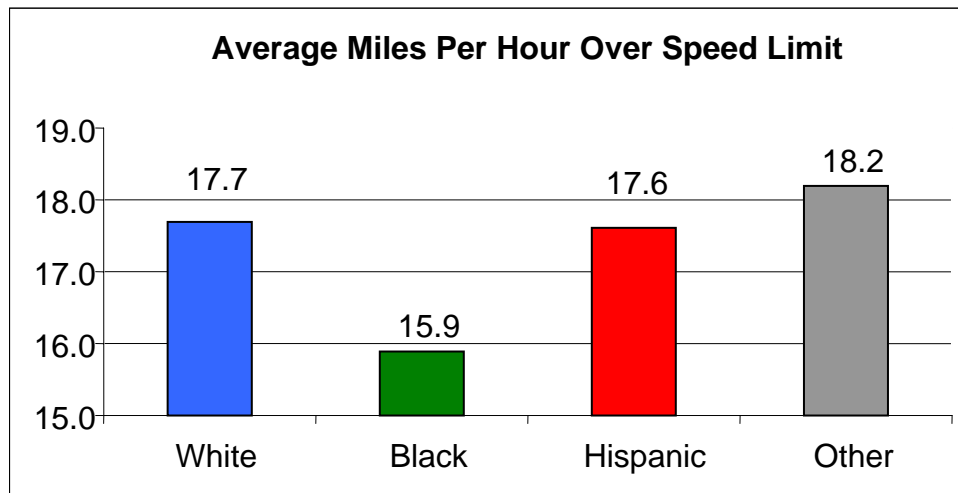
There are several plausible reasons for the differences in racial/ethnic stop patterns documented in these data. The first, and most obvious, is that different racial/ethnic groups differ in their offending behaviors. That is, Caucasians are simply more likely to speed, and minority groups are more likely to engage in other (more minor) types of traffic violations. Results from the observation study, however, do not support this hypothesis. Independent observations of traffic offenses indicated that Black motorists were significantly more likely to exceed the speed limit compared to Caucasian motorists. Differences in the distribution of wealth in American society (and the City of Cleveland more specifically) do support, however, the finding that Black and Hispanic motorists are more likely to be driving vehicles in poor condition and thus more likely to incur traffic stops related to equipment, registration, and license violations.

A second interpretation of the differences in racial/ethnic stops is that the focus on particular types of offenses is area specific (and as a result, race specific). For example, if the violation of speeding is more likely to be enforced on Interstates and major commuter thoroughfares, we would expect larger proportions of Caucasian motorists to be stopped for these offenses, as they make up a large portion of the commuter population. If other types of violations are more likely enforced in residential areas, we would expect equipment violations, registration violations, etc. to be more heavily represented among the residential population, which in the City of Cleveland is predominately Black (and Hispanic in some zones).

The final possibility, that cannot be confirmed nor denied with these data, is that CDP officers target particular racial/ethnic groups for differential types of enforcement. Some researchers have argued that minorities are targeted for more minor offenses in the form of pre-text stops so that officers can attempt to search their vehicles. While this behavior is possible, the data available simply cannot determine the motivation of individual officers.

Another data analyses used to examine racial/ethnic differences in the treatment of motorists is to compare the severity of the offense for which different racial/ethnic groups are stopped. In the case of speeding, the number of miles per hour the motorist is traveling in excess of the speed limit is recorded on the traffic stop forms, and is an objective measure of the severity of the offense. A comparison of the average speed over the limit for different racial/ethnic groups is one way to determine if there are racial/ethnic differences in the reasons motorists are stopped. Examining only the motorists who were stopped for speeding, the findings demonstrate that Black motorists are stopped for average speeds over the limit that are significantly lower than other racial groups. Specifically, the average speed over the limit recorded for Black motorists stopped for speeding was 15.9 m.p.h., compared to an average speed of 17.7 m.p.h. over the limit for Caucasian motorists, 17.6 m.p.h. over the limit for Hispanic motorists, and 18.2 m.p.h. over the speed limited for motorists of other racial/ethnic origins. These differences are graphically displayed in **Figure 5.5** below. Analysis of variance tests demonstrate that the average speed over the limit recorded for Black drivers is statistically significantly lower than the average speed over the limit recorded for Caucasians, Hispanics, and other racial groups. That is, Black motorists stopped for speeding are significantly more likely to be violating the law at a *lower* level of severity compared to other motorists stopped for speeding from other racial/ethnic groups. This suggests that for speeding violations, Black motorists are treated slightly more harshly (in terms of the reasons for an initial traffic stop) compared to other racial/ethnic groups.

Figure 5.5: Racial/Ethnic Comparisons of the Average Speed over the Limit for Speeding Traffic Stops



SUMMARY

This section of the report addressed the construction of different benchmarks, the limitations associated with each type of benchmark, the data used to conduct the benchmark analyses and the difficulties interpreting the benchmark comparisons. In addition, alternative analyses were presented for assessing traffic stops using the available traffic stop data.

- Two sources of benchmark data (residential Census data and stationery observations of motorists) were used to create four different comparisons to traffic stop data.
 - Comparison #1: All traffic stop data were compared to residential Census data by police zones.
 - Comparison #2: Only motorists stopped in the zones where they reside were compared to residential Census data by police zones
 - Comparison #3: Only motorists stopped during daylight hours were compared to daytime observations of motorists by police zones.
 - Comparison #4: Only motorists stopped during daylight hours for speeding offenses were compared to daytime observations of speeding motorists by police zones.
- There are reasons to believe that Comparisons #3 and #4 may be more accurate than the comparisons for traffic stop data to residential Census data, though there are major limitations associated with each benchmarking method.
- Due to budgetary limitations, only nine of the forty-two police zones across the city had locations where traffic observations were conducted; thus, benchmark Comparisons #3 and #4 were conducted in only these nine zones.
- The results suggest that residential Census data and traffic observation data do not match – that is, Census data cannot be used as a reliable proxy for observation data that was not collected in the remaining thirty-three police zones across the city of Cleveland.
- The comparisons across benchmarking techniques resulted in a wide range of disproportionality ratios. Further, the disproportionality ratios varied dramatically across policing zones. There is little consistency in these results.
- Results from comparisons of traffic stop data to traffic observation data (the benchmark data in which we have the most confidence) suggest that there are racial and ethnic disparities in stopping patterns. Black motorists were more than 1.5 times more likely to be stopped compared to Caucasians in six of nine police zones observed. In two of these zones, Blacks were over 4 times more likely to be stopped compared to Caucasians. The disparities in these police zones should be more closely examined by CDP officials.
- Additional analyses were conducted to examine racial/ethnic differences in stopping patterns. Results show that there is significant variation across racial/groups for the initial reasons for traffic stops. Caucasians are significantly more likely than other

groups to be stopped for speeding. Black motorists were significantly more likely than Caucasians to be stopped for moving felony violations, equipment violations, registration violations, license violation, as the result of special traffic enforcement programs, and for other / unknown reasons. Hispanic motorists were significantly more likely than Caucasians to be stopped for equipment violations, preexisting information, registration violations, license violations, and other/ unknown reasons.

- Of the motorists who were stopped for speeding, Blacks were stopped for lower levels of speeding severity compared to motorists of other racial/ethnic groups. That is, for speeding stops, Black motorists were stopped for slightly more minor offenses compared to all other racial/ethnic groups.

6. POST-STOP OUTCOMES

OVERVIEW

In this section, differences in types of post-stop outcomes (e.g., warnings, citations, arrests and searches) are examined. That is, once traffic stops are made, differences in the outcomes of those stops for different types of citizens are explored. This section is divided into three components: frequencies of post-stop outcomes, stop outcomes based on driver and officer characteristics, and multivariate analyses predicting stop outcomes.

First, the frequencies of post-stop outcomes are assessed. **Table 6.1** illustrates the number of stops and percentage of drivers' post-stop outcomes by Department, District, and Zone. **Table 6.2** reports comparisons of post-stop outcomes by drivers' race and gender for the department as a whole and by districts. Second, differences in traffic stops and post-stop outcomes based on citizens' characteristics (race and gender) and officers' characteristics (e.g., race, gender, assignment, experience, and rank) are explored in **Tables 6.2 – 6.6**. Finally, these relationships are further explored in multivariate statistical analyses presented in **Tables 6.7 and 6.8** that predict two different officer actions (i.e., arrests and searches).

DESCRIPTION OF POST-STOP OUTCOMES

The disposition of traffic stops (e.g., warnings, citations, arrests, and searches) was collected on the Cleveland Traffic Stop Form. **Table 6.1** documents the following information at the department, district, and zone levels: 1) the total number of number of traffic stops, 2) percentages of *drivers* issued formal warnings, citations and/or arrested, 3) percentages of *passengers* issued formal warnings, citations and/or arrested, and 4) the number and percentages of occupants or vehicles searched.

Table 6.1 documents the collection of data from July 1st, 2005 through February 28th, 2006. During this 8-month time period, the CDP reported traffic stops of 43,707 drivers for which we have valid data. In 96.7% of these traffic stops at least one citation was issued to the driver. In the remaining 3.3% of stops, some other enforcement action (not including a warning) was taken on the driver or passenger (e.g., arrest, citation of the passenger, or search). Thus, in nearly every traffic stop reported by the CDP during this 8-month time period, an official coercive action (other than a warning) was administered to the driver or passenger.

This information calls into question the validity of this data collection effort, which was designed to code *all* traffic stops. As reported in **Section 1**, the purpose of collecting traffic stop data is to gather information about police-citizen interactions during traffic stops that may not give rise to a citation, arrest or search. That is, it is important to gather information on all traffic stops *regardless* of their disposition, in an effort to understand how officers make decisions regarding which motorists to take some form of formal action against. Short of a departmental policy requiring CDP officers to issue a citation or make an arrest during every traffic stop, it is unrealistic to believe that this data collection effort was successful in gathering information regarding *all* traffic stops (regardless of disposition) conducted by the CDP. The more likely explanation is that traffic stops that did not result in a citation, arrest, and/or search simply were

not consistently recorded by officers on the Traffic Stop Data Form. Therefore, these data are better described as traffic *citation* and *arrest* data, rather than traffic *stop* data. This has implications for the types of statistical analyses that can be performed. For example, the University of Cincinnati research team is unable to develop a statistical model that will compare the probabilities of stopped Caucasian, Black, and Hispanic motorists who are issued a citation while controlling for other legal and extralegal factors. Thus, multivariate statistical models will only be produced predicting arrest and search rates.

As demonstrated in **Table 6.1**, in the traffic stops reported, 4.8% involved an in-custody arrest of the driver, and 8.8% involved a search of the occupants and/or the vehicle. **Table 6.1** also reports differences in post-stop outcomes across districts and zones. Note that some variation across districts and zones in the percentages of traffic stops that result in arrests and searches is to be expected based on community and organizational differences.

At the district level, officers assigned to District 3 arrested the largest percentage of stopped motorists (7.7%), while officers assigned to the Traffic Unit arrested the smallest percentage (2.3%). The percentage of searches conducted also varied considerably across Districts. For example, officers assigned to District 3 searched 15.1% of the motorists they stopped, compared to only 2.3% of motorists stop by the Traffic Unit.

There also appeared to be significant variation in arrest and search rates at the zone level. The percentage of drivers arrested varied from a high of 10.6% of drivers stopped in Zone 321 to a low of 2.0% of drivers stopped in Zone 411. Search rates also varied dramatically across zones. For example, only 3.3% of motorists stopped in Zone 122 were searched, compared to 17.3% of motorists stopped in Zone 412. The variations in arrest and search rates across zones were also observed across zones *within the same district*. Thus, it is likely that these variations in post-stop outcomes are due to differences in community characteristics associated with crime rates in addition to organizational factors.

Table 6.1: Stop Outcomes for Drivers and Passengers by Department, District, and Zone (p.1 of 2)

Zone	Total # of Stops	% Driver Warned	% Driver Cited	% Driver Arrested	% Passenger Warned	% Passenger Cited	% Passenger Arrested	Total # of Searches	% Person or Vehicle Searched
CDP Dept	43,707	4.0	96.7	4.8	0.4	2.1	0.6	3,847	8.8
Traffic Unit	11,283	3.4	99.4	1.4	0.0	0.4	0.0	262	2.3
District 1	4,370	4.1	96.6	6.0	0.3	2.6	1.2	393	9.0
District 2	3,702	3.2	97.6	6.9	0.5	2.1	0.5	484	13.1
District 3	5,126	2.2	98.9	7.7	0.6	3.7	1.4	775	15.1
District 4	7,736	3.4	96.8	6.2	0.6	2.1	0.6	945	12.2
District 5	4,099	7.0	94.7	5.1	0.5	2.0	0.8	339	8.3
District 6	7,385	5.5	91.4	4.5	0.6	3.3	0.7	649	8.8
Zone Level									
Zone 111	849	4.0	97.3	3.2	0.2	1.3	0.2	30	3.5
Zone 112	1,994	3.0	97.9	4.7	0.3	2.2	1.1	147	7.4
Zone 113	788	7.0	93.4	8.0	0.6	4.3	2.5	111	14.1
Zone 121	717	3.0	97.9	4.0	0.0	0.6	0.4	41	5.7
Zone 122	940	2.0	98.2	2.3	0.0	0.4	0.2	31	3.3
Zone 123	1,186	4.0	97.0	3.8	0.3	1.4	0.4	60	5.1
Zone 211	901	2.0	99.0	4.8	0.2	1.7	0.4	65	7.2
Zone 212	863	4.0	97.7	6.3	0.4	2.1	0.5	87	10.1
Zone 213	929	2.0	99.3	2.1	0.1	0.4	0.2	35	3.8
Zone 221	953	3.0	98.9	4.8	0.4	2.1	0.3	132	13.9
Zone 222	2,057	2.0	98.9	3.8	0.2	0.9	0.2	147	7.2
Zone 223	434	7.0	96.3	6.0	0.2	1.6	0.2	43	9.9
Zone 224	561	5.0	97.3	3.7	0.2	1.1	0.5	36	6.4
Zone 311	2,956	3.0	99.4	2.5	0.2	1.5	0.2	149	5.0
Zone 312	1,187	2.0	99.1	4.9	0.3	2.2	1.3	169	14.2
Zone 313	791	1.0	99.0	8.5	0.1	3.2	0.9	118	14.9
Zone 321	653	4.0	99.1	10.6	0.5	4.0	1.7	99	15.2
Zone 322	847	1.0	99.2	5.2	0.2	3.1	0.9	77	9.1
Zone 323	1,216	3.0	99.3	7.0	0.4	3.7	1.5	152	12.5
Zone 324	606	3.0	98.4	7.9	0.8	3.0	0.8	89	14.7

Table 6.1: Stop Outcomes for Drivers and Passengers by Department, District, and Zone (p.2 of 2)

Zone	Total # of Stops	% Driver Warned	% Driver Cited	% Driver Arrested	% Passenger Warned	% Passenger Cited	% Passenger Arrested	Total # of Searches	% Person or Vehicle Searched
CDP Dept	43,707	4.0	96.7	4.8	0.4	2.1	0.6	3,847	8.8
Zone Level									
Zone 411	1,817	2.0	98.0	2.0	0.3	1.4	0.2	124	6.8
Zone 412	590	5.0	95.9	9.2	0.7	2.2	0.9	102	17.3
Zone 413	1,199	3.0	97.1	9.7	0.5	2.5	1.0	179	14.9
Zone 414	517	5.0	95.6	7.7	0.8	2.1	0.2	82	15.9
Zone 421	580	6.0	96.2	8.3	0.7	2.6	0.5	93	16.0
Zone 422	1,575	5.0	96.4	5.3	0.6	1.7	0.8	157	10.0
Zone 423	1,087	4.0	97.0	7.1	0.5	1.8	0.9	155	14.3
Zone 424	951	3.0	98.2	3.2	0.7	2.0	0.2	60	6.3
Zone 425	274	1.0	98.2	3.3	0.0	1.8	0.0	22	8.0
Zone 511	977	5.0	96.8	6.2	0.5	1.6	0.5	83	8.5
Zone 512	713	5.0	96.6	3.2	0.0	1.8	0.7	36	5.1
Zone 513	1,023	9.0	93.9	4.7	0.7	1.9	1.1	94	9.2
Zone 514	684	5.0	96.6	4.0	0.3	2.1	0.4	48	7.0
Zone 521	554	4.0	95.7	5.1	0.7	2.5	0.7	47	8.5
Zone 522	374	3.0	97.6	3.5	0.8	0.8	0.0	19	5.1
Zone 523	952	8.0	95.4	2.2	0.3	1.0	0.2	34	3.6
Zone 611	959	5.0	96.4	4.6	0.5	1.9	0.9	99	10.3
Zone 612	2,006	5.0	80.8	4.5	0.4	2.3	1.0	162	8.1
Zone 613	1,704	6.0	95.9	4.1	1.1	3.2	0.4	134	7.9
Zone 621	562	3.0	97.7	3.9	0.4	2.0	0.4	36	6.4
Zone 622	1,450	5.0	95.4	4.1	0.1	4.2	0.6	112	7.7
Zone 623	1,596	5.0	95.7	4.5	0.4	3.5	0.5	140	8.8

DIFFERENCES IN POST-STOP OUTCOMES ACROSS TYPES OF DRIVERS

Table 6.2 illustrates the variation in two post-stop outcomes (i.e., the percentage of drivers arrested and the percentage of drivers or vehicles searched) by drivers' race and gender for the CDP and individual Districts. For these comparisons, drivers' race is collapsed into four categories – Caucasian, Black, Hispanic, and other – where Hispanic includes both Caucasian Hispanic and Black Hispanic, and the other category includes Native American, Middle Eastern, and Asian. Traffic stops where officers classified drivers' race as “unknown” or left the race missing on the forms (759 stops, 1.7% of the total number of forms collected) are excluded from these analyses.

The results in **Table 6.2** show that across the department, Black and Hispanic drivers are *more* likely to be arrested compared to Caucasians (5.7% of Black and 4.7% of Hispanic drivers, compared to 3.3% of Caucasian drivers and 1.7% of drivers of other races). Likewise, Black and Hispanic drivers were more likely to be searched (10.5% and 9.0%, respectively) compared to Caucasian drivers (5.9%) and drivers of other races (3.6%). These patterns are relatively consistent across districts.

Gender differences are also evident in post-stop outcomes. Across the department, male drivers were *more* likely to be arrested and searched compared to female drivers. These differences in post-stop outcomes between male and female drivers were found in all the districts as well.

Table 6.2: Stop Outcomes by Race and Gender for Department and Districts (p. 1 of 2)

Zone	Drivers	Total # of stops	% drivers arrested	# of drivers searched	% drivers searched
CDP	Caucasian	13,341	3.3	786	5.9
	Black	26,877	5.7	2,825	10.5
	Hispanic	2,028	4.7	183	9.0
	Other race	702	1.7	25	3.6
	Male	29,115	6.2	3,244	11.1
	Female	14,556	1.9	599	4.1
Traffic	Caucasian	5,396	0.6	59	1.1
	Black	4,811	2.2	180	3.7
	Hispanic	655	2.3	19	2.9
	Other race	179	0.0	2	1.1
	Male	7,182	1.9	207	2.9
	Female	4,096	0.4	55	1.3
District 1	Caucasian	2,442	4.8	199	8.1
	Black	1,118	9.4	14	12.6
	Hispanic	527	5.7	40	7.6
	Other race	251	3.6	13	5.2
	Male	3,114	7.0	327	10.5
	Female	1,252	3.4	66	5.3
District 2	Caucasian	1,927	6.3	202	10.5
	Black	991	8.8	177	17.9
	Hispanic	677	6.2	96	14.2
	Other race	80	2.5	5	6.3
	Male	2,687	7.6	377	14.0
	Female	1,013	5.1	107	10.6
District 3	Caucasian	1,342	5.9	150	11.2
	Black	3,502	8.7	595	17.0
	Hispanic	106	6.6	22	20.8
	Other race	78	1.3	4	5.1
	Male	3,784	9.3	646	17.1
	Female	1,341	3.2	129	9.6

Table 6.2: Stop Outcomes by Race and Gender for Department and Districts (p. 2 of 2)

Zone	Drivers	Total # of stops	% drivers arrested	# of drivers searched	% drivers searched
District 4	Caucasian	526	4.8	50	9.5
	Black	6,987	6.4	887	12.7
	Hispanic	17	0.0	1	5.9
	Other	30	0.0	0	0.0
	Male	5,044	8.6	836	16.6
	Female	2,686	1.6	108	4
District 5	Caucasian	744	1.2	14	1.9
	Black	3,235	6.2	320	9.9
	Hispanic	22	0.0	3	13.6
	Other	47	0.0	1	2.1
	Male	2,646	7.0	301	11.4
	Female	1,449	1.6	38	2.6
District 6	Caucasian	964	5.1	112	11.6
	Black	6,229	4.6	525	8.4
	Hispanic	24	4.2	2	8.3
	Other	37	0.0	0	0
	Male	4,654	6.1	550	11.8
	Female	2,717	1.8	96	3.5

Table 6.2 illustrates the wide variation in outcomes across racial/ethnic and gender groups at the department and district levels. It is important to reiterate that the information provided in **Table 6.2** is only bivariate. That is, the relationships reported in **Table 6.2** do not statistically control for other relevant legal and extralegal factors that might be expected to influence officer decision-making. Therefore, the information provided in these tables cannot determine whether or not differences in outcomes across racial/ethnic and gender groups are due to officers’ decision making based on drivers’ characteristics.

It is plausible that racial/ethnic and gender differences in post-stop outcomes exist due to legal and extralegal reasons other than race, ethnicity, and gender. To explore these possibilities, more advanced statistical analyses that control for other legal and extralegal variables are presented in the multivariate section below. The information reported in **Table 6.2** is included in this report solely to provide details to CDP administrators regarding differences in post-stop outcomes across Districts. Although this information will allow CDP administrators to identify potential problems and target specific districts for policy interventions, this information cannot directly examine questions of whether or not officers in these districts are engaging in racial profiling.

OFFICER DIFFERENCES IN TRAFFIC STOPS AND POST-STOP OUTCOMES

It is possible that differences in stop and post-stop outcome patterns exist based in part on officers' differences. That is, it is plausible that male and female officers, Caucasian and minority officers, etc. have different patterns of stopping, arresting, and searching drivers, and further that these differences may be related to drivers' race/ethnicity. To begin exploring these possibilities, **Tables 6.3 – 6.6** present the bivariate relationships between officers' characteristics and their decisions to stop, arrest, and search different racial and ethnic groups. As with all the bivariate statistics presented in this report, these analyses are provided to explore trends and patterns in officers' behaviors and cannot directly assess individual bias or discrimination by CDP officers.

Table 6.3 documents the relationship between officers' characteristics and traffic stops for different racial/ethnic groups. Officers' characteristics include: sex (measured as male, female), race (measured as Caucasian, non-Caucasian), years of experience with CDP (measured as less than five years, five years or more), assignment (measured as patrol, traffic, or other) and rank (measured as officer, sergeant or higher).

The race/ethnicity of drivers is captured in three categories: Caucasian, Black, and a combined category of any non-Caucasian (which includes Black, Hispanic, Asian, Native American, and Middle Eastern). Note that the first three categories (Caucasian, Black, and Hispanic) are mutually exclusive however, the fourth category (any non-Caucasian) includes drivers previously classified as Black and Hispanic.

As shown in **Table 6.3**, there were some differences in stopping patterns for different racial/ethnic groups based on officers' characteristics. For example, male officers, officers with less than five years of experience, district officers, and officers with the rank of patrol were more likely to stop Black motorists compared to female officers, officers with more than five years of experience, traffic officers, and officers with a rank higher than patrol. Note, however, that no significant differences in the stopping patterns of Caucasian and Black officers were detected. The differences in the percentage of Black motorists stopped based on officer characteristics may be due to the specific areas to which these types of officers are assigned. For example, it is possible that male officers, officers with less experience, district officers, and offices with lower rank are assigned to areas that would naturally result in the stopping of more Black motorists. That is, the differences reported in **Table 6.3** are likely, at least partially, due to differences in patrol areas and assignments of different types of officers.

Table 6.3: Officer Differences in Stops of Racial Groups

Officer Characteristics	Total # of Stops	% Caucasian drivers stopped	% Black drivers stopped	% Hispanic drivers stopped	% Non-Caucasian drivers stopped
Female	772	21.6	74.6	2.7	78.4
Male	41,597	31.2	62.4	4.8	68.8
Caucasian	28,672	31.4	62.0	4.8	68.6
Non-Caucasian	13,697	30.1	64.0	4.6	69.9
Less than 5 years experience	2,097	9.4	88.7	1.1	90.6
5 years experience or more	40,382	32.1	61.3	4.9	67.9
District Assignment	31,639	25.3	68.6	4.4	74.7
Traffic Assignment	10,172	49.2	43.4	6.0	50.8
Other Assignment	669	21.5	73.1	1.5	78.5
Rank of Patrol Officer	41,674	30.7	62.9	4.8	69.3
Rank above Patrol Officer	806	44.3	46.3	3.8	55.7

Table 6.4 documents the relationship between officers’ characteristics and traffic stop outcomes for all drivers (regardless of drivers’ race/ethnicity). Post-stop outcomes reported in this table include the percentage of drivers stopped by officers who were arrested and searched. **Table 6.4** also includes the actual number of drivers searched and the percentage of these searches that resulted in the seizure of contraband. Due to the small number of searches in some categories, differences in officers’ search success rates should be interpreted with caution.

As shown in **Table 6.4**, female officers, Caucasian officers, officers with less than five years of experience, officers with assignments other than district patrol and traffic, and officers with ranks above patrol were *more* likely to arrest motorists they stopped, compared to male officers, non-Caucasian officers, officers with more experience, officers with district or traffic assignments, and officers with patrol rank. For example, female officers arrested 8.2% of motorists they stopped, compared to 4.7% of motorists stopped by male officers.

The patterns displayed for arrest of motorists also held for searches of motorists. That is, female officers, Caucasian officers, officers with less than five years of experience, officers with assignments other than district patrol and traffic, and officers with ranks above patrol were *more* likely to search motorists they stopped, compared to male officers, non-Caucasian officers, officers with more experience, officers with district or traffic assignments, and officers with patrol rank. Again using officers’ gender as an example, 13.7% of motorists stopped by female officers were searched, compared to 8.7% of motorists stopped by male officers.

Of the different types of officers identified above that search higher percentages of motorists, only Caucasian officers have search success rates (i.e., percentage of searches that result in the seizure of contraband) that are not lower than their comparison group. That is, female officers,

officers with less than five years of experience, officers with assignments other than district and traffic, and officers with ranks above patrol were *more* likely to search the motorists they stopped, but *less* likely to discover contraband during these searches, compared to male officers, officers with more experience, officers with district or traffic assignments, and officers with patrol rank.

Table 6.4: Officer Differences in Stop Outcomes of ALL Drivers

Officer Characteristics	Total # of Stops	% drivers arrested	% drivers searched	# drivers searched	% drivers searched resulting in seizure
Female	789	8.2	13.7	108	40.7
Male	42,331	4.7	8.7	3,670	55.7
Caucasian	29,170	5.5	10.3	3,010	56.3
Non-Caucasian	13,950	3.1	5.5	768	51.4
Less than 5 years experience	2,227	5.7	10.0	223	30.9
5 years experience or more	41,007	4.7	8.7	3,584	56.5
District Assignment	32,155	5.8	10.8	3,487	55.7
Traffic Assignment	10,401	1.3	2.1	216	49.5
Other Assignment	679	9.4	15.3	104	45.2
Rank of Patrol Officer	42,423	4.7	8.8	3,732	55.4
Rank above Patrol Officer	812	7.8	9.2	75	38.7

Table 6.5 reports these relationships for only Black (non-Hispanic) drivers. That is, the post-stop outcomes for Black drivers are examined based on officers' characteristics. As **Table 6.5** demonstrates, similar patterns to those reported for all drivers emerge. Specifically, female officers, Caucasian officers, officers with assignments other than district patrol and traffic, and officers with ranks above patrol were *more* likely to arrest Black motorists they stopped, compared to male officers, non-Caucasian officers, officers with district or traffic assignments, and officers with patrol rank. For example, Caucasian officers arrested 6.5% of the Black motorists they stopped, compared to 4.0% of Black motorists stopped by non-Caucasian officers.

The patterns displayed for arrest of Black motorists also held for searches of Black motorists. Once again, female officers, Caucasian officers, officers with assignments other than district patrol and traffic, and officers with ranks above patrol were *more* likely to search Black motorists they stopped, compared to male officers, non-Caucasian officers, officers with district or traffic assignments, and officers with patrol rank. Again using officers' race as an example, 12.2% of Black motorists stopped by Caucasian officers were searched, compared to only 6.9% of Black motorists stopped by non-Caucasian officers.

While Caucasian officers searched a significantly larger proportion of Black motorists they stopped compared to non-Caucasian officers, their search success rate of Black motorists (57.5%) were not different than the search success rate for non-Caucasian officers (51.2%). That is, although White officers searched larger percentages of Black motorists compared to Black officers, these searches resulted in roughly equivalent rates of contraband seizures. This is not true, however, of the other officer groupings displayed in **Table 6.5**. Female officers, officers with assignments other than district patrol and traffic, and officers with ranks above patrol officer searched higher percentages of Black drivers that they stopped, but found less contraband during these searches of Black motorists, compared to their counterparts. In addition, officers with less than five years of experience, though not different from more experienced officers in the percentage of Black motorists they search, had much less success (in terms of contraband seizures) during these searches of Black motorists compared to the more experienced officers. So, for example, combined with the information provided in **Table 6.3**, female officers, officers with less than five years of experience, officers with assignments other than district and traffic, and officers with ranks above patrol were *more* likely to search the motorists they stopped, but *less* likely to discover contraband during these searches, compared to male officers, officers with more experience, officers with district or traffic assignments, and officers with patrol rank.

Considering officers' gender, when the findings in **Tables 6.3 and 6.5** are combined, it demonstrates that female officers are *less* likely to stop Black motorists, however, once stopped, they are more likely than their male counterparts to perform in-custody arrests and searches, and less likely to discover contraband during these searches.

Table 6.5: Officer Differences in Stop Outcomes of BLACK Drivers

Officer Characteristics	Total # of Stops	% drivers arrested	% drivers searched	# drivers searched	% drivers searched resulting in seizure
Female	576	7.8	14.2	82	40.2
Male	25,963	5.6	10.4	2,698	56.6
Caucasian	17,773	6.5	12.2	2,177	57.5
Non-Caucasian	8,766	4.0	6.9	603	51.2
Less than 5 years experience	1,861	6.0	9.7	180	30.0
5 years experience or more	24,740	5.7	10.6	2,615	57.7
District Assignment	21,700	6.3	11.8	2,553	56.5
Traffic Assignment	4,413	2.2	3.4	151	51.0
Other Assignment	489	11.2	18.6	91	48.4
Rank of Patrol Officer	26,229	5.6	10.4	2,738	56.2
Rank above Patrol Officer	373	12.6	15.3	57	40.4

Table 6.6 examines the same relationships between officers' characteristics and stop outcomes, but examines all minority drivers (Black, Hispanic, Asian, Middle Eastern, and Native

American). When these additional minority racial groups are added to Black drivers, the findings reported in **Table 6.5** remain relatively consistent.

Table 6.6: Officer Differences in Stop Outcomes of NON-CAUCASIAN Drivers

Officer Characteristics	Total # of Stops	% drivers warned	% drivers searched	# drivers searched	% drivers searched resulting in seizure
Female	605	5.6	14.0	85	38.8
Male	28,639	4.1	10.1	2,896	56.7
Caucasian	19,667	4.6	11.9	2,348	57.5
Non-Caucasian	9,577	3.2	6.6	633	51.2
Less than 5 years experience	1,900	6.2	9.6	183	30.6
5 years experience or more	27,416	4.0	10.3	2,818	57.6
District Assignment	23,626	4.4	11.6	2,740	56.6
Traffic Assignment	5,166	2.5	3.3	168	50.0
Other Assignment	525	11.2	17.7	93	48.4
Rank of Patrol Officer	28,868	4.1	10.2	2,938	56.3
Rank of Supervisor or higher	449	11.1	14.0	63	38.1

As noted for some of the previous analyses, caution must be used when interpreting these results. The analyses are based strictly on bivariate relationships – that is, there are no statistical controls for other factors that might influence traffic stop outcomes. These statistical controls are utilized in the multivariate analyses presented below.

MULTIVARIATE ANALYSES OF TRAFFIC STOP OUTCOMES

In **Tables 6.7 and 6.8**, the results of four logistic regression models are presented. A multivariate statistical model is one that takes many different factors into account when attempting to explain a particular behavior. Unlike a bivariate model, it does not simply assess the relationship between two variables. Rather, a multivariate model examines many variables simultaneously, and therefore provides a more thorough and accurate interpretation of the data. The multivariate analyses to follow examine the associations between drivers’ characteristics and post-stop outcomes (i.e., arrests and searches) when other characteristics likely associated with these outcomes are statistically controlled.

Many factors other than drivers’ race/ethnicity are likely to influence officers’ decision-making once a traffic stop has been made. For example, other driver characteristics (e.g., drivers’ gender, age, residency, demeanor), vehicle characteristics (e.g., condition of the vehicle, after-market modifications, registration, number of passengers), stop characteristics (e.g., time of day, day of the week, season, and roadway type), reasons for the stop (speeding, moving violations, equipment violations, etc.), other legal variables (e.g., number of reasons for the stop, evidence

found during a search), officer characteristics (e.g., sex, race, experience, assignment, rank), and community characteristics where the stop occurred (e.g., residential populations, poverty, factors related to traffic patterns, etc.) have all been hypothesized to influence post-stop outcomes. Multivariate analyses allow for the examination of the effect of each of these predictor variables, while simultaneously controlling for the influence of the remaining variables. For example, the influence of drivers' race can be examined while holding constant the predictive power of drivers' age, reason for the stop, time of day, etc.

The inclusion of officer and community characteristics in the analyses introduces additional statistical complexity with the use of data at multiple levels of aggregation. Therefore, the application of a specialized statistical program called hierarchical linear and nonlinear modeling (HLM) is sometimes required. After examining this option, it was determined that standard logistic regression models would be appropriate for these analyses.¹⁵ Therefore, the multivariate analyses that follow are logistic regression models predicting arrest and search outcomes during traffic stops. Logistic regression is used because the two dependent variables (i.e., arrest and search) are dichotomous, and thus the use of ordinary least squares regression techniques would be inappropriate.

The analyses are designed to determine if drivers' race/ethnicity has an independent influence over the likelihood of being arrested or searched during a traffic stop over and above the influence of other legal and extralegal variables. The legal and extralegal variables that have been measured and included in the analyses are listed below.

- Driver characteristics: race/ethnicity (four dichotomous variables – Caucasian, Black, Hispanic, other; Caucasian is the excluded comparison category in the analyses), gender (1=male), age (in years), residency in zone where stop occurred (1=yes), driver was disrespectful to officer (1=yes), driver was noncompliant, verbally resistant or physically resistant toward the officer (1=yes)

¹⁵ Using data at two or more levels of aggregation introduces a statistical dilemma where regression residuals for the level 1 cases (e.g., traffic stops) within the same level 2 units (e.g., officers) may be correlated. This 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 (Raudenbush & Bryk, 2002). Hierarchical linear modeling (HLM) is a modeling procedure that can overcome this statistical dilemma (Raudenbush & Bryk, 2002). HLM includes an extra error term, U_i , that reflects the extra variation common to all level 1 cases within the level 2 unit, so the level 1 error term (R_{ij}) can be independent. That is, HLM explicitly models the dependence of the residuals through this error term. For binary outcome variables like the ones utilized here, hierarchical models cannot use the standard level 1 model which 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 this type of dependent variable, a nonlinear form of hierarchical modeling that uses a binomial sampling model with a Bernoulli distribution must be employed, as opposed to a normal sampling model, and a logit link instead of an identity link (Guo & Zhao, 2000; Raudenbush & Bryk, 2002). It was determined that when Census characteristics were examined at level 2, a hierarchical model was not necessary. When officer characteristics were examined at level 2, a hierarchical model was deemed appropriate; however the findings of these analyses did not differ substantially from the standard logistics regression analyses performed. Therefore, the logistic regression analyses are reported within this document.

- Vehicle characteristics: registration (1= no registration, 0=OH or out of state registration), after-market vehicle modifications (1=yes), vehicle in poor operating condition (1=yes), number of passengers in the vehicle (range 1-5)
- Stop characteristics: time of day (1=daytime) volume of traffic (1=rush hour), day of the week (1=weekend), roadway type (1= interstate or main roadway)
- Reason for the stop: five dichotomous variables (i.e., moving misdemeanor violation, equipment/inspection violation, license/registration violation, preexisting information, other – unknown – reason), with speeding or moving felony violations as the excluded comparison category
- Other legal characteristics: number of reasons for the stop (range 1-6), contraband seized during a search (1=contraband seized)
- Officer characteristics: race (1=Caucasian), gender (1=male), assignment (1=Traffic), years of service, (range 3.5 – 36 years)
- Community characteristics of the zones where the stops occurred: total driving-age population, % Black in driving-age population, % Hispanic in driving-age population, % Males in driving-age population, poverty (measured as a factor score combining the following variables: percent female headed households with children, percent labor force unemployed, percent vacant households, percent living under the poverty limit, percent households with no vehicle)

Table 6.7 presents the results of two separate multivariate analyses predicting whether or not motorists are placed under ARREST. **Table 6.8** presents the findings for similar multivariate models that predict whether or not a SEARCH was conducted. Two separate models are displayed in each table. Model 1 represents the base model and Model 2 is the base model with both officer and zone characteristics included (hereafter referred to as the Full Model).

For each of these models, numerous independent variables were included that could potentially influence officers decisions to arrest and search motorists. As shown in the left hand column, the predictor variables used in the first model (Base Model) include: 1) driver characteristics, 2) vehicle characteristics, 3) stop characteristics, 4) reasons for the stop, and 5) other legal variables. The predictor variables for Model 2 (Full model) include: 1) driver characteristics, 2) vehicle characteristics, 3) stop characteristics, 4) reasons for the stop, 5) other legal variables, 6) officer characteristics, and 7) characteristics of the zone where the stop occurred. It is believed that each of these types of variables has the potential to influence officer behavior, and therefore must be statistically controlled to examine the variables of interest (i.e., drivers' race/ethnicity).

The number of traffic stops included in the various logistic regression models reported in **Tables 6.7 and 6.8** vary based on missing data of the variables included in the models. A traffic stop is excluded from the analyses if information is missing on any of the variables included in the model.

Each of the independent variables is assessed relative to their effect upon the dependent variable examined (i.e., arrest or search). It is important to note, though, that some variables are excluded from the model for comparison purposes. For example, the drivers' race is captured in the model as Black, Hispanic, and other. The excluded category is Caucasian. Thus, the coefficients in the model should be interpreted as compared to Caucasians – that is, the likelihood of Black drivers

being issued a citation compared to Caucasian drivers. The excluded category of the reason for the stop is speeding or moving felonies. Dichotomous variables are simply compared against their opposite (e.g., male drivers are compared to female drivers).

The first column for each model in **Tables 6.7** and **6.8** displays the coefficient or predicted log-odds for each independent variable. The coefficient represents an additive expression of a particular variable. In the “coefficient” column, there are two things to examine: 1) the presence of an asterisk following the coefficient indicating a statistically significant relationship, and 2) the presence or non-presence of a negative sign preceding the number. The asterisk reveals whether or not a significant relationship exists between the independent variable (e.g., male drivers) and the dependent variable (e.g., arrest). If an asterisk is not present, the relationship is not considered statistically significant. Due to the extremely large sample size (i.e., the large number of traffic stops), the statistical significance of the relationships is assessed at the 0.001 level. The asterisks indicate that the relationships between variables are due to chance less than 0.1% of the time. The sign of the coefficient (i.e., positive or negative) indicates the direction of the relationship. For example, a positive sign on the “driver male” variable would indicate that male drivers are *more* likely than female drivers to receive a particular outcome, while a negative sign would indicate that males are *less* likely than females to receive a particular outcome.

Since the interpretation of log-odds is not intuitively straightforward, this type of coefficient is usually exponentiated to allow for interpretation in terms of odds (Liao, 1994). The second column—the odds ratio—represents this antilog transformation of the coefficient into the multiplicative odds of the outcome variable based on the predictor variable, everything else being equal. The odds ratio indicates the strength of the relationship. For example, an odds ratio of 3.0 indicates that the presence of the variable (e.g., being a male driver) leads to three times the likelihood of receiving the outcome (e.g., conducting a search). The strength of the relationship is one of the most important considerations. Even if the relationship between variables is statistically significant (that is, it receives an asterisk in the table), it may not be substantively important. That is, the strength of the relationship may not be very large. As a general guide with this number of traffic stops being analyzed, a log odds would be considered “substantively” important if it were over 1.25 (for positive coefficients) and under 0.75 (for negative coefficients).

MULTIVARIATE FINDINGS

Table 6.7 reports results for two logistic regression models predicting arrest. In the base model (Model 1), 42,570 traffic stops were analyzed (97.4% of the total number of traffic stops recorded). When officer characteristics and characteristics of the zone where the stop occurred are added to the base model (Model 2), the analysis is based on 41,998 traffic stops (96.1% of the total number of traffic stops recorded).

Arrest Model 1 – Base Model

The base model reported in the first column of **Table 6.7** is substantively strong, explaining 35.1% of the variance in the likelihood of arrest. The base model demonstrates that drivers’ race/ethnicity does *not* significantly and independently influence whether or not drivers are

arrested once other legal and extralegal factors are considered. That is, although the bivariate relationships reported in the beginning of this section demonstrated that Black and Hispanic motorists were significantly more likely than Caucasians to be arrested, after considering additional legal and extralegal reasons that might influence whether or not an arrest is made, the race/ethnicity of the driver is no longer a significant factor.

Some drivers' characteristics other than race/ethnicity, however, do have a significant independent influence over whether or not an arrest is made during traffic stops. For example, male drivers, younger drivers, disrespectful drivers, noncompliant or resistant drivers, and drivers who are stopped in the zone where they reside are significantly *more* likely to be arrested compared to female drivers, older drivers, respectful drivers, complaint drivers, and drivers who reside outside of the zone in which they are stopped, respectively. Of the drivers' characteristics that significantly predict an arrest, drivers' gender, disrespect, and noncompliance were the most substantively important predictors of arrest. Specifically, male drivers were 2.7 times more likely than female drivers to be arrested. Drivers that were described by police officers as disrespectful were 2.4 times more likely to be arrested compared to those described as civil. Likewise, drivers who were described by police officers as noncompliant, verbally resistant, or physically resistant were 3.7 times more likely to be arrested compared to drivers who complied with police.

Some characteristics of the vehicle also had a significant influence over the likelihood of drivers being arrested during traffic stops. Drivers of vehicles that had no registration and drivers of vehicles in poor condition were significantly more likely to be arrested compared to drivers of vehicles that were registered and drivers of vehicles in fair or good condition. Specifically, drivers of vehicles with no registration were 2.4 times more likely to be arrested and drivers of vehicles in poor condition were 1.7 times more likely to be arrested, compared to drivers of registered vehicles and vehicles in better condition, respectively.

Two stop characteristics were significant predictors of arrest – time of day and day of the week. Drivers stopped during non-daylight hours and drivers stopped on a weekend day (i.e., Saturday or Sunday) were significantly more likely to be arrested compared to drivers stopped during daylight hours or on a weekday.

Likewise, the reason for the stop was a significant predictor of arrest. All of the reasons for the stop except one (equipment) significantly predicted the likelihood of arrest. That is, drivers who were stopped for a moving misdemeanor, license or registration violation, preexisting information, or some other (unknown) reason were significantly more likely to be arrested compared to drivers stopped for speeding or a felony moving violation.

Finally, both of the additional legal variables included in the model significantly predicted arrest. Drivers who were stopped for more reasons and drivers with contraband found during a search were significantly more likely to be arrested compared to drivers stopped for fewer reasons and those without contraband found. As one would expect, the discovery of contraband was by far, the most substantively important predictor of arrest. Drivers with contraband discovered were 21.7 times more likely to be arrested compared to drivers without the discovery of contraband. While this finding is intuitive, it is important to include this type of legal variable in the model

predicting arrest so that the effect of other extralegal variables can be examined after this legal variable is statistically controlled.

Arrest Model 2 – Full Model

Model 2 in **Table 6.7** documents the likelihood of arrest when officers' characteristics and the characteristics of the zone where the stop occurred are added to the base model. The change in the explained variance from the base model to the Model 2 was very modest (35.1% to 35.7%), suggesting that the inclusion of these additional variables generates very little additional explanatory effect. It is important to note that all of the main effects from the base model reported above remain significant even after adding officer and zone characteristics. The only substantive change to the model is that one officer characteristic and one zone characteristic become significant predictors of the likelihood of arrest. Specifically, traffic officers are significantly *less* likely to arrest motorists compared to officers with some other assignment. Also, drivers who are stopped in zones with higher percentages of males over 18 years old are significantly *less* likely to be arrested compared to drivers who are stopped in zones with smaller populations of males. Note, however, that of these two variables, only assignment as a traffic officer is also substantively meaningful. Officers with a traffic assignment are 1.7 times *less* likely to arrest motorists compared to those with other assignments. There was no substantive change to the model when characteristics of the zone where the stop occurred were considered, as the only statistically significant variable (% population male over 18 years old) was not substantively important (i.e., the odds ratio indicated little substantive significance, suggesting that the significance testing for this variable was influenced by the sample size).

Therefore, the finding that Black and Hispanic motorists are *not* significantly more likely than Caucasians to be arrested during a traffic stop holds even when the characteristics of the officer and the characteristics of the zone where the stopped occurred are taken into account.

Table 6.7: Logistic Regression Analyses Predicting Arrests

Variables	Model 1: Base Model (N = 42,570)		Model 2: Full Model (N = 41,998)	
	Coeff.	Odds Ratio	Coeff.	Odds Ratio
Intercept	-4.68	0.01	-3.28	0.04
Driver Characteristics				
Black	0.19	1.20	0.16	1.17
Hispanic	0.02	1.02	0.01	1.01
Other	-0.80	0.45	-0.88	0.41
Male	0.98*	2.65	0.96*	2.60
Age	-0.01*	0.99	-0.01*	0.99
Disrespectful	0.87*	2.38	0.87*	2.39
Non-Compliant / Resistant	1.32*	3.74	1.33*	3.80
Resides in zone where stopped	0.26*	1.29	0.17	1.18
Vehicle Characteristics				
No Registration	0.88*	2.40	0.77*	2.16
Modifications	-0.13	0.88	-0.16	0.85
Poor Condition	0.55*	1.73	0.54*	1.71
Number of Passengers	-0.01	0.99	-0.01	0.99
Stop Characteristics				
Daytime	-0.55*	0.57	-0.49*	0.61
Rush Hour	0.14	1.15	0.15	1.16
Weekend	0.31*	1.36	0.36*	1.44
Interstate / Main Roadway	-0.19	0.83	-0.12	0.88
Reason for the Stop				
Moving Misdemeanor	0.35*	1.42	0.30*	1.35
Equipment	0.21	1.23	0.18	1.19
License / Registration	0.78*	2.18	0.75*	2.12
Preexisting Information	1.09*	2.99	0.99*	2.70
Other	1.10*	3.01	1.02*	2.79
Other Legal Variables				
Number of Reasons for the Stop	0.24*	1.27	0.27*	1.31
Contraband Found During Search	3.08*	21.68	3.05*	21.12
Officer Characteristics				
Caucasian	--	--	0.07	1.07
Male	--	--	-0.29	0.75
Traffic Assignment	--	--	-0.50*	0.61
Years of Experience	--	--	-0.02	0.99
Census Characteristics				
Population	--	--	0.00	1.00
% Pop. Black 18+	--	--	0.00	1.00
% Pop. Hispanic 18+	--	--	0.00	1.00
% Pop. Male 18+	--	--	-0.02*	0.98
Poverty Factor	--	--	-0.04	0.96
Model Chi square	5078.8*		5087.7*	
Nagelkerke R-square	0.351		0.357	

Search Model 1 – Base Model

Table 6.8 reports results for two logistic regression models predicting the likelihood of a search during a traffic stop. In the base model (Model 1), 42,570 traffic stops were analyzed (97.4% of the total number of traffic stops recorded). When officer characteristics and characteristics of the zone where the stop occurred are added to the base model (Model 2), the analysis is based on 41,978 traffic stops (96.1% of the total number of traffic stops recorded).

Similar to the arrest model reported above, the base model reported in the first column of **Table 6.8** is a relatively strong model, explaining 17.8% of the variance in the likelihood of conducting a search. Note, however, that this model explains much less of the variation in search patterns compared to the explained variation in arrest patterns. This is primarily because the contraband seized variable that was so strong in the arrest model is excluded in the search model (i.e., the seizure of contraband cannot be used to predict whether or not a search is conducted).

Unlike the arrest model, the base model examining searches does suggest that drivers' race/ethnicity significantly influences whether or not drivers are searched, even after other legal and extralegal factors are considered. That is, the bivariate relationships reported in the beginning of this section demonstrating that Black motorists were significantly more likely than Caucasians to be searched continues even after considering additional legal and extralegal reasons that also influence whether or not a search is conducted. Two racial groups (Black and others) were significantly different compared to Caucasians. Specifically, Black motorists were 1.4 times more likely to be searched compared to Caucasian motorists stopped for a traffic offense by CDP officers. In contrast, drivers of other races / ethnicities (e.g., Asian, Middle Eastern, Native American) were significantly *less* likely than Caucasians to be searched during a traffic stop.

Several other driver characteristics demonstrated a significant independent influence over whether or not a search is conducted during a traffic stop. For example, male drivers, younger drivers, disrespectful drivers, noncompliant or resistant drivers, and drivers who are stopped in the zone where they reside are significantly *more* likely to be searched compared to female drivers, older drivers, respectful drivers, complaint drivers, and drivers who reside outside of the zone in which they are stopped, respectively. Of the drivers' characteristics that significantly predict a search, drivers' gender and noncompliance were the most substantively important predictors of searches. Specifically, male drivers were 2.9 times more likely than female drivers to be searched. Likewise, drivers that were described by police officers as noncompliant, verbally resistant, or physically resistant were 3.6 times more likely to be searched compared drivers who were compliant and showed no resistance to officers. Note that it is unknown whether or not drivers were noncompliant and/or resistant as a result of being searched. That is, temporal ordering cannot be established with this variable (this also applies to disrespect).

Two vehicle characteristics also had a significant influence over the likelihood of drivers being searched during traffic stops. As found with arrest, drivers of vehicles that had no registration and drivers of vehicles in poor condition were significantly more likely to be searched compared to drivers of vehicles that were registered and drivers of vehicles in fair or good condition.

Specifically, drivers of vehicles with no registration were 1.6 times more likely to be searched and drivers of vehicles in poor condition were 2.5 times more likely to be searched, compared to drivers of registered vehicles and vehicles in better condition, respectively.

Two stop characteristics were significant predictors of searches – time of day and roadway type. Drivers stopped during daylight hours and drivers stopped on interstates or main roadways were significantly *less* likely to be searched, compared to drivers stopped during non-daylight hours and drivers stopped on secondary streets or other roadways.

Search Model 2 – Full Model

Model 2 in **Table 6.8** documents the likelihood of conducting a search when officers' characteristics and the characteristics of the zone where the stop occurred are added to the base model. The change in the explained variance from the base model to the Model 2 is modest, but important (17.8% explained variance in the base model compared to 20.1% of the explained variance in the full model). This suggests that at least some of the added variables are important predictors of search decisions. All of the main effects from the base model reported above remain significant even after adding officer and zone characteristics, with the exception of one (drivers' residency in the zone where the stop occurred). This variable was initially significant in the Base Model, however it loses significance when additional variables are added to the model. In addition, the inclusion of officer characteristics in the model adds explanatory power. Three of the four officer characteristics significantly predict whether or not searches are conducted during traffic stops. Specifically, Caucasian officers are 1.4 times *more* likely than minority officers to conduct searches during traffic stops. In contrast, traffic officers and officers with more experience are significantly less likely to conducted searches compared to officers with non-traffic assignments and officers with fewer years of experience. Note however, that only officers' race and assignment (and not years of experience) are substantively important predictors of whether or not searches are conducted.

Perhaps the most important finding in the full model, however, is that Black motorists are still 1.3 times more likely compared to Caucasians to be searched during a traffic stop, even after statistically controlling for other driver characteristics, vehicle characteristics, stop characteristics, reasons for the stop, other legal variables, officer characteristics, and characteristics of the zone where the stop occurred.

Table 6.8: Logistic Regression Analyses Predicting Searches

Variables	Model 1: Base Model (N = 42,570)		Model 2: Full Model (N = 41,998)	
	Coeff.	Odds Ratio	Coeff.	Odds Ratio
Intercept	-3.42	0.03	-2.86	0.06
Driver Characteristics				
Black	0.37*	1.44	0.27*	1.31
Hispanic	0.11	1.11	-0.01	0.99
Other	-0.84*	0.43	-0.93*	0.39
Male	1.05*	2.87	1.04*	2.83
Age	-0.02*	0.98	-0.02*	0.98
Disrespectful	0.45*	1.56	0.45*	1.57
Non-Compliant / Resistant	1.28*	3.60	1.28*	3.59
Resides in zone where stopped	0.17*	1.19	0.09	1.09
Vehicle Characteristics				
No Registration	0.44*	1.55	0.28*	1.32
Modifications	0.11	1.11	0.02	1.02
Poor Condition	0.91*	2.48	0.91*	2.47
Number of Passengers	0.05	1.05	0.06*	1.06
Stop Characteristics				
Daytime	-0.58*	0.56	-0.29*	0.75
Rush Hour	-0.11	0.89	-0.17	0.85
Weekend	0.06	1.06	0.15*	1.17
Interstate / Main Roadway	-0.38*	0.68	-0.28*	0.76
Reason for the Stop				
Moving Misdemeanor	0.63*	1.88	0.56*	1.75
Equipment	0.84*	2.31	0.80*	2.22
License / Registration	1.50*	4.48	1.48*	4.41
Preexisting Information	1.50*	4.47	1.42*	4.13
Other	1.23*	3.42	1.12*	3.07
Other Legal Variables				
Number of Reasons for the Stop	0.40*	1.49	0.46*	1.58
Officer Characteristics				
Caucasian	--	--	0.32*	1.38
Male	--	--	-0.08	0.92
Traffic Assignment	--	--	-1.11*	0.33
Years of Experience	--	--	-0.01*	0.99
Census Characteristics				
Population	--	--	0.00	1.00
% Pop. Black 18+	--	--	0.00	1.00
% Pop. Hispanic 18+	--	--	0.00	1.00
% Pop. Male 18+	--	--	-0.01	0.99
Poverty Factor	--	--	0.07	1.08
Chi-Square	3552.4*		3974.3*	
Nagelkerke R-Square	0.178		0.201	

POST-STOP OUTCOMES SUMMARY

The bivariate and multivariate findings regarding post-stop outcomes reported in this section, though instructive, should not be considered definitive. As noted in **Section 1**, there are a number of factors that might influence officer behavior which have not been captured on the Cleveland Traffic Stop Form, and therefore cannot be included in the statistical analyses. This problem, known as specification error, is a limitation of all multivariate models used in social science research. It simply is not possible to measure all of the factors that could possibly influence officers' decision making during traffic stops. Therefore, the findings must be interpreted with this limitation in mind. Second, given the large number of cases department-wide, smaller differences among groups are more likely to reach statistical significance. Therefore, it is more instructive to examine the log odds to assess substantive significance, rather than rely strictly on indicators of statistical significance.

With these limitations in mind, the findings from the multivariate logistic regression models suggest that, after statistically controlling for driver characteristics, vehicle characteristics, stop characteristics, community factors, the reason for the stop, other legal variables, officer characteristics, and the characteristics of the zone where the stop occurred, the following relationships remain:

ARRESTS SUMMARY

- **Black and Hispanic motorists are *not* significantly more likely than Caucasians to be arrested during traffic stops when other legal and extralegal factors are considered.**
- Male drivers are 2.6 times more likely than females to be arrested when all other measured extralegal and legal factors are equal.
- Drivers described as “disrespectful” by officers were 2.4 times more likely to be arrested compared to those described as civil.
- Drivers who were noncompliant or verbally / physically resistant were 3.8 times more likely to be arrested compared to drivers who complied with officers.
- Motorists in vehicles with no registration were 2.2 times more likely to be arrested compared to motorists traveling in registered vehicles.
- Drivers of vehicles described by officers as being in “poor” working condition were 1.7 times more likely to be arrested compared to drivers of vehicles in “fair” or “good” condition.
- Stops conducted during non-daylight hours were 1.6 times more likely to lead to an arrest compared to traffic stops during daylight hours.
- Traffic stops conducted during weekend days were 1.4 times more likely than stops during weekdays to result in an arrest of the motorist.
- Drivers initially stopped for moving misdemeanors were 1.4 times more likely to be arrested compared to drivers stopped for speeding or moving felony violations.

- Drivers initially stopped for license or registration violations were 2.1 times more likely to be arrested compared to drivers stopped for speeding or moving felony violations.
- Drivers initially stopped based on preexisting information were 2.7 times more likely to be arrested compared to drivers stopped for speeding or moving felony violations.
- Drivers initially stopped for other (unknown) reasons were 2.8 times more likely to be arrested compared to drivers stopped for speeding or moving felony violations.
- Drivers stopped for more traffic offenses were 1.3 times more likely to be arrested compared to those stopped for fewer violations.
- Drivers with contraband found during a search were 21.1 times more likely to be arrested compared to drivers without contraband found.
- Drivers stopped by non-Traffic officers were 1.7 times more likely to be arrested compared to drivers stopped by Traffic officers.

SEARCHES SUMMARY

- **After controlling for other relevant legal and extra legal factors drivers' race/ethnicity does show a significant influence over whether or not searches are conducted. The odds of being searched are 1.3 times higher for Black drivers compared to Caucasian drivers.**
- Drivers of "other" races (i.e., Asian, Middle Eastern, and Native American) are 2.5 times *less* likely to be searched compared to Caucasian drivers.
- Drivers described as "disrespectful" by officers were 1.6 times more likely to be searched compared to those described as civil.
- Drivers who were noncompliant or verbally / physically resistant were 3.6 times more likely to be searched compared to drivers who complied with officers.
- Motorists in vehicles with no registration were 1.3 times more likely to be searched compared to motorists traveling in registered vehicles.
- Drivers of vehicles described by officers as being in "poor" working condition were 2.5 times more likely to be searched compared to drivers of vehicles in "fair" or "good" condition.
- Stops conducted during non-daylight hours were 1.3 times more likely to lead to an arrest compared to traffic stops during daylight hours.
- Traffic stops conducted on secondary streets and other roadways were 1.3 times more likely to result in a search compared to traffic stops conducted on interstates and main roadways.
- Drivers initially stopped for moving misdemeanors were 1.8 times more likely to be searched compared to drivers stopped for speeding or moving felony violations.
- Drivers initially stopped for equipment violations were 2.2 times more likely to be searched compared to drivers stopped for speeding or moving felony violations.
- Drivers initially stopped for license or registration violations were 4.4 times more likely to be searched compared to drivers stopped for speeding or moving felony violations.
- Drivers initially stopped based on preexisting information were 4.1 times more likely to be searched compared to drivers stopped for speeding or moving felony violations.

- Drivers initially stopped for other (unknown) reasons were 3.1 times more likely to be searched compared to drivers stopped for speeding or moving felony violations.
- Drivers stopped for more traffic offenses were 1.6 times more likely to be searched compared to those stopped for fewer violations.
- Drivers stopped by Caucasian officers were 1.4 times more likely to be searched compared to drivers stopped by minority officers.
- Drivers stopped by non-Traffic officers were 3.0 times more likely to be searched compared to drivers stopped by Traffic officers.

Based on the findings presented in the section, it is the conclusion of this report that no racial/ethnic disparities in arrest rates were found with these data. The findings do show, however, that after controlling for other measured legal and extralegal factors, Black drivers were 1.3 times more likely to be searched compared to Caucasian drivers. To explore the reasons associated with this racial disparity in search rates, a separate section of this report is dedicated to further examining searches and seizures. It is possible that Black motorists are more likely than others to be in possession of contraband and thus would provide legal justification for higher search rates. It is also possible that Black motorists are more likely than other motorists to be searched during circumstances in which a search is required by departmental policy (rather than based on officer discretion). These and other possibilities are further explored in **Section 7**, which focuses specifically on the search and seizure rates documented in this data collection effort.

7. SEARCH & SEIZURES

OVERVIEW

The material presented in this section is focused specifically on vehicle and person searches conducted during traffic stops. As reported in **Section 6**, searches are one form of post-stop outcomes conducted by CDP officers that have unexplained racial and ethnic disparities. After statistically controlling for some of the other relevant legal and extralegal factors, Black drivers are approximately 1.3 times more likely than Caucasians to be searched during a traffic stop. The purpose of the analyses presented in this section is to further examine searches and seizures conducted by CDP officers.

Section 7 begins with a description of search and seizure rates for the department as a whole, by district, and zone. This information is documented in **Table 7.1**. **Table 7.2** reports the reasons for searches by the department and districts. **Table 7.3** documents the different types of searches conducted by the department and districts. The types of searches are collapsed into three categories: Type I (mandatory), Type II (discretionary), and Type III (consent only). Using these three search types, **Table 7.4** documents the search rates for different types of drivers and officers.

Table 7.5 reports the success rate for the three types of searches at the department and district level. **Table 7.6** reports the search success rates for each of the three collapsed search type categories by driver and officer characteristics. Finally, **Table 7.7** documents the success rates and different types of contraband seized by the CDP and individually by districts. **Section 7** concludes with a summary of the main findings.

SEARCH RATES

As reported in **Section 6**, 8.8% of the traffic stops reported by the CDP during this 8-month period resulted in a search of the vehicle or motorist. While the overwhelming majority of traffic stops never result in a vehicle or person search, the physical and psychological intrusion of a person or vehicle search merits further exploration. Furthermore, nationwide a concern is growing that searches conducted during police-initiated traffic stops could be used in a manner to profile particular types of drivers. Although searching motorists is a statistically infrequent event, it is a highly visible form of coercive police action that merits further scrutiny.

Table 7.1 below reports the total numbers of traffic stops, total number of searches conducted during those stops, the percentage of stops that result in a search, the total number of contraband seizures, and the percentage of searches that result in a seizure of contraband. This information is provided for the department as a whole, followed by districts and zones. As shown in **Table 7.1**, the percentage of traffic stops conducted by CDP officers that result in a search of the driver or vehicle ranges from 2.3% of traffic stops conducted by the Traffic Division to 15.1% of all traffic stops conducted by officers assigned to District 3. When

considering geographic areas (zones), the variation in the rate of searches is even more pronounced. For example, only 3.3% of traffic stops conducted by CDP officers in Zone 122 resulted in a search of the vehicle or person, compared to 17.3% of the stops in Zone 412.

Table 7.1: Search Rates & Search Success Rates by Department, District, and Zone (p. 1 of 2)

Zone	Total # of Stops	Total # of Searches	% of Stops Resulting in Person or Vehicle Search	# of Seizures	% of Searches Resulting in Seizure
CDP Dept	43,707	3,847	8.8	2,125	55.2
Traffic Unit	11,283	262	2.3	130	49.6
District 1	4,370	393	9.0	157	39.9
District 2	3,702	484	13.1	339	70.0
District 3	5,126	775	15.1	525	67.7
District 4	7,736	945	12.2	471	49.8
District 5	4,099	339	8.3	192	56.6
District 6	7,385	649	8.8	311	47.9
Zone Level					
Zone 111	849	30	3.5	11	36.7
Zone 112	1,994	147	7.4	70	47.6
Zone 113	788	111	14.1	43	38.7
Zone 121	717	41	5.7	17	41.5
Zone 122	940	31	3.3	10	32.3
Zone 123	1,186	60	5.1	18	30.0
Zone 211	901	65	7.2	35	53.8
Zone 212	863	87	10.1	70	80.5
Zone 213	929	35	3.8	21	60.0
Zone 221	953	132	13.9	98	74.2
Zone 222	2,057	147	7.2	98	66.7
Zone 223	434	43	9.9	32	74.4
Zone 224	561	36	6.4	20	55.6
Zone 311	2,956	149	5.0	99	66.4
Zone 312	1,187	169	14.2	114	67.5
Zone 313	791	118	14.9	76	64.4
Zone 321	653	99	15.2	66	66.7
Zone 322	847	77	9.1	51	66.2
Zone 323	1,216	152	12.5	94	61.8
Zone 324	606	89	14.7	50	56.2

Table 7.1: Search Rates & Search Success Rates by Department, District, and Zone (p. 2 of 2)

Zone	Total # of Stops	Total # of Searches	% of Stops Resulting in Person or Vehicle Search	# of Seizures	% of Searches Resulting in Seizure
CDP Dept	43,707	3,847	8.8	2,125	55.2
Zone Level					
Zone 411	1,817	124	6.8	68	54.8
Zone 412	590	102	17.3	56	54.9
Zone 413	1,199	179	14.9	81	45.3
Zone 414	517	82	15.9	39	47.6
Zone 421	580	93	16.0	48	51.6
Zone 422	1,575	157	10.0	93	59.2
Zone 423	1,087	155	14.3	75	48.4
Zone 424	951	60	6.3	24	40.0
Zone 425	274	22	8.0	10	45.5
Zone 511	977	83	8.5	41	49.4
Zone 512	713	36	5.1	18	50.0
Zone 513	1,023	94	9.2	51	54.3
Zone 514	684	48	7.0	32	66.7
Zone 521	554	47	8.5	27	57.4
Zone 522	374	19	5.1	13	68.4
Zone 523	952	34	3.6	21	61.8
Zone 611	959	99	10.3	45	45.5
Zone 612	2,006	162	8.1	72	44.4
Zone 613	1,704	134	7.9	63	47.0
Zone 621	562	36	6.4	14	38.9
Zone 622	1,450	112	7.7	58	51.8
Zone 623	1,596	140	8.8	73	52.1

The search success rates also varied significantly across districts and zones. Department wide, 55.2% of the searches conducted by CDP officers resulted in the seizure of contraband. The districts ranged in their search success rates from a low of 39.9% in District 1 to 70.0% in District 2. At the zone level, geographic areas ranged in their search success rates from a low of 30.0% in Zone 123, to a high of 80.5% in Zone 212. As previously mentioned in **Section 6**, this discrepancy may be due to the types of searches conducted in these districts and zones. The likelihood of finding contraband varies based on the type of search conducted. Typically, searches based on discretionary reasons such as probable cause, canine alerts, etc. are the most successful in terms of seizing contraband, followed by searches that are conducted for mandatory (i.e., departmental policy) reasons, such as inventory searches, searches incident to an arrest. Typically the least successful searches in terms of recovering contraband are searches based solely on drivers' consent. If the types of searches conducted varied dramatically across districts and zones, one would expect that their search success rates would vary accordingly. To examine this possibility, the specific types of searches conducted are examined later in this section of the report.

TYPES OF SEARCHES

Table 7.2 documents the number of searches and the percentage of searches for each reason indicated on the Cleveland Traffic Stop Form (e.g., consent, drug /alcohol odor, plain view, incident to arrest, Canine alert, inventory, probable cause, search warrant, and other) by department and district. Officers may have indicated that a search was conducted for multiple reasons. As a result, the sum of percentages across search categories reported in **Table 7.2** may exceed 100%.

As shown in **Table 7.2**, searches based on administrative inventory were the most common across the department (52.5% of searches were described by CDP officers as inventory searches) and the majority of districts. Only in District 4 is one other type of search (incident to arrest) represented at a slightly larger percentage compared to inventory searches. For the department as a whole, and all Districts other than District 4, incident to arrest was the second most common reason indicated for conducting searches.

The use of probable causes searches varied dramatically across districts, with the Traffic unit and District 2 using them very infrequently (2.3% and 4.1% of all searches conducted, respectively) to extensive use by officers assigned to District 5 (34.8% of all searches). Somewhat unusual is the extensive use of the “other” category by officers in District 2 (12.2% of all searches) and this likely represents a problem with those officers properly using the form.

The use of consent searches department wide was relatively low at 8.5% of all searches conducted. Consent searches were the most infrequently used by officers in Districts 2 and 3 (3.1% and 2.6% of all searches, respectively) and were the most frequently used by officers assigned to District 6 (17.9% of all searches). It is also interesting to note the nearly non-existent use across the CDP of canines and search warrants as reasons for conducting searches during traffic stops.

Table 7.2: Reasons for Search by Department and District

Zone	# Search	% Consent	% Drugs/ Alcohol Odor	% Plain View	% Incid. to Arrest	% K-9 Alert	% Invent.	% Prob. Cause	% Sea. Warr.	% Oth.
CDP Dept	3,847	8.5	14.7	11.0	31.6	0.2	52.0	13.9	0.0	6.0
Traffic	262	6.1	2.7	1.9	31.3	0.8	72.9	2.3	0.0	7.6
District 1	393	10.2	11.5	8.4	32.8	0.3	47.8	13.5	0.0	2.0
District 2	484	3.1	9.9	4.8	23.8	0.2	79.3	4.1	0.0	12.2
District 3	775	2.6	13.6	16.3	37.2	0.1	62.8	8.9	0.0	6.7
District 4	945	9.0	21.8	11.1	36.3	0.0	36.2	21.3	0.0	4.7
District 5	339	9.7	18.9	16.8	33.6	0.3	37.8	34.8	0.0	6.2
District 6	649	17.9	13.9	11.3	22.3	0.0	43.5	10.6	0.0	4.0

While examining the specific reasons for a search is instructive, this information is better analyzed when collapsed into discrete categories, or types of searches. These types of searches, although based on different reasons, have similar characteristics that warrant them being considered collectively. For the analyses reported in **Table 7.3** below, searches were divided into three categories based on the presumed level of officer discretion for different situations. The first search category (Type I) includes searches that are required by CDP policy and therefore, mandatory for officers to perform. Type I (Mandatory) searches include searches incident to arrest, based on a pre-existing warrant, and inventory searches. The second search category (Type II) includes searches that are not mandatory, but rather are based on suspicion and officer discretion. Specifically, Type II (Discretionary) searches include plain view searches, canine alert searches, drug odor searches, and probable cause searches. The Type III search category (Consent) includes only those searches that are based solely on consent, and therefore are the most discretionary for officers. If a search was based on multiple reasons, it was assigned to the search category with the least officer discretion (e.g., if a search is based on a probable cause [Type II] and consent [Type III], it was defined as a Type II search). Therefore, the analyses below examining the success rates for Type I, II, and III searches are mutually exclusive. In addition, 46 searches (1.2% of all searches) where officers indicated the only reason for the search was “other” or did not code any reason for the search have been eliminated from these analyses.

Table 7.3: Types of Searches by Department, District, and Zone (p. 1 of 2)

Zone	# Search Initiated	% Search Initiated	Type 1: Mandatory Searches	Type 2: Discretionary Searches	Type 3: Consent Searches
CDP Dept	3,847	8.8	71.2	23.7	4.7
Traffic Unit	262	2.3	91.3	5.9	2.8
District 1	393	9.0	70.5	22.6	6.9
District 2	484	13.1	87.9	10.4	1.7
District 3	775	15.1	80.0	18.0	1.9
District 4	945	12.2	63.3	33.4	3.3
District 5	339	8.3	57.7	37.5	4.8
District 6	649	8.8	59.2	28.6	12.2
Zone Level					
Zone 111	30	3.5	73.3	16.7	10.0
Zone 112	147	7.4	62.1	31.0	6.9
Zone 113	111	14.1	67.3	24.5	8.2
Zone 121	41	5.7	82.5	12.5	5.0
Zone 122	31	3.3	87.1	3.2	9.7
Zone 123	60	5.1	79.7	10.2	10.2
Zone 211	65	7.2	87.1	9.7	3.2
Zone 212	87	10.1	91.8	7.1	1.2
Zone 213	35	3.8	82.4	17.6	0.0
Zone 221	132	13.9	86.4	12.9	0.8
Zone 222	147	7.2	89.0	9.6	1.4
Zone 223	43	9.9	90.7	9.3	0.0
Zone 224	36	6.4	88.9	8.3	2.8
Zone 311	149	5.0	83.2	16.1	0.7
Zone 312	169	14.2	81.9	15.7	2.4
Zone 313	118	14.9	88.1	11.0	0.8
Zone 321	99	15.2	75.5	21.4	3.1
Zone 322	77	9.1	70.7	20.0	9.3
Zone 323	152	12.5	79.5	19.9	0.7
Zone 324	89	14.7	78.7	19.1	2.2

Table 7.3: Types of Searches by Department, District, and Zone (p. 2 of 2)

Zone	# Search Initiated	% Search Initiated	Type 1: Mandatory Searches	Type 2: Discretionary Searches	Type 3: Consent Searches
CDP Dept	3,847	8.8	71.2	23.7	4.7
Zone Level					
Zone 411	124	6.8	58.9	37.1	4.0
Zone 412	102	17.3	79.2	18.8	2.0
Zone 413	179	14.9	82.0	16.9	1.1
Zone 414	82	15.9	63.0	32.1	4.9
Zone 421	93	16.0	52.2	43.5	4.3
Zone 422	157	10.0	62.8	36.5	0.6
Zone 423	155	14.3	52.6	42.1	5.3
Zone 424	60	6.3	67.8	27.1	5.1
Zone 425	22	8.0	42.9	52.4	4.8
Zone 511	83	8.5	73.5	24.1	2.4
Zone 512	36	5.1	61.1	38.9	0.0
Zone 513	94	9.2	54.3	39.4	6.4
Zone 514	48	7.0	60.9	34.8	4.3
Zone 521	47	8.5	47.8	45.7	6.5
Zone 522	19	5.1	73.7	21.1	5.3
Zone 523	34	3.6	60.6	36.4	3.0
Zone 611	99	10.3	59.4	22.9	17.7
Zone 612	162	8.1	60.8	29.7	9.5
Zone 613	134	7.9	64.1	28.2	7.6
Zone 621	36	6.4	61.1	25.0	13.9
Zone 622	112	7.7	63.1	27.0	9.9
Zone 623	140	8.8	56.5	29.0	14.5

The influences of drivers’ characteristics and officers’ characteristics are examined within the three aggregate categories of searches and are reported in **Table 7.4**. The results suggest that while mandatory searches are the most common across all motorists, Hispanic motorists are the ethnic group most likely to be searched for mandatory reasons. Black motorists are the racial group mostly likely to be searched for discretionary reasons, and Caucasian motorists are the group most likely to be searched based solely on consent.

Female and older drivers are significantly more likely than male and younger drivers to be searched for mandatory reasons and less likely to be searched for discretionary reasons, though rates of consent only searches across gender and age groups are statistically equivalent. There were no differences detected in the types of searches conducted based on drivers’ residency.

There were also some differences in the reasons for searches across different types of officers. Caucasian officers were significantly more likely than minority officers to search

motorists based on discretionary reasons, and solely on consent, while minority officers conducted a larger percentage of their searches for mandatory reasons. Female officers were slightly more likely to conduct searches based on mandatory reasons and less likely to conduct searches for discretionary reasons, compared to male officers. Male and female officers however were equally likely to search based solely on consent. Officers with more experience were slightly more likely compared to officers with less experience to search based on mandatory reasons and significantly less likely to search based solely on consent. These differences in the reasons for the searches conducted by different types of officers might partially explain the differences in their search success rates.

Table 7.4: Reasons for Search (by search type) by Driver and Officer Characteristics

	Total # of Searches**	% Mandatory (Type I) Searches	% Discretionary (Type II) Searches	% Consent (Type III) Searches
All Drivers	3,801	71.2	24.0	4.8
By Drivers' Characteristics				
Caucasian Driver	786	71.7	19.1	9.1
Black Driver	2,825	70.0	26.1	3.9
Hispanic Driver	183	83.0	15.9	1.1
Other Driver	25	82.6	8.7	8.7
Male Driver	3,244	69.7	25.4	4.9
Female Driver	599	79.2	16.4	4.4
Driver 25 years old or under	1,329	69.3	26.0	4.7
Driver over 25 years old	2,518	72.2	22.9	4.8
Driver Resides in Zone where Stopped	1,382	70.2	25.5	4.3
Driver Does Not Reside in Zone where Stopped	2,449	71.8	23.1	5.1
By Officers' Characteristics				
Caucasian Officer	3,010	68.3	26.4	5.4
Non-Caucasian Officer	768	81.3	16.0	2.8
Male Officer	3,670	70.8	24.3	4.9
Female Officer	108	74.1	22.2	3.7
Less than 5 years experience	223	65.9	24.4	9.7
5 years experience or more	3,584	71.4	24.1	4.5

** The total number of searches excluded 46 searches where the only reason indicated for the search was "other."

SEARCH SUCCESS RATES

The discovery of contraband during person and vehicle searches is an important outcome to consider when examining potential bias by police officers. Often referred to as search "success rates," or "hit rates" (i.e., the percent of searches conducted that produce contraband

and/or resulted in arrest), some scholars and police officials have argued that searches of minorities are more likely to produce contraband compared to searches of Caucasians (Herszenhorn, 2000; Knowles, Persico, & Todd, 2001). Others have argued that minority citizens are not more likely to be carrying illegal substances, and that a comparison of search success rates shows that racial profiling policies are ineffective (Cole, 1999; Harris, 2002).

Researchers have typically utilized the “outcome test” to identify racial and ethnic disparities by examining differential outcomes in search success rates. Originally applied by Becker (1957) to examine economic disparate treatment of minorities, the basic notion of the outcome test is to analyze whether outcomes are systematically different across groups. Ayres (2001, 2002) has argued that the “outcome test” can be used to successfully examine racial disparities in police practices, including searches. When applied to police searches, the outcome test is essentially a comparison of the successfulness of those searches – or a statistical comparison of “hit rates.”

To better understand racial and ethnic disparities in search and seizure rates, however, the outcome test should only be applied to discretionary searches (Engel, forthcoming). Outcome test comparisons of searches that are mandatory – that is, searches conducted as a result of departmental policy rather than officer discretion – should not be considered when determining racial/ethnic disparities due to officer decision making. Based on CDP policies, officers have little or no discretion over the following types of searches: inventory searches, searches incident to arrest, and searches based on a preexisting warrant. Likewise, the inclusion of *consent* searches in outcome test analyses is problematic because, as with mandatory searches, the decision of whether or not to search is not entirely based on the officers’ decision. Although officers initially decide whom to request a consent search from, ultimately it is citizens, not officers, who decide whether or not consent searches are conducted. That is, citizens have the right to refuse search requests, and if the officer has no probable cause to conduct the search, their denial of the police request must be honored.

Information contained in the tables previously presented demonstrated that searches based on different reasons lead to varying search success rates. **Table 7.5** further documents this finding. Specifically, **Table 7.5** illustrates the overall search success rate, and the search success rates for the three types of searches (Mandatory, Discretionary, and Consent) at the department and district levels. Department-wide, the overall search success rate is 55.2%. This rate, however, varies dramatically across search types as exemplified by the range from a high of 64.7% for Type II (Discretionary) searches, to a low of only 21.4% for Type III (Consent) searches. That is, discretionary searches are the most likely to result in the seizure of contraband, followed closely by mandatory searches. Consent only searches have significantly lower search success rates and therefore are the least productive type of search in terms of seizing contraband. These patterns remain relatively consistent across districts within the department, with only two exceptions. In District 5, mandatory searches are slightly more successful in discovering contraband, followed closely by discretionary searches. For the Traffic unit, mandatory searches are also the most effective; however their search success rate for discretionary searches is much lower compared to all other districts.

Table 7.5: Search Type Success Rates by Department and Districts

Zone	Overall Search Success Rate	Type 1: Mandatory Searches Success Rate	Type 2: Discretionary Searches Success Rate	Type 3: Consent Searches Success Rate
CDP	55.2	55.2	64.7	21.4
Traffic	49.6	53.7	26.7	28.6
District 1	39.9	38.9	52.3	14.8
District 2	70.0	70.4	78.0	37.5
District 3	67.7	67.7	75.5	6.7
District 4	49.8	43.0	67.3	22.6
District 5	56.6	60.8	54.8	31.3
District 6	47.9	46.9	64.3	21.8

It is also important to examine whether the search success rates for different types of searches varies based on drivers' and officers' characteristics. These findings are reported in **Table 7.6** below. Recall that to understand racial/ethnic disparities, only the results of the outcome test (i.e., comparisons of search success rates) should be considered for *discretionary* searches. Of importance here is that discretionary searches of Black motorists are the *most productive* in the seizure of contraband, followed by Hispanics and then Caucasians. Combining these results with those reported in the previous section indicate that although Black motorists are significantly more likely than Caucasians to be searched by CDP officers, searches of Black motorists are more likely than searches of Caucasians to result in the seizure of contraband. **That is, although Black motorists are searched at higher rates compared to Caucasians, discretionary searches of Black motorists yield better results in terms of the seizures of contraband, compared to searches of Caucasians.**

Similar findings are presented for male and younger drivers. That is, although male and younger drivers are significantly more likely to be searched compared to female and older drivers, the discretionary searches conducted for male and younger drivers are more likely to result in seizures of contraband compared to female and younger drivers. No significant differences in search success rates for discretionary searches were found based on drivers' residency.

When discretionary searches are examined by officers' characteristics, important differences emerge. Male officers, Caucasian officers, and officers with more experience are significantly more likely than their counterparts to engage in discretionary searches that result in seizures of contraband. That is, although male and Caucasian officers engage in more searches, they are more successful during these searches compared to female and

minority officers. In contrast, officers with less experience are *more* likely to engage in discretionary searches compared to officers with more experience, but officers with less experience are less successful in terms of contraband seizures. These findings have important implications for training, which will be explored in the final section of this report.

Table 7.6: Search Type Success Rates by Citizen and Officer Characteristics

	Total # Searches	Overall Search Success Rate	% Mandatory (Type I) Search Success Rate	% Discretionary (Type II) Search Success Rate	% Consent (Type III) Search Success Rate
All Drivers	3,847	55.2	55.2	64.7	21.4
By Drivers' Characteristics					
Caucasian Driver	786	52.9	57.4	57.8	20.0
Black Driver	2,825	56.1	54.7	66.4	23.1
Hispanic Driver	183	57.9	58.9	58.6	0.0
Other Driver	25	48.0	52.6	0.0	0.0
Male Driver	3,244	55.6	55.4	65.2	21.8
Female Driver	599	53.4	54.6	60.8	19.2
Driver 25 years old or under	1,329	55.2	53.0	69.2	25.8
Driver over 25 years old	2,518	55.2	56.3	62.0	19.2
Driver Resides in Zone where Stopped	1,382	51.6	49.5	65.8	15.3
Driver Does Not Reside in Zone where Stopped	2,449	57.0	58.1	63.9	24.4
By Officers' Characteristics					
Caucasian Officer	3,010	56.3	56.1	65.9	21.3
Non-Caucasian Officer	768	51.4	52.5	57.5	19.0
Male Officer	3,670	55.7	55.8	65.5	20.3
Female Officer	108	40.7	41.3	37.5	50.0
Less than 5 years experience	223	30.9	25.9	52.8	19.0
5 years experience or more	3,584	56.5	56.6	65.4	21.3

TYPES OF SEIZURES

Table 7.7 documents the types of evidence and/or contraband confiscated during searches conducted by CDP officers. For this 8-month period of data collection, 3,847 searches resulted in 2,125 seizures (55.2%). The type of contraband seized as the result of vehicle and person searches (from most to least likely) included: vehicles, drugs, alcohol, cash, weapons, other, and stolen property. One traffic stop search could result in several types of contraband seized, so the categories reported in Table 6.9 are not mutually exclusive. The highest percentage of

the seizures was vehicles, followed by drugs. Specifically, over half (52.1%) of the seizures made by CDP officers were vehicles, while just under half (47.9%) were drugs. It is likely that the large percentage of vehicle seizures is based on the reporting instrument. Police possession of the vehicle is a requirement of administrative inventory “searches.” Inventory “searches” were the most commonly reported search type, and those would explain the large percentage of vehicles reported as contraband “seized.” This also explains the extremely high search success rate at over 50%. That is, inventory searches (the most frequent type of search indicated) by definition result in a “seizure” of the vehicle. This underscores the importance of removing mandatory searches from Outcome Test analyses designed to understand racial/ethnic differences in search success rates.

Variation in the types of contraband seized is also evident across districts. For example, Districts 1, 4, 5 & 6 have larger percentages of drug seizures and smaller percentages of vehicle seizures, while the reverse is true for the Traffic District and Districts 2 & 3.

Table 7.7: Types of Evidence Seized by Department, District, and Zone

Zone	# of Searches	% Searches W/Contra. found	# Seized	<u>Property Seized</u>						
				% Cash	% Drug	% Veh.	% Weap.	% Stolen Prop.	% Alcoh.	% Oth.
CDP Dept	3,847	55.2	2,125	6.0	47.9	52.1	4.7	2.1	12.2	4.6
Traffic	262	49.6	130	3.1	12.3	89.2	0.0	1.5	3.8	1.5
District 1	393	40.0	157	7.6	75.8	24.8	5.1	3.8	5.1	5.1
District 2	484	70.0	339	4.1	25.7	82.0	1.5	1.2	3.5	2.1
District 3	775	67.7	525	7.0	43.0	62.3	5.1	1.5	12.8	6.7
District 4	945	49.8	471	5.7	66.2	30.6	5.3	2.8	19.3	3.8
District 5	339	56.6	192	6.8	51.6	44.3	5.7	2.1	17.7	4.2
District 6	649	47.9	311	6.8	50.8	38.3	7.4	2.3	13.8	6.1

SEARCH & SEIZURE SUMMARY

- Searches can generally be divided into 3 types based on the level of officer discretion: 1) mandatory, 2) discretionary, and 3) consent only.
- A majority of the searches conducted by officers (71.2%) were mandatory (i.e., required by departmental policy). In contrast 23.7% of the searches conducted were

discretionary, while only 4.7% of the searches were based solely on the motorists consent.

- The most common reason for a search was administrative inventory (52.0%), followed by incident to an arrest (31.6% of searches). The reasons for searches varied somewhat across districts.
- Department wide, 55.2% of all searches resulted in the seizure of contraband. This is a very higher search success rate, and likely is an artifact of the data collection effort that counted vehicles as “seizures” during administrative inventory “searches.”
- Generally, discretionary searches were the most productive in the seizure of contraband, followed by mandatory searches. The least productive searches were based on consent only. Specifically, 64.72% of discretionary searches resulted in the discovery of contraband, compared to 55.2% of mandatory searches and only 21.4% of consent searches.
- Hispanic motorists were more likely to be searched for mandatory reasons, compared to other racial groups, while Black motorists were more likely to be searched for discretionary reasons. Caucasian motorists were more likely to be searched based solely on consent, compared to other racial ethnic groups. **Thus, there is no consistent evidence to suggest that minority motorists are singled out for the most discretionary types of searches.**
- Discretionary searches of Black motorists are the *most productive* in the seizure of contraband, followed by Hispanics and then Caucasians. Combining these results with those reported in the previous section indicate that **although Black motorists are significantly more likely than Caucasians to be searched by CDP officers, searches of Black motorists are more likely than searches of Caucasians to result in the seizure of contraband.**
- Male officers, Caucasian officers, and officers with more experience are significantly more likely than their counterparts to engage in discretionary searches that result in seizures of contraband. That is, although male and Caucasian officers engage in more searches, they are more successful during these searches compared to female and minority officers. In contrast, officers with less experience are *more* likely to engage in discretionary searches compared to officers with more experience, but officers with less experience are less successful in terms of contraband seizures.

8. SUMMARY AND CONCLUSIONS

OVERVIEW

The UC research team encountered many obstacles during the planning and implementation stages of this traffic stop study. While a few key CDP officials worked tirelessly to reduce these problems, at times their efforts were thwarted by managerial impediments within the CDP and the City of Cleveland. Despite these obstacles, CDP officials and the UC research team managed to work together to produce a research study with some important findings regarding the equitable treatment of all citizens encountered by CDP officers.

TRAFFIC STOPS AND BENCHMARK ANALYSES

Traffic stop data were collected and analyzed for an 8-month period from July 1st, 2005 through February 28th, 2006. Of the 43,707 motorists stopped during this time period, 96.7% were issued a citation, 8.8% were searched, and 4.8% were arrested. Over half of the stopped drivers were characterized by police officers as Black (61.5%), compared to a little under a third of the drivers who were characterized as Caucasian (30.5%), and less than five percent characterized as Hispanic (4.6%). The average age of drivers was 36.3 years, and 66.6% of the drivers stopped by officers were males. Almost all drivers were Ohio residents (97.8%), while many were also Cleveland residents (62.3%). Yet the data also indicated that some drivers' characteristics, particularly race/ethnicity and Cleveland residency, varied considerably by district, zone, and traffic or patrol assignment. This dramatic variation is likely due to a combination of residential and commuter traffic patterns, along with CDP deployment practices.

For the entire department, the most frequent violation observed prior to a traffic stop was moving misdemeanor violations (53.8%), followed by speeding violations (25.4%). The average speed over the limit was recorded at 16.8 miles per hour, but ranged widely across districts (13.7 m.p.h. to 18.5 m.p.h.) and across zones (13.3 m.p.h. to 19.1 m.p.h.). The majority of traffic stops occurred on a weekday (80.5%), during the daylight hours (55.3%), on a main city roadway (71.6%) or local neighborhood street (19.8%), and lasted between 1-15 minutes (80.2%). Officers described 46.4% of the vehicles they stopped as being in good condition, 45.7% in fair condition, and 7.8% in poor condition.

As part of the data collection process, the UC research team conducted observations of the roadways in an effort to observe and record traffic flow patterns and driving behavior. In addition, observations allowed for the collection of driver characteristics (e.g., race/ethnicity) that were used as a benchmark against which the traffic stop data was compared. Traffic observation data were also compared to residential Census data to determine if residential Census data could be used as a proxy measure for roadway usage in the locations throughout the city where there were no traffic observations.

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. UC students were trained to

conduct traffic observations and assess law violating behaviors, including speeding. Information relating to the observation location and period (date, time, type of area, violations observed, number of lanes on the roadway, lane observed, speed limit of roadway, visibility/weather conditions, and sampling technique), vehicle (type, color, condition, whether any aftermarket modifications were visible, whether there were any passengers in the vehicle, and whether the vehicle had an Ohio license plate), and driver of the vehicle (race, age, gender) were collected. Observations were conducted between May 5th and November 19th, 2005, during which there were a total of 37,926 observations used for benchmarking purposes over the course of 557 hours. A speed detection device was used in 437 of the observation hours (78.5%).

Two sources of benchmark data (residential Census data and stationery observations of motorists) were used to create four different comparisons to traffic stop data.

- Comparison #1: All traffic stop data were compared to residential Census data (in 42 police zones).
- Comparison #2: Only stops of drivers who lived in the zone of interest were compared to residential Census data (in 17 police zones).
- Comparison #3: Motorists stopped during daylight hours were compared to daytime observations of motorists (in 9 police zones).
- Comparison #4: Motorists stopped during daylight hours for speeding offenses were compared to daytime observations of speeding motorists (in 5 police zones).

There are reasons to believe that Comparisons #3 and #4 may be more accurate than the comparisons for traffic stop data to residential Census data, though there are major limitations associated with each benchmarking method.

Due to budgetary limitations, only nine of the forty-two police zones across the city had locations where traffic observations were conducted; thus, benchmark Comparisons #3 and #4 were conducted in only these nine zones. The results suggest that residential Census data and traffic observation data do not match – that is, Census data cannot be used as a reliable proxy for observation data that was not collected in the remaining thirty-three police zones across the city of Cleveland.

The comparisons across benchmarking techniques resulted in a wide range of disproportionality ratios. Further, the disproportionality ratios varied dramatically across policing zones. There is little consistency in these results. Results from comparisons of traffic stop data to traffic observation data (the benchmark data in which we have the most confidence) suggest that there are racial and ethnic disparities in stopping patterns. Black motorists were more than 1.5 times more likely to be stopped compared to Caucasians in six of nine police zones observed. In two of these zones, Blacks were over 4 times more likely to be stopped compared to Caucasians. The disparities in these police zones should be more closely examined by CDP officials.

Additional analyses were conducted to identify any racial/ethnic differences in stopping patterns. Results show that there is significant variation across racial/ethnic groups for the initial reasons for traffic stops. Caucasians are significantly more likely than other groups to

be stopped for speeding. Black motorists were significantly more likely than Caucasians to be stopped for moving felony violations, equipment violations, registration violations, license violation, as the result of special traffic enforcement programs, and for other/unknown reasons. Hispanic motorists were significantly more likely than Caucasians to be stopped for equipment violations, preexisting information, registration violations, license violations, and other/unknown reasons.

Of the motorists who were stopped for speeding, Blacks were stopped for lower levels of speeding severity compared to motorists of other racial/ethnic groups. That is, for speeding stops, Black motorists were stopped for slightly more minor offenses compared to all other racial/ethnic groups.

ANALYSES OF POST-STOP OUTCOMES

Concerns of biased-based policing do not end with the initial traffic stop. Indeed, post-stop outcomes are an important consideration of any profiling data collection effort because the potential exists for differential treatment based on the drivers' race, ethnicity, gender, and/or age after the initial stop has been made. Therefore, in addition to benchmark comparisons of traffic stop data, analyses of post-stop outcomes (e.g., warnings, citations, arrest, searches, and seizures) were conducted. Specifically, multivariate statistical models were estimated to determine the independent influence of drivers' race/ethnicity over the likelihood of being arrested and searched during traffic stops.

The multivariate statistical analyses examining whether or not motorists were arrested produced the following findings:

- Black and Hispanic motorists are *not* significantly more likely than Caucasians to be arrested during traffic stops when other legal and extralegal factors are considered.
- Male drivers are 2.6 times more likely than females to be arrested when all other measured extralegal and legal factors are equal.
- Drivers described as “disrespectful” by officers were 2.4 times more likely to be arrested compared to those described as civil.
- Drivers who were noncompliant or verbally/physically resistant were 3.8 times more likely to be arrested compared to drivers who complied with officers.
- Motorists in vehicles with no registration were 2.2 times more likely to be arrested compared to motorists traveling in registered vehicles.
- Drivers of vehicles described by officers as being in “poor” working condition were 1.7 times more likely to be arrested compared to drivers of vehicles in “fair” or “good” condition.
- Stops conducted during non-daylight hours were 1.6 times more likely to lead to an arrest compared to traffic stops during daylight hours.
- Traffic stops conducted during weekend days were 1.4 times more likely than stops during weekdays to result in an arrest of the motorist.
- Drivers initially stopped for moving misdemeanors were 1.4 times more likely to be arrested compared to drivers stopped for speeding or moving felony violations.

- Drivers initially stopped for license or registration violations were 2.1 times more likely to be arrested compared to drivers stopped for speeding or moving felony violations.
- Drivers initially stopped based on preexisting information were 2.7 times more likely to be arrested compared to drivers stopped for speeding or moving felony violations.
- Drivers initially stopped for other/unknown reasons were 2.8 times more likely to be arrested compared to drivers stopped for speeding or moving felony violations.
- Drivers stopped for more traffic offenses were 1.3 times more likely to be arrested compared to those stopped for fewer violations.
- Drivers with contraband found during a search were 21.1 times more likely to be arrested compared to drivers without contraband found.
- Drivers stopped by non-Traffic officers were 1.7 times more likely to be arrested compared to drivers stopped by Traffic officers.

Likewise, the multivariate statistical analyses predicting whether or not motorists were searched produced the following findings:

- After controlling for other relevant legal and extra legal factors, drivers' race/ethnicity continues to have a significant influence over whether or not searches are conducted. The odds of being searched are 1.3 times higher for Black drivers compared to Caucasian drivers.
- Drivers of "other" races (i.e., Asian, Middle Eastern, and Native American) are 2.5 times *less* likely to be searched compared to Caucasian drivers.
- Drivers described as "disrespectful" by officers were 1.6 times more likely to be searched compared to those described as civil.
- Drivers who were noncompliant or verbally/physically resistant were 3.6 times more likely to be searched compared to drivers who complied with officers.
- Motorists in vehicles with no registration were 1.3 times more likely to be searched compared to motorists traveling in registered vehicles.
- Drivers of vehicles described by officers as being in "poor" working condition were 2.5 times more likely to be searched compared to drivers of vehicles in "fair" or "good" condition.
- Stops conducted during non-daylight hours were 1.3 times more likely to lead to an arrest compared to traffic stops during daylight hours.
- Traffic stops conducted on secondary streets and other roadways were 1.3 times more likely to result in a search compared to traffic stops conducted on interstates and main roadways.
- Drivers initially stopped for moving misdemeanors were 1.8 times more likely to be searched compared to drivers stopped for speeding or moving felony violations.
- Drivers initially stopped for equipment violations were 2.2 times more likely to be searched compared to drivers stopped for speeding or moving felony violations.
- Drivers initially stopped for license or registration violations were 4.4 times more likely to be searched compared to drivers stopped for speeding or moving felony violations.

- Drivers initially stopped based on preexisting information were 4.1 times more likely to be searched compared to drivers stopped for speeding or moving felony violations.
- Drivers initially stopped for other/unknown reasons were 3.1 times more likely to be searched compared to drivers stopped for speeding or moving felony violations.
- Drivers stopped for more traffic offenses were 1.6 times more likely to be searched compared to those stopped for fewer violations.
- Drivers stopped by Caucasian officers were 1.4 times more likely to be searched compared to drivers stopped by minority officers.
- Drivers stopped by non-Traffic officers were 3.0 times more likely to be searched compared to drivers stopped by Traffic officers.

Based on these findings, it is the conclusion of this report that no racial/ethnic disparities in arrest rates were found with these data. The findings do show, however, that after controlling for other measured legal and extralegal factors, Black drivers were 1.3 times more likely to be searched compared to Caucasian drivers. To explore the reasons associated with this racial disparity in search rates, a separate section of this report was dedicated to further examining searches and seizures.

The focus on searches and seizures produced the following findings:

- A majority of the searches conducted by officers (71.2%) were mandatory (i.e., required by departmental policy). In contrast, 23.7% of the searches conducted were discretionary, while only 4.7% of the searches were based solely on the motorists consent.
- The most common reason for a search was administrative inventory (52.0%), followed by incident to an arrest (31.6% of searches). The reasons for searches varied somewhat across districts.
- Department wide, 55.2% of all searches resulted in the seizure of contraband. This is a very high search success rate, and likely is an artifact of the data collection effort that counted vehicles as “seizures” during administrative inventory “searches.”
- Generally, discretionary searches were the most productive in the seizure of contraband, followed by mandatory searches. The least productive searches were based on consent only. Specifically, 64.72% of discretionary searches resulted in the discovery of contraband, compared to 55.2% of mandatory searches and only 21.4% of consent searches.
- Hispanic motorists were more likely to be searched for mandatory reasons, compared to other racial groups, while Black motorists were more likely to be searched for discretionary reasons. Caucasian motorists were more likely to be searched based solely on consent, compared to other racial ethnic groups. Thus, there is no consistent evidence to suggest that minority motorists are singled out for the most discretionary types of searches.
- Discretionary searches of Black motorists are the *most productive* in the seizure of contraband, followed by Hispanics and then Caucasians. Combining these results with those reported in the previous section indicates that although Black motorists are

significantly more likely than Caucasians to be searched by CDP officers, searches of Black motorists are more likely than searches of Caucasians to result in the seizure of contraband.

- Male officers, Caucasian officers, and officers with more experience are significantly more likely than their counterparts to engage in discretionary searches that result in seizures of contraband. That is, although male and Caucasian officers engage in more searches, they are more successful during these searches compared to female and minority officers. In contrast, officers with less experience are *more* likely to engage in discretionary searches compared to officers with more experience, but officers with less experience are less successful in terms of contraband seizures.

POLICY ISSUES AND RECOMMENDATIONS

Analyses of arrests and searches demonstrated significant variation in behavior across CDP officers. While some variation across officers is to be expected based on assignment, patrol location, and shift, it is imperative that police agencies seek to regulate police behavior to produce more consistent outcomes for citizens. That is, the outcomes citizens receive during traffic stops should be based on legal considerations and citizen behavior, rather than differences across officers.

It is recommended that CDP officials seek to understand the best practices of their officers and replicate these practices across the department. To influence officer discretion in this manner is a lengthy process, and involves managerial dedication and departmental commitment of resources. At a minimum, a dedicated effort to increase the use of best practices would involve a three-stage process. First, the best practices within the department (and the officers that routinely engage in these best practices) must be identified. Second, training curriculum must be designed and implemented in an effort to reproduce these best practices. Finally, these best practices must be emphasized and rewarded within the department by administrators and supervisors.

To promote equitable treatment across racial/ethnic groups during traffic stops, it is also recommended that a systematic data collection of both traffic and pedestrian stops be incorporated into the daily practices and procedures of the CDP. This type of data collection is becoming routine in police agencies across the country. Currently, 19 states legislatively mandate the collection of traffic stop data for all agencies in their state, while an additional 11 states have legislation pending. Numerous municipal and state law enforcement agencies voluntarily collect traffic and pedestrian stop data. This trend is likely to continue, as an increasing number of states collect information on all officer initiated traffic stops.

Many of the problems associated with this data collection effort (documented throughout this report) could be eliminated with a systematic, long-term data collection strategy that would best benefit the CDP and Cleveland residents. The routine collection and analyses of traffic stop data could aid CDP administrators regarding potential problem areas and increase citizens' perceptions of the department's legitimacy. A data collection system that is immersed within CDP's current practices may be a cost-effective solution for information

gathering during all officer initiated traffic stops, including those that do not result in an official disposition.

It is further recommended that any long-term data collection system or follow-up study be developed in a working partnership between CDP management and union officials. Many of the problems associated with this research study were the result of poor working relationships among CDP officials, City of Cleveland officials, and police union officials. The result was a study that likely produced more questions than answers. A long-term strategy for equitable treatment toward citizens, and progressive leadership to implement this strategy is necessary for the CDP to prosper and regain its reputation as an innovative and professional police department.

9. REFERENCES

- American Civil Liberties Union. (2000). Plaintiff's Fifth Monitoring Report: Pedestrian and Car Stop Audit. [On-line] Available: <http://www.aclupa.org/report.htm>.
- Allison, P.D. (1999). Multiple Regression: A Primer. Thousand Oaks, CA: Sage Publications.
- Ayres, I. (2001). Pervasive Prejudice? Unconventional Evidence of Racial and Gender Discrimination. Chicago: The University of Chicago Press.
- Ayres, I. (2002). Outcome tests of racial disparities in police practices. *Justice Research And Policy*, 4, 131-143.
- Becker, G.S. (1957). The Economics of Discrimination. Chicago: University of Chicago Press.
- 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.
- Brantingham, P.L. & Brantingham, P.J. (1982). Mobility, notoriety, and crime: A study of crime patterns in urban nodal points. *Journal of Environmental Systems* 11:89-99.
- _____. (1993). Nodes, Paths, and Edges: Considerations on the Complexity of Crime and the Physical Environment. *Journal of Environmental Psychology* 13:3-28.
- Census Data & Information. <http://www.census.gov/geo/www/tiger/glossry2.pdf>.
- Cole, D. (1999). No Equal Justice: Race and Class in the American Criminal Justice System. New York: The New Press.
- Cordner, G., Williams, B., & Zuniga, M. (2001). Vehicle Stop Study: Year End Report. San Diego, CA: San Diego Police Department.
- 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.
- Criminal Justice Training Commission. (2001). Report to the legislature on routine traffic stop data. Seattle: Washington State Patrol and Criminal Justice Training Commission.
- Decker, S. H., Rosenfeld, R., & Rojek, J. (2002). Annual report on 2001 Missouri traffic stops [On-line]. Available: <http://www.ago.state.mo.us/rpexecsummary2001.htm>.

- Engel, R. S., Calnon, J. M., Liu, L., Johnson, R. R. (2004). Project on Police-Citizen Contacts: Year 1 Final Report. Harrisburg, PA: Pennsylvania State Police. [On-line] Available: <http://www.psp.pa.us>.
- Engel, R. S. (forthcoming). A critique of the outcome test in racial profiling research. *Justice Quarterly*.
- 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(1): 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(1): 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.
- 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.
- Farrell, A., McDevitt, J., Bailey, L., Andresen, C., & Pierce, E. (2004). Massachusetts Racial and Gender Profiling Study. [On-line]. Available: http://www.racialprofilinganalysis.neu.edu/IRJsite_docs/finalreport.pdf.
- Fridell, L. (2003). Issues surrounding benchmarking in racial profiling research. Presentation at The Third National Symposium on Racial Profiling, sponsored by Northwestern University Center for Public Safety and the Police Executive Research Forum, Chicago, November 5, 2003.
- Fridell, L. (2004). By the Number: A Guide for Analyzing Race Data from Vehicle Stops. Washington, D.C.: Police Executive Research Forum.
- Guo, G. & Zhao, H. (2000). Multilevel modeling for binary data. *Annual Review of Sociology*, 26: 441-462.
- Harris, D. A. (1999). The stories, the statistics, and the law: Why "driving while black" matters. *Minnesota Law Review*, 84: 265-326.
- Harris, D. A. (2002). Profiles in Injustice: Why Racial Profiling cannot work. New York: The New Press.
- Herszenhorn, D. M. (2000, October 22). Police and union chiefs meet to address racial profiling. *New York Times*, p.1.41.

- Knowles, J., Persico, N., & Todd, P. (2001). Racial bias in motor vehicle searches: Theory And evidence. *The Journal of Political Economy*, 109: 203-229.
- LaFree, G. 1995. Race and crime trends in the United States, 1946-1990. In D.F. Hawkins (Ed.) *Ethnicity, Race, and Crime: Perspectives Across Time and Place*, pp.169-193. Albany, NY: State University of New York Press.
- Lamberth, J. (1996). A Report to the ACLU. New York: American Civil Liberties Union.
- 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.
- Lansdowne, W. M. (2000). Vehicle stop demographic study. San Jose, CA: San Jose Police Department.
- 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.
- Liao, T.F. (1994). Interpreting Probability Models: Logit, Probit, and Other Generalized Linear Models. Thousand Oaks, CA: Sage.
- Lockwood, D., Pottieger, A. E. & Inciardi, J. A. (1995). Crack use, crime by crack users, and ethnicity. In D. F. Hawkins (Ed.) Ethnicity, Race, and Crime: Perspectives Across Time and Place, pp.213-234. Albany, NY: State University of New York Press.
- 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.
- Rojek, J., Rosenfeld, R., & Decker, S. (2004). The influence of driver's race on traffic stops in Missouri. *Police Quarterly*, 7: 126-148.
- Smith, William R., Donald Tomaskovic-Devey, Matthew T. Zingraff, H. Marcinda Mason, Patricia Y. Warren, and Cynthia Pfaff Wright. 2003. *The North Carolina Highway Traffic Study*. Final report submitted to the National Institute of Justice, Grant No. 1999-MU-CX-0022. Washington, D.C.: National Institute of Justice.
- Texas Department of Public Safety (2001). Traffic stop data report [On-line]. Available: http://www.txdps.state.tx.us/director_staff/public_information/trafrep2001totals.pdf.

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.

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

Wison, J. (2000). Analysis of Motorists Stops on I-17 by Race/Ethnic Origin. Unpublished report.

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

Whren et al. v. United States, 517 US 806 (1996)

APPENDIX A

TIMELINE FROM ORIGINAL PROPOSAL: 10/10/03

Timeline and Deliverables

PROJECT INITIATION: January 1, 2004 - January 31, 2004

- Establish contract
- Meet DOP Citizen Contact Committee
- Meet with DOP police unions
- Meet with DOP command staff
- Meet with Neighborhood Police/Community Relations Committees 0 Determine content to be include on traffic stop form

INITIAL FORM DEVELOPMENT: February 1, 2004 - February 28, 2004

- Work with outside vendor to design form
- Customize scanner software to *read* form
- Customize statistical software to read data file
- Identify and train officers involved in pilot test
- Print and distribute forms

PILOT TEST: March 1, 2004 - April 30, 2004

- Collect one month of data for pilot test
- Analyze pilot test data
- Make adjustments to the form (if needed)
- Work with outside vendor to redesign form
- Customize scanner software to read redesigned form
- Begin compiling information for GIS analyses

DATA COLLECTION INITIATION: May 1, 2004 - May 31, 2004

- Train officers department-wide
- Print and distribute form department-wide
- Meet DOP Citizen Contact Committee
- Meet with DOP police unions
- Meet with DOP command staff
- Meet with Neighborhood Police/Community Relations Committees
- Begin collect official data for benchmarking analyses (e.g., Census data, accident data, calls for service, arrest data, etc.)

FIRST QUARTER: June 1, 2004 - August 31, 2004

- Traffic stop data collection period begins department-wide

- Continue collecting official data and GIS information for benchmarking analyses
- Recruit and train observers
- Begin observation data collection
- Meet DOP Citizen Contact Committee
- Meet with DOP police unions
- Meet with DOP command staff
- Meet with Neighborhood Police/Community Relations Committees
- Meet with City Council Safety Committee
- Deliver bi-monthly status reports
- Deliver bi-weekly data integrity checks

SECOND QUARTER: September 1, 2004 - November 30, 2004

- Traffic stop data collection continues
- Continue observation data collection
- Correct errors in official data and GIS information used for benchmarking
- Meet and provide updates to the DOP Citizen Contact Committee
- Meet and provide updates to DOP police unions
- Meet and provide updates to DOP command staff
- Meet with and provide updates to Neighborhood Police/Community Relations Committees
- Deliver bi-monthly status reports 0 Deliver bi-weekly data integrity checks

THIRD QUARTER: December 1, 2004 - February 28, 2005

- Continue traffic stop data collection 0 Continue to refine official data sources
- Meet and provide updates to the DOP Citizen Contact Committee
- Meet and provide updates to DOP police unions
- Meet and provide updates to DOP command staff
- Meet and provide updates to Neighborhood Police/Community Relations Committees
- Meet and provide updates to City Council Safety Committee
- Deliver bi-monthly status reports
- Deliver bi-weekly data integrity checks

FOURTH QUARTER: March 1, 2005 - May 31, 2005

- Continue traffic stop data collection
- Finalize all benchmarks
- Meet and provide updates to the DOP Citizen Contact Committee
- Meet and provide updates to DOP police unions
- Meet and provide updates to DOP command staff
- Meet and provide updates to Neighborhood Police/Community Relations Committees
- Deliver bi-monthly status reports

- Deliver bi-weekly data integrity checks

PROJECT WRAP-UP: June 1, 2005 - August 31, 2005

- Compile, aggregate and merge all traffic stop data
- Correct errors in traffic stop data
- Perform statistical analyses to create disproportionality indices based on different benchmarks
- Perform GIS mapping for final report
- FINAL REPORT delivered August 31, 2005
- Final report will include a summary of the data collection results, comparisons with multiple benchmark comparisons, analyses of post-stop outcomes, and policy recommendations based on the findings
- Meet and deliver project results to the DOP Citizen Contact Committee
- Meet and deliver project results to DOP police unions
- Meet and deliver project results to DOP command staff
- Meet and deliver project results to Neighborhood Police/Community Relations Committees
- Meet and deliver project results to City Council Safety Committee

APPENDIX B

CODING INSTRUCTIONS FOR PILOT TEST

Traffic Stop Data Report Form F-19157-COC

A. Purpose

1. The traffic stop data report shall be used to record information regarding all contacts an officer has with the public as a result of officer-initiated traffic stops.

B. Special Instructions

1. The form shall be completed in original only, using black ink or lead pencil. Black gel pens and felt tip markers are acceptable. However, when using the latter, special care must be taken to ensure that ink does not bleed through the form and contaminate the response ovals on an underlying contact data report form.
2. Fill in response ovals completely.
3. Ensure that no stray marks or ink smears intrude into adjacent response ovals. Correction fluid may be used to cover any mistakes.
4. A response is required for each block.
5. The rectangular blocks directly above the response ovals must also be completed (applicable to blocks 1, 2, 7, 9, 14, and 21).
6. If the response category "Other" appears in a block, provide a brief description (applicable to blocks 7, 19, and 20).
7. Supervisors are required to review and sign all forms to ensure accuracy and completeness. If the supervisor's signature strays into any of the response ovals, or if there are any marks on the bar code, the scanner will not read the form.

C. Block Instructions

1. Month/Day/Time: Record the month, day, and time of the traffic stop, using military time.
2. Zone of Stop: Record the standard Zone code for the location of the traffic stop.

3. Roadway: Indicate the appropriate roadway on which the stop was initiated. Categories include:
 - i. Interstate – This would include any highway within Cleveland city limits that is identified by an ‘I’ and crosses into another state. Additionally, Interstate highways do not have traffic lights.
 - ii. Main Roadway – This would include any main thoroughfare that is heavily populated with traffic. These are roadways, or portion thereof, on which vehicular traffic is given preferential right-of-way, and at the entrances to which vehicles from intersecting roadways are required to stop or yield by law. They may include divided highways, four-lane roads, or two-lane roads.
 - iii. Secondary Street – These are local streets or roads and are typically found in residential areas where most of the traffic generated is by citizens who live in the area. They are located on the side of arterial roadways for service to adjacent areas and often may include uncontrolled intersections.
 - iv. Other – This would include parking lots, corporate property, or any other areas where a stop may be initiated that does not meet the above criteria.
4. Vehicle Modified: Indicate whether the vehicle has any aftermarket modifications such as but not limited to: tinted windows, high performance exhaust systems, spinners (aftermarket rims), etc.
5. Vehicle Condition: Indicate the condition of the vehicle:
 - i. Good – No visible blemishes or cosmetic defects to the exterior of the vehicle.
 - ii. Fair – Visible blemishes (scratches or minor dents) to the exterior but no cosmetic defects (broken head or taillight(s), mirror(s), muffler, window(s), or severe body damage).
 - iii. Poor – Visible cosmetic defects to the exterior of the vehicle (broken head or taillight(s), mirror(s), muffler, window(s), or severe body damage).
6. Registration Displayed: Indicate whether or not the registration was displayed on the vehicle when the traffic stop was initiated. The registration can be obtained from the license plate on the vehicle or by examining the paper registration provided by the driver. The vehicle is either registered in Ohio, another state, or does not have registration.
7. Reason(s) for Stop (mark all that apply): Column “P” refers to infractions observed prior to the traffic stop. That is, record the initial reason(s) the vehicle was stopped. If the stop is made as a result of a special traffic enforcement program, the corresponding ovals should be completed in

addition to the violation(s). Column “S” refers to infractions discovered subsequent to the traffic stop. That is, once a stop has been initiated, record all subsequent infractions that are noted (regardless of the decision to issue warnings or citations for these offenses). In addition to prior and subsequent infractions, the amount over the speed limit shall be recorded when applicable.

8. Result of Stop: Row “D” is designated for outcomes experienced by the driver of the vehicle. Row “P” is reserved for outcomes experienced by the passenger(s) of the vehicle. Non-traffic citations are counted as citations. Warnings refer to official written warnings. The “Other” response is used if the driver was not issued a written warning, citation, or arrested. Examples for the use of the “Other” category include if the driver is given a verbal warning, if a vehicle was mistakenly pulled over for what appeared to be an expired registration decal, or a stop initiated as a result of a “Be On The Lookout” broadcast which, upon investigation, is discovered not to be the target vehicle.
9. Citation No.: Record the citation number for the primary citation issued for the traffic stop. If multiple citations are issued, record the citation number for the most serious citation. If multiple citations are issued for multiple infractions of equivalent severity, record the citation number for the citation corresponding to the initial reason for the stop.
10. Duration of Stop (in minutes): Record the length of time the vehicle occupants are temporarily detained. This period includes the time from when the vehicle is stopped until the occupant(s) are either arrested or released. Time spent filling out paper work shall not be included in the duration of the stop.
11. Driver Gender: Indicate the perceived gender of the driver. The driver should not be asked to supply this information.
12. Driver Race/Ethnicity: Indicate the perceived race/ethnicity of the driver. The driver should not be asked to supply this information. The “Unknown” category should only be used when the officer has no indication whatsoever of race/ethnicity.
13. Driver Demeanor (mark all that apply): indicate the perceived demeanor of the driver.
 - i. Civil – complies with officer requests and defers to officers’ authority. For the “civil” category to apply, the driver does not necessarily have to be “courteous,” but simply not disrespectful. This is the default category.
 - ii. Disrespectful – mark if the officer perceives the driver to act in a disrespectful manner. Disrespect is defined as any behavior

(verbal or non-verbal) that is discourteous, rude, or indicates an unwillingness to defer to the officer's authority. This behavior may or may not include the behaviors indicated in the categories below.

- iii. Non-compliant – mark if the driver refuses to comply with officers' requests or refuses to answer officers' questions.
- iv. Verbally resistant – mark if the driver is verbally abusive to the officer, including cursing at or threatening the officer.
- v. Physically resistant – mark if the driver displays resistance toward the officer that is physical in nature. Physical resistance may include but is not limited to: fleeing from officers, physically threatening officers, striking officers, etc.

14. Driver Yr. of Birth and Driver Zip Code:

- i. Driver Yr. of Birth: indicate the driver's year of birth using the last two digits of the year they were born. This information should be taken from the driver's operator license. For example, if the driver was born in 1980, the ovals corresponding with 8 and 0 would be filled in.
- ii. Driver Zip Code: Record the zip code that indicates the driver's place of residence. This information should be taken from the driver's operator license. Use the code "00000" to indicate a non-U.S. resident.

15. Cleveland Resident: Indicated whether the driver is a resident of the City of Cleveland based on the information included on their driver's license.

16. Number of Passengers: Indicated the number of occupants, excluding the driver, in the vehicle at the time the stop is initiated.

17. Consent Search Requested: Indicate whether or not the officer asked for the driver's permission to search the vehicle. Indicate "yes" if a consent search was requested, but the driver refused.

18. Search Initiated: Indicate whether or not the officer searched the vehicle, driver, or other item.

19. Reason(s) for Search (mark all that apply): This pertains to a search of any person, vehicle, or other item. If no search was performed, mark "Not Applicable." Multiple reasons for the search may be indicated.

20. Property Seized (mark all that apply): Indicate the type of property the officer found and seized from the driver. Even if no search was conducted, this block still needs to be filled out. In situations where no search was conducted, the appropriate response is "None."

21. District, Unit #, Badge No.:

- i. District: Record the district the officer was assigned to during the shift in which the traffic stop was initiated.
- ii. Unit #: Indicate the officer's unit number during the shift in which the traffic stop was initiated.
- iii. Badge No.: Record the officer's badge number.

D. Processing

Completed forms should be submitted after every shift to the shift supervisor. Each week, the forms must be submitted to the District Commander and subsequently mailed from each District on Monday morning to:

Dr. Robin Engel
Cleveland Traffic Stop Data Collection Project
PO Box 19628
Cincinnati, OH 45219

APPENDIX C

OBSERVATION DATA COVERSHEET

Cover Sheet for Observation Forms
(New Sheet Every Half Hour or if observation area changes)

Observer Names: _____

Date of observation: _____

Trip Number: _____

Day of Week: _____

Time of Observation (every half hour): _____

Violations being observed: _____

R = Radar; L = Laser; MV = Moving Violations

Location: _____

(road name/number, direction of observed cars, intersection, etc. – Ex. - Route 30W, 30 & Blue Road)

Type of Area: _____

R = Residential; C = Commercial; I = Industrial; M = Mixed (specify) _____

Speed Limit of Road: _____

Type of Road: _____

(Interstate, State Highway, County/Local Road, Other (specify) _____)

Direction of traffic: _____

Number of lanes on the roadway (include both directions and turning lanes): _____

Lane being observed: _____

D = Driving; P = Passing; B = Both; O = Other (specify) _____

Visibility/Weather Conditions: _____

VG=very good, G=good, F=fair, P=poor

(If fair or poor provide a description of the condition _____)

Sampling Technique Used: _____

1 = Every car; 2 = every other car; 3 = every third car; etc.

OBSERVATION DATA COLLECTION FORM

Roadway Observation Form Page ____ of ____

SPEED DETECTED	TYPE OF VEHICLE	COLOR OF VEHICLE	VEHICLE CONDITION	VEHICLE MODIFIED	RACE OF DRIVER	GENDER OF DRIVER	AGE OF DRIVER	PASSENGERS	OH LICENSE PLATE
Record speed R – Red light violation S – Stop sign violation T – Right turn on red	S -Sedan SC -Sports Car/Coupe SUV -Sport Util. Veh. MV -Minivan, Wagon T -Pickup Truck M -Motorcycle W – Station Wagon V - Van	R -Red BU -Blue G -Green S -Silver/Gray BK -Black W -White GD - Gold O -Other	G -Good F -Fair P -Poor	Y -Yes N -No	W -White B -Black H -Hispanic A -Asian/Pac. Isl. NA -Nat. Amer. ME -Mid. East. NW – Non-Wh. O -Other	M -Male F -Female	Y -25 & under M -26 to 65 O -Over 65	Y -Yes N -No	Y -Yes N -No

APPENDIX D

OBSERVATION DATA LOGISTIC REGRESSION

ANALYSIS AND EXPLANATION

A multivariate statistical model is one that takes many different factors into account when attempting to explain a particular behavior. Unlike a bivariate model, it does not simply assess the relationship between two variables. Rather, a multivariate model examines many variables simultaneously, and therefore provides a more thorough and accurate interpretation of the data. The multivariate analyses to follow examine the associations between drivers' characteristics and post-stop outcomes (i.e., arrests and searches) when other characteristics likely associated with these outcomes are statistically controlled.

Many factors other than drivers' race/ethnicity are likely to influence officers' decision-making once a traffic stop has been made. For example, other driver characteristics (e.g., drivers' gender, age, residency, demeanor), vehicle characteristics (e.g., condition of the vehicle, after-market modifications, registration, number of passengers), stop characteristics (e.g., time of day, day of the week, season, and roadway type), reasons for the stop (speeding, moving violations, equipment violations, etc.), other legal variables (e.g., number of reasons for the stop, evidence found during a search), officer characteristics (e.g., sex, race, experience, assignment, rank), and community characteristics where the stop occurred (e.g., residential populations, poverty, factors related to traffic patterns, etc.) have all been hypothesized to influence post-stop outcomes. Multivariate analyses allow for the examination of the effect of each of these predictor variables, while simultaneously controlling for the influence of the remaining variables. For example, the influence of drivers' race can be examined while holding constant the predictive power of drivers' age, reason for the stop, time of day, etc.

The coefficient represents an additive expression of a particular variable. In the "coefficient" column, there are two things to examine: 1) the presence of an asterisk following the coefficient indicating a statistically significant relationship, and 2) the presence or non-presence of a negative sign preceding the number. The asterisk reveals whether or not a significant relationship exists between the independent variable (e.g., male drivers) and the dependent variable (e.g., arrest). If an asterisk is not present, the relationship is not considered statistically significant. Due to the extremely large sample size (i.e., the large number of traffic stops), the statistical significance of the relationships is assessed at the 0.001 level. The asterisks indicate that the relationships between variables are due to chance less than 0.1% of the time. The sign of the coefficient (i.e., positive or negative) indicates the direction of the relationship. For example, a positive sign on the "driver male" variable would indicate that male drivers are *more* likely than female drivers to receive a particular outcome, while a negative sign would indicate that males are *less* likely than females to receive a particular outcome.

Since the interpretation of log-odds is not intuitively straightforward, this type of coefficient is usually exponentiated to allow for interpretation in terms of odds (Liao, 1994). The second column—the odds ratio—represents this antilog transformation of the coefficient into the multiplicative odds of the outcome variable based on the predictor

variable, everything else being equal. The odds ratio indicates the strength of the relationship. For example, an odds ratio of 3.0 indicates that the presence of the variable (e.g., being a male driver) leads to three times the likelihood of receiving the outcome (e.g., conducting a search). The strength of the relationship is one of the most important considerations. Even if the relationship between variables is statistically significant (that is, it receives an asterisk in the table), it may not be substantively important. That is, the strength of the relationship may not be very large. As a general guide with this number of traffic stops being analyzed, a log odds would be considered “substantively” important if it were over 1.25 (for positive coefficients) and under 0.75 (for negative coefficients).

Logistic Regression Results for Speeding (Observation Data)

Variables	Base Model (N = 32,373)	
	Coeff.	Odds Ratio
Intercept	-2.48*	.084
Driver Characteristics		
Black	.16*	1.168
Hispanic	-.62*	.537
Other	.21	1.228
Male	.07	1.071
< 25 Years Old	.14	1.146
> 65 Years Old	-.26*	.770
Vehicle Characteristics		
Passengers Present	-.32*	.724
Fair Condition	-.25*	.776
Poor Condition	-.53*	.587
Vehicle Modified	.16	1.171
Sports Coupe	.05	1.056
Sport Utility Vehicle	.02	1.021
Mini Van	-.30*	.738
Truck	-.35*	.707
Other Type of Vehicle	-.28	.757
Ohio License Plate	.04	1.044
Observation Characteristics		
Rush Hour	.30*	1.350
Weekend	.40*	1.495
Residential Area	-.89*	.409
Industrial Area	-.20	.820

* - p = .001

APPENDIX E

BENCHMARKING DETAILS

APPORTIONMENT

Apart from the limitations associated with using Census variables to approximate driving behavior, rarely do the Census boundaries (e.g., block groups¹⁶) match the geographical boundaries of the police zones. As described previously, all information regarding the traffic stops was collected at the police zone level, and in order to have comparable geographic units, a Geographic Information System (GIS) is used to calculate the appropriate values for the Census variables. That is, to calculate the disproportionality indices, the percent of the population by race must be calculated for each police zone. Recall that to create a DI for each police zone, the number of stops of one racial/ethnic group is divided by the “expected” percent of the same racial/ethnic group based on the benchmark. In this comparison, the Census provides the denominator for the DI for each police zone; however, due to the spatial incongruence between police zones and Census areas, an appropriate Census value is not obvious.

Due to the fact that there are a multitude of block groups within a police zone, the value for that police zone is calculated by summing all the block groups that fall within the geographic boundaries of the police zone. Unfortunately, some block groups are bisected by multiple police zones. To address this difficulty, the apportionment method is used, which spatially adjusts the Census units so they conform to the police zones. Any error associated with the apportionment method is reduced when small geographic units are used. In this case, the smallest geographic Census unit, the block group, was used. Using a GIS to spatially overlay the two geographic units (i.e., the police zones and the block groups from the Census), the surface area in square miles of the block group is calculated. The percentage of the block group that falls into one police zone is then used to calculate the percent of the Census variables to assign to the police zone. In other words, when a block group was bisected by a police zone, the actual surface area that falls into the police zone is used as a weight to calculate a new value for that particular block group. Once that new value has been determined, it is added to the existing block group that are completely contained within one police zone, with the product representing the Census variables for that police zone.

For example, within Zone 112 in District 1, there are a multitude of block groups. The goal is to sum the Census variables from each of the block groups that fall within Zone 112 to create the benchmark (e.g. denominator for the disproportionality index and disproportionality ratio). A problem arises, however, when one of the block groups is bisected by the perimeter of Zone 112. The apportionment method is one means of addressing this problem. If fifty percent of the land area of a block group (e.g., 111101) is within Zone 112, then fifty percent of each variable for block group #111101 is used to create the overall value for Zone 112. If there are 6 block groups that fall completely within

¹⁶ A block group is defined as "a subdivision of a census tract, generally containing between 600 and 3,000 people, with an optimum size of 1,500 people. Most block groups were delineated by local participants as part of the US Census Bureau's Participant Statistical Areas Program. It is the lowest level of the geographic hierarchy for which the US Census Bureau tabulates and presents sample data."

Zone 112, and a seventh (e.g., block group #111101) is bisected by the perimeter of the zone, the percentage of the land area falling within the zone (in this example, fifty percent) is then used as a weight for each variable of interest (in this case, population and racial composition). In other words, fifty percent of the values for all variables of interest (e.g., race of the residents) from block group #111101 are added to 100% of the values from all other block groups that spatial fall within Zone 112.

The primary limitation to the apportionment method is the assumption that the variables of interest (e.g., race of the residents) are spatially evenly distributed across the block group. In other words, it is necessary to assume that all race groups live in random locations across each block group. While this is a questionable assumption, the apportionment method is superior to any alternative methods. One alternative method would be to use the centroid of the block group. For example, if a block group was bisected by a police zone, the centroid of the block group could be determined and the entire block group could be assigned to the police zone that the centroid fell within. Alternatively, the surface area of each block group could be calculated and whichever police zone had the majority of the surface area of the block group would receive the entire block group values. Both of these options are concerning as Census values are assigned to police zones even when it is known that the values do not belong to that police zone. While the apportionment method does rest on the assumption that residents are spatially random across the block group; however, it does not include Census values that are knowingly not part of the police zone in question. Using the apportionment method, all forty-two police zones in Cleveland were assigned Census values representing population and racial composition.

MEASURING HOME ZONES

One of the difficulties in analyzing police traffic stops at the police zone level is the incongruence between data sources. In Comparison #1, the unit of analysis difficulties were restricted to the creation of the denominator for the disproportionality ratios. That is, the Census jurisdictions that do not match the police zones were apportioned to provide Census values for each police zone. In this comparison, the same difficulties arise in the creation of the denominator, and the same procedure is used to create the denominator. In addition, the identification of within zone stops is complicated by the fact that the only information available as to the home location of the stopped driver is their zip code. In other words, on the traffic stop form, the home zip code for the driver was recorded. Unfortunately, similar to the Census jurisdictions, the zip code geographic boundaries do not match the police zones. In order to assign a police zone to each of the drivers stopped by the police, a different assignment method than apportionment was used.

There are twenty-five zip codes within the area patrolled by the CDP, and in some cases, police zones overlap zip codes and in other cases zip codes overlap police zones. As a result, the following rule was used to assign a police zone to every driver stopped by the CDP. If the drivers' zip code within a police zone, it was assigned that police zone as its home zone. For example, a zip code of 45102 fell across Zone 111 and Zone 112. For the purposes of this analysis, all drivers with that zip code were considered as living in both

the analysis for Zone 111 and Zone 112. Due to the fact that the analysis is done zone by zone and there is not direct comparison across zones, counting one driver in more than one zone should not bias the results. This method should not affect the results of the analysis, and it is superior to arbitrarily assigning a police zone to a zip code.

ALTERNATIVE COMPARISONS

As discussed previously, there are a multitude of benchmarking techniques available to assess the traffic stopping patterns of a police department. This analysis has reported on four different methods in an attempt to provide a comprehensive picture of the traffic stopping patterns of the CDP. To further this goal, an additional benchmarking option was pursued (i.e., a traffic flow model), but is not reported in **Section 5** for reasons to be outlined below. The traffic flow model was based on the use of both traffic stop data and Census variables, similar to Comparisons #1 and #2, but with modified Census values.

Traffic Flow Model

To effectively understand the decision to not report the findings of the traffic flow model, it is important to explain the creation of the model, and more importantly, highlight the significant limitations of such a model. The traffic flow model was developed by the research team in order to better model the “expected” rate of traffic by race across the city. In other words, it was created to address one of the primary limitations of Comparison # 1 and Comparison #2 – the assumption that drivers only drive in the geographic zone of interest (in this study, police zones). While the traffic model does not completely overcome this limitation, it does attempt to model the “expected” rate of drivers more accurately than the Census variables

Creation of Traffic Flow Model

To create a traffic flow model, both the stop data and the Census variables are used. The primary purpose of the traffic flow model is to modify the Census variables used in the denominator of the disproportionality index to more accurately reflect the proportion of drivers by race/ethnicity. As previously described, within any one police zone, there are drivers from other geographic regions (in this case, other police zones). Consequently, the development of the traffic flow model involves selecting one police zone and identifying the percentage of drivers by their home zones who were stopped within the zone of interest. For example, within only Zone 111, it is necessary to identify the percent of traffic stops that occurred of drivers from other police zones across Cleveland (the drivers’ home police zone is based on the drivers’ reported home zip code). The percentage by zone becomes a weight which is applied to the Census variables to create a new weighted baseline against which to compare the traffic stops. In order to calculate the percent of stops by zone, several steps must be taken.

Due to the aforementioned incongruence between the spatial area of the police zones and the Census boundaries, the apportionment method is used to properly identify the drivers’ home police zone. In order to accurately identify the percent of stops that occur within

one zone of drivers from other zones, it is necessary to identify the home zone of every driver stopped. This produces some difficulties, as the only information that was available was the drivers' home zip code. It is at this point that the apportionment method is used to identify the drivers' home police zone. Recall that all analyses are conducted at the police zone level, and as such, all data included in the analyses must be reflective of the police zone.

Similar to the apportionment used earlier in Comparison #1 with the Census data, the apportionment method is used here with two modifications. First, instead of using the Census variables as the value to apportion as in Comparison #1, the traffic flow model requires that the traffic stop data be accessed and the drivers' home zip code be used. In this case, the apportionment method calculated the percent of spatial area of a zip code that falls within a police zone and that percentage is used as a weight. For example, if one zip code (e.g., 45102) falls across two police zones, the percentage of spatial area that falls within each police zone will determine the percent of stops with that drivers' zip code that are assigned to each police zone. If the spatial area is fifty percent in one zone and fifty percent in another zone, each zone will receive fifty percent of all stops with that zip code. Recall that this is done for each zone separately, so in actuality, it is only fifty percent of the stops within the area of interest with that zip code.

The second difference from the apportionment used in Comparison #1 is that not only does the apportionment need to be used for the drivers' zip code in relation to police zones; it must also reflect the racial breakdown of the traffic stops. In other words, for the zone of interest, the percent of stops from other zones is calculated in combination with the racial/ethnic composition of those stops. For example, of stops in Zone 111 with a drivers' zip code of 45102 not only do they get analyzed by the spatial percentage discussed previously, they must also reflect the racial/ethnic composition of the stops. That is, for the stops that have a drivers' zip code of 45102, if twenty percent of those drivers were Black, twenty percent of the fifty percent of stops assigned to one of zones will also be Black. This is done to maintain the accuracy of the racial/ethnic composition to ensure that the subsequent analysis is not biased.

Once every stop has been assigned a home police zone based on the drivers' zip code, it is now possible to calculate within one zone the percentage of stops from other zones. In effect, every police zone is calculated independently and the percentage of stops from other jurisdictions becomes the weight for a re-calculation of the Census values. For example, Zone 111 is considered initially and the percentage of stops from all other zones is calculated. Instead of simply taking the Census values of Zone 111 as the denominator, the traffic flow model calculates new Census values for all police zones based on the percent of stops from those jurisdictions and produces a new modified Census value for Zone 111. In a simple example, one hundred stops occurred within Zone 111. Fifty of those stops were of drivers from Zone 111, twenty-five were from Zone 112, and twenty-five were from Zone 113. The traffic flow model requires that for the Census variables of interest (population over eighteen, population Caucasian, population Black, population Hispanic, and population Non-Caucasian) they are multiplied by the appropriate percentage. In this example, fifty percent of the Census variables from Zone 111, twenty-

five percent of the Census variables from Zone 112, and twenty-five percent of the Census variables from Zone 113 would be combined together to create the new value for Zone 111. In this manner, the baseline of the benchmark is reflective of the home location of the drivers stopped in any one jurisdiction.

This method is replicated for all police zones within the city of Cleveland, and as such, only the stops of drivers that live within the city boundaries are used in this calculation. While it is possible to use all the stops, which would include non-Cleveland residents, the calculations would be exponentially increased, and the weights created would be incredibly small that no bias is believed to be introduced by not including those stops in this comparison. While this method addresses the limitation in Comparison #1 of assuming that only within zone residents drive within a police zone, the traffic model does have several other considerable limitations that need to be highlighted.

Traffic Flow Model Limitations

There are at least 4 limitations to the creation of the traffic flow model. First, the goal of the traffic flow model is to create a new benchmark of “expected” values against which the traffic stops conducted by the CDP could be compared. As described in the previous section, the creation of the traffic flow model relies on the traffic flow model to weight the development of new values for the denominator of the benchmark. Statistically, using the traffic stop data in both the numerator and a modified form of the traffic stop data in the denominator is problematic. By using the same data in both components of the benchmark, a bias toward equality is introduced. In other words, if the numerator is .4 based on the traffic stop data, and then the same .4 value is then used as a weight to create the denominator, when the numerator is divided by the denominator, the result is biased toward a value of 1.0 indicating no disparity. The only difference in the outcome of the traffic flow model will be provided by the differing Census values from the various jurisdictions. In effect, the traffic flow model is more heavily impacted by jurisdictions that have a substantially different racial / ethnic composition than the jurisdiction in question. This bias was evident in the results of this analysis. Nonetheless, the traffic flow model biased the results toward no disparity due to the use of the traffic stop data in both the numerator and the denominator.

Second, the traffic flow model suffers from the same assumption that Comparison #1 exhibits in that it assumes that the Census values are an accurate reflection of who actually drives from that area. The traffic flow model assumes that all members of the Census drive a vehicle and that they drive in the police zone of interest. While only the driving aged population is used in the analysis, it is still a significant assumption to presume that all citizens drive. Furthermore, similar to the problems detailed in relation to Comparison #1, the Census variables do not have any measure of the level of risk of being stopped.

Third, the traffic flow model is built upon the apportionment method and as a result has all the limitations of that method associated with the creation of the values for this comparison. As described above, the primary assumption associated with the apportionment method is that

all citizens are evenly distributed across the spatial area of the jurisdiction. Recall that in order to create the traffic flow model it was necessary to assign a home police zone for all stops and this was done based on the percent of area that fell within a police jurisdiction based on the drivers' zip code. This method assumes that all citizens with a zip code are evenly represented spatially across the zip code in order to be assigned a police zone. As argued previously, this assumption is superior to other alternatives, such as the centroid method, but it still relies on an assumption that is not necessarily accurate.

Fourth, while using the traffic stop data to weight the "new" Census values, it does not consider numerous other factors that affect the likelihood of driving in a particular police zone. For example, the design of the street network, the accessibility of freeways, and natural barriers, such as rivers, are not considered in the development of the traffic flow model. Furthermore, research has demonstrated that certain paths through the city receive more traffic due to the draw of certain social institutions (Brantingham & Brantingham, 1982, 1993). For example, shopping areas, business centers, and recreational facilities may significantly affect the likelihood that certain areas will provide more drivers into one area than from another area. These factors and others not mentioned here are likely to effect the traffic patterns within a police zone and the traffic flow model does not incorporate such factors into the analysis.

In summary, the traffic flow model has several significant limitations that limit the confidence any reader should have in the subsequent results. Statistically, using the same data source (traffic stops) in both the numerator and the denominator artificially biased the results. Furthermore, similar to Comparison #1, the traffic flow model assumes that all residents in the Census drive and that they drive in a similar manner to ensure that their individual risk of being stopped is equivalent. In addition, the traffic flow model suffers from the same assumptions associated with the apportion method used in Comparison #1. Finally, there are a host of factors not considered in the traffic flow model that could affect the results of the analysis, including the street network, natural barriers that might exist and the "pull" of social institutions, such as work or play centers.

As a result of these limitations, the traffic flow model is not provided in this report for two main reasons. First, the significant number and magnitude of the limitations upon which the development of a traffic flow model are based leaves the research team with little confidence in the accuracy of any results produced using the traffic flow model. Second, to assess the accuracy of our concerns regarding the traffic flow model, one was developed and the results confirmed the instability in the disproportionality ratios. For example, most of the disproportionality ratios were much higher than other comparisons, but only in areas that were of primarily one race/ethnicity group. Districts 4, 5, and 6, which are primarily comprised of Black residents, showed much high disproportionality ratios using the traffic flow model in comparison to other methods. Importantly, due to the method used in creating the traffic flow model discussed previously, areas comprised of one race/ethnicity group and have significant commuter traffic produce less stable results with the traffic flow model.

Due to the numerous limitations associated with the traffic flow model and the inconsistent results produced when this model was created, the traffic flow model is not reported here. While the intent of the traffic flow model is worthwhile, the means by which it is created present a situation in which too many severe assumptions must be accepted prior to having any faith in the results of this type of analysis. For these reasons, the traffic flow model is not reported.