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Racial Profiling and the Police: Utilizing the Census Transportation Planning Package to Benchmark Traffic Stops made by the North Carolina State Highway Patrol

by Michael R. Herb

Masters in Science, Technology, and Public Policy Thesis Submitted in Fulfillment of the Graduation Requirements for the

> College of Liberal Arts/Public Policy Program at ROCHESTER INSTITUTE OF TECHNOLOGY

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Racial Profiling and the Police: Utilizing the Census Transportation Planning Package to Benchmark Traffic Stops made by the North Carolina State Highway Patrol

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Abstract:

Racial profiling, or the practice of using race, ethnicity, or other racially based characteristics to decide when to stop, cite, or search drivers, has been studied and analyzed by researchers for decades. Attempts have been made to gain an understanding of why officers commit acts of racial profiling and to identify different evaluation methods that allow for accurate analysis of racial profiling data. This study attempts to create a new method of evaluation by utilizing the Census Transportation Planning Package (CTPP) as a benchmark for racial profiling data. Variables from the CTPP are used to create estimates of the transient travel population, or driving population. Using traffic stop data from the North Carolina State Highway Patrol (NCSHP), analyses are conducted to evaluate whether the CTPP can be utilized to accurately benchmark traffic stop data. An assessment is also conducted to determine whether there is any evidence of racial profiling by the NCSHP. The results of this research show not only that the CTPP can be utilized to efficiently and accurately benchmark traffic stop data, but also that the prior method of utilizing basic Census statistics severely underestimates racial profiling. Evidence is also produced to show that several counties in North Carolina were subject to racial profiling by the NCSHP.

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1. Introduction

For decades, researchers have been studying police and the use of racial profiling. Attempts have been made to answer many different questions in this area, such as the extent to which racial profiling is used, the number of officers and citizens involved in racial profiling cases, and police policies and procedures that may lead to higher rates of racial profiling. More recently, researchers have been attempting to identify proper data collection and analysis techniques that allow for accurate measurement of cases. Regardless of the research focus, it is obvious that racial profiling is an important social issue in the United States. In a July, 2001 Gallup Poll, it was found that a great deal of Americans believe that racial profiling still exists in many police departments around the country. According to the survey, 83% of African Americans believe that racial profiling is widespread throughout the United States. The survey also found that 55% of whites believe that racial profiling is widespread throughout the United States. The survey also found that 55% of whites believe that racial profiling is widespread as well (Gallup, 2001). Regardless of whether these people know the actual extent to which racial profiling exists, a similar study in 1999 found that 81% of all respondents believe that the practice is wrong and should not be done (Gallup, 1999).

Today, the government and academics continue to research police departments that are believed to be involved in cases of racial profiling. Generally, the government becomes involved after several reports or cases are made public. Civil rights groups or the victims will often make the stories known so as to draw attention to the particular police department (Holbert and Rose, 2004). A well-known example would be the New Jersey State Police. In the late 1980's and early 1990's there had been many accusations of racial profiling by the State Police. These accusations culminated with a joint lawsuit that was filed in 1990. The case of *State v. Pedro Soto* went on for years. Finally, in 1996, the Honorable Robert Francis would rule that the State Police were guilty of, not only several individual cases of racial profiling, but also promoting the practice through all levels of the organization. The ruling of the case coupled with a tragic and heinous case of racial profiling in the spring of 1998 would lead to a Department of Justice consent decree that was filed in early 1999 (Harris, 2002). There have been many similar cases in recent years and citizens continue to file complaints against police departments today.

One of these cases involved the North Carolina State Highway Patrol (NCSHP). In 2001, a group of academics set out to collect and analyze all of the traffic stop data for the NCSHP for the given year. The researchers were attempting to find whether the Highway Patrol was engaged in any type of racial profiling practices. After collecting the stop data, the researchers utilized traffic accident data and a list of all licensed drivers in North Carolina to conduct their analyses. In the end, utilizing their own formula to benchmark the traffic stop data, the researchers found that there was no conclusive evidence of widespread racial profiling but that there were some localized areas of racial profiling (Smith, Tomaskovic-Devey, Zingraff, Mason, Warren, & Wright, 2004).

This thesis will examine the data that were collected by Zingraff, Smith, and Tomaskovic-Devey in 2001. The author will attempt to identify a new formula to generate an estimated travel population utilizing the Census Transportation Planning Package of 2000. This standard formula will generate a population estimate to benchmark the traffic stop data and will be capable of being applied to any geographic county in the United States. Analyses will then be conducted to

test the effectiveness of the formula and assess whether racial profiling practices are present in any of the counties of North Carolina.

2. Background

2.1 History of Racial Profiling

Racial profiling can be dated back hundreds of years to well before the existence of organized police departments in the United States. As we look back in history, there have been several notable times during which certain types of people or leaders believed that certain races or ethnicities were inferior. During the beginning years of the settlement of the United States, it was believed that Africans were good for slave labor and nothing else. During the reign of Adolf Hitler in Germany, he believed that white people with blonde hair and blue eyes were genetically superior to all other races in the world. As history has displayed, racial profiling has deep roots.

Racial profiling in these early days was utilized as a way to control people of other races and ethnicities. Over the years, while slavery would end and other amendments to the United States Constitution would give minorities equal rights, racial profiling would continue to be used as a form of social control. Police departments, especially in their early days of existence in the United States, had many corrupt practices. Some police officers or whole departments would utilize race to decide who they would arrest. Others would simply "turn the other way" or assist in the assaulting of minorities. Early police officers were said to rule their beats with the "ends of their nightsticks." These officers believed they were simply helping to keep the norms of their neighborhoods, warding off any strangers that they felt threatened the community (Kelling & Moore, 1988).

While police may have been practicing racial profiling for hundreds of years, it would not be until the 1970's that researchers would begin to study this subject. Racial profiling in law enforcement began to gain some recognition in law enforcement during the 1950's. Howard Teten, a former chief of research for the Federal Bureau of Investigation (FBI), would develop a method that he believed would help him to identify a criminal's personality traits and character. This practice, which would later become known as "criminal profiling," was considered a science to the 30 year law enforcement veteran with a background in psychology. Twenty years later, the practice of profiling grew to be utilized by untrained professionals and slowly, it would lose its place in the criminal justice field (Holbert and Rose, 2004).

Police officers and other federal agencies began to use the premise of Teten's work but added another variable to his methods: race. With the implementation of race into the profiling framework, Teten's image of criminal profiling lost its scientific method. A method that, at one time, was strongly routed in psychology and human behavior, had now diverted to personal beliefs that one's race or ethnicity could help to predict criminal behavior. The addition of race to Teten's criminal profiling methods would cause a sort of "re-birth" of police practices in racial discrimination. The use of the term criminal profiling would appear to mask the fact that police departments were utilizing race as a predictor of crime and almost 'justify' their practices.

With no scientific data to prove that race could help to predict crime, police and government agencies began training their officers in practices of racial profiling (Harris, 2002). Racial profiling would gain even more momentum and become more widespread while the United States went through the so-called "war era." Spurred by a perceived growth in drug use and sales the United States would begin their "War on Drugs" in an attempt to rid the country of the 'problem.' Without statistical proof that drug activity had increased, the FBI and other law

enforcement agencies drastically increased the number of arrests that they made during this era. In 1981, 400,000 drug possession arrests were made by state and local police agencies. By 1988, this number had nearly doubled to 762,718. Not surprisingly, minorities made up a disproportionate number of these arrests as compared with their representation in the overall population (Harris, 1999).

The United States would go through two similar periods of war as they declared war on both crime and terrorism. While the profiles that would be developed for these separate wars would be different, the main problem was still that race and/or ethnicity was being included in the profile despite the serious lack of any scientific data that proved race was a direct predictor of crime. As the practice of racial profiling has evolved into current times, the question still exists as to the extent to which it is practiced today. While it is widely believed that the government utilizes racial profiling practices in airports, there is little to say about racial profiling in the criminal justice and policing world (Delattre, 2002).

2.2 Defining Racial Profiling

Researchers have long been debating the proper definition of racial profiling. There are two main schools of thought on what constitutes an act of racial profiling. The first definition is very strict in the sense of the term. Some people define racial profiling as the act of performing a particular action, such as pulling someone over or requesting to search the car, when race or ethnicity is the *sole* reason for performing that action. If race is only one, out of a number of factors that lead to an arrest or a ticket, however, these officers believe that racial profiling has not occurred. Thus,

the debate as to what constitutes racial profiling in policing continues (Walker, Spohn, & DeLone, 2004).

For the purpose of most research, a broader definition is utilized due to the difficulty in providing proof that race or ethnicity is ever the only factor that is used to make a traffic stop. A common definition that is frequently used is the practice of using race, ethnicity, or other racially based characteristics to decide when to stop, cite, or search offending drivers encountered by the police (Holbert & Rose, 2004; Smith, et al., 2004). This means that race need only be part of the reason that an officer makes a stop; it is still considered racial profiling. It would be extremely difficult to prove when, if ever, race was the only factor involved in making a traffic stop. It would simply not be possible to learn what was going on inside the head of the police officer that was making the stop. Instead, a broad definition is utilized so that statistical analyses can be conducted in an attempt to assess when, if ever, out of the total number of traffic stops, race is being utilized as a factor in making stops. This definition provides researchers with the opportunity to conduct analyses on officers who may be unaware of their biases. After analysis of their total consent to search requests within a given year, for example, it may be found that the officer was only conducting searches on African American drivers between the ages of 18 to 25 and not on any white drivers.

2.3 Importance of Focusing on Racial Profiling

As was previously stated, racial profiling is a very important social issue. As the Gallup polls displayed, citizens believe that racial profiling exists, despite the fact that most people feel it is wrong and should not be done. This brings up another important issue with racial profiling,

which is government involvement. There are several reasons that a police department may begin to collect data to assess the possibility of the existence of racial profiling. The first reason, and most infrequent, is that they are voluntarily collecting the data to conduct their own analysis. The reason that this type of collection happens so infrequently is because police departments generally do not have the time or the resources to conduct an internal investigation into something that has not been publicly noticed, and thus, probably does not occur frequently. Also, no agency has the motivation to highlight an internal problem. This will only draw attention to the problem and create tension between the department and the community. Occasionally, however, some police departments do begin a 'voluntary' data collection and analysis process. In these few instances where it appears that the department is voluntarily collecting the data, they are usually facing some outside pressure or threat. For example, they may be facing increased public pressure to take action, or the government may be threatening that they are going to take formal action if the department does not begin the evaluation process.

The second reason that a police department may begin to collect data to assess the possibility of racial profiling would be if the county or state required the collection of racial data through a law or some other form of legislation. This is also not a frequently occurring circumstance, but is becoming more popular as states become more proactive against racial profiling issues. In 1999, North Carolina became the first state to enact a bill that required certain police departments to collect demographic data for all traffic stops. This bill was passed after a period of intense public pressure surrounding several claims of racial profiling against the state police (Walker, et al., 2004).

The final reason that police departments would begin to collect data to assess racial profiling would be a consent decree from the government. More specifically, consent decrees relating to racial profiling come directly from the United States Department of Justice. Under these consent decrees, the police department agrees to collect and analyze certain data under the threat of penalty. If a police department were to refuse to collect the data after signing the consent decree, they could be taken through the United States Federal Court System. Two of the most notable consent decrees in recent years have been with the New Jersey State Police and the Los Angeles Police Department.

The reason that racial profiling continues to be a government issue is best shown by the number of police departments that begin to conduct their own self-assessments. As stated previously, self-assessments are rare and are usually not completely voluntary. If the police are not going to voluntarily collect the data to conduct assessments, then the government must step in to make the data collections occur. Without government intervention, no one person or organization would step in to help control for the possible police abuse of power. The question then becomes, what level of government should become involved?

While there may not be any definite answer to this question, author Edwin Delattre attempts to examine it. In the book <u>Character and Cops: Ethics in Policing</u> (2002), Delattre examines the question of "Can the police, police themselves?" While making many different arguments Delattre appears to suggest that the answer to the question is "yes," but different situations call for different circumstances. He attempts to explain how using police corruption as an example. He believes that in order for the police to police themselves, they must have a 'neutral' party

conducting the evaluation. To Delattre, this does not mean that the person cannot be a police officer. Instead he is referring to having someone conduct the evaluation that is not part of the potential problem. In many cases, where entire police departments are under review, it is generally a good idea to utilize an outside evaluator that has no ties to the department. In most cases, this is why a higher level of government steps in. They can then name a person whom they believe will conduct the analysis while being impartial. This allows for an objective voice in the analysis, whether it is an academic or someone who actually works for that level of the government (Delattre, 2002).

In a 2001 symposium article by David Harris, he attempts to illustrate the current situation of racial profiling by examining three police departments that had recently been intensely researched. Police departments in New Jersey, Maryland, and Ohio were looked at due to both government order (New Jersey and Maryland) and academic grant research (Ohio). In all three cases, the researchers made similar conclusions. Though the intensity level in the three areas was not the same, all of the studies did conclude that African American drivers were more likely than whites to be stopped and ticketed by the police. The reports also concluded that African Americans were stopped and ticketed at a disproportional rate to their representation in the actual population.

According to Harris, the current status of racial profiling appears to be right where Americans believed it to be in 1999 and 2001 (Gallup, 1999, 2001). However, these studies cannot be relied upon completely to support the argument that racial profiling is a widespread problem. After all, the areas that were examined had been publicly reporting problems between the African

American population and the police for a number of years. So before any assumptions are made that the problem of profiling occurs in every town and city, another question must be examined. If racial profiling is not widespread across the United States and is only concentrated in certain areas, then why is racial profiling an issue that is of national concern? The answer gets back to the underlying job and responsibilities of the police force in the United States.

All police departments are charged with protecting and serving their community. Police officers are in a position of trust, and should never be spreading fear among citizens. For many African Americans and other minorities that experience an act of racial profiling, however, the exact opposite is occurring. Harris states that bad experiences with racial profiling can affect the victim deeply. "They are experiences that can wound the soul and cause psychological scar tissue to form," (Harris, 1999, p. 12). In other words rash generalizations are often made by victims. One bad experience with a police officer in New Jersey may lead a person to distrust all police across the country. Close friends of the victim may hear of the incident and then begin to distrust the police as well. One incident can have a severely compounding effect.

The victims and their close friends are not the only people that are being affected by acts of racial profiling, however. Individual police officers, entire community-based police departments, court systems, correctional institutions, and even the greater social world all feel the impacts of racially biased actions of a hand full of police officers. Aside from the previously mentioned deep cynicism that develops among many people that are witness to acts of racial profiling, police departments also are effected by the role that they play within the community. A once, heavily community-oriented, service driven police department, may see a great reduction in their

calls for service in the time surrounding a racial profiling incident. This type of reduction only magnifies the distrust that people are developing in the police department. People gain their trust in the department by watching them perform their duties in the community and socially interacting with the police. When the number of calls for service is dropped, people begin to see police performing less of these duties and do not experience the social interaction with the police that they may have once had.

The court systems and correctional institutions also can be greatly impacted by racial profiling practices also. It is already well-known that African Americans generally tend to receive longer sentences than whites for committing the same crimes (Mustard, 2001). If the court systems have a greater number of African Americans going to trial due to the discretionary techniques of a police officer practicing racial profiling, then one would assume that a greater number of African Americans are going to be sentenced to more severe penalties. This is especially true in the cases of narcotics searches that are conducted by the police. With the multitude of the primary effects of racial profiling, it is clear that it is an extremely important social issue and requires a great deal of attention by the police, the public and the academic world.

2.4 Theory

While there has been a great deal of research conducted on police and the practice of racial profiling, most of it has been purely descriptive research. In other words, researchers collect data on the race of drivers stopped by the police, compare these data to local demographics, and then report on the extent to which racial profiling exists. Generally, following the analyses are some recommendations about how racial profiling can be reduced. According to research by Bernard

and Ritti (1990) there has been a lack of scientific research examining racial profiling. Researchers are rarely attempting to apply and test an explicit theory that would explain why officers actually practice racial profiling. Instead, only implicit theories are being applied to profiling. It is merely assumed that officers are making stops based upon race, but the potential reasons that officers are behaving this way are not being tested (Bernard & Ritti, 1990).

While the research in racial profiling has been mostly descriptive in nature, there are a few researchers that have begun to apply and test theories in racial profiling. One theory that attempts to explain racial profiling based upon officer behavior is known as the theory of coercive actions. Originally created by researchers Tedeschi and Felson (1994), the theory states that a person's need to establish or protect their social identity often leads to the use of coercive actions. In other words, a person may challenge an officer or be more disrespectful to the officer if they feel that their social identity is being challenged. This behavior, theorists say, could then lead the officer to treat the driver improperly. The officer may also feel that their social identity is being challenged based upon the driver's actions. The officer may conduct a search or write a citation based upon their poor interaction with the driver. While this theory may explain why an altercation or consent to search request would take place, it should be noted that this does not explain what caused the traffic stop in the first place (Engel, Calnon, & Bernard, 2002).

Another theory that researchers have applied to racial profiling is known as conflict theory. Conflict theory basically states that the power of a given social group dictates social control over everyone else in order to maintain the status quo. As such, the people that are in power do what is necessary to remain in power. The group in power will make laws and utilize the police in

order to suppress other groups who are perceived to be a threat. According to Petrocelli, Piquero, & Smith (2003), white officers have a lower threshold of suspicion for minorities than they do for other whites. Research has been done to test this belief by examining police shootings of suspects. It has lead to the infamous belief that "police have one trigger finger for whites, another for blacks." The research that has been done to examine conflict theory in racial profiling looks at task forces designed to stop drug use and sales. The research shows that police tend to focus their efforts in those areas considered to be predominately African American neighborhoods. Of the people that the police were targeting to arrest for drug sales and purchase, most all of them were young, African American males. In a similar study conducted by William Chambliss (1994), he also noticed this disturbing pattern. After over 100 hours of observation of the Rapid Deployment Unit (RDU) of the Washington, D.C., Metropolitan Police, Chambliss observed that the RDU only patrolled predominately African American sections of Washington, D.C. In predominately white areas, cars were only stopped when there was a clear traffic infraction. The minor offenses that would get African American drivers stopped in other areas of the city were overlooked in these communities. It appeared clear to Chambliss in 1994, and Petrocelli, Piquero, and Smith in 2003, that the officers were targeting this specific type of individual (Petrocelli, Piquero, & Smith, 2003; Chambliss, 1994).

Another theory that has been applied to racial profiling claims that race is not the sole factor that causes officers to profile drivers. In other words, a spurious relationship exists due to a number of factors such as area, crime patterns, driver error, and car problems. This theory, generally referred to by the authors as the 'Race and Place Theory,' suggests that these ecological or neighborhood factors are also considered when racial profiling occurs. It is not based on the

premise that an officer would stop an African American driver simply because of their race. Such behavior would imply that an individual officer had a form of racially based bias directed toward nearly everyone that was African American. This theory says this may not be the case. Officers may be participating in racial profiling, but the race of the driver is not the only factor that motivates a stop. Instead, a stop is initiated when an officer sees a member of a minority group that looks out of place. An example would be an African American driver in a predominately white neighborhood. Once again, this theory explains the officer's actions as a combination of the race of the driver and the ecological setting in which the driver was located (Meehan & Ponder, 2003). In 2003, researcher Larry Gaines found support for this theory when he studied the traffic stop practices of the police in Riverside, California. While he found that African Americans were stopped at a disproportionate rate compared with their overall representation in the population, he did not find that officers were stopping the drivers simply due to their race. Instead, he believed that the stop numbers were a result of the department's enforcement patterns. A majority of the disproportion appears to be explained by the fact that the police department would deploy more officers in high crime areas. These areas, which had higher levels of crime, disorder and calls for service, were found to be predominately African American neighborhoods. There were not only more officers in these neighborhoods, but these officers were aware that they were patrolling high crime areas. While this finding does not completely disprove that racial profiling exists, it does lend support to Meehan and Ponder's ecological theory of 2003 (Gaines, 2003).

More recently, researcher Jerome Skolnick wrote a reaction paper to a 2007 study that was conducted with the Miami-Dade Police Department. Skolnick attempts to examine the study to

develop a 'theory' of his own. Racial profiling, according to Skolnick, has not been an extraordinary phenomenon in history. Instead, it has simply been that police officers have "expressed the prejudices of their times," (Skolnick, 2007, p. 65). Skolnick goes on to talk about the "symbolic assailant" and the stereotypes that police have often fallen back upon to make quick judgments of character when they see potential criminals. The landmark case of Terry v. *Ohio* (1968) displays these judgments well. An officer sees two men who appear to be preparing to rob a jewelry store. Without any hard evidence to go on other than the feeling that the men "didn't look right," the officer went over and frisked the men. After discovering that both men were armed, the officer arrested both men and later a third assailant. This landmark case essentially opened the doors for officers in the future to utilize reasonable suspicion to conduct 'stop and frisks' when they felt that a crime was about to be committed. With such a loose definition as to what was justifiable to stop and frisk someone, it remained up in the air that, as long as the officer could explain their feeling about the situation, they would be able to stop someone who may look out of place solely due to their race and location. Skolnick, and a few other researchers seem to conclude that utilizing race as an indicator can be acceptable and within the limits of the law. They are all quick to state, however, that the utilization of race should not create a population of a race that is disproportionate to the distribution of offending by that particular racial group (Skolnick, 2007).

3. Literature Review

3.1 The Current Status of Racial Profiling Research

Over the past couple of years, allegations of racial profiling practices by the police have increased drastically. Part of this pattern of increase can be attributed to the steady growth of knowledge about the topic by the general population of Americans (Harris, 2001). Through increased exposure in the daily news as well as an increased amount of research and publications by criminal justice academics, Americans are becoming more aware of what constitutes an act of racial profiling. The previously mentioned Gallup polls of recent years display what many believe is the current situation with police and racial profiling. In an attempt to keep the public from making 'blind' assumptions about the current status, academics are constantly attempting to develop new methods for both data collection and analyses that strive to inform as well as educate. The main goal behind a great deal of the research being conducted is that an accurate model must be created to help correctly evaluate current police practices.

The fact still remains, however, that researchers and academics are still struggling to answer some of the most basic questions about these practices. As was previously stated, researchers cannot even agree on a single definition for racial profiling. Without a single, concise definition it is difficult to attempt to answer more complex questions such as identifying these proper data collection and analysis methods, or developing theories and policies that will help to severely reduce or even stop the occurrences of racial profiling practices. This has left the field of racial profiling in need of some guidance. New methods of data collection and analysis must continually be developed with the hope that researchers can build off of other models to develop more efficient and valid methods. Researchers Batton and Kadleck state that if we are ever going

to be able to fully understand the causal factors of racial profiling, the development of multivariate models that can take into account complex variables such as the strategies of a given agency are essential. In other words, we must create flexible models that allow us to evaluate multiple police departments on more than one level. The days of creating a model or analysis method for one specific police department must become a practice of the past (Batton and Kadleck, 2004).

3.2 Data Collection Processes

In order to begin to develop more complex models to examine racial profiling, we must first have a thorough understanding of the current methods that are utilized to collect and analyze police department traffic stop data. As stated previously, examining possible instances of racial profiling has been a growing concern for many police departments across the country. This has led to a great deal of publications by not only academics who study police behavior but also different government agencies that are attempting to guide police departments along in their quest to conduct proper analysis. One such government publication is the "Resource Guide on Racial Profiling Data Collection Systems." This report was published by the United States Department of Justice (USDOJ) in November of 2000. The guide book not only described the best type of data to collect but it also listed four major cities that had developed promising data collection processes.

Ramirez, McDevitt, and Farrell (2000) begin their report by stating that a police department cannot simply just collect data for a certain amount of time and expect that the problem of racial profiling will dissipate. Instead the department must implement an entire data collection system

that not only sets a standard for *what* data will be collected, but also sets a standard for *how* the data will be collected and the punishment or sanction that an officer would receive for failing to collect. Therefore, the report does not simply urge departments to implement data collection systems, but also discusses some of the potential problems that a city might experience when attempting to implement their system. The most useful portion of this report, however, is the information it gives on four areas' data collection systems that have already been implemented.

The four police departments that were discussed in the 2000 USDOJ report were San Jose, California; San Diego, California; North Carolina State Highway Patrol; and the New Jersey State Police. All four of these areas have implemented mandatory data collection systems for their officers. This means that, every time an officer pulls someone over, regardless of whether they give the driver a ticket, they must collect general demographic information about the driver and any other passengers that may be in the vehicle. In all four of these areas the officer cannot be cleared to go back on duty until this information is cleared through their respective systems. In the case of San Jose, California, the officer collects this data and simply radios the information into dispatch. Dispatch then records the information on a computer for further analysis. In San Diego and North Carolina, the systems that were implemented included the use of either new computer software or new computers. In both cases the officer must record the information into the computer before they can write the ticket or move on to another call. New Jersey has implemented a \$15 million system in accordance with their consent decree with the USDOJ. They are currently working toward implementing a laptop system for the officers to replace calling the information in through their radio (Ramirez, McDevitt, & Farrell, 2000).

Following this 2000 report, the USDOJ also released a similar guide in 2004. While the report entitled "By the Numbers: A Guide for Analyzing Race Data from Vehicle Stops" is similar to the previous guide book, it has a slightly more directed audience. This guide, which is much longer and more extensive, is aimed at helping departments that are required to meet the rules of a consent decree. Police departments that are mandated to collect data can utilize this report for a form of guidance to help them remain in compliance. The report goes through both the collection process as well as proper analysis techniques. Some of the most important information in the report, however, describes the type of data that must be collected in order to conduct a meaningful analysis.

It begins by stating that there are two types of data that, at the very least, must be collected. The first types of data are the stops that are made by the officer in which they are making a proactive decision to stop a car. In these cases, the officer has made the decision to stop one car as opposed to other cars. These personal decisions, when analyzed properly, could help lead to officers that are making biased decisions in stopping cars. The next data that must be collected are all of the stops in which the officer knew or thought they knew the race of the driver before they actually made the stop. While the report states that these two types of data must be collected, they do not say that this is the only data that can be collected. Other data that are strongly recommended to be collected by this report included vehicle consent to search requests and hit rates when vehicle searchers are conducted. In this instance a hit rate refers to the rate of successful searches in which contraband is found, as compared with the total number of searches that were conducted (Fridell, 2004).

Prior to the release of both of these guidebooks, researcher David Harris made a plea to Congress to take action in the area of racial profiling data collection. On March 30, 2000, Harris met with the Senate subcommittee on the Constitution, Federalism, and the Property Rights. The special topic that they were covering on that day was specifically racial profiling within law enforcement. For the third time in recent years, Congress had a proposed bill that would set forth national legislation requiring the collection of demographic data on all traffic stops made by police departments across the country.

The Traffic Stops Act of 2000 was not the first of its kind, but the impact, Harris states, was unlike that of the previous bills. Similar to the previous bills, this act would eventually be rejected by Congress; however, the effects that were felt by state and local police departments were unequaled in the past. Many states, having heard about the Traffic Stops Act, attempted to be proactive and handle the situation on their own. In 1999, North Carolina became the first state to require any type of demographic data be collected on all traffic stops. Many cities and a few other states would follow suit. Generally these areas would be pressured politically as well as publicly. Areas such as North Carolina and New Jersey had received a great deal of media attention that had revealed what appeared to be racially biased policies and practices (Hearing on Racial Profiling within Law Enforcement Agencies, 2000).

In 2004, Congress would once again introduce a bill that was aimed specifically at ending racial profiling. For the fourth time on record, however, no federal law would be passed to reduce racial profiling. The End Racial Profiling Act of 2004 was introduced in February of 2004. Despite being introduced early in the Congressional term, however, the bill was never scheduled

for debate. At the end of the two year Congressional term, the bill was once again cleared from the books. Though there have been several rumors that the now majority democratic Congress will propose another racial profiling bill, there has been no action taken since the beginning of the term of the one hundred tenth Congress (S. 2132, 2004).

Despite these numerous attempts to address racial profiling at the federal level, David Harris has always stood by his belief of keeping the federal government out of this matter. Recognizing the fact that the bills have had a great impact on state and local governments, Harris believes that this is the best solution. There are two distinct advantages to allowing local police departments to deal with racial profiling issues as opposed to the federal government. The first is that there is not some unusual, father-type figure reigning down on an entire police department. Instead, the investigations and decisions come from within. The administration that all of the officers in the department are familiar with are conducting the evaluation. The second reason that it is better to stay local is that the level of evaluation can fit the department. If there was a federal statute, the evaluation would have to fit departments of small cities all the way to state police agencies. Modifying a program to fit one's own circumstances allows for a greater amount of flexibility and ensures that specific issues within the department are properly evaluated.

Harris continued in his symposium with a list of six points that all data collection systems must have. The first, and most important, item is that independent analysis is conducted. Harris states that someone external from the department should complete the evaluation. If the whole police department is being accused of racial profiling, an internal evaluation will look poorly upon the department, especially if the researchers actually find that the accusations are unfounded. The second issue that Harris states is extremely important is that the data collection occurs over a long period of time. This allows the researchers to examine the long-term patterns of the department and its behavior as new programs and policies are adopted. The third item that must be addressed is explicitly written documentation of what constitutes racial profiling. This includes utilizing a definition of racial profiling that, as stated previously, does not require that an act of racial profiling be based entirely on race.

The fourth item that Harris discusses is oversight of the data collection process. Every department must be checked upon from time to time to ensure that they are completing their data collection both properly and in a timely manner. There can be no lapses in the collection or the effectiveness of the evaluation will be lost. The fifth item that is identified relates to the treatment of motorists during stops. There should be policies that explicitly deal with the type of behavior that is expected of an officer during a traffic stop. This includes not only all stops but all tickets and searches as well. Anytime a search is conducted, the officer should help to put items back in their proper place rather than simply ripping the car apart and leaving the mess for the motorist to clean up. The final item that Harris addresses is utilizing technology to help with the problem. Any items that can be utilized to make the data collection process easier should be utilized at all times. Laptop computers, mobile data terminals (MDT's), mapping computer software, and video cameras are all excellent resources that can make the data collection process occur much more seamlessly (Harris, 2001).

In recent years there have been many police departments that have utilized the guidelines created by the Department of Justice and David Harris to guide the implementation of their own racial

profiling analysis program. A current example that has followed Harris' guidelines very closely is the Riverside Police Department of Riverside, California. This police department, which serves a population of over 250,000 (United States Census Bureau, Census 2000), has been collecting and analyzing racial profiling data for over five years. The current system that is in place began in 2001 due to a judgment between the city and the California Office of the Attorney General. Many changes were made to the administration of the police department and a mandatory racial profiling evaluation was put in place.

In the previously mentioned 2003 report, researcher Larry Gaines examined the department's collection system and evaluated the data that had been collected for the year 2002. While he did find that African Americans were stopped at a disproportionate rate compared with their overall representation in the population, he did not find that officers were stopping drivers simply due to their race. In this study, the population demographics were taken from the 2000 census, which, according to Gaines, were the most accurate projection available at the time. Gaines theorized that the city's stop numbers were a result of the department's enforcement patterns. Gaines observed that the police department deploys more of its officers in the areas of the city with the highest crime rates. These areas tend to have high African American populations. In other words, a larger amount of the city's officers are being placed in predominately African American communities, explaining the higher number of African American stops.

The Riverside data collection process is simple and concise. Similar to the previously mentioned methods of San Jose, California, the officer must radio in the basic information which they are required to collect. In this case, officers must call in the driver's race or ethnicity, the driver's

gender, the reason for the stop, the disposition of the stop, whether a search was conducted, and whether the search yielded any illegal materials or contraband. Officers are trained in how the computer dispatch system works, and thus, they simply call in codes that correspond to the particular circumstances. The dispatchers record the information into the computer where it remains for future examination and evaluation.

With the exception of specific by-laws that govern officer behavior related to the searching of vehicles, the methods used in Riverside comply with David Harris' guide to efficient data collection and analysis. This system, though it may seem a bit simplistic, is perfect for a department of this size. It allows for accurate data collection without becoming a burden on the police officers that are making the stops. It also allows for a researcher to come in and examine several years worth of data, knowing that all of the data was collected utilizing the same method (Gaines, 2003).

Despite being substantially larger, and covering a much greater stretch of highway, the New Jersey State Police (NJSP) have also adopted a call-in system that forces the officer to alert the dispatcher of the status of a traffic stop. During the late 1990's the NJSP received many accusations that their policing of the New Jersey Turnpike was racially biased and that nearly all of their stops were made because the driver of the vehicles were African American. Under the restrictions of a major consent decree, the NJSP adopted the call-in method of data collection in 2000. They currently continue to monitor their data in this way, but are moving toward a more advanced computer system that would allow the individual officers to record their own data without having to use the dispatcher (Holbert & Rose, 2004).

The current knowledge on efficient methods of data collection is immense and only growing as more police departments develop new processes. The guidelines that have been released by the Department of Justice and researchers such as David Harris are vastly helping to direct police departments into acceptable collection methods. With accurate data collection occurring in departments across the United States, researchers have begun to focus a great deal of their attention onto how this massive amount of data can be analyzed accurately and expeditiously. The question as to the validity of the analyses as well as methods to properly measure the extent to which racial profiling exists are currently very important topics of research.

3.3 Analysis Processes

Over the past few decades, researchers have developed numerous methods to conduct analyses of racial profiling data. Through the utilization of data on traffic stops, warnings, citations, and automobile searches, there have been a number of analysis processes that have been tested and used. Researchers have attempted to answer not only whether profiling may exist in a given area, but why racial disparities may appear. While attempting to answer these types of questions, two main areas of analysis have emerged. The first type of analysis examines automobile searches. The question that researchers are generally attempting to answer is whether police are searching minorities' cars more often than whites', despite the fact that they may be less likely to find contraband in the cars of minorities. The second type of research that is being conducted examines whether the number of minority drivers that are stopped and given citations is disproportionate from their representation in the overall driving population.

Analysis of automobile searches has been growing steadily over the last decade. This is due in large part to the fact that nearly all states require that demographic data be collected when a search is conducted. This is a special circumstance that is generally handled differently by police departments than a regular traffic stop and citation. The general manner in which this data is analyzed is also fairly consistent and simple, no matter the size or demographics of a police departments' jurisdictional area. Another reason that automobile search analysis has been growing is due to the advantage this type of analysis has over traffic stop and citation rates. In traffic stop analysis, the researcher needs some population estimate with which to compare their numbers. They are attempting to find whether minority drivers are stopped at a disproportionate rate with their overall representation in the population. This requires the researchers to calculate and use population estimations for a given area. When researchers examine hit rates, the researchers do not need this population number to benchmark their data. Instead they are examining how often contraband is found in comparison with how many times cars are searched.

In order to conduct hit rate analysis, a department will first examine the raw numbers of what type of drivers are being searched. They may examine race, ethnicity, age, and/or gender. This will give the researcher the general idea of whether, for example, minorities in a given area are being searched at twice the rate of white drivers. The next part of this analysis to be conducted is defining a 'hit rate.' A hit rate refers to how often a particular race of driver is found to be in possession of illegal contraband. For example, if a particular group was found to have contraband 20 times out of 50 searches, than the hit rate for this group would 0.40. Researchers are generally not extremely concerned with how high or low these individual rates are on their own, but rather they are concerned with how these numbers compare to that of other groups. If

minorities are searched twice as often as whites, but are found to have a lower hit rate, there is a disparity between the treatments of these different types of drivers.

In February of 2005, researchers Steward and Totman released a report on law enforcement agencies in the state of Texas. This report, which was released on behalf of the American Civil Liberties Union and the National Association for the Advancement of Colored People, attempted to examine whether these individual law enforcement agencies were searching minorities automobiles at a higher rate than that of whites. They also examined the hit rate for each individual agency to examine whether these departments were justified in their search policies. In the end, their simple methods of evaluation led to the identification of many police departments which *appeared* to be practicing some type of racial profiling when they decided to conduct automobile searches.

Throughout the entire state of Texas, they were able to find that approximately two out of every three police agencies were more likely to search African Americans and Latinos than whites following a traffic stop. While the researchers did generate hit rates for the different departments, they were not able to make general conclusions for the entire state. Some departments were found to search African Americans more often and have a higher hit rate than whites, while others appeared to search African Americans more often and have a lower hit rate than whites. Though their conclusions were somewhat weak as the data were scattered between departments that were in compliance and departments that were in violation, the report was helpful in identifying some departments that had major issues in their search policies. The study was also

extremely helpful in identifying a number of areas in which the data was weak, thus requiring better, or sometimes more, data collection (Steward and Totman, 2005).

Researchers Engel and Johnson utilized a similar method in 2006 when they took readily available state police agency data and analyzed hit rates for different state police departments. Like many studies that had been previously conducted on these data, the researchers found that African American and Hispanic drivers were generally more likely to be searched during a traffic stop, but notably less likely to be found in possession of contraband. The researchers were fairly certain that this would be the case and rather than conduct repetitive statistical analyses, they decided to take the study one step farther. They attempted to answer the question as to why these states had disparities present. In the end, the researchers believed that the state and federal training which the police officers receive were at least partially to blame for the outcomes which they found (Engel and Johnson, 2006).

The second main area of racial profiling data analysis, which compares stops and citations of a particular group to their overall representation in the population, is a more complex and involved process. There are a few additional steps in this process that are not needed when examining hit rates of automobile searches. The process begins the same, however. The researcher examines the overall patterns of the data. They are attempting to learn the demographic characteristics of the drivers that are stopped, warned, and/or given a citation. In other words, what percentage of the drivers stopped are of a minority race? What percentage is white?

These patterns, though they may appear to be useful, cannot be utilized at all until they are paired with data that represents the demographics of the overall population. For example, some people may feel that if 75% of a police department's traffic tickets are issued to African Americans, that some type of racial profiling is present. In actuality, however, if the police department serves an area that has a 75% African American driving population, then the rates are what should be expected. The most difficult process in this type of analysis is determining the proportions for an area's driving population. This process, which is formally known as 'benchmarking,' refers to finding accurate demographic data to set a police department's stop data in the correct context. Proper and accurate methods to benchmark traffic stop data are of growing concern to researchers. How can one accurately and efficiently measure the driving population of an area?

3.3.1 Benchmarking

A benchmark, according to authors Steve Holbert and Lisa Rose, is best defined as "a point of reference from which measurements, evaluations, and comparisons can be made," (Holbert and Rose, 2004, p.192). Acquiring an accurate method to generate benchmarks is an extremely important task when analyzing racial profiling data. In many cases, the difference between accurate and inaccurate benchmarks can be the difference between whether a researcher concludes that racial profiling is occurring. Over the past several decades, a number of methods have been utilized to generate a population that can be used for comparison. Through analysis of previous studies, researchers have begun to develop newer, more accurate methods. The hope is to develop, an accurate and easily calculable method of generating what has become known to researchers as the 'transient travel population.' In other words, the transient travel population is the population of people that are actually driving on the road.
The earliest forms of racial profiling data analysis began by utilizing simple census statistics to generate what was believed to be the transient travel population. Over the years, however, researchers such as Larry Gaines in his 2003 study of Riverside, California, began to realize that the census data was a very poor representation of the driving population. People that lived in a given area did not necessarily drive there all of the time. Often, in large cities, everyone did not have access to cars, or they rarely drove because of the availability of public transportation. Another problem with utilizing census data was that it became old and inaccurate very fast. With the census only being conducted every ten years, it did not take long for the data to become stale. Slowly, researchers faded from using only census data, and eventually new methods were developed that would take into consideration the general population of the area, but not rely solely on the census data (Engel and Calnon, 2004).

In April of 2006, researchers Farrell and McDevitt attempted to utilize transportation planning data for the state of Rhode Island to generate a more accurate transient travel population. In order to conduct their analysis, they utilized data that had been collected by state transportation experts. The researchers utilized a combination of census data with transportation data that estimated the flow of people into and out of major metropolitan areas. The only major problem that researchers discovered was that their data was not broken down specifically by race. They had an idea of the sheer volume of drivers, but were uncertain of their racial demographics. This meant that, in order to stratify their data by race, they would have to combine it with the census figures from the previous census.

In order to test the accuracy and validity of their method, the researchers conducted an observational study to view the actual driving population on the roads. While the researchers could still not guarantee that their method was completely accurate, they were certain that the method was more accurate than utilizing census data alone. In the end, they were able to find that a number of police departments in Rhode Island reduced racial disparities in traffic stops. While there were still a number of police departments that were stopping minority drivers at a disproportionate rate, there had been some improvement from the time that the previous study had been conducted. Minority drivers were still more likely to be searched than white drivers; however, the majority of the departments had reduced the overall disparity between whites and non-whites. In the end, it appeared to the researchers that, while the departments still needed to improve, they were heading in the right direction.

While the researcher's population estimate methods do appear to be fairly reliable and accurate at generating the transient travel population numbers, there is one major problem. The data which the researchers were able to utilize is not readily available across the country. The 'flow model' that was generated by transportation experts takes a great deal of time and resources to generate. While some major cities may have information that is as detailed as the Rhode Island data, on a whole, the country does not have these numbers readily available (Farrell and McDevitt, 2006).

A very similar study utilizing less complex transportation data was conducted in Missouri by Rojek, Rosenfeld, and Decker (2004). The researchers attempted to take into account the effects of surrounding areas on the flow of traffic in and out of an area. By creating an inverse distance

matrix, the researchers were able to shift the population demographics based upon the immediate surrounding areas. Municipalities that were close to each other had a greater weight on each others demographic population than municipalities that were far away. In a sense, this created a 'floating population' of drivers between municipalities that were close together. While the researchers did find their method to be mildly successful, it did have one major weakness. The matrix did not take into consideration the availability of cars or whether people within a given municipality even utilized cars to transport themselves around. Despite this weakness, the researchers were able to prove that, after creating a more accurate travel population estimate, there is in fact a disparity in the treatment of drivers of different races. While utilizing general residential population numbers may mask the existence of this disparity, their inverse matrix did show that minority drivers are disproportionately represented in both stops, citations, and searches by the police (Rojek, Rosenfeld, and Decker, 2004).

Another common type of benchmarking that was utilized in the previous Rhode Island study was conducting observations of the driving population. In December, 2003, Dr. John Lamberth of Lamberth Consulting conducted an analysis of the San Antonio Police Department attempting to determine if the department was utilizing any type of racial profiling when making traffic stops. In the end, Lamberth concluded that it did not appear, based upon his population projections that the San Antonio police were practicing in any type of racial profiling. In order to come to this conclusion, Lamberth first had to calculate some type of population estimate. To do this, he conducted several different observations on many of the highways in San Antonio. Researchers, sitting stationary in cars, were attempting to capture the race of drivers as they drove by on the highways. While this method of research has been utilized a great deal to validate other data collection methods, such as the Rhode Island case, alone it is very weak.

The major problem with conducting observational studies is that it is extremely difficult to be positive of the race and/or ethnicity of a driver 100% of the time. It is difficult to say, with assurance that all of the drivers that sped past on a highway were of a particular race. While police officers may patrol all different types of roads, researchers rarely conduct their observational studies anywhere except the main highways. This is because these roads tend to be utilized the most and have the highest volume of traffic. Although these highways may have a great deal of drivers on them, it is very difficult to accurately project the driving population from the fast moving traffic. Another problem with observational studies is the collection of data at night. If a highway is dark at night, and there is no light coming from the interior of a car, it is next to impossible to identify the race of the driver. Removing any night observations would assume that the demographics of the travel population are the same at night as they are during the day. Statistically, this has been proven false in the 1995 National Transportation Survey which stated that African Americans are disproportionately found on the highway in the evening and nighttime hours (Smith et al., 2004). Finally, the last problem with conducting observational studies is that it is impossible to observe all of the highways or roadways where a particular police department will make traffic stops. All research has a limited amount of time and resources. Researchers simply cannot cover all of the highways with the police department's jurisdiction (Lamberth, 2003).

In June of 2005, researchers Lange, Johnson, and Voas attempted to create yet another method to accurately estimate the travel population. In order to do this, the researchers conducted a survey on the New Jersey Turnpike and evaluated the patterns of traffic violations that were observed by Turnpike cameras. In the end, the researchers found their methods to be fairly accurate at estimating the driving population. Their final results displayed that, when compared with the population estimates which they calculated, minority drivers were stopped in proportion to their representation among speeders. In other words, the researchers found that minority drivers exceeded the speed limit by 15 mph more often than white drivers, and this is why they were stopped more. These observations would appear to explain why the general census population figures were so disparate from the stop numbers. They are quick to state that these results do not show that racial profiling is absent but rather the results display a plausible explanation for the disparity in traffic stops.

While this method was truly the first of its kind, there were a few notable weaknesses. The first, and most obvious, is that the method only applied to one roadway. While this can be helpful if a police department, such as the New Jersey State Police, is accused of profiling along one stretch of road, it cannot be applied to other state roads which the State Police patrol. A second weakness is that while the researchers conducted a survey in the tollbooths of the Turnpike and allowed the driver to identify their own race, the police officers were determining the race of the driver based upon their own personal opinion. While this may seem like a minor detail, it can throw off the numbers of the overall analysis of whether the police are actually profiling the highway. This method of analysis, despite its weaknesses is original and appears to be a fairly accurate travel population predictor (Lange, Johnson, and Voas, 2005).

There is one final benchmarking method that is relatively new and unique in its methods to estimate the approximate driving population. In January of 2004, researchers Smith, Tomaskovic-Devey, Zingraff, Mason, Warren, and Wright set out to estimate the driving population for the entire state of North Carolina. In order to calculate these estimations, the researcher relied on three different 'proxy' measures, or approximate measures of citizen driving behavior. The first proxy measure that was utilized to generate an approximate driving population was a list of licensed drivers provided by the North Carolina Department of Motor Vehicles. The researchers believed that utilizing a list of licensed drivers, based upon their place of residence would provide a fairly accurate idea of the overall driving population. The main problem with this assumption, however, is that not all drivers that have licenses have access to cars. In some cases, drivers that have cars may not rely on them heavily for transportation. They may utilize public transportation or live in an area that does not require them to drive often.

The second proxy measure that the researchers examined attempted to take into account the effects of the demographics of surrounding neighborhoods and the commuting population. In order to make their approximations, researchers estimated that the number of drivers that drove out of their respective county and into a surrounding county for work was directly proportional to their actual representation of the home county's population. For example, if 30% of the population of the original county is African American, then 30% of the people that are commuting out of this county are African American. This method, while it is attempting to weigh in the effects of surrounding areas, does not have any statistical support to affirm its accuracy. The researchers assume that the commuting population is directly proportional to the

overall population statistics of each individual county. This is a considerable assumption to make with little statistical evidence to speak to the accuracy of the approximation method.

The final proxy measure that the researchers utilized in this study is, according to the researchers, their most powerful measure of the driving population. In order to generate travel population numbers, the researchers examined the demographic patterns that existed for all traffic accidents that occurred on the state's highways for a given year. Making the general assumption that people of all races are equally likely to violate traffic laws and become involved in traffic accidents, the researchers theorized that the patterns in the traffic accidents were directly proportional to the patterns of the overall driving population. While, once again, this method of estimation is difficult to prove its statistical significance, the researchers, at least from their experience, felt that it was their strongest method of estimation. In the end, the researchers did not find any substantial evidence that the North Carolina State Highway Patrol had been practicing in any type of racial profiling. While they had found a slight disparity in the number of African American drivers that had been stopped, the researchers stated that these numbers are not noteworthy enough to show profiling. Instead, they believe that the disparity could simply be a result of their population estimation methods. Lastly, the researchers found that the number of searches that were conducted on African American drivers were directly proportional to their overall representation in the population estimates (Smith, Tomaskovic-Devey, Zingraff, Mason, Warren, and Wright, 2004).

Researchers Year	Department Analyzed Type of Analysis	Benchmarking Method	Findings
Gaines 2003	Riverside, California Traffic Stop Analysis	Basic Census Data	Disproportionate stop rates but not due to racial profiling. Due to location of officer deployment.
Steward & Totman 2005	Many Departments in Texas Search and Hit Rate Analysis	Not Applicable	Identification of several departments that appeared to be practicing racial profiling.
Engel & Johnson 2006	Twelve State Police/State Highway Patrol Agencies Search and Hit Rate Analysis	Not Applicable	Disparity existed in nearly all departments. Minorities searched more but less likely to be in possession of contraband.
Farrell & McDevitt 2006	Rhode Island Stop and Search Rate Analysis	State Transportation Planning Data and Observational Study	Many departments showed some disparity in stops and searches though they had improved since the last analysis.
Rojek, Rosenfeld, & Decker 2004	Missouri Stop and Search Rate Analysis	Inverse Distance Matrix of Census Data	Disparity in stops, citations, and searches.
Lamberth 2003	San Antonio Stop, Search and Hit Rate Analysis	Observational Study	No appearance of any type of profiling.
Lange, Johnson, & Voas 2005	New Jersey State Police Stop Analysis	Driver Survey and Analysis of Traffic Violations on Highway Cameras	Found that stop rates are proportional to the rate at which minority drivers are said to be speeding.
Smith, Tomaskovic- Devey, Zingraff, Mason, Warren, & Wright 2004	North Carolina State Highway Patrol Stop, Search, and Hit Rate Analysis	List of Licensed Drivers, Weighted Census Data, and Traffic Accident Reports	No substantial evidence of racial profiling. There was a slight overall disparity in stops but it was not enough to conclude that racial profiling was present.

4. Methodology

4.1 Research Goals

Researchers have been attempting for years to create straightforward, universal methods to both collect and analyze racial profiling data. Oftentimes, however, these methods become either far too simplistic or increasingly complex. This results in collection and analysis processes that are either widely inaccurate, or are too specific to be applied to multiple police departments in various jurisdictions. A major inadequacy in recent years has been in the ability to create concise and accurate methods of estimating the driving population by which police stop data can be compared, or benchmarked. Researchers have proven that basic census data are inaccurate and many of the other methods that have been developed require a great deal of time and resources. In this research, the author attempts to identify a technique to accurately estimate the transient travel population, or driving population. This will be done by utilizing Census survey data that is readily available for all jurisdictions in the United States. Finally, the estimation method will be tested against traffic stop data from the North Carolina State Highway Patrol (NCSHP), in an attempt to both assess the validity of the method as well as analyze the current state of racial profiling by the NCSHP.

4.2 Estimating the Transient Travel Population

4.2.1 The Census Transportation Planning Package

As previously mentioned, there are two main ways that researchers examine traffic stop racial profiling by the police. One method is to examine the search and seizure practices of a given department. In order to do this, basic data is collected every time that an officer searches a person or vehicle after a traffic stop. The main data that is collected is the race of the driver, the

reason that the search is being conducted (i.e. search incident to arrest, probable cause, plain view, consent search, search warrant), and whether any contraband, or illegal materials were found. Analysis of these data allows researchers to see whether it appears that minority drivers are being searched at a disproportionate rate to that of white drivers. It also allows the researcher to examine hit rates, or the rate at which contraband is found in the vehicles. A general sign that racial profiling practices may be present would be a high rate of minority drivers being searched despite a low rate of contraband hits. One major disadvantage to this type of research is that it only takes into account the possibility of racial profiling after the traffic stop has been made. It cannot answer the question as to why the officer stopped the driver initially.

The advantage to this type of research, however, is that there is no need to calculate what is known as the transient travel population, or driving population. The transient travel population is best defined as the population of people that are actually driving on the roads. Like any other type of population, the transient travel population can relate to any geographic area. It could be one specific stretch of highway or something as big as an entire state. There are many factors that can effect a given area's transient travel population, but a few major influences would be: the number of licensed drivers in an area, the amount of adequate routes and roadways between different areas, and the commuting practices of residents in a given area. Researchers have often attempted to mix these types of data with actual census data in an attempt to generate estimations of the driving population.

One source of driving population data which researchers have yet to examine extensively is the Census Transportation Planning Package, or CTPP. The CTPP is a special collection of data put

together by the United States Census Bureau every ten years. The data are collected from the long form of the Census which is sent to approximately one in every six households. The CTPP is put together in conjunction with the State Departments of Transportation in an effort to provide meaningful commuting and transportation information to transportation planners. The data provide these planners with a unique look at the commuting population at the county and state level. The CTPP is composed of three different sections based upon where the residents live, where they work, and flow statistics about their commuting practices.

Based upon previous research findings (Farrell & McDevitt, 2006; Rojek, Rosenfeld, & Decker, 2004; & Smith et al., 2004), residential commuting data appear to be a fairly accurate predictor of an area's overall driving population. Utilizing the CTPP as a predictor of the transient travel population will make the benchmarking process quicker and much more efficient. There are very few resources needed as compared with other forms of estimation. There is no need to spend time and money making thousands of observations of the traffic on the roads. While there is some complexity to interpreting the survey results, time is saved because the data are already collected. Another advantage to utilizing this data is that they are available for all counties and states in the United States. Also, according to the Census Bureau, going out to one in every six households makes the error term very minute when dealing with larger populations. When examining counties, for example, the Census Bureau states that the error term in their estimates would be very small, generally close to zero. While this is not problematic when examining larger populations, it is possible that areas with very small populations (under 10,000) could have greater, more noticeable error terms.

The CTPP calculates many different variables for the commuting population including the average amount of time it takes residents to get to work, what type of transportation the residents use to get to work, the residents' occupations, and the residents' salary. In order to estimate the transient travel population, the author identified two major variables that are believed to be accurate predictors of driving practices. The first variable that was identified is stratified by race and represents the means of transportation to work. While there were eight different means of transportation in this variable, they were consolidated into two much simpler categories. The categories were driver and non-driver. The belief is that people that drive to work on a daily basis, are the main composition of the roadways at other times of the day. People that rely on other forms of transportation to get to work, especially those located in major metropolitan areas will probably rely on this type of transportation to get other places as well. While they may own a car, they will not drive it on a regular basis. The second variable that was identified was also stratified by race and represents whether the resident had any vehicles available for use. This variable will help to eliminate the problem that researchers have run into when attempting to utilize lists of licensed drivers. In this case, people may be licensed, but if they do not have a car available to them, then they would have no impact on the driving population.

The two variables will be utilized to create two different estimations of the driving population. At this time, it is unknown whether one of the variables will be a better predictor of the driving population than the other. An exploratory research approach will be utilized to identify which variable, if either, is believed to be more accurate and can be utilized in any geographic area. Both variables stratified race into four separate categories, but for the purpose of this research, the race categories were combined into three: white, African American, and other. The Asian and

'all other races' categories were combined to form the 'other' category that will be used in this research. The variables were also split into two ethnicity categories: Hispanic and Non-Hispanic. Both race and ethnicity will later be examined separately in an attempt to identify racial and ethnicity-based profiling practices.

After consolidating the categories, the figures will then be turned into percentages by county in

the following manner:

Formula for CTPP Commuting Pattern Variable

 $\frac{R_{1,2,3,4,5}}{W_1} * 100 = \%$ Race/Ethnicity Driving

 R_1 = Number of White Workers Driving Cars to Work R_2 = Number of African American Workers Driving Cars to Work R_3 = Number of Workers of Some Other Race Driving Cars to Work R_4 = Number of Hispanic Workers Driving Cars to Work R_5 = Number of Non-Hispanic Workers Driving Cars to Work W_1 = Total Number of Workers within Each County

Formula for CTPP Car Availability Variable

$$\frac{R_{6,7,8,9,10}}{W_2} * 100 = \%$$
 Race/Ethnicity Driving

 R_6 = Number of White Workers with Cars Available R_7 = Number of African American Workers with Cars Available R_8 = Number of Workers of Some Other Race with Cars Available R_9 = Number of Hispanic Workers with Cars Available R_{10} = Number of Non-Hispanic Workers with Cars Available W_2 = Total Number of Workers in Households within Each County

The result will be two sets of driving population estimates displayed as a percentage of the entire

driving population. One estimate will be based upon the variable that identified the commuting

practices for each county and the other estimate will be based upon the variable that represented

the residents' access to cars. For example, based upon the commuting practices of the residents, one county may have an estimate that 60% of the drivers are white, 30% are African American, and 10% are of another race. However, based upon the residents' access to cars, the same county may estimate that 65% of the drivers are white, 25% are African American, and 10% are of another race. These estimates will then be compared against one another, and also against the overall Census population figures. The goal of these comparisons is not to validate the estimations, but rather to determine whether the estimation method is plausible. It is well known that the original Census data are inaccurate, and thus, these estimates must be noticeably different or they too are obviously inaccurate. The comparison of the estimates to each other will be utilized to look for differences between the predictions and identify which CTPP variable, if either, can be used to accurately predict the driving population. This method of estimation will later be tested against an already existing data set of traffic stops in North Carolina to attempt to validate the estimate.

4.2.2 Limitations of the CTPP

While numerous researchers do believe that commuting population figures are a fairly accurate predictor of the overall driving population, there are two main limitations to utilizing the Census Transportation Planning Package. First, the data are taken for all workers within a given county. Only people that have been employed for the last calendar year are included in each county's total population. This means that young drivers and those that have been unemployed are not included in the calculations even though they may have access to cars. This could mean that minority drivers will be underrepresented in the population estimates, as they have a higher unemployment rate (Bureau of Labor Statistics, 2007). It also means that tourists will not be

accounted for in the estimations. In some counties where there are large tourist populations, or seasonal travelers, the estimations could be distorted from the actual driving population. Second, there is the issue that this survey data is only taken once every ten years. For the purposes of this research, the 2000 Census survey will be utilized to evaluate data that was taken during the first half of 2001. The issue of the data being stale and inaccurate will most likely not be a factor in this research. In the future, however, when data are used several years after the initial survey year, projections will have to be made to update the population estimations.

4.3 Analysis of the Population Estimates

After analyzing the CTPP data and creating the transient travel population estimates, an already existing data set will be utilized to attempt to test the accuracy of the estimation methods. The previously mentioned study conducted by Smith et al. in 2004, will serve as the test data. The researchers collected and analyzed traffic stop data for the North Carolina State Highway Patrol from 2000 to 2001. Data collected from January to July of 2001 will be the main focus of this research. This data set contains information of more than 330,000 traffic stops. The data will be analyzed by county and utilized not only to test the estimation method, but also to evaluate whether it appears that any type of racial profiling occurred during the time period.

The major limitation in testing the estimation method will be that there is no true way to prove the method is 100% accurate. Generally, observational research would be conducted to test the estimations, but this research is far too costly to conduct for all 100 counties in North Carolina. Thus, a different method will be used to assess the validity of the estimation method. As was previously mentioned, the analysis of police searches and hit rates are an effective method of

analyzing racial profiling. The main advantage to this method is that it can identify racial profiling practices without an estimate of the transient travel population. In this research, it will not only be used to identify counties that may be practicing racial profiling, but also test the accuracy of the methods utilized to create the transient travel population estimates. Utilizing these estimates as benchmarks, the traffic stop data will help to identify a list of counties that show some evidence of racial profiling. In other words, these are counties in which there are considerable differences between the characteristics of drivers stopped and the estimates of the driving population. Simultaneously, search rate analysis, independent of the driving population, will be used to create a second list of counties that show evidence of racial profiling in police search practices. It is believed that racial profiling in traffic stops and racial profiling in police searches have the same underlying motivations. For this reason, the two lists of county level data will be compared to look for similarities. If the driving population estimates are accurate, the lists should identify many of the same counties.

4.3.1 Racial Profiling and the NCSHP Data

Unlike many police departments, the North Carolina State Highway Patrol did not begin to collect traffic stop data and examine racial profiling to meet the mandates of a consent decree. The data collection process began, rather, because of state legislation that was passed in 1999. This legislation was brought about partly by several news articles that were run in the Raleigh News and Observer in both 1996 and 1999. The articles focused on the practices of the Criminal Interdiction Team (CIT). The 1996 article claimed that the CIT stopped and ticketed black male drivers at about twice the rate of all other troopers (Neff and Smith, July 28, 1996). The article from 1999 also stated that the black drivers were twice as likely as white drivers to have their

cars searched by the CIT (Neff, February 19, 1999). Following the publishing of these articles, State Senator Frank Balance and State Representative Ronnie Sutton, along with members of the American Civil Liberties Union (ACLU) introduced a bill that required state law enforcement officers to collect certain demographic data for all traffic stops. According to the legislation, officers are required to collect the race and/or ethnicity, age, and gender of the driver, the reason for the stop, the type of action that was taken, whether there was any resistance from the driver, and finally, whether a search was conducted. Other, more detailed data must also be collected if a search is conducted.

While traffic stop data have been collected by the NCSHP since 1999, it was not until 2004 that researchers released an in-depth, final report on their overall analysis of the NCSHP. Along with the final report, statewide data became publicly available on stops that had been made in 2001. As previously stated, part of this data set will be utilized to test the validity of the driving population estimates. While these data have many different variables including time of stop, reason for stop, officer action, race of driver, and approximate location of stop, only some of the variables will be utilized in this analysis. The main focus will be on the race and ethnicity of the driver for each stop that was made. The data will be analyzed at the county level, and similar to the driving population estimates, the stops will be turned into percentages based upon the race and ethnicity of the driver. For example, if 5,000 stops were made in a given county and 2,500 of them were of African American drivers, 1,500 were of white drivers, and 1,000 were drivers of another race; then the data would show that 50% of the stops were of African Americans, 30% were of whites, and 20% were of other races. Similar to the previously mentioned formulas, the following formulas will be utilized:

 $\frac{S_{1,2,3,4,5}}{T} * 100 = \%$ Race/Ethnicity Stopped

 S_1 = Number of White Drivers Stopped S_2 = Number of African American Drivers Stopped S_3 = Number of Drivers of Some Other Race Stopped S_4 = Number of Hispanic Drivers Stopped S_5 = Number of Non-Hispanic Drivers Stopped T = Total Number of Stops within Each County

These data can then be directly compared with the driving population estimates to assess whether it appears that officers within a given county appear to be practicing some type of racial profiling. If a county displays notable differences between their stop data and population estimates, the county will be identified as potentially problematic and will later undergo more detailed analysis. This analysis will help to examine the apparent disparity more closely.

To assist in the validation of the estimation procedures, analyses will also be conducted on all of the stops that resulted in police searches. This analysis will begin with an examination of all searches that were made in each county. The searches will also be turned into a percentage based upon the race and ethnicity of the driver. The percentages will represent the proportion of the total searches that were conducted for each race and ethnicity category. For example if 20 searches were conducted in a given county and 15 were of white drivers, 3 were of African American drivers, and 2 were of drivers of some other race; the data would show that 75% of the searches were of white drivers, 15% were of African American drivers, and 10% were of drivers of some other race. In order to calculate these percentages the following formula will be used:

 $\frac{C_{1,2,3,4,5}}{P} * 100 = \%$ Race/Ethnicity Searched

 C_1 = Number of White Drivers Searched C_2 = Number of African American Drivers Searched C_3 = Number of Drivers of Some Other Race Searched

C_4 = Number of Hispanic Drivers Searched C_5 = Number of Non-Hispanic Drivers Searched P = Total Number of Police Searches within Each County

These percentages can then be compared with the original stop data for each county. If a county is searching all races at roughly the same rate, then the search percentages for each race should be equal to the stop percentage of that particular race. In other words, if 70% of a county's stops are of white drivers, and 30% are of African American drivers, then 70% of their searches should be of whites, and 30% should be of African Americans. This would mean that both races are being searched at the same rate. When an obvious difference appears between these percentages, then the department must be searching one race at a higher rate than the other. Researchers Steward and Totman (2005) state that evaluating all police searches, whether discretionary or non-discretionary is a valid initial step that can be utilized to identify counties where racial profiling may be occurring.

After these percentages are calculated and compared with the stop data, counties will be identified where there is evidence of racial profiling. Counties that are found to have notable differences between the stop and search percentages will be identified as potential problem areas. There will be one additional factor that will be examined when determining which counties are potential problem areas. The number of searches is substantially lower than the total number of stops (2,932). Thus, some counties have very few searches that were conducted in the county. For this reason, any county that has had fewer than ten searches conducted during the time period will be ruled inconclusive. This is because having low search numbers will be sensitive to random error and could be very misleading. An example would be a county that has conducted two searches. If all searches were of African Americans, this county would most likely be

identified as a potential problem area. With only two searches, however, it is unreasonable to conclude that the officers were profiling African Americans. The data simply are not strong enough to support this conclusion.

This second list of potential problem areas will serve to help in the validation of the driving population estimates that were created for the police stop analysis. As previously stated, the advantage to search rate analysis is that is does not require the generation of driving population figures to identify areas that are practicing racial profiling. In order to test the accuracy of the driving population estimates that were made, the two lists of potential problem counties will be compared. If the driving population estimates are accurate, then the two lists should contain a great deal of overlap. Counties which were identified as profiling based upon stop rates should also be identified based upon the search rates. Correlations will also be done between the two lists to test whether the counties with high levels of profiling in stops have a statistically significant association to counties with high levels of profiling in police searches.

Correlation Coefficient =
$$\frac{\sum (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum (x_i - \overline{x})^2 \sum (y_i - \overline{y})^2}}$$

where x = % Difference in Stop Rates and y = % Difference in Search Rates

4.3.2 Analysis of 'Problem Areas' in North Carolina

Areas which have been identified as 'potential problem areas' in the stop analysis will undergo a more detailed examination in an attempt to identify whether there is in fact evidence of racial profiling. In order to conduct this analysis two other variables will be examined for these counties. The two variables relate specifically to all of the stops that were made in each county.

The variables are the officer's reason for making the traffic stop and the officer's action following the stop. Ideally the counties that were identified as potentially problematic from the search analysis would be examined more closely as well. As stated previously, hit rate analysis is generally utilized when dealing with police searches. Unfortunately the time frame during which the data were collected did not have a substantial amount of searches, thus making hit rate analysis very weak and inconclusive.

There are nine 'stop purposes' in the data set: driving while impaired, investigation, safe movement violation, seat belt violation, stop light/sign violation, vehicle equipment violation, vehicle regulatory violation, other moving violation, and speeding. There are five possible courses of action that an officer may take: arrest, citation, no action, verbal warning, and written warning. Each variable and its possible alternatives will be examined by race and ethnicity. Once again, percentages will be used for easier comparison. In this case, however, the interest is in how one's race or ethnicity affects the treatment they receive from the police. In other words, are the police officers consistent across race in their reasons for making traffic stops and the actions they take following a stop?

There are a few specific patterns in the data that are believed to be important indicators of racial profiling. One indicator is the use of 'investigations' or 'other moving violations' as an officer's reason to make a stop. These types of stops, which are made at the officer's discretion, generally make up a low percentage of the total number of stops and are ambiguous to the type of infraction that occurred to warrant a stop. Thus, if minorities show considerably higher rates for these types of stops, it is believed the officers are utilizing race and/or ethnicity to determine

when stops should be made. Another indicator of profiling has to do with the officer's actions following a stop. If a minority driver is much more likely than a white or non-Hispanic driver to receive a ticket as opposed to a written warning, the officers would appear to be either showing favoritism to the white and non-Hispanic drivers or acting more harshly to minority drivers. Once again, the officer has the discretion to give the driver a citation or warning. Drivers of any race should be equally likely to receive a written warning instead of a citation.

While these results cannot definitively answer the question as to whether racial profiling is occurring, they can help to examine more closely counties that have been identified as potential problem areas. Simply comparing the stop data with driving population estimates is not enough on its own, but it is a good way to identify these potentially problematic counties. The more indepth analysis allows a closer look at the police officer behavior which could help to explain the disparities. The major goal of this in-depth analysis is to examine whether there is evidence of racial profiling in the counties which have been labeled as potentially problematic. Evidence of profiling in counties that were identified would suggest that the identification methods that were utilized are accurate.

4.3.3 Limitations of NCSHP Data

There are several limitations to utilizing the North Carolina State Highway Patrol data. The first is a problem that is very common when collecting and examining racial profiling data. The individual police officers that are making the traffic stops are the collectors for all of the data. The officers are responsible for recording the race and ethnicity of the driver of the car. Generally, they are not asking the driver to identify their own race, like the Census does, but

rather they are using their own judgment on where they believe this person belongs. While this generally is not a problem that causes large errors in data analysis, it could cause some researchers to overlook an area which may in fact be practicing racial profiling.

The second limitation to utilizing this data is that the author is limited by what data was collected and made publicly available. The original researchers made the initial decisions about what variables to collect and how they would record this data. The final limitation of the data is that the stop location was only recorded by the county where the stop was made. The original plan of the researchers was to have geographic locations that corresponded to each stop. In the end, there were very few cases that had more detail about the location than the county. This meant that the county was the smallest spatial unit that could be used for analysis. This does not prohibit the overall analysis, but it does make it impossible to examine major metropolitan areas more closely. These metropolitan areas are important because they may have different population demographics than the rest of the surrounding county.

4.4 Hypotheses

Researchers have been attempting for years to create general evaluation methods that can help to identify police departments that are practicing racial profiling in traffic stops. Though many different methods have been tested, most of them are either so specific that the method can only be used on the police department for which it was designed, or so involved that it requires a great deal of time and resources. The major issue in racial profiling evaluation techniques has always been how to benchmark the traffic stop data. Many complex methods have been developed and shown to be accurate, but the issue is once again having the available time and resources. The

author has attempted to identify a universal method of evaluation that relies on publicly available Census survey data for benchmarking. This method will be much more straightforward than previous evaluation methods and require less time and resources. Thus, for this thesis I make the following hypotheses:

Hypothesis 1- The driving population estimates that are created utilizing the Census Transportation Planning Package will be notably different than the original Census data.

Hypothesis 2- There will be a great deal of overlap in the lists of problem counties that were identified using the CTPP benchmark and the search rate analysis indicating that utilizing the CTPP is an accurate method of estimation.

Hypothesis 3- Counties identified as being potentially problematic in stops will show that minority drivers are considerably more likely than whites and non-Hispanics to be stopped for discretionary reasons, such as 'investigations' and 'other moving violations.'

Hypothesis 4- Counties identified as being potentially problematic in stops will show that minority drivers are considerably less likely than whites and non-Hispanics to receive written warnings and more likely to receive citations.

5. Results and Findings

5.1 CTPP Census Estimates

5.1.1 Race

The two variables that were taken from the Census Transportation Planning Package (mode of transportation to work and access to a car) were thoroughly compared, county by county, in an attempt to identify which variable, if either, would be a more accurate predictor of the transient travel population (See Appendix A). Overall, both variables were found to have very similar results. Within each county there was generally about a 1% or less difference between the two variables' predictions. For example in Chatham County, the mode of transportation to work variable estimates the driving population to be 78.8% white, 14.3% African American, and 6.9% some other race. The car availability variable estimates the population to be 79.5% white, 13.5% African American, and 7.0% some other race. This shows that the car availability variable estimates the white population to be a slightly larger portion of the overall driving population while the minority population is slightly less. This pattern is consistent in nearly all of the remaining 99 counties.

In the end, the overall estimates for the entire state of North Carolina are very close. The estimates based upon the mode of transportation variable are 76.5% white, 17.8% African American, and 5.7% some other race. The estimates based upon the car availability variable are 77.2% white, 17.2% African American, and 5.6% some other race. While both variables appear consistent in their predictions, ultimately the car availability variable was chosen as the benchmark to be used for the police stop data. There was one main reason this variable was chosen, and that is because this variable was much more general than the mode of transportation

variable. The underlying question for this variable was whether individuals have cars available for their own personal everyday use. The question was not specific to whether they were utilizing this car to get to and from work. The mode of transportation variable was specifically aimed at gathering a person's commuting practices.

5.1.2 Ethnicity

After examining the ethnicity population estimates for each county and for the overall state, it was noticed that the two methods of prediction were even closer in value than the race statistics (See Appendix B). This could be due to the fact that the overall Hispanic population is very small in North Carolina. While there are some counties that are around the national average of 12.5%, most of the counties are well below this percentage. The overall Hispanic population for the entire state according to the 2000 Census is only 4.63%. The prediction of the overall Hispanic driving population according to the mode of transportation to work variable is 4.31%. Based upon the availability of a car variable, the estimated Hispanic driving population is 4.18%. Despite having such a small difference between the two predictions, the car availability prediction is still believed to be the more accurate choice for the previously mentioned reasons. Thus, the estimates of the Hispanic driving population from the car availability variable will be utilized rather than the estimates from the mode of transportation variable.

5.2 Original Census Data versus Car Availability Data

5.2.1 Race

As stated previously, past researchers have shown the basic Census statistics to be inaccurate at estimating the driving population. Researchers have also shown that, despite being slightly more

accurate than the basic census data, the census figures for all people over the age of 16 are also inaccurate. Thus, in order for the CTPP estimation methods to be considered at all, they must show noticeable quantitative differences from the Census statistics for everyone over the age of 16. After selecting the population estimates made from the car availability variable, a general comparison with the original census data does show several important differences (See Appendix C). First, the overall population percentages have changed substantially for the white and African American populations. The percent white population has changed from 74.1% in the 16 and older census data, to 77.2% in the car availability data. The African American population has changed from 20.2% to 17.2%. Finally, the other race population, though it has changed only slightly, has gone from 5.7% to 5.6%.

While the entire state shows only a 3.1% increase in the white population percentage, some of the counties have a much more noticeable difference. In Hyde County, for example, the white population has changed from 65.0% to 77.2%, and the African American population has changed from 33.7% to 20.5% of the total driving population. While not all of the counties have large differences in the two population figures, very few of the 100 counties have had virtually no change. Most all show an increase in their percent white demographic and a decrease in both the African American and people of other race demographics.

5.2.2 Ethnicity

Similar to the previous population comparison of the two CTPP variables, there is virtually no difference between the Hispanic figures from the two population estimates (See Appendix D). The original census data shows a Hispanic population of 4.24% of the overall state population

that is 16 and older, while the new estimate shows a Hispanic population of 4.18%. Nearly all of the counties show no difference in their figures from the census data to the driving population estimate. As stated previously, this could be a result of the very small Hispanic population in North Carolina. It could also indicate that the original census data may be a fairly accurate estimate of the driving population, or that utilizing the CTPP is a poor estimate of the Hispanic driving population.

5.3 Transient Travel Population versus NCSHP Traffic Stops

5.3.1 Race

The analysis of the individual traffic stops made by the North Carolina State Highway Patrol had two goals: to identify 'potential problem counties' where racial profiling may have occurred and to assess whether the CTPP driving population estimates are accurate enough to benchmark racial profiling data. In order to identify these potential problem areas based upon race of the driver, the population estimates were cross-referenced with the stop data and a standard was set at 10%. In other words, if whites are found to be stopped at a rate that is 10% less than their population estimate, then the county is identified as a potential problem area. A difference in the white population percentage that is greater than 10% means that the minority population (African American and Other combined) has been stopped at a notably higher rate than their representation in the population estimate. The overall data for the state (See Table 2) shows that, for the state as a whole, whites are stopped at a rate that is about 8% less than their population estimate. While there is a disparity between the population estimate and stop percentage, it is not over the 10% standard. Thus, it is not believed that the entire state of North Carolina has a racial profiling issue, only a select number of counties.

	Total Number of Stops White Drivers	Pop. Est. by Car Av. White Drivers	Stop Percentage White Drivers	Pop. Est Stop Per. White Drivers
North Carolina State Totals	332,538	77.24%	69.56%	7.68%

 Table 2: North Carolina White Driving Population Estimate versus White Stop Percentage

There were 11 counties that were identified as having a greater percentage of white stops than the population estimate (See Table 3). Based upon the total number of stops in these counties and the small differences between the population estimates and the stop percentages, it was not believed that any of these counties were racially profiling white drivers. One of these 11 counties (Swain) did have differences between the stop percentages and population percentages that were greater than 10%, however, it was disregarded as it was believed to be an effect of having a small number of stops (556 total stops; 488 white stops, 10 African American stops, and 58 'Other' stops).

County Names	Total Number of Stops All Drivers	Pop. Est. by Car Av. White Drivers	Stop Percentage White Drivers	Pop. Est Stop Per. White Drivers
Cherokee	520	93.96%	96.35%	-2.39%
Forsyth	8112	73.69%	74.12%	-0.44%
Graham	360	91.08%	94.17%	-3.08%
Jackson	2280	87.85%	91.27%	-3.43%
Jones	1037	65.94%	74.73%	-8.80%
Pasquotank	2346	67.28%	67.90%	-0.62%
Robeson	5857	39.38%	41.18%	-1.80%
Swain	556	72.12%	87.77%	-15.65%
Tyrrell	1014	70.45%	74.26%	-3.81%
Warren	1585	45.32%	46.44%	-1.11%
Washington	1775	56.02%	59.66%	-3.64%

Table 3: Counties with White Stop Percentage Greater than White Population Estimate

There were 30 counties where the white stop percentage was within 5% below the driving population (See Table 4). This means that minorities were stopped at a slightly disproportional rate to their population estimate. These differences could be the result of several factors including having a limited time frame which the stops were recorded, or simply that the driving populations are off slightly.

County Names	Total Number of Stops All Drivers	Pop. Est. by Car Av. White Drivers	Stop Percentage White Drivers	Pop. Est Stop Per. White Drivers
Alexander	1610	93.65%	88.94%	4.71%
Ashe	1034	97.71%	95.94%	1.78%
Avery	701	97.12%	94.86%	2.25%
Bertie	1522	47.67%	44.15%	3.52%
Buncombe	6272	91.21%	90.74%	0.48%
Burke	2419	89.73%	88.26%	1.47%
Caldwell	2621	93.51%	92.18%	1.33%
Catawba	7714	87.98%	83.33%	4.65%
Chowan	1517	67.31%	63.61%	3.70%
Clay	378	98.35%	97.88%	0.47%
Columbus	4491	72.10%	68.78%	3.32%
Craven	4654	74.91%	72.24%	2.67%
Cumberland	8296	60.24%	57.03%	3.22%
Currituck	1734	91.83%	87.77%	4.05%
Dare	2122	95.30%	92.79%	2.51%
Edgecombe	3774	49.36%	48.22%	1.14%
Guilford	10922	69.34%	65.76%	3.59%
Hertford	2202	47.74%	43.87%	3.87%
Iredell	5287	85.77%	82.22%	3.55%
Lenoir	4297	64.59%	61.86%	2.73%
McDowell	3344	93.44%	90.82%	2.62%
Macon	938	97.43%	93.60%	3.83%
Mitchell	655	96.73%	95.27%	1.46%
New Hanover	4120	85.21%	81.80%	3.42%
Onslow	7172	76.11%	75.31%	0.81%
Stokes	2530	94.38%	90.55%	3.83%
Transylvania	1100	94.13%	93.36%	0.76%
Watauga	2148	96.89%	96.42%	0.48%
Wilkes	3859	93.91%	91.60%	2.30%
Wilson	3642	65.13%	60.79%	4.34%

 Table 4: Counties where White Stop Percentage was within 5% below White Population Estimate

Out of the 100 counties, 34 were found to have a white stop percentage between 5% and 10% below the white driving population (See Table 5). Once again, minorities are stopped at a disproportional rate to their representation in the driving population. As was previously stated, there are many possible explanations for these slight differences, not all of which relate to racial profiling. It is not believed that this marginal evidence of profiling will lead to the identification of counties with serious racial profiling issues. Therefore, these counties will not be examined any closer, and counties with even larger disparities in their stop practices will be studied.

County Names	Total Number of Stops All Drivers	Pop. Est. by Car Av. White Drivers	Stop Percentage White Drivers	Pop. Est Stop Per. White Drivers
Alleghany	1038	95.51%	88.82%	6.68%
Bladen	4587	65.03%	56.64%	8.39%
Brunswick	3174	83.95%	77.10%	6.86%
Camden	1210	83.82%	76.94%	6.88%
Carteret	4525	91.41%	85.10%	6.31%
Caswell	1272	69.19%	59.51%	9.67%
Davie	4494	91.24%	83.64%	7.60%
Duplin	4521	66.39%	56.40%	9.99%
Durham	5781	57.35%	51.43%	5.92%
Greene	1934	60.84%	54.71%	6.13%
Halifax	4096	53.88%	44.80%	9.08%
Haywood	3771	97.07%	90.19%	6.88%
Henderson	2661	92.40%	85.08%	7.31%
Hyde	789	77.18%	69.96%	7.21%
Lincoln	2703	92.56%	87.24%	5.33%
Madison	1385	98.49%	93.14%	5.35%
Martin	1740	63.69%	58.28%	5.41%
Mecklenburg	7935	69.35%	60.58%	8.77%
Nash	5836	69.15%	60.33%	8.81%
Northampton	1784	50.34%	41.76%	8.58%
Pamlico	608	81.92%	72.53%	9.39%
Pender	4925	80.20%	74.64%	5.56%
Person	2052	74.90%	65.98%	8.91%
Pitt	4579	71.08%	61.11%	9.98%
Polk	1701	93.19%	85.24%	7.94%
Rockingham	5313	81.53%	73.12%	8.40%

 Table 5: Counties where White Stop Percentage was between 5% and 10% below White Population Estimate

Rutherford	1598	90.53%	84.86%	5.67%
Scotland	2366	61.00%	51.65%	9.35%
Stanly	2930	88.92%	83.34%	5.58%
Surry	2269	92.31%	87.09%	5.23%
Vance	2535	58.20%	49.66%	8.53%
Wayne	5446	68.43%	59.40%	9.02%
Yadkin	2309	94.79%	86.96%	7.83%
Yancey	1227	98.18%	92.75%	5.43%

Finally, there were 25 counties that had white stop percentages that were more than 10% below their driving population estimates (See Table 6). This means that minority drivers are being stopped at a disproportionately high rate compared with their representation in the population. While there could be some underlying factors, outside of racial profiling, that explain these differences, there is definitely a need to more closely examine these extreme cases. Further analysis of detailed stop information should help to explain whether these disparities are happening for other factors or whether officers are practicing racial profiling. Figure 1 displays a graph that summarizes the different groups of counties that were found through stop analysis by race.

County Names	Total Number of Stops White Drivers	Pop. Est. by Car Av. White Drivers	Stop Percentage White Drivers	Pop. Est Stop Per. White Drivers
Alamance	4231	78.48%	66.08%	12.40%
Anson	1817	59.24%	48.16%	11.08%
Beaufort	4138	78.23%	66.43%	11.80%
Cabarrus	4953	87.10%	76.72%	10.38%
Chatham	3156	79.46%	58.68%	20.78%
Cleveland	3711	81.28%	70.71%	10.58%
Davidson	5999	89.40%	76.01%	13.38%
Franklin	1914	73.41%	56.74%	16.67%
Gaston	7490	86.61%	74.70%	11.91%
Gates	1063	65.33%	51.08%	14.25%
Granville	3665	69.03%	54.95%	14.08%
Harnett	4495	76.99%	63.11%	13.88%

 Table 6: Counties where White Stop Percentage was greater than 10% below White Population Estimate

Hoke	2163	53.20%	33.29%	19.91%
Johnston	5623	83.25%	66.83%	16.42%
Lee	2013	75.20%	61.15%	14.05%
Montgomery	1866	77.79%	62.59%	15.19%
Moore	2848	83.05%	70.19%	12.86%
Orange	3460	81.91%	62.80%	19.11%
Perquimans	1673	77.65%	66.17%	11.48%
Randolph	2539	91.15%	79.64%	11.52%
Richmond	2655	73.05%	59.89%	13.16%
Rowan	4902	84.12%	71.11%	13.01%
Sampson	5207	67.45%	49.34%	18.11%
Union	4300	86.96%	70.49%	16.48%
Wake	13046	76.30%	66.14%	10.15%

Figure 1:

County Travel Populations versus NCSHP Traffic Stops by Race



5.3.2 Ethnicity

Due to the very small Hispanic population in North Carolina, the stop data based on ethnicity were examined individually in an attempt to develop a different standard than the 10% which

was utilized in the stop analysis by race. After cross-referencing the Hispanic stop percentages and the estimated Hispanic driving populations, a standard was set at 2%. This standard was determined because the Hispanic population only accounts for an estimated 4.18% of the driving population. A 2% disparity in traffic stops is a noteworthy sign that some type of profiling is occurring. Counties where Non-Hispanics are found to be stopped at a rate that is 2% less than their population estimate were identified as potential problem counties. This difference in Non-Hispanic stop percentage would imply that Hispanics are being stopped at a considerably higher rate than their representation in the population. Once again upon examining the overall state statistics, it does not appear that racial profiling is a problem for all counties (See Table 7). When comparing the population estimates with the stop percentages there is only a difference of 0.73%, well below the 2% standard.

 Table 7: North Carolina Non-Hispanic Driving Population Estimate versus Non-Hispanic Stop Percentage

	Total Number of Stops All Drivers	Pop. Est. by Car Av. Non- Hisp. Drivers	Stop Percentage Non-Hisp. Drivers	Pop. Est Stop Per. Non- Hisp. Drivers
North Carolina State Totals	332,538	95.82%	95.09%	0.73%

With the standard set at 2%, a county by county comparison showed that there were 19 potential problem counties (See Table 8). 8 of the 19 counties identified had Non-Hispanic stop percentages that were more than 3% below their driving population estimates. The largest difference between the Non-Hispanic driving population estimate and the stop percentage is 9.07% in Sampson County. In general, the other 81 counties were around a 1% difference between the Hispanic stop percentage and the population estimate. Unlike the previous stop data

based upon race, there were many counties that had negative values because the Non-Hispanic stop percentage was greater than the population estimate. There were two counties (Bladen and Onslow) that were found to have negative values that were greater than 2% (-3.54% and -2.47% respectively). These counties are not believed to be profiling white drivers, however, as these differences, though substantial when compared to the overall Hispanic population (4.18%), are negligible when compared with the overall Non-Hispanic population (95.82%). These small differences could also mean that the driving population estimates are simply incorrect in these counties (See Appendix E). Figure 2 displays a graph that summarizes the different groups of counties that were found through stop analysis by ethnicity.

County Names	Total Number of Stops All Drivers	Pop. Est. by Car Av. Non- Hisp. Drivers	Stop Percentage Non-Hisp. Drivers	Pop. Est Stop Per. Non- Hisp. Drivers
Alleghany	1038	95.10%	92.00%	3.09%
Anson	1817	99.57%	96.81%	2.76%
Avery	701	98.23%	95.58%	2.65%
Chatham	3156	90.96%	85.90%	5.06%
Cleveland	3711	99.02%	97.01%	2.01%
Davidson	5999	97.17%	94.55%	2.62%
Durham	5781	93.10%	90.36%	2.73%
Henderson	2661	94.33%	91.58%	2.75%
Hoke	2163	92.79%	87.75%	5.04%
Johnston	5623	95.21%	90.15%	5.06%
Lenoir	4297	97.30%	94.79%	2.51%
Pitt	4579	97.29%	94.80%	2.49%
Randolph	2539	94.55%	92.44%	2.11%
Robeson	5857	95.40%	93.26%	2.14%
Rockingham	5313	97.53%	94.45%	3.08%
Sampson	5207	91.38%	82.31%	9.07%
Washington	1775	98.69%	95.38%	3.31%
Wayne	5446	95.63%	88.12%	7.51%
Yancey	1227	96.50%	93.97%	2.53%

 Table 8: Counties where Non-Hispanic Stop Percentage was greater than 2% below Non-Hispanic Population Estimate





County Travel Populations versus NCSHP Traffic Stops by Ethnicity

5.4 NCSHP Traffic Stops versus Searches

5.4.1 Race

In an attempt to validate the transient travel population estimates that were made for the previous analysis, a different technique was utilized to generate a list of potential problem counties. All searches conducted by the NCSHP were examined and compared with the overall traffic stop data. Similar to the previous methods of the traffic stop analysis by race, a standard was once again set at 10%. Any county (with more than ten searches) which had a difference between the white stop percentage and the white search percentage that was greater than 10% was identified as a potential problem county. This method of evaluation produced a list of 33 problem counties. There was also one county (Hoke) which had a negative value that was greater than 10 away from the stop percentage (-11.16). Once again, it is not believed that officers in this county are
profiling white drivers, but rather that this could be a result of having relatively few searches in Hoke County (18 total searches). The overall state percentages were also examined. They appear to show that racial profiling in police searches is evident for North Carolina as a whole, as the difference between white stop percentage and white search percentage is 14.92% (See Tables 9 and 10- Other Counties in Appendix F). A pie chart that displays the breakdown of all 100 county comparisons is displayed in Figure 3.

Table 9: North Carolina White Search Percentage versus White Stop Percentage

	Total Number of Searches All Drivers	Stop Percentages White Drivers	Search Percentage White Drivers	Stop Per Search Per. White Drivers
North Carolina State Totals	2,932	69.56%	54.64%	14.92%

 Table 10: Counties where White Search Percentage was greater than 10% below White

 Stop Percentage

County Names	Total Number of Searches All Drivers	Stop Percentages White Drivers	Search Percentage White Drivers	Stop Per Search Per. White Drivers	
Alamance	17	66.08%	52.94%	13.14%	
Beaufort	53	66.43%	30.19%	36.24%	
Chatham	27	58.68%	25.93%	32.76%	
Craven	26	72.24%	50.00%	22.24%	
Davidson	60	76.01%	51.67%	24.35%	
Davie	19	83.64%	57.89%	25.75%	
Duplin	94	56.40%	56.40% 25.53%		
Durham	73	51.43% 32.88%		18.55%	
Edgecombe	28	48.22%	28.57%	19.65%	
Granville	25	54.95% 28.00%		26.95%	
Halifax	15	44.80%	26.67%	18.13%	
Harnett	19	63.11%	52.63%	10.48%	
Iredell	38	82.22%	68.42%	13.80%	
Johnston	227	66.83%	53.30%	13.53%	
Lee	13	61.15%	46.15%	15.00%	
Lenoir	56	61.86%	46.43%	15.43%	
Mecklenburg	54	60.58%	50.00%	10.58%	

Montgomery	14	62.59%	28.57%	34.02%
Onslow	134	75.31%	63.43%	11.87%
Pender	42	74.64%	50.00%	24.64%
Pitt	19	61.11%	47.37%	13.74%
Randolph	11	79.64%	45.45%	34.18%
Rockingham	43	73.12%	48.84%	24.29%
Rowan	23	71.11%	56.52%	14.59%
Sampson	70	49.34%	35.71%	13.62%
Scotland	112	51.65%	36.61%	15.04%
Stokes	15	90.55%	73.33%	17.22%
Tyrrell	20	74.26%	40.00%	34.26%
Union	66	70.49%	57.58%	12.91%
Wake	28	66.14%	46.43%	19.71%
Washington	22	59.66%	27.27%	32.39%
Wayne	71	59.40%	46.48%	12.92%
Yadkin	12	86.96%	66.67%	20.30%

Figure 3:





 Number of Counties where White Search Percentage was Greater than 10% below White Stop Percentage
 Number of Counties where Less than 10 Searches were Conducted
 Number of Counties where White Search Percentage was Less than 10% below White Stop Percentage
 Number of Counties where White Search Percentage was Greater than White Stop Percentage

5.4.2 Ethnicity

As previously stated, a major advantage to conducting search rate analyses is that there is no need to generate driving population statistics. In this case, not having to calculate a driving population means that there is no need to worry about how small the Hispanic population is. Thus, this allows for the use of the same rule which was utilized to conduct the analysis of search rates by race. Any county (with more than ten searches) which had a difference between the Non-Hispanic stop percentage and the Non-Hispanic search percentage that was greater than 10% was identified as a potential problem county. This method generated a list of 26 counties where racial profiling appeared to be occurring based on the ethnicity of the driver. The overall state statistics, similar to the search analysis by race, show that North Carolina as a whole has racial profiling present based upon the ethnicity of the driver. The difference of 10.10%, though not as large as that of the search analysis by race, is still greater than 10% (See Tables 11 and 12-Other Counties in Appendix G). The overall breakdown of all 100 counties is shown in Figure 4.

 Table 11: North Carolina Non-Hispanic Search Percentage versus Non-Hispanic Stop

 Percentage

	Total Number of Searches All Drivers D		Search Percentage Non-Hisp. Drivers	Stop Per Search Per. Non-Hisp. Drivers	
North Carolina State Totals	a 2,932 95.09%		84.99%	10.10%	

County Names	Total Number of Searches All Drivers	Stop Percentages Non-Hisp. Drivers	Search Percentage Non-Hisp. Drivers	Stop Per Search Per. Non-Hisp. Drivers
Alamance	17	93.38%	70.59%	22.79%
Beaufort	53	95.60%	77.36%	18.24%
Brunswick	14	96.53%	85.71%	10.82%
Burke	11	98.26%	81.82%	16.45%
Cabarrus	38	95.30%	84.21%	11.09%
Chatham	27	85.90%	44.44%	41.46%
Duplin	94	83.59%	64.89%	18.69%
Durham	73	90.36%	57.53%	32.83%
Forsyth	63	92.75%	82.54%	10.21%
Guilford	223	95.43%	83.86%	11.57%
Harnett	19	94.26%	68.42%	25.84%
Lee	13	87.88%	69.23%	18.65%
Lenoir	56	94.79%	82.14%	12.64%
Montgomery	14	91.59%	78.57%	13.01%
Pitt	19	94.80%	73.68%	21.12%
Randolph	11	92.44%	63.64%	28.80%
Rockingham	43	94.45%	67.44%	27.01%
Sampson	70	82.31%	68.57%	13.74%
Tyrrell	20	95.76%	75.00%	20.76%
Union	66	93.12%	81.82%	11.30%
Wake	28	93.50%	82.14%	11.36%
Warren	21	97.60%	85.71%	11.89%
Washington	22	95.38%	59.09%	36.29%
Wayne	71	88.12%	70.42%	17.70%
Wilson	37	92.94%	70.27%	22.67%
Yadkin	12	94.20%	75.00%	19.20%

Table 12: Counties where Non-Hispanic Search Percentage was greater than 10% below Non-Hispanic Stop Percentage

Figure 4:

NCSHP Traffic Stops versus Searches by Ethnicity



5.5 Validation of CTPP Population Estimates

5.5.1 Race

To validate the driving population estimation method utilized in the traffic stop analysis, the two lists of counties that were generated by analyzing stop and search data based upon race were compared to look for counties that had been identified on both lists. The result was that 14 of the original 25 counties that were identified in the stop analysis by race were listed again on the search analysis by race list. Of the 11 counties that were on the traffic stop list but not the search list, five counties were dismissed because they had less than ten searches conducted. This meant that only six counties from the original list of 25 counties were not included in the search analysis list because they did not appear to have racial profiling occurring in police searches.

In addition to simply comparing the two lists that were generated, a correlation analysis using Pearson's r was also done to assess whether there is a relationship between stop profiling and search profiling based upon race. Indexes were calculated in the same manner that was used to generate the two problem county lists and then the correlation analysis was done for all 100 counties. The theory was that if the stop rate had a high profiling index then the search rate would also show a high profiling index. No strong correlation was found between the two variables. The correlation coefficient was 0.15 and was not found to be significant (See Appendix H).

5.5.2 Ethnicity

Another simple comparison between the two lists that were generated by examining stop and search data based on ethnicity was conducted to look for similarities. Out of the 19 counties that were originally identified in the stop analysis by ethnicity, nine were listed again on the search analysis by ethnicity list. Out of the ten counties that were not listed again, five had been dismissed from the search analysis because they had fewer than ten total searches. This left five counties that were not on the search list despite having more than ten searches. One again a correlation analysis using Pearson's r was done to examine whether there was a relationship between stop profiling and search profiling based upon ethnicity. This time, however, a statistically-significant, weak relationship was found between the two variables. The correlation coefficient was 0.31 and was significant at the 0.01 level (two-tailed).

5.6 Detailed Analysis of Potential Problem Counties

Four separate lists of potential problem counties were generated through the previous analyses. As previously stated, there were not enough searches conducted during the time frame the data was collected to conduct hit rate analyses on the two problem counties identified through search rates. Thus, only the counties that were deemed a potential problem county through traffic stop disparities underwent further analysis. The main purpose of this analysis was to examine whether there is evidence of racial profiling in the counties which have been labeled as potentially problematic. This analysis will help to validate the previous methods utilized to identify these counties. If the methods are accurate at predicting problem counties, there should be some evidence of racial profiling practices in the police behavior.

5.6.1 Counties Identified through Stop Analysis by Race

The 25 problem counties that were originally identified through the stop analysis which was analyzed by race underwent some additional analysis relating specifically to racial profiling in stops. To assess whether these counties were identified correctly and to test whether there was any evidence of racial profiling during traffic stops, two additional variables were examined for these counties. The additional variables were the officer's reason for making the stop and the officer's action following a stop. As previously stated, these variables each had several options for the officer to choose from when they were recording the data. This analysis attempted to examine whether officers were consistent across different races in their reasons for making stops and their actions following a stop. Once again, percentages representing the rates at which officers take certain actions against people of different races were used. In other words, they may give whites citations 50% of the time and the other 50% of the time they give whites written

warnings, whereas with African Americans they give out citations 80% of the time and written warnings 20% of the time. In order to identify racial profiling through this more detailed analysis, the counties' data were aggregated so as to identify overall patterns for all 25 counties. Similar to the methods that were utilized to identify the counties, notable differences in the treatment of one race to another were used to indicate the presence of racial profiling.

After carefully examining the data for the 25 counties, several indicators of racial profiling were noticed (See Table 13). First, both African American drivers and drivers of some other race were more likely to be stopped for 'investigation' and 'other moving violation' stops. While African Americans were only stopped at a slightly higher rate than whites for these discretionary stops, drivers of another race showed a substantial difference. To contrast this large increase, it appears that drivers of some other race were stopped less often for speeding violations. Driving while impaired, or DWI is also slightly elevated for drivers of some other race, however, this is not believed to be a highly discretionary stop. Officers have specific driving practices that they look for when attempting to identify if someone is under the influence when driving. The remainder of the 'stop purposes' appear to be fairly equal rates for all races.

Another apparent indicator of racial profiling has to do with the differences in the officer's actions following the stop. There were considerable differences in the arrest, citation, and written warning rates. In this case, however, it is not all minority drivers that are being profiled, but only the drivers that are of some other race. Drivers of some other race appear to be considerably more likely than whites and African Americans to be arrested or given a citation and less likely to receive a written warning. As discussed before, this would appear to show that officers are

'cutting more breaks' for white and African American drivers rather than drivers of some other race. One possible explanation of the differences that appear in these rates could be the previously mentioned theory of coercive actions (Tedeschi and Felson, 1994; Engel, Calnon, & Bernard, 2002). An officer's actions following a stop could be the result of having poor interactions with the driver. If the officer felt that the driver was being disrespectful, they may take more strict actions such as an arrest or citation.

While none of these disparities are explicit evidence of racial profiling, they do show that the counties which were previously identified have some questions that must be answered regarding their police stop practices. More in-depth analyses that more closely examine the officers' behavior should be done to identify the reasons for the disparities. This would help to determine, for example, whether the officers' actions following the stops are a result of racial profiling or having poor interactions with minority drivers.

Counties Identified by Race (98,927 Stops)							
Stop Purpose	Total Number of Stops All Drivers	Proportion of Purposes White	Proportion of Purposes African American	Proportion of Purposes Other			
DWI	1.952	1.66%	1.85%	4.54%			

1.66%

1.85%

4.54%

1,952

DWI

Table 13: Percent Purposes of Stop and Actions Aggregated for all Potentially Problematic

Investigation	5,576	4.19%	6.84%	12.57%
Other Moving Viol.	6,234	5.80%	6.66%	8.87%
Safe Movement				
Viol.	2,640	2.49%	2.81%	3.55%
Speeding	55,255	56.66%	57.41%	45.97%
Seat Belt Viol.	13,811	15.28%	11.61%	11.07%
Stop Light/Sign				
Viol.	2,163	2.28%	1.90%	2.28%
Equipment Viol.	5,816	5.68%	6.08%	6.72%
Regulatory Viol.	5,480	5.96%	4.85%	4.42%
Action Taken		Proportion of Actions White	Proportion of Actions African American	Proportion of Actions Other
Arrest	2,144	1.66%	2.52%	4.76%
Citation	75,022	75.94%	74.50%	78.75%
No Action	745	0.70%	0.88%	0.77%
Verbal Warning	2,494	2.35%	2.93%	2.61%
Written Warning	18,522	19.35%	19.16%	13.11%

5.6.2 Counties Identified through Stop Analysis by Ethnicity

There were 19 counties which were identified through examining stop analysis by ethnicity. Similar to the method used in Section 5.6.1, the data for the 19 counties were aggregated in an attempt to identify overall patterns for all of the counties. As is shown in Table 14, there are notable differences in the officers' purpose of stop in driving while impaired, 'investigations,' and 'other moving violations.' As previously stated, it is not believed that the difference in driving while impaired is an indicator of racial profiling. There are substantial differences in the rates between Hispanics and non-Hispanics for 'investigations' and 'other moving violations.' These differences are even greater than those noticed in the detailed examination done by race.

Once again, the substantial increase in 'investigations' and 'other moving violations' is contrasted by a severe decrease in speeding violations.

Other noteworthy differences also exist in the officer action following the stops. Similar to the previous analysis there are considerable differences in arrests, citations, and written warnings. Hispanics are more likely than non-Hispanics to be arrested and given a citation and less likely to be given a written warning. There is about a 5% difference between arrests and citations, while the difference in written warning percentages is about 10%. This means that Hispanics are substantially less likely to receive a written warning following a stop. Once again, these basic indications that appear to show racial profiling are not explicit evidence. They are, however, important indicators that these counties should be looked at closer and that the previous identification methods are accurate at recognizing counties where racial profiling appears to be occurring.

Table 14: Percent Purposes of Stop and Actions Aggregated for all Potentially Problematic Counties Identified by Ethnicity (68,890 Stops)

	Total Number of Stops Hispanic and Non- Hispanic	Proportion of Purposes Hispanic	Proportion of Purposes Non-Hispanic
Stop Purpose			
DWI	1,187	5.01%	1.42%
Investigation	5,517	20.36%	6.89%
Other Moving Viol.	4,604	10.78%	6.31%
Safe Movement Viol.	1,750	3.53%	2.45%
Speeding	36,018	34.25%	53.92%
Seat Belt Viol.	10,742	12.32%	15.89%
Stop Light/Sign Viol.	1,455	2.36%	2.09%
Equipment Viol.	4,488	7.46%	6.43%
Regulatory Viol.	3,129	3.93%	4.60%
Action Taken		Proportion of Actions Hispanic	Proportion of Actions Non-Hispanic
Arrest	1,600	6.52%	1.94%
Citation	50,640	78.35%	73.07%
No Action	356	0.37%	0.53%
Verbal Warning	1,356	1.83%	1.98%
Written Warning	14,938	12.93%	22.48%

6. Discussion and Policy Implications

Researchers and academics have been examining the policies and procedures surrounding racial profiling in police traffic stops for many decades. They have examined how to correctly identify, analyze, and reduce racial profiling in police departments around the world. More recently researchers have been attempting to find a method to accurately create estimations of the driving population by which to benchmark their data. This study sought to create a method of estimating the driving population that could be utilized by any police department in the United States. Utilizing the Census Transportation Planning Package of the United States Census, estimates were created for all counties in the state of North Carolina. These estimates were then evaluated against North Carolina State Highway Patrol stop and search data that was collected for North Carolina in 2001. The NCSHP stop and search data were not only utilized to test the validity of the estimation method, but they were also used to examine whether the NCSHP has practiced any type of racial profiling.

Past research (Smith et al., 2004) on the NCSHP has shown there to be some isolated locations where racial profiling in traffic stops has taken place. Thus, if this method of estimation were accurate, evaluation of the NCSHP traffic stop and search data should show some signs of racial profiling practices. This research and evaluation has positively identified several counties in North Carolina which appear to show evidence of racial profiling in police traffic stops and searches.

6.1 Evidence for the Existence of Racial Profiling

Four different types of analysis were utilized in an attempt to examine whether the North Carolina State Highway Patrol had any indication that their officers were practicing racial profiling when making traffic stops. In the end, evidence was found for numerous counties in North Carolina that appear to be practicing racial profiling based on race and ethnicity in both police stops and searches. Analysis of police stop and search data that were broken down by race and ethnicity not only produced four separate lists of potential problem counties, but, upon more detailed evaluation, was able to display evidence of unequal treatment of drivers of different races and ethnicities within these counties. My third hypothesis stated that minorities would be considerably more likely than whites and non-Hispanics to be stopped for discretionary reasons such as 'investigations' and 'other moving violations.' My fourth hypothesis stated that minority drivers would be more likely than whites and non-Hispanics to be given citations and less likely to receive written warnings. Both of these hypotheses were confirmed through the more detailed analysis of the potentially problematic counties.

Examination of the overall state data does not appear to show racial profiling in police stops to be a statewide issue. While there does appear to be a disparity in the number of minority drivers that are stopped, it is not believed that this is the result of widespread racial profiling. Inaccurate driving population estimates, or enforcement patterns rather than overall department behavior could explain these differences. Overall state data on police searches displays a completely different result, however. Statewide search rates based on both race and ethnicity do appear to show that there is an extensive problem. Due to the low number of searches that were conducted during the time frame of this research, however, it is believed that a limited number of officers

could cause this skew in the data. Several officers could be practicing racial profiling in searches while the rest of the NCSHP are utilizing acceptable police practices in their search procedures. The low number of total searches (2,932) could make the actions of only a few officers have a notable impact on the overall data. This is less likely when examining the stop data as the total number of stops is extremely large (332,538).

6.2 Accuracy of the Driving Population Estimates

Comparisons of the four lists of potential problem counties appear to demonstrate a great deal of overlap between the different prediction methods. Based upon the assumption that officers who profile drivers during traffic stops will also profile when making the decision to conduct a search, this would appear to show that the Census Transportation Planning Package can be utilized to make accurate estimations of the overall driving populations. This supports my second hypothesis that the different analysis methods would have a great deal of overlap, thus proving the accuracy of the CTPP estimates. Correlations between the data show only weak associations, but it may be that this type of analysis is too rigorous to conduct between these data. The limited timeframe of data collection caused problems in other analyses and may have also adversely effected this correlation. It is unknown what effects collecting data over a longer period of time would have on the overall analyses.

Though these simple comparisons would appear to show that the driving population estimates are accurate, this is difficult to confirm. As previously stated, researchers have been attempting to find accurate methods of generating these population estimates for years. It has become clear, however, through this study and the research of other professionals that the raw Census figures

would have fully underestimated racial profiling in a number of counties. Even utilizing the Census figures for people over the age of 16 would have led to many potentially problematic counties being overlooked. This supports my first hypothesis that stated that the CTPP estimates would be notably different from the original Census figures. Though extremely costly, and not completely accurate, one approach to verifying the estimations would be to conduct observational studies for all 100 counties in North Carolina. Another option would be to hire transportation experts to conduct statewide analyses of the travel patterns of these counties. At this time, researchers generally believe these to be the best methods that can be utilized to confirm the accuracy of new driving population estimation methods. Though complex and costly, conducting this type of research now could help to save many other police jurisdictions time and money knowing that they have a cost-effective and accurate method of estimating the driving population.

6.3 Limitations to Data and Research Design

The implications of the findings in this study are not only applicable to the North Carolina State Highway Patrol, but to any police department in the United States that has collected or is collecting race and ethnicity data for traffic stops and searches. Thus, the limitations of this study are extremely important to consider when evaluating its' implications. The first and most notable limitation of this study relates to the actual recording of the data. In this study and all other police jurisdictions where race and ethnicity data is collected, the individual officers are responsible for collecting the pertinent information about the driver's race. Thus, the study and its findings are only valid if the police officers are correctly obtaining and recording this data. Like many studies that revolve around race and ethnicity questions, it is difficult to determine how accurate the data are when the underlying question of a person's race is never explicitly asked. In these cases, officers are told to record the race and ethnicity of the individual whom they stop along with other information. Information such as age and sex are confirmed when they check the driver's license, but race and ethnicity are not listed on the license. The officer must determine on her/his own the race and ethnicity of the driver. This could lead to a great deal of incorrect coding of data. A common error in the recording of race data is to list all Hispanic people as a race other than white. Recording in this manner is not uncommon when the people collecting the data are not properly educated on how to record the data. In the case of police departments, often officers are just told that they must record the data, and not given formal instruction on how this data should be collected. This is a case where a policy maker must get involved beyond simply creating legislation that requires the data be collected. They must ensure that the officers know how to collect this data properly through mandatory education. Another option to help alleviate this problem would be to require the officers to ask the driver about their demographic information. If after explaining why they are collecting the data, the person does not want to give the information, only then should the officer use their own judgment to decide the race and ethnicity of the driver.

Another limitation to the data that was collected in this study is the identification of where the stops and/or searches took place. Originally the researchers set out to collect specific geographic information that would allow for more exact locations. In the end, however, officers collected specific geographic information in only a handful of cases. This limited the analysis to being analyzed by the county in which the stop occurred. If more specific geographic data had been

available, it may have been possible to identify stretches of highway or specific towns where there was evidence of racial profiling. Once again, this is an area where policy makers can have a substantial impact on the effectiveness of the evaluation. All police officers call in the location of where they make a stop so that if something were to happen during the stop, the dispatcher knows where to send aid to the officer. If policy makers required location to be collected, along with the basic demographic data, it would allow for a much more in-depth analysis.

The main focus of this research was to identify and validate an efficient and accurate method of estimating the driving population. Thus, the analysis of whether racial profiling existed in North Carolina was very rudimentary. Common issues that are examined such as time of day, age of drivers, sex of drivers, and identification of specific problem officers were ignored. A more thorough examination into the existence of racial profiling should assess each of these variables in the analysis. This research was not able to identify the root cause of the disparities in the stop data. As the previously mentioned theories state, these disparities could be the result of a number of different situations. There could be individual officers that are in fact profiling drivers by their race and ethnicity, or the disparities could be a result of the overall department patrol practices. Individual troops could have senior officers and supervisors that are demonstrating this type of behavior to the younger officers, causing the profiling practices to spread throughout the troop. While this was not the major goal of this research, it is a limitation that leaves unanswered questions in the NCSHP. The inability to identify the exact cause of the disparities leads to only theoretical answers about the apparent profiling practices.

Finally, based upon the previous research of Smith et al. in 2004, this study of the NCSHP was able to identify a line (10% difference) that divided the counties which were believed to have racial profiling and the counties which were believed did not have racial profiling. In other jurisdictions and other studies more analysis should be conducted to better evaluate this division, and careful consideration should be given to those counties that are very near this 'profiling line.' Once again, this was not the main goal of this research so while careful consideration was paid, detailed analysis was not conducted to ensure that this was the best breaking point between profiling and non-profiling counties.

6.4 Recommendations and Future Work

6.4.1 Utilize Different Tools to Estimate the Driving Population

While this research has found evidence to show that utilizing the Census Transportation Planning Package can be an accurate method of estimating the driving population, other methods of estimation should be evaluated. The tests that were used to check the accuracy of the estimations were not entirely conclusive. Ideally, the estimates that were created would have been compared with known driving population figures. Without having access to or knowing these numbers, however, alternative methods were used. Researchers should continue to test different methods of estimation and make comparisons in an attempt to identify which methods are most accurate. Even if a more complex and expensive method is utilized, it can help to verify more costeffective methods such as the one utilized in this research. Direct comparison of driving population estimates will allow for the identification of the best possible method of estimation and evaluation.

6.4.2 Apply the Estimation Methods to Other Types of Police Jurisdictions

The estimation methods that were created for this study utilizing the Census Transportation Planning Package appear to be both efficient and accurate at predicting the driving populations for all of the counties in North Carolina. This does not, however, show that the data can be applied to any police jurisdiction in the United States. While the CTPP is a very versatile data set, it has not yet been tested on smaller police jurisdictions or city police departments. The CTPP is able to give estimates in geographic areas as small as Census tract block groups. While this level of geographic specificity may not be needed for most police departments, it could certainly allow for better identification of problem areas. In this research, counties were the units of analysis. Some of these counties had populations well over 500,000 and were larger than 500 square miles. This generality is simply not specific enough for pinpointing the problem. While it would have been easier to locate more specific problem areas utilizing smaller units of analysis, this would have required more search data. This research, utilizing the stops and searches that were conducted from January to July of 2001, had an adequate amount of data to analyze stop and search rates. However, due to the limited number of discretionary searches that took place during this timeframe, the study was unable to conduct detailed hit rate analysis. If the unit of analysis were to be made smaller, the problem would be magnified and a longer period of data collection would be necessary.

6.4.3 Test Theories and Identify the Cause of the Problems

The main goal of this research was to identify a simple and efficient method to estimate the driving population. Thus, the analysis of the NCSHP was not in-depth and did not attempt to identify the specific problems that may exist in the department. In the future, research should

look to examine departments much closer and attempt to find what exactly may be the cause of the disparities in the stop and search data. Testing different racial profiling theories could help departments to answer the overall question of why the officers are profiling, or why these large disparities exist in the stop data. For example, if researchers were to closely examine the patrol patterns of a police department they could test both conflict theory and the recent theory that was developed by researchers Meehan and Ponder. In the case of conflict theory, researchers could test to see if the disparities in stop and search numbers are a result of the police department's attempt to keep control over the minority population. While this research did not examine overall patrol patterns, it is possible that the NCSHP is more suspicious of minority drivers and thus, stop them at a much higher rate. This suspicion could also cause the NCSHP to patrol minority neighborhoods more than white neighborhoods leading to the overall disparities in the stop data.

Examining patrol patterns as well as other factors such as the overall driving behaviors of different race groups and the mechanical and physical conditions of cars that are stopped could help to determine if there are other factors other than race contributing to the stop disparities, as suggested by the theory developed my Meehan and Ponder. In the case of North Carolina, it is possible that minority drivers take more risks when driving (i.e. speed more often) or they drive cars that look as though they are mechanically or physically in disrepair. These factors would explain that the stop disparities were a result of socioeconomic factors rather than simply the race of the driver.

Finally, a closer examination of the actions and conversations between an officer and a person who has been stopped could help to test the theory of coercive actions. While this research did

not directly test this theory, there do appear to be patterns in the data consistent with Tedeschi and Felson's theory of coercive actions. As previously discussed, there is evidence that officers were considerably more likely to give out harsher punishments (in counties identified as potentially problematic) to drivers of some other race as compared with both white and African American drivers. A closer examination into the officer and driver's behavior following the stops would enable a researcher to determine whether it was a person's attempt to defend their social identity that caused the outcome of the stop. It is possible that officers in the NCSHP act in a manner which challenges the social identity of minority drivers causing them to be disrespectful to the officer, ultimately resulting in searches or harsher punishments.

As a result of not specifically testing any of these theories, this research was unable to identify an overall explanation or theory for the disparities in the NCSHP stop and search data. It was also unable to determine if the disparities were a result of the behavior of a few individual officers, or the behavior was present in entire police troops. If researchers test these specific theories and are able to identify the underlying causes of the disparities in the traffic stop data, it will help policymakers when they are attempting to resolve the problems through the development of new policies. For example if a department were to learn that the cause of the disparities were the result of only a few individual officers, their policies would be much different than if they learned that the disparities were being caused by their overall patrol patterns. In the first case, only a few officers must be dealt with but in the latter case, the policymaker must reevaluate the disparities were a direct result of officer's challenging the social identity of minority drivers. In this case, the policymaker must address the problem where it is being learned (i.e. the police

academy or field training). In any case, closer examination of the data and testing currently existing theories play a critical role in policy development and implementation. Testing existing theories may even lead researchers to develop their own theories and help to resolve the situation in many other departments and jurisdictions.

6.4.4 Utilize Technology

As previously stated, the geographic areas utilized in this study were much too large to identify specific stretches of highway or neighborhoods where racial profiling is occurring. If data were to be collected that would identify each location where a stop was made, however, not only could these specific locations be identified, but also, in-depth geographic analysis could allow for valuable explanations as to why racial disparities exist. For example, perhaps a large number of Hispanics are being stopped on a small stretch of highway. The number of Hispanics that are being stopped is not proportional to their representation in the driving population estimates. Utilizing geographic information systems, or GIS, analysis it is discovered that a Hispanic church is located just off this section of the highway. Utilizing GIS to control for time of day and week, it is also noticed that a disproportionate number of these stops are made around the times of the various services of the church.

GIS analysis can be an extremely valuable tool when attempting to conduct spatial analysis. In the case of racial profiling research and analysis, it can help to not only identify potential problem areas but it can also create maps and control for a number of variables. It could also assist police policy makers when they are making decisions on where to deploy their officers. They can send officers to areas where they have seen the most problems, or send officers where they feel they are not making their presence felt. GIS is an adaptable tool that will become an essential part of any racial profiling analysis. Policymakers must have GIS analysis in mind when creating legislation on the collection of racial demographic data. They should require that the specific location of the stop be recorded as well as the demographic data. This will allow for more thorough and rewarding analysis.

6.4.5 Mandate Meaningful Analysis

In 1999, North Carolina became the first state in the United States to enact state legislation which required the collection of demographic data on all traffic stops made by the highway patrol. The state required that basic race data and information surrounding a traffic stop be collected every time an officer stopped a car, no matter the reason. Despite having this new and original policy, the state left out one major requirement to this legislation. There were no requirements as to what had to be done with this data. The legislation simply said that the data had to be collected, not analyzed. Not being required to analyze the data, the North Carolina State Highway Patrol did nothing with any of the data until researchers Smith et al. came around in 2001. At this time, the researchers began to work with the data and began an in-depth analysis of the state highway patrol. The two year lag from the beginning of the data collection to the initial analysis was unnecessary and could have easily been avoided.

Police jurisdictions in the future, whether they are large state agencies or small cities, should learn from the mistake of North Carolina. Not requiring that meaningful analysis be done on this data has continued to cause problems with the NCSHP. There still are no active policies that require that the demographic data that officers are collecting be analyzed. The only major

analysis that has been done to any of the data collected by the NCSHP was that of Smith et al. (2004). Data continues to be collected with no major analysis being conducted. While it is simply not possible for a yearly study to be conducted with the thoroughness of the previous researchers, the data should be examined each year. Simple, efficient methods of evaluation should be conducted each year to ensure that the officers are not radically changing their behavior from previous years. This type of analysis will hold officers accountable for their actions and they will feel that they are continuously being watched and evaluated. They will no longer feel that they are collecting data that is never utilized or examined. Continuous evaluation of police officers and their departments can help to severely reduce and even eliminate acts of racial profiling.

7. Conclusion

Researchers have been studying and evaluating instances of racial profiling in police traffic stops for decades. They have long been attempting to not only find ways to reduce the practices of racial profiling but also find accurate and efficient methods of evaluation. In 1999, legislation was passed in North Carolina requiring that all North Carolina State Highway Patrol troopers collect basic racial demographic information each time they make a traffic stop. This legislation, though the first of its kind would quickly show its major flaw, however, as it would take two years for any meaningful analyses to be conducted on the data. Researchers Smith, Tomaskovic-Devey, Zingraff, Mason, Warren, and Wright began collecting and analyzing the stop data in 2001 and would eventually release a final report in 2004. Their methods of analysis and estimating the driving population, though believed to be fairly accurate were complex, timeconsuming, and demanded a great deal of data collection and resources.

The goal of this research was to identify a fast, efficient and accurate method for estimating the driving population. This would allow for quicker, more straightforward analysis of racial profiling data. A survey collected by the United States Census Bureau called the Census Transportation Planning Package was utilized to generate the driving population estimates for all counties in North Carolina. The study assessed the accuracy of utilizing the CTPP data by conducting analysis of all NCSHP stop and search data from January to July of 2001. Comparisons between different evaluation methods appear to show that the driving population estimates that utilizing the basic Census statistics would have underestimated racial profiling in many counties. Even if one were to utilize the Census statistics for those who are over the age of 16, many

counties would still be overlooked. Though a correlation showed only weak relationships between the stop and search data, it is possible that this type of analysis was too rigorous of a test for these data. The general comparisons of the lists of potentially problematic counties showed a great deal of overlap between the different methods of identification.

While these findings appear to show that the CTPP estimates are accurate in predicting the driving population, these results should be taken with caution. No direct comparison between the estimates and the actual driving population has been done. Utilizing the CTPP data to benchmark the racial profiling data, however, does appear to be a valid method of identifying problematic counties. Nearly all of the counties that have been identified in this study as potentially problematic display some signs of racial and/or ethnicity-based profiling. This study has presented a new and efficient method to identify and analyze police jurisdictions where racial profiling may be occurring. This evaluation technique has the potential to become a valuable tool for policymakers as they implement mandatory data collection and evaluation programs.

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	Mode of	Car	Mode of	Car	Mode of	Car
	Trans.	Availability	Trans.	Availability	Trans.	Availability
	Percent	Percent White	Percent Af.	Percent Af.	Percent Other	Percent Other
	White Driving	Driving	Am. Driving	Am. Driving	Driving	Driving
North Carolina State Totals	76.48%	77.24%	17.81%	17.16%	5.70%	5.60%

Appendix A: CTPP Variable Comparison Based on Race

County Name	Mode of Trans. Percent White Driving	Car Availability Percent White Driving	Mode of Trans. Percent Af. Am. Driving	Car Availability Percent Af. Am. Driving	Mode of Trans. Percent Other Driving	Car Availability Percent Other Driving
Alamance	77.99%	78.48%	17.13%	16.51%	4.88%	5.02%
Alexander	93.25%	93.65%	4.23%	3.92%	2.49%	2.43%
Alleghany	95.04%	95.51%	1.33%	0.92%	3.80%	3.68%
Anson	57.35%	59.24%	41.53%	39.67%	1.10%	1.08%
Ashe	97.60%	97.71%	0.97%	0.89%	1.42%	1.40%
Avery	97.00%	97.12%	0.23%	0.22%	2.82%	2.66%
Beaufort	76.29%	78.23%	21.68%	19.85%	2.03%	1.92%
Bertie	45.18%	47.67%	53.61%	50.80%	1.24%	1.45%
Bladen	63.59%	65.03%	31.16%	29.98%	5.25%	4.95%
Brunswick	83.33%	83.95%	13.58%	13.03%	3.10%	3.03%
Buncombe	91.04%	91.21%	5.32%	5.16%	3.63%	3.63%
Burke	89.38%	89.73%	4.77%	4.65%	5.86%	5.62%
Cabarrus	86.53%	87.10%	10.28%	9.67%	3.20%	3.23%
Caldwell	93.28%	93.51%	4.24%	4.17%	2.49%	2.33%
Camden	82.75%	83.82%	15.08%	14.08%	2.01%	1.94%
Cateret	91.16%	91.41%	6.15%	5.97%	2.69%	2.61%
Caswell	67.79%	69.19%	30.52%	29.20%	1.69%	1.62%
Catawba	87.70%	87.98%	6.71%	6.41%	5.59%	5.61%
Chatham	78.79%	79.46%	14.37%	13.54%	6.87%	7.00%
Cherokee	93.63%	93.96%	1.58%	1.59%	4.86%	4.45%
Chowan	65.62%	67.31%	32.57%	31.30%	1.70%	1.37%
Clay	98.30%	98.35%	0.28%	0.28%	1.36%	1.35%
Cleveland	80.45%	81.28%	17.55%	16.77%	2.00%	1.96%
Columbus	70.94%	72.10%	23.57%	22.54%	5.49%	5.36%
Craven	73.66%	74.91%	21.34%	20.43%	5.00%	4.65%
Cumberland	59.82%	60.24%	31.08%	30.92%	9.10%	8.83%
Currituck	91.94%	91.83%	5.74%	5.73%	2.32%	2.45%
Dare	95.12%	95.30%	2.32%	2.25%	2.49%	2.45%
Davidson	88.82%	89.40%	7.70%	7.20%	3.48%	3.40%
Davie	91.03%	91.24%	6.18%	6.15%	2.76%	2.64%
Duplin	65.18%	66.39%	22.69%	21.27%	12.19%	12.31%
Durham	56.32%	57.35%	34.47%	33.57%	9.21%	9.08%
Edgecombe	48.01%	49.36%	49.45%	48.31%	2.53%	2.33%

Franklin 72.40% 73.41% 24.35% 23.34% 3.20% 3.28% Gates 63.85% 66.53% 10.84% 10.46% 2.93% 2.93% Gates 63.85% 66.33% 33.54% 32.12% 2.53% 2.25% Granamile 66.31% 60.03% 27.08% 26.48% 4.61% 4.52% Greene 59.17% 60.84% 33.47% 33.01% 7.28% 6.14% Guillord 68.34% 69.34% 26.10% 25.14% 5.55% 5.51% Hailtax 51.73% 53.88% 44.27% 42.13% 4.00% 3.99% Harwood 96.96% 97.07% 11.33% 11.28% 1.90% 1.81% Harwood 96.86% 97.07% 11.82% 49.94% 2.44% 2.39% Harwood 96.86% 97.07% 11.82% 49.94% 2.44% 2.39% Harwood 96.86% 97.07% 11.82% 10.94% 16.37% 16.30% <th>Forsyth</th> <th>72.79%</th> <th>73.69%</th> <th>21.81%</th> <th>20.99%</th> <th>5.40%</th> <th>5.33%</th>	Forsyth	72.79%	73.69%	21.81%	20.99%	5.40%	5.33%
Gaston 86.18% 66.13% 10.84% 10.46% 2.93% 2.33% Gates 63.85% 65.33% 33.54% 32.12% 2.55% 2.55% Granam 91.64% 91.08% 0.00% 0.00% 8.36% 8.92% Grannelle 68.31% 69.03% 27.08% 26.48% 4.615% 4.52% Guilford 68.34% 69.34% 26.10% 25.14% 5.55% 5.51% Hairett 76.44% 76.99% 18.03% 17.29% 5.54% 5.73% Harwett 76.44% 76.99% 18.03% 17.29% 5.85% 5.57% Hertford 45.72% 47.74% 51.82% 49.94% 2.44% 2.39% Hoke 51.70% 53.20% 31.85% 30.54% 10.37% 16.37% Jackson 87.20% 87.85% 12.39% 11.02% 11.13% Jackson 87.20% 87.85% 33.95% 31.75% 2.12% Jones 6	Franklin	72.40%	73.41%	24.35%	23.34%	3.20%	3.28%
Gates 63.85% 65.33% 33.54% 32.12% 2.53% 2.55% Graham 91.64% 91.08% 0.00% 0.00% 8.36% 8.32% Greene 59.17% 60.84% 33.47% 33.01% 7.28% 6.14% Guilford 68.34% 69.34% 26.10% 25.14% 5.55% 5.51% Haltrax 51.73% 53.88% 44.27% 42.13% 4.00% 3.39% Harwood 96.96% 97.07% 11.13% 11.28% 1.90% 1.81% Harwood 96.96% 97.07% 1.13% 1.12% 1.90% 1.81% Harwood 96.86% 97.07% 1.13% 1.12% 1.63% 5.57% Harwood 96.86% 97.07% 1.85% 30.54% 16.37% 16.30% Hoke 57.70% 17.17% 11.17% 11.17% 3.11% 30.65% 2.12% Jones 63.96% 65.94% 33.85% 31.75% 2.19% 2.31% <td>Gaston</td> <td>86.18%</td> <td>86.61%</td> <td>10.84%</td> <td>10.46%</td> <td>2.99%</td> <td>2.93%</td>	Gaston	86.18%	86.61%	10.84%	10.46%	2.99%	2.93%
Graham 91.64% 91.08% 0.00% 0.00% 8.36% 8.92% Garanville 66.31% 60.03% 27.08% 26.48% 4.61% 4.52% Greene 55.17% 60.64% 33.47% 53.81% 4.22% 5.55% 5.51% Halifax 51.73% 53.88% 44.27% 4.13% 4.00% 3.99% Hanrett 76.44% 76.99% 11.80% 17.29% 5.54% 5.73% Hanrett 76.44% 76.99% 11.31% 1.12% 1.00% 1.81% Henderston 91.83% 92.40% 2.30% 2.04% 5.85% 5.57% Hentford 45.72% 47.74% 51.82% 49.94% 2.44% 2.39% Hoke 51.70% 63.20% 31.85% 30.54% 16.37% 16.30% Jackson 82.54% 83.25% 12.39% 10.247% 2.12% Jackson 82.54% 83.25% 12.39% 10.247% 2.31%	Gates	63.85%	65.33%	33.54%	32.12%	2.53%	2.55%
Granville 68.31% 69.03% 27.08% 26.48% 4.61% 4.52% Greene 59.17% 60.84% 33.47% 33.01% 7.28% 6.14% Guilford 68.34% 69.34% 25.14% 5.55% 5.51% Hallfax 51.73% 53.88% 44.27% 42.13% 4.00% 3.99% Harwood 96.69% 97.07% 1.13% 1.12% 1.90% 1.81% Harwood 96.69% 97.07% 1.13% 1.12% 1.90% 1.81% Henderson 91.83% 92.40% 2.30% 2.04% 2.39% 1.637% 16.30% Hoke 51.70% 53.20% 31.85% 30.54% 16.37% 16.30% Hyde 74.61% 77.14% 53.20% 31.85% 30.54% 16.37% 16.30% Jackson 87.20% 87.75% 11.71% 11.17% 31.15% 3.17% 3.17% 3.36% Jones 63.96% 65.94% 3.365%	Graham	91.64%	91.08%	0.00%	0.00%	8.36%	8.92%
Greene 59.17% 60.84% 33.47% 33.01% 7.28% 6.14% Guillord 68.34% 69.34% 26.10% 25.14% 5.55% 5.51% Halfax 51.73% 55.88% 44.27% 42.13% 4.00% 3.99% Harnett 76.44% 76.99% 18.03% 17.29% 5.54% 5.73% Henderson 91.83% 92.04% 2.30% 2.04% 5.85% 5.57% Hertford 45.72% 47.74% 51.82% 49.94% 2.44% 2.39% Hoke 51.70% 53.20% 31.85% 30.54% 16.37% 16.30% Hyde 74.61% 77.18% 23.30% 20.47% 2.36% 2.12% Jackson 87.20% 87.85% 1.29% 1.02% 11.50% 11.13% Jones 63.96% 65.94% 33.65% 32.29% 2.99% 3.12% Lenoir 63.38% 64.59% 33.65% 32.29% 2.99% 3.12% <	Granville	68.31%	69.03%	27.08%	26.48%	4.61%	4.52%
Guillord 68.34% 69.34% 26.10% 25.14% 5.55% 5.51% Hallrax 51.73% 53.88% 44.27% 42.13% 4.00% 3.99% Hamett 76.44% 76.99% 11.03% 1.12% 1.90% 1.81% Haywood 96.96% 97.07% 1.13% 1.12% 1.90% 1.81% Hentford 45.72% 47.74% 51.82% 42.04% 2.39% Hentford 45.72% 47.74% 51.82% 49.94% 2.44% 2.39% Hoke 51.70% 65.20% 31.85% 30.54% 16.30% 16.30% Hyde 74.61% 77.18% 23.30% 20.47% 2.36% 1.13% Jackson 87.20% 87.85% 1.29% 1.02% 11.13% 3.06% Jones 63.96% 65.94% 33.95% 31.75% 2.19% 2.31% Lee 74.60% 75.20% 16.81% 16.44% 8.47% 8.36% Leonin	Greene	59 17%	60.84%	33 47%	33.01%	7 28%	6 14%
Data Data <thdata< th=""> Data Data <thd< td=""><td>Guilford</td><td>68.34%</td><td>69.34%</td><td>26 10%</td><td>25 14%</td><td>5 55%</td><td>5 51%</td></thd<></thdata<>	Guilford	68.34%	69.34%	26 10%	25 14%	5 55%	5 51%
Harnett 76.39% 11.02% 17.29% 5.54% 5.73% Haywood 96.96% 97.07% 1.13% 17.29% 5.54% 5.73% Henderson 91.83% 92.40% 2.30% 2.04% 5.85% 5.57% Hertford 45.72% 47.74% 51.82% 49.94% 2.44% 2.39% Hoke 51.70% 53.20% 31.85% 30.54% 16.37% 16.30% Hyde 74.61% 77.18% 23.30% 20.47% 2.38% 2.12% Iredell 85.17% 85.77% 11.71% 11.17% 3.11% 3.06% Jones 63.96% 65.94% 33.95% 31.75% 2.19% 2.31% Lee 74.60% 75.20% 16.91% 16.44% 8.36% 3.65% Lincoln 92.01% 92.56% 5.43% 2.03% 2.00% Matison 98.36% 3.68% 3.69% 2.42% 1.40% Matison 99.35% 23.56%	Halifax	51 73%	53 88%	44 27%	42 13%	4 00%	3 99%
Haywood 96.96% 97.07% 1.13% 1.12% 1.90% 1.81% Henderson 91.83% 92.40% 2.30% 2.04% 5.85% 5.57% Hertford 45.72% 47.74% 51.82% 49.94% 2.44% 2.39% Hoke 51.70% 53.20% 31.85% 30.54% 16.37% 16.30% Hyde 74.61% 77.18% 23.30% 20.47% 2.36% 2.12% Iredell 85.17% 81.74% 1.13% 11.17% 3.11% 30.06% Jackson 87.20% 87.85% 1.29% 1.02% 11.50% 11.13% Jones 63.96% 65.94% 33.95% 31.75% 2.19% 2.31% Lee 74.60% 75.20% 16.91% 16.44% 8.47% 8.36% Lincoin 92.266% 5.95% 5.43% 2.09% 2.86% McDowell 93.22% 93.44% 3.86% 3.69% 2.89% 2.86% Macon	Harnett	76 44%	76 99%	18.03%	17 29%	5 54%	5 73%
Thy Bob 50:25% 51:37% 11:37% 11:37% 11:37% Henderson 91:83% 92:40% 2.30% 2.04% 5.85% 5.57% Hentford 45.72% 47.74% 51.82% 49.94% 2.34% 2.39% Hoke 51.70% 53.20% 31.85% 30.54% 16.37% 16.30% Hyde 74.61% 77.18% 23.30% 20.47% 2.36% 2.12% Iredell 85.17% 85.77% 11.171% 11.17% 3.11% 3.06% Jackson 87.20% 87.85% 12.31% 11.96% 5.15% 4.73% Jones 63.96% 65.94% 33.95% 31.75% 2.19% 3.17% Lenoir 63.38% 64.59% 33.65% 32.29% 2.99% 3.17% Lincoin 92.11% 92.56% 5.95% 5.43% 2.03% 2.00% McDowell 93.32% 97.43% 0.73% 0.53% 1.71% 2.04% Mactinc	Haywood	96.96%	97.07%	1 13%	1 12%	1 90%	1 81%
Instruction 0.103/0 0.103/0 0.103/0 0.103/0 0.103/0 0.103/0 Hertford 45.72% 47.74% 51.82% 49.94% 2.44% 2.39% Hoke 51.70% 53.20% 31.85% 30.54% 16.37% 16.30% Hyde 74.61% 77.18% 23.30% 20.47% 2.36% 2.12% Iredell 85.17% 85.77% 11.71% 11.17% 3.11% 3.06% Jackson 87.20% 87.85% 1.29% 1.02% 11.50% 11.13% Jones 63.96% 65.94% 33.85% 31.75% 2.19% 2.31% Lee 74.60% 75.20% 16.91% 16.44% 8.47% 8.36% Lincoin 92.01% 93.44% 3.86% 36.9% 2.89% 2.86% Macon 97.57% 97.43% 0.73% 0.24% 1.31% 1.27% Maclison 98.36% 98.49% 0.37% 0.24% 1.35% 1.25%	Henderson	91.83%	92 40%	2 30%	2 04%	5.85%	5 57%
Holde 51.70% 53.20% 31.85% 30.54% 16.37% 16.30% Hyde 74.61% 77.18% 23.30% 20.47% 2.36% 2.12% Iredell 85.17% 11.71% 11.17% 3.11% 3.06% Jackson 87.20% 87.85% 1.29% 1.02% 11.50% 11.13% Johnston 82.54% 83.25% 12.31% 11.96% 5.15% 4.78% Jones 63.96% 65.94% 33.95% 31.75% 2.19% 2.31% Lee 74.60% 75.20% 16.91% 16.44% 8.47% 8.36% Lenoir 63.38% 64.59% 33.65% 32.29% 2.99% 3.12% Lincoln 92.01% 92.56% 5.95% 5.43% 2.03% 2.00% Macon 97.57% 97.43% 0.73% 0.53% 1.71% 2.04% Macino 92.26% 69.35% 23.66% 1.35% 1.25% Macinin 62.22%	Hertford	45 72%	47 74%	51.82%	49.94%	2 44%	2 39%
Intel 31.10% 30.20% 20.24% 10.05% Hyde 74.61% 77.18% 23.30% 20.47% 2.36% 2.12% Iredell 85.17% 11.71% 11.17% 3.11% 3.06% Jackson 87.20% 87.85% 1.29% 1.02% 11.50% 11.13% Jones 63.96% 65.94% 33.95% 31.75% 2.19% 2.31% Lee 74.60% 75.20% 16.91% 16.44% 8.47% 8.36% Lenoir 63.38% 64.59% 33.65% 32.29% 2.99% 3.12% Lincoln 92.01% 92.56% 5.95% 5.43% 2.03% 2.00% Macon 97.57% 97.43% 0.73% 0.53% 1.71% 2.04% Macison 98.36% 69.35% 23.26% 7.69% 7.39% Mecklenburg 68.75% 69.35% 23.26% 7.69% 7.39% Montgomery 76.19% 77.79% 15.42% 14.05% <td>Hoke</td> <td>51 70%</td> <td>53 20%</td> <td>31.85%</td> <td>30.54%</td> <td>16 37%</td> <td>16 30%</td>	Hoke	51 70%	53 20%	31.85%	30.54%	16 37%	16 30%
Inyde 14.51% 17.11% 11.11% 11.17% 2.03% 2.13% 2.13% Jackson 87.20% 87.85% 1.29% 1.02% 11.50% 11.13% Johnston 82.54% 83.25% 12.31% 11.96% 5.15% 4.78% Jones 63.96% 65.94% 33.95% 31.75% 2.19% 2.31% Lee 74.60% 75.20% 16.91% 16.44% 8.47% 8.36% Lenoir 63.38% 64.59% 33.65% 32.29% 2.99% 3.12% Lincoln 92.01% 92.56% 5.95% 5.43% 2.03% 2.00% Macon 97.57% 97.43% 0.73% 0.53% 1.71% 2.04% Macison 98.36% 98.49% 0.37% 0.24% 1.31% 1.27% Mecklenburg 68.75% 63.36% 23.66% 7.39% 1.37% 1.25% Mortpomery 76.19% 77.79% 15.42% 14.05% 8.44% 8.16%<	Hyde	7/ 61%	77 18%	23 30%	20.47%	2 36%	2 12%
Internal 11.11% 11.11	Irodoll	95 17%	95 77%	23.30 %	20.47 /6	2.30%	2.12/0
Jackson 67.20% 67.20% 11.29% 11.29% 11.30% 11.13% Jones 63.96% 65.94% 33.95% 31.75% 2.19% 2.31% Lee 74.60% 75.20% 16.91% 16.44% 8.47% 8.36% Lenoir 63.38% 64.59% 33.65% 32.29% 2.99% 3.12% Lincoln 92.01% 92.56% 5.95% 5.43% 2.03% 2.00% Macon 97.57% 97.43% 0.73% 0.53% 1.71% 2.04% Macison 98.36% 98.49% 0.37% 0.24% 1.31% 1.27% Matrin 62.22% 63.69% 36.42% 35.06% 1.35% 1.25% Mecklenburg 68.75% 69.35% 23.26% 7.69% 7.39% Mitchell 96.73% 96.73% 0.37% 2.98% 2.97% Montgomery 76.19% 77.79% 15.42% 14.05% 8.44% 8.16% Moore 81.95% <td>lockoon</td> <td>97 200/</td> <td>03.11/0</td> <td>1 200/</td> <td>1 0 2 9/</td> <td>11 500/</td> <td>3.00%</td>	lockoon	97 200/	03.11/0	1 200/	1 0 2 9/	11 500/	3.00%
Johnstoff 22.34% 23.25% 12.31% 11.90% 5.15% 4.78% Jones 63.96% 65.94% 33.85% 31.75% 2.19% 2.31% Lee 74.60% 75.20% 16.91% 16.44% 8.47% 8.36% Lenoir 63.38% 64.59% 5.95% 5.43% 2.03% 2.00% McDowell 92.22% 93.44% 3.86% 3.69% 2.89% 2.86% Macon 97.57% 97.43% 0.73% 0.24% 1.31% 1.27% Mattin 62.22% 63.69% 36.42% 35.06% 1.35% 1.25% Mecklenburg 68.75% 69.35% 23.26% 7.69% 7.39% Motore 81.95% 83.05% 14.02% 14.05% 8.44% 8.16% Moore 81.95% 83.05% 14.02% 13.07% 4.05% 3.27% Nosh 68.09% 69.15% 28.47% 27.48% 3.45% 3.36% Meore	Jackson	07.20%	07.00%	12.29%	11.02%	F 150%	11.13%
Johles 63.99% 63.99% 75.20% 16.19% 16.44% 8.47% 8.36% Lenoir 63.38% 64.59% 33.65% 32.29% 2.99% 3.12% Lincoln 92.01% 92.56% 5.95% 5.43% 2.03% 2.00% McDowell 93.22% 93.44% 3.86% 3.69% 2.89% 2.86% Macon 97.57% 97.43% 0.73% 0.53% 1.71% 2.04% Madison 98.36% 98.49% 0.37% 0.24% 1.31% 1.27% Matrin 62.22% 63.69% 36.42% 35.06% 1.35% 1.25% Mecklenburg 68.75% 69.35% 23.56% 23.26% 7.69% 7.39% Montgomery 76.19% 77.79% 15.42% 14.05% 8.44% 8.16% Moore 81.95% 83.05% 14.02% 13.07% 4.05% 3.90% Nash 68.09% 69.15% 28.47% 2.48% 3.45% 3.36%<	Johnston	62.04%	03.23%	12.31%	11.90%	0.10%	4.70%
Lee 74.60% 75.20% 16.91% 16.44% 8.47% 8.36% Lenoir 63.38% 64.59% 33.65% 32.29% 2.99% 3.12% Lincoln 92.01% 92.56% 5.95% 5.43% 2.03% 2.00% McDowell 93.22% 93.44% 3.86% 3.69% 2.89% 2.86% Macon 97.57% 97.43% 0.73% 0.53% 1.71% 2.04% Madison 98.36% 98.49% 0.37% 0.24% 1.31% 1.27% Martin 62.22% 63.69% 36.42% 35.06% 1.35% 1.25% Mecklenburg 68.75% 69.35% 23.26% 7.69% 7.39% Mitchell 96.73% 0.37% 0.37% 2.98% 2.97% Montgomery 76.19% 77.79% 15.42% 14.02% 8.44% 8.16% Moore 81.95% 83.05% 14.02% 13.07% 4.05% 3.36% New Hanover 84.70%<	Jones	63.96%	65.94%	33.95%	31.75%	2.19%	2.31%
Lenoir 63.38% 64.59% 33.65% 52.29% 2.99% 3.12% Lincoln 92.01% 92.56% 5.95% 5.43% 2.03% 2.00% McDowell 93.22% 93.44% 3.86% 3.69% 2.89% 2.86% Macon 97.57% 97.43% 0.73% 0.53% 1.71% 2.04% Mattin 62.22% 63.69% 36.42% 35.06% 1.35% 1.25% Meklenburg 68.75% 69.35% 23.36% 23.26% 7.69% 7.39% Mitchell 96.73% 0.37% 0.37% 2.98% 2.97% Montgomery 76.19% 77.79% 15.42% 14.05% 8.44% 8.16% Moore 81.95% 83.05% 14.02% 13.07% 4.05% 3.90% Nash 68.09% 69.15% 28.47% 27.48% 3.45% 3.32% Northampton 48.45% 50.34% 50.40% 48.42% 1.19% 1.17% Orange	Lee	74.60%	75.20%	16.91%	16.44%	8.47%	8.36%
Lincoin 92.15% 5.95% 5.43% 2.03% 2.00% McDowell 93.22% 93.44% 3.86% 3.69% 2.89% 2.86% Macon 97.57% 97.43% 0.53% 1.71% 2.04% Madison 98.36% 98.49% 0.37% 0.24% 1.31% 1.27% Martin 62.22% 63.69% 36.42% 35.06% 1.35% 1.25% Mecklenburg 68.75% 69.35% 23.56% 23.26% 7.69% 7.39% Mitchell 96.73% 9.37% 0.37% 2.98% 2.97% Montgomery 76.19% 77.79% 15.42% 14.05% 8.44% 8.16% Moore 81.95% 83.05% 14.02% 13.07% 4.05% 3.90% Nash 68.09% 69.15% 28.47% 27.48% 3.45% 3.27% Northampton 48.45% 50.34% 50.40% 48.42% 1.19% 1.17% Onslow 75.07% 76.11	Lenoir	63.38%	64.59%	33.65%	32.29%	2.99%	3.12%
McDowell 93.22% 93.44% 3.86% 3.69% 2.89% 2.86% Macon 97.57% 97.43% 0.73% 0.53% 1.71% 2.04% Madison 98.36% 98.49% 0.37% 0.24% 1.31% 1.27% Martin 62.22% 63.69% 36.42% 35.06% 1.35% 1.25% Mecklenburg 68.75% 69.35% 23.56% 23.26% 7.69% 7.39% Mitchell 96.73% 0.37% 0.37% 2.98% 2.97% Montgomery 76.19% 77.79% 15.42% 14.05% 8.44% 8.16% Moore 81.95% 83.05% 14.02% 13.07% 4.05% 3.36% New Hanover 84.70% 85.21% 11.98% 11.51% 3.32% 3.27% Northampton 48.45% 50.34% 50.40% 48.42% 1.19% 1.17% Orslow 75.07% 76.11% 16.86% 15.67% 2.41% 2.30% <t< td=""><td>Lincoln</td><td>92.01%</td><td>92.56%</td><td>5.95%</td><td>5.43%</td><td>2.03%</td><td>2.00%</td></t<>	Lincoln	92.01%	92.56%	5.95%	5.43%	2.03%	2.00%
Macon 97.57% 97.43% 0.73% 0.53% 1.71% 2.04% Madison 98.36% 98.49% 0.37% 0.24% 1.31% 1.27% Martin 62.22% 63.69% 36.42% 35.06% 1.35% 1.25% Mecklenburg 68.75% 69.35% 23.56% 23.26% 7.69% 7.39% Mitchell 96.73% 96.73% 0.37% 0.37% 2.98% 2.97% Montgomery 76.19% 77.79% 15.42% 14.05% 8.44% 8.16% Moore 81.95% 83.05% 14.02% 13.07% 4.05% 3.90% Nash 68.09% 69.15% 28.47% 27.48% 3.45% 3.36% New Hanover 84.70% 85.21% 11.98% 11.51% 3.32% 3.27% Northampton 48.45% 50.34% 50.40% 48.42% 1.19% 1.17% Onslow 75.07% 76.11% 18.84% 16.36% 8.09% 7.53% <td>McDowell</td> <td>93.22%</td> <td>93.44%</td> <td>3.86%</td> <td>3.69%</td> <td>2.89%</td> <td>2.86%</td>	McDowell	93.22%	93.44%	3.86%	3.69%	2.89%	2.86%
Madison 98.48% 0.37% 0.24% 1.31% 1.27% Martin 62.22% 63.69% 36.42% 35.06% 1.35% 1.25% Mecklenburg 68.75% 69.35% 23.56% 23.26% 7.69% 7.39% Mitchell 96.73% 96.73% 0.37% 0.37% 2.98% 2.97% Montgomery 76.19% 77.79% 15.42% 14.05% 8.44% 8.16% Moore 81.95% 83.05% 14.02% 13.07% 4.05% 3.90% Nash 68.09% 69.15% 28.47% 27.48% 3.45% 3.36% New Hanover 84.70% 85.21% 11.98% 11.51% 3.32% 3.27% Northampton 48.45% 50.34% 50.40% 48.42% 1.19% 1.17% Onslow 75.07% 76.11% 16.84% 16.36% 8.09% 7.53% Orange 81.60% 81.92% 11.03% 6.58% 7.06% Pasquotank	Macon	97.57%	97.43%	0.73%	0.53%	1.71%	2.04%
Martin 62.22% 63.69% 36.42% 35.06% 1.35% 1.25% Mecklenburg 68.75% 69.35% 23.56% 23.26% 7.69% 7.39% Mitchell 96.73% 0.37% 0.37% 2.98% 2.97% Montgomery 76.19% 77.79% 15.42% 14.05% 8.44% 8.16% Moore 81.95% 83.05% 14.02% 13.07% 4.05% 3.90% Nash 68.09% 69.15% 28.47% 27.48% 3.45% 3.36% New Hanover 84.70% 85.21% 11.98% 11.51% 3.32% 3.27% Northampton 48.45% 50.34% 50.40% 48.42% 1.19% 1.17% Onslow 75.07% 76.11% 16.84% 16.36% 8.09% 7.53% Orange 81.60% 81.92% 16.96% 15.67% 2.41% 2.30% Pamlico 80.80% 81.92% 16.96% 15.67% 2.41% 2.55%	Madison	98.36%	98.49%	0.37%	0.24%	1.31%	1.27%
Mecklenburg 68.75% 69.35% 23.56% 23.26% 7.69% 7.39% Mitchell 96.73% 96.73% 0.37% 0.37% 2.98% 2.97% Montgomery 76.19% 77.79% 15.42% 14.05% 8.44% 8.16% Moore 81.95% 83.05% 14.02% 13.07% 4.05% 3.90% Nash 68.09% 69.15% 28.47% 27.48% 3.45% 3.36% New Hanover 84.70% 85.21% 11.98% 11.51% 3.32% 3.27% Northampton 48.45% 50.34% 50.40% 48.42% 1.19% 1.17% Onslow 75.07% 76.11% 16.84% 16.36% 8.09% 7.53% Orange 81.60% 81.91% 11.82% 11.03% 6.58% 7.06% Pamlico 80.80% 81.92% 16.96% 15.67% 2.41% 2.30% Perguimans 76.41% 77.65% 22.36% 2.094% 1.23% 1.41% <td>Martin</td> <td>62.22%</td> <td>63.69%</td> <td>36.42%</td> <td>35.06%</td> <td>1.35%</td> <td>1.25%</td>	Martin	62.22%	63.69%	36.42%	35.06%	1.35%	1.25%
Mitchell 96.73% 0.37% 0.37% 2.98% 2.97% Montgomery 76.19% 77.79% 15.42% 14.05% 8.44% 8.16% Moore 81.95% 83.05% 14.02% 13.07% 4.05% 3.90% Nash 68.09% 69.15% 28.47% 27.48% 3.45% 3.36% New Hanover 84.70% 85.21% 11.98% 11.51% 3.32% 3.27% Northampton 48.45% 50.34% 50.40% 48.42% 1.19% 1.17% Onslow 75.07% 76.11% 16.84% 16.36% 8.09% 7.53% Orange 81.60% 81.91% 11.82% 11.03% 6.58% 7.06% Pamlico 80.80% 81.92% 16.96% 15.67% 2.41% 2.30% Pasquotank 66.28% 67.28% 31.33% 30.21% 2.45% 2.55% Pender 78.75% 80.20% 18.43% 17.10% 2.82% 2.70%	Mecklenburg	68.75%	69.35%	23.56%	23.26%	7.69%	7.39%
Montgomery76.19%77.79%15.42%14.05%8.44%8.16%Moore81.95%83.05%14.02%13.07%4.05%3.90%Nash68.09%69.15%28.47%27.48%3.45%3.36%New Hanover84.70%85.21%11.98%11.51%3.32%3.27%Northampton48.45%50.34%50.40%48.42%1.19%1.17%Onslow75.07%76.11%16.84%16.36%8.09%7.53%Orange81.60%81.91%11.82%11.03%6.58%7.06%Pamlico80.80%81.92%16.96%15.67%2.41%2.30%Pasquotank66.28%67.28%31.33%30.21%2.35%2.55%Pender78.75%80.20%18.43%17.10%2.82%2.70%Perquimans76.41%77.65%22.36%20.94%1.23%1.41%Person74.27%74.90%23.23%22.68%2.50%2.45%Pitt70.09%71.08%26.05%25.08%3.87%3.85%Polk92.61%93.19%5.44%5.09%1.92%1.72%Randolph90.88%91.15%4.71%4.47%4.42%4.37%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rowan83.56%84.12%12.71%12.22%3.73%3.66% <t< td=""><td>Mitchell</td><td>96.73%</td><td>96.73%</td><td>0.37%</td><td>0.37%</td><td>2.98%</td><td>2.97%</td></t<>	Mitchell	96.73%	96.73%	0.37%	0.37%	2.98%	2.97%
Moore81.95%83.05%14.02%13.07%4.05%3.90%Nash68.09%69.15%28.47%27.48%3.45%3.36%New Hanover84.70%85.21%11.98%11.51%3.32%3.27%Northampton48.45%50.34%50.40%48.42%1.19%1.17%Onslow75.07%76.11%16.84%16.36%8.09%7.53%Orange81.60%81.91%11.82%11.03%6.58%7.06%Pamlico80.80%81.92%16.96%15.67%2.41%2.30%Pasquotank66.28%67.28%31.33%30.21%2.35%2.55%Pender78.75%80.20%18.43%17.10%2.82%2.70%Perquimans76.41%77.65%22.36%20.94%1.23%1.41%Person74.27%74.90%23.23%22.68%2.50%2.45%Pitt70.09%71.08%26.05%25.08%3.87%3.85%Polk92.61%93.19%5.44%5.09%1.92%1.72%Randolph90.88%91.15%4.71%4.47%4.42%4.37%Richmond72.45%73.05%22.69%22.13%4.86%4.85%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rowan83.56%84.12%12.71%12.22%3.73%3.66%	Montgomery	76.19%	77.79%	15.42%	14.05%	8.44%	8.16%
Nash68.09%69.15%28.47%27.48%3.45%3.36%New Hanover84.70%85.21%11.98%11.51%3.32%3.27%Northampton48.45%50.34%50.40%48.42%1.19%1.17%Onslow75.07%76.11%16.84%16.36%8.09%7.53%Orange81.60%81.91%11.82%11.03%6.58%7.06%Pamlico80.80%81.92%16.96%15.67%2.41%2.30%Pasquotank66.28%67.28%31.33%30.21%2.35%2.55%Pender78.75%80.20%18.43%17.10%2.82%2.70%Perquimans76.41%77.65%22.36%20.94%1.23%1.41%Person74.27%74.90%23.23%22.68%2.50%2.45%Pitt70.09%71.08%26.05%25.08%3.87%3.85%Polk92.61%93.19%5.44%5.09%1.92%1.72%Randolph90.88%91.15%4.71%4.47%4.42%4.37%Richmond72.45%73.05%22.69%22.13%4.86%4.85%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rowan83.56%84.12%12.71%12.22%3.73%3.66%Rutherford90.27%90.53%8.14%7.83%1.60%1.64%<	Moore	81.95%	83.05%	14.02%	13.07%	4.05%	3.90%
New Hanover84.70%85.21%11.98%11.51%3.32%3.27%Northampton48.45%50.34%50.40%48.42%1.19%1.17%Onslow75.07%76.11%16.84%16.36%8.09%7.53%Orange81.60%81.91%11.82%11.03%6.58%7.06%Pamlico80.80%81.92%16.96%15.67%2.41%2.30%Pasquotank66.28%67.28%31.33%30.21%2.35%2.55%Pender78.75%80.20%18.43%17.10%2.82%2.70%Perquimans76.41%77.65%22.36%20.94%1.23%1.41%Person74.27%74.90%23.23%22.68%2.50%2.45%Pitt70.09%71.08%26.05%25.08%3.87%3.85%Polk92.61%93.19%5.44%5.09%1.92%1.72%Randolph90.88%91.15%4.71%4.47%4.42%4.37%Richmond72.45%73.05%22.69%22.13%4.86%4.85%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rutherford90.27%90.53%8.14%7.83%1.60%1.64%	Nash	68.09%	69.15%	28.47%	27.48%	3.45%	3.36%
Northampton48.45%50.34%50.40%48.42%1.19%1.17%Onslow75.07%76.11%16.84%16.36%8.09%7.53%Orange81.60%81.91%11.82%11.03%6.58%7.06%Pamlico80.80%81.92%16.96%15.67%2.41%2.30%Pasquotank66.28%67.28%31.33%30.21%2.35%2.55%Pender78.75%80.20%18.43%17.10%2.82%2.70%Perquimans76.41%77.65%22.36%20.94%1.23%1.41%Person74.27%74.90%23.23%22.68%2.50%2.45%Pitt70.09%71.08%26.05%25.08%3.87%3.85%Polk92.61%93.19%5.44%5.09%1.92%1.72%Randolph90.88%91.15%4.71%4.47%4.42%4.37%Richmond72.45%73.05%22.69%22.13%4.86%4.85%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rutherford90.27%90.53%8.14%7.83%1.60%1.64%	New Hanover	84.70%	85.21%	11.98%	11.51%	3.32%	3.27%
Onslow75.07%76.11%16.84%16.36%8.09%7.53%Orange81.60%81.91%11.82%11.03%6.58%7.06%Pamlico80.80%81.92%16.96%15.67%2.41%2.30%Pasquotank66.28%67.28%31.33%30.21%2.35%2.55%Pender78.75%80.20%18.43%17.10%2.82%2.70%Perquimans76.41%77.65%22.36%20.94%1.23%1.41%Person74.27%74.90%23.23%22.68%2.50%2.45%Pitt70.09%71.08%26.05%25.08%3.87%3.85%Polk92.61%93.19%5.44%5.09%1.92%1.72%Randolph90.88%91.15%4.71%4.47%4.42%4.37%Richmond72.45%73.05%22.69%22.13%4.86%4.85%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rutherford90.27%90.53%8.14%7.83%1.60%1.64%	Northampton	48.45%	50.34%	50.40%	48.42%	1.19%	1.17%
Orange81.60%81.91%11.82%11.03%6.58%7.06%Pamlico80.80%81.92%16.96%15.67%2.41%2.30%Pasquotank66.28%67.28%31.33%30.21%2.35%2.55%Pender78.75%80.20%18.43%17.10%2.82%2.70%Perquimans76.41%77.65%22.36%20.94%1.23%1.41%Person74.27%74.90%23.23%22.68%2.50%2.45%Pitt70.09%71.08%26.05%25.08%3.87%3.85%Polk92.61%93.19%5.44%5.09%1.92%1.72%Randolph90.88%91.15%4.71%4.47%4.42%4.37%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rutherford90.27%90.53%8.14%7.83%1.60%1.64%	Onslow	75.07%	76.11%	16.84%	16.36%	8.09%	7.53%
Pamlico80.80%81.92%16.96%15.67%2.41%2.30%Pasquotank66.28%67.28%31.33%30.21%2.35%2.55%Pender78.75%80.20%18.43%17.10%2.82%2.70%Perquimans76.41%77.65%22.36%20.94%1.23%1.41%Person74.27%74.90%23.23%22.68%2.50%2.45%Pitt70.09%71.08%26.05%25.08%3.87%3.85%Polk92.61%93.19%5.44%5.09%1.92%1.72%Randolph90.88%91.15%4.71%4.47%4.42%4.37%Richmond72.45%73.05%22.69%22.13%4.86%4.85%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rutherford90.27%90.53%8.14%7.83%1.60%1.64%	Orange	81.60%	81.91%	11.82%	11.03%	6.58%	7.06%
Pasquotank66.28%67.28%31.33%30.21%2.35%2.55%Pender78.75%80.20%18.43%17.10%2.82%2.70%Perquimans76.41%77.65%22.36%20.94%1.23%1.41%Person74.27%74.90%23.23%22.68%2.50%2.45%Pitt70.09%71.08%26.05%25.08%3.87%3.85%Polk92.61%93.19%5.44%5.09%1.92%1.72%Randolph90.88%91.15%4.71%4.47%4.42%4.37%Richmond72.45%73.05%22.69%22.13%4.86%4.85%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rutherford90.27%90.53%8.14%7.83%1.60%1.64%	Pamlico	80.80%	81.92%	16.96%	15.67%	2.41%	2.30%
Pender78.75%80.20%18.43%17.10%2.82%2.70%Perquimans76.41%77.65%22.36%20.94%1.23%1.41%Person74.27%74.90%23.23%22.68%2.50%2.45%Pitt70.09%71.08%26.05%25.08%3.87%3.85%Polk92.61%93.19%5.44%5.09%1.92%1.72%Randolph90.88%91.15%4.71%4.47%4.42%4.37%Richmond72.45%73.05%22.69%22.13%4.86%4.85%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rutherford90.27%90.53%8.14%7.83%1.60%1.64%	Pasquotank	66.28%	67.28%	31.33%	30.21%	2.35%	2.55%
Perquimans76.41%77.65%22.36%20.94%1.23%1.41%Person74.27%74.90%23.23%22.68%2.50%2.45%Pitt70.09%71.08%26.05%25.08%3.87%3.85%Polk92.61%93.19%5.44%5.09%1.92%1.72%Randolph90.88%91.15%4.71%4.47%4.42%4.37%Richmond72.45%73.05%22.69%22.13%4.86%4.85%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rutherford90.27%90.53%8.14%7.83%1.60%1.64%	Pender	78.75%	80.20%	18.43%	17.10%	2.82%	2.70%
Person74.27%74.90%23.23%22.68%2.50%2.45%Pitt70.09%71.08%26.05%25.08%3.87%3.85%Polk92.61%93.19%5.44%5.09%1.92%1.72%Randolph90.88%91.15%4.71%4.47%4.42%4.37%Richmond72.45%73.05%22.69%22.13%4.86%4.85%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rowan83.56%84.12%12.71%12.22%3.73%3.66%Rutherford90.27%90.53%8.14%7.83%1.60%1.64%	Perquimans	76.41%	77.65%	22.36%	20.94%	1.23%	1.41%
Pitt70.09%71.08%26.05%25.08%3.87%3.85%Polk92.61%93.19%5.44%5.09%1.92%1.72%Randolph90.88%91.15%4.71%4.47%4.42%4.37%Richmond72.45%73.05%22.69%22.13%4.86%4.85%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rowan83.56%84.12%12.71%12.22%3.73%3.66%Rutherford90.27%90.53%8.14%7.83%1.60%1.64%	Person	74.27%	74.90%	23.23%	22.68%	2.50%	2.45%
Polk92.61%93.19%5.44%5.09%1.92%1.72%Randolph90.88%91.15%4.71%4.47%4.42%4.37%Richmond72.45%73.05%22.69%22.13%4.86%4.85%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rowan83.56%84.12%12.71%12.22%3.73%3.66%Rutherford90.27%90.53%8.14%7.83%1.60%1.64%	Pitt	70.09%	71.08%	26.05%	25.08%	3.87%	3.85%
Randolph90.88%91.15%4.71%4.47%4.42%4.37%Richmond72.45%73.05%22.69%22.13%4.86%4.85%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rowan83.56%84.12%12.71%12.22%3.73%3.66%Rutherford90.27%90.53%8.14%7.83%1.60%1.64%	Polk	92.61%	93.19%	5.44%	5.09%	1.92%	1.72%
Richmond72.45%73.05%22.69%22.13%4.86%4.85%Robeson39.13%39.38%19.86%19.20%41.03%41.43%Rockingham80.90%81.53%16.32%15.70%2.77%2.78%Rowan83.56%84.12%12.71%12.22%3.73%3.66%Rutherford90.27%90.53%8.14%7.83%1.60%1.64%	Randolph	90.88%	91.15%	4.71%	4.47%	4.42%	4.37%
Robeson 39.13% 39.38% 19.86% 19.20% 41.03% 41.43% Rockingham 80.90% 81.53% 16.32% 15.70% 2.77% 2.78% Rowan 83.56% 84.12% 12.71% 12.22% 3.73% 3.66% Rutherford 90.27% 90.53% 8.14% 7.83% 1.60% 1.64%	Richmond	72.45%	73.05%	22.69%	22.13%	4.86%	4.85%
Rockingham 80.90% 81.53% 16.32% 15.70% 2.77% 2.78% Rowan 83.56% 84.12% 12.71% 12.22% 3.73% 3.66% Rutherford 90.27% 90.53% 8.14% 7.83% 1.60% 1.64%	Robeson	39.13%	39.38%	19.86%	19.20%	41.03%	41.43%
Rowan 83.56% 84.12% 12.71% 12.22% 3.73% 3.66% Rutherford 90.27% 90.53% 8.14% 7.83% 1.60% 1.64%	Rockingham	80.90%	81.53%	16.32%	15.70%	2.77%	2.78%
Rutherford 90.27% 90.53% 8.14% 7.83% 1.60% 1.64%	Rowan	83,56%	84.12%	12.71%	12.22%	3.73%	3.66%
	Rutherford	90.27%	90.53%	8.14%	7.83%	1.60%	1.64%

Sampson	66.63%	67.45%	24.94%	24.17%	8.48%	8.40%
Scotland	60.56%	61.00%	29.85%	29.58%	9.56%	9.42%
Stanly	88.70%	88.92%	8.29%	8.08%	3.00%	3.00%
Stokes	94.39%	94.38%	3.87%	3.83%	1.75%	1.79%
Surry	92.05%	92.31%	3.13%	3.15%	4.79%	4.54%
Swain	70.79%	72.12%	1.24%	1.19%	27.97%	26.69%
Transylvania	93.84%	94.13%	4.16%	3.83%	1.94%	2.09%
Tyrrell	71.32%	70.45%	25.00%	23.71%	3.97%	5.84%
Union	86.37%	86.96%	9.65%	9.26%	3.97%	3.78%
Vance	56.90%	58.20%	40.19%	38.78%	2.91%	3.02%
Wake	75.77%	76.30%	17.09%	16.66%	7.14%	7.05%
Warren	43.00%	45.32%	49.66%	47.00%	7.42%	7.60%
Washington	54.32%	56.02%	42.57%	41.37%	3.01%	2.61%
Watauga	96.68%	96.89%	1.08%	0.97%	2.23%	2.13%
Wayne	67.13%	68.43%	27.54%	26.24%	5.33%	5.34%
Wilkes	93.43%	93.91%	3.94%	3.59%	2.65%	2.52%
Wilson	63.93%	65.13%	31.39%	30.26%	4.67%	4.63%
Yadkin	94.83%	94.79%	2.51%	2.44%	2.66%	2.77%
Yancey	98.33%	98.18%	0.47%	0.40%	1.29%	1.42%

	Mode of Trans.	Car Availability	Mode of Trans.	Car Availability
	Percent	Percent Hispanic	Percent Non-	Percent Non-
	Hispanic Driving	Driving	Hispanic Driving	Hispanic Driving
North Carolina State Totals	4.31%	4.18%	95.69%	95.82%

Appendix B: CTPP Variable Comparison Based on Ethnicity

County Name	Mode of Trans. Percent Hispanic Driving	Car Availability Percent Hispanic Driving	Mode of Trans. Percent Non- Hispanic Driving	Car Availability Percent Non- Hispanic Driving
Alamance	5.73%	5.63%	94.28%	94.37%
Alexander	2.08%	1.77%	97.92%	98.23%
Alleghany	5.07%	4.90%	95.14%	95.10%
Anson	0.58%	0.43%	99.41%	99.57%
Ashe	1.56%	1.54%	98.44%	98.46%
Avery	2.15%	1.77%	97.92%	98.23%
Beaufort	2.46%	2.43%	97.51%	97.57%
Bertie	0.91%	1.02%	99.14%	98.91%
Bladen	4.02%	4.07%	96.02%	95.89%
Brunswick	3.13%	3.00%	96.85%	97.00%
Buncombe	2.67%	2.64%	97.33%	97.36%
Burke	3.16%	3.06%	96.85%	96.94%
Cabarrus	3.79%	3.79%	96.21%	96.21%
Caldwell	2.43%	2.31%	97.58%	97.69%
Camden	1.68%	1.62%	98.16%	98.22%
Cateret	1.69%	1.43%	98.31%	98.57%
Caswell	1.27%	1.30%	98.63%	98.70%
Catawba	5.55%	5.52%	94.45%	94.48%
Chatham	9.34%	9.04%	90.66%	90.96%
Cherokee	1.17%	1.08%	98.83%	98.92%
Chowan	1.52%	1.20%	98.48%	98.80%
Clay	0.42%	0.41%	99.58%	99.59%
Cleveland	1.00%	0.98%	99.01%	99.02%
Columbus	1.88%	1.87%	98.07%	98.16%
Craven	4.07%	3.70%	95.92%	96.30%
Cumberland	6.51%	6.15%	93.49%	93.86%
Currituck	0.72%	0.78%	99.33%	99.22%
Dare	2.28%	2.18%	97.72%	97.82%
Davidson	2.84%	2.83%	97.14%	97.17%
Davie	3.39%	3.45%	96.61%	96.55%
Duplin	14.20%	14.65%	85.83%	85.35%
Durham	7.22%	6.90%	92.78%	93.10%
Edgecombe	2.66%	2.40%	97.34%	97.60%

Forsyth	5.54%	5.59%	94.46%	94.41%
Franklin	4.00%	4.09%	96.00%	95.91%
Gaston	2.46%	2.49%	97.55%	97.51%
Gates	0.10%	0.10%	99.88%	100.00%
Graham	2.38%	2.23%	97.91%	97.77%
Granville	3.82%	3.76%	96.18%	96.24%
Greene	8.11%	6.08%	91.82%	93.92%
Guilford	3.62%	3.67%	96.38%	96.33%
Halifax	0.58%	0.54%	99.41%	99.46%
Harnett	5.54%	5.60%	94.45%	94.41%
Haywood	1.00%	1.01%	99.00%	98.99%
Henderson	5.92%	5.67%	94.07%	94.33%
Hertford	2.14%	2.20%	97.86%	97.80%
Hoke	7.85%	7.21%	92.11%	92.79%
Hyde	3.40%	3.06%	97.12%	96.94%
Iredell	2.91%	2.73%	97.08%	97.27%
Jackson	1.15%	0.95%	98.88%	99.05%
Johnston	5.34%	4.80%	94.65%	95.21%
Jones	2.09%	2.19%	98.03%	97.81%
Lee	10.81%	10.92%	89.19%	89.08%
Lenoir	2.87%	2.70%	97.13%	97.30%
Lincoln	5.20%	5.26%	94.77%	94.74%
McDowell	2.08%	2.01%	97.89%	97.99%
Macon	1.19%	1.31%	98.76%	98.69%
Madison	1.14%	1.21%	98.93%	98.79%
Martin	1.56%	1.60%	98.44%	98.40%
Mecklenburg	6.10%	5.66%	93.90%	94.34%
Mitchell	2.01%	2.01%	97.99%	97.99%
Montgomery	9.67%	9.07%	90.37%	90.89%
Moore	3.75%	3.64%	96.25%	96.36%
Nash	2.46%	2.40%	97.56%	97.60%
New Hanover	2.20%	2.22%	97.79%	97.78%
Northampton	0.31%	0.28%	99.66%	99.72%
Onslow	6.59%	5.64%	93.41%	94.36%
Orange	4.52%	4.42%	95.48%	95.58%
Pamlico	1.79%	1.67%	98.33%	98.33%
Pasquotank	1.15%	1.29%	98.81%	98.71%
Pender	3.21%	3.16%	96.76%	96.84%
Perquimans	0.61%	0.59%	99.39%	99.41%
Person	1.49%	1.49%	98.55%	98.51%
Pitt	2.80%	2.71%	97.20%	97.29%
Polk	2.09%	1.92%	97.91%	98.08%
Randolph	5.43%	5.45%	94.56%	94.55%
Richmond	2.72%	2.43%	97.25%	97.57%
Robeson	4.93%	4.60%	95.09%	95.40%
Rockingham	2.50%	2.47%	97.50%	97.53%
Rowan	3.48%	3.37%	96.52%	96.63%
Rutherford	1.52%	1.57%	98.46%	98.42%

Sampson	8.79%	8.62%	91.23%	91.38%
Scotland	1.06%	1.05%	98.98%	98.95%
Stanly	2.33%	2.24%	97.65%	97.76%
Stokes	1.61%	1.58%	98.39%	98.42%
Surry	5.40%	5.26%	94.60%	94.74%
Swain	0.72%	0.60%	99.28%	99.40%
Transylvania	0.78%	0.72%	99.22%	99.28%
Tyrrell	3.60%	5.50%	97.06%	94.50%
Union	5.48%	5.15%	94.52%	94.85%
Vance	3.55%	3.67%	96.48%	96.33%
Wake	4.76%	4.73%	95.24%	95.27%
Warren	1.09%	1.68%	98.95%	98.32%
Washington	1.91%	1.31%	98.09%	98.69%
Watauga	1.59%	1.05%	98.41%	98.97%
Wayne	4.25%	4.37%	95.75%	95.63%
Wilkes	3.08%	3.02%	96.93%	96.98%
Wilson	5.73%	5.79%	94.27%	94.21%
Yadkin	5.51%	5.65%	94.49%	94.35%
Yancey	3.54%	3.57%	96.59%	96.50%
Appendix C: CTPP Driving Population Estimates versus Census 2000 Statistics (Age 16+) Comparison Based on Race

	Car Availability Percent White Driving	Percent White Population 16+	Car Availability Percent Af. Am. Driving	Percent Af. Am. Population 16+	Car Availability Percent Other Driving	Percent Other Population 16+
North Carolina State Totals	77.24%	74.08%	17.16%	20.19%	5.60%	5.73%

County Name	Car Availability Percent White Driving	Percent White Population 16+	Car Availability Percent Af. Am. Driving	Percent Af. Am. Population 16+	Car Availability Percent Other Driving	Percent Other Population 16+
Alamance	78.48%	77.13%	16.51%	17.73%	5.02%	5.14%
Alexander	93.65%	92.68%	3.92%	4.75%	2.43%	2.57%
Alleghany	95.51%	94.96%	0.92%	1.36%	3.68%	3.69%
Anson	59.24%	52.31%	39.67%	46.56%	1.08%	1.13%
Ashe	97.71%	97.38%	0.89%	0.88%	1.40%	1.74%
Avery	97.12%	93.05%	0.22%	4.12%	2.66%	2.83%
Beaufort	78.23%	70.71%	19.85%	27.34%	1.92%	1.95%
Bertie	47.67%	39.18%	50.80%	59.69%	1.45%	1.13%
Bladen	65.03%	59.68%	29.98%	36.02%	4.95%	4.30%
Brunswick	83.95%	84.21%	13.03%	12.97%	3.03%	2.82%
Buncombe	91.21%	89.92%	5.16%	6.70%	3.63%	3.37%
Burke	89.73%	87.64%	4.65%	6.83%	5.62%	5.53%
Cabarrus	87.10%	84.70%	9.67%	11.64%	3.23%	3.67%
Caldwell	93.51%	92.51%	4.17%	5.32%	2.33%	2.16%
Camden	83.82%	81.56%	14.08%	16.59%	1.94%	1.85%
Cateret	91.41%	91.02%	5.97%	6.44%	2.61%	2.54%
Caswell	69.19%	61.58%	29.20%	36.61%	1.62%	1.80%
Catawba	87.98%	86.97%	6.41%	7.60%	5.61%	5.43%
Chatham	79.46%	76.71%	13.54%	16.74%	7.00%	6.55%
Cherokee	93.96%	94.74%	1.59%	1.47%	4.45%	3.79%
Chowan	67.31%	63.66%	31.30%	34.86%	1.37%	1.47%
Clay	98.35%	98.63%	0.28%	0.12%	1.35%	1.25%
Cleveland	81.28%	78.79%	16.77%	19.19%	1.96%	2.02%
Columbus	72.10%	65.99%	22.54%	29.11%	5.36%	4.91%
Craven	74.91%	72.11%	20.43%	23.25%	4.65%	4.64%
Cumberland	60.24%	57.58%	30.92%	33.32%	8.83%	9.09%
Currituck	91.83%	90.48%	5.73%	6.64%	2.45%	2.89%
Dare	95.30%	95.20%	2.25%	2.64%	2.45%	2.16%
Davidson	89.40%	87.93%	7.20%	8.62%	3.40%	3.45%
Davie	91.24%	90.76%	6.15%	6.71%	2.64%	2.53%
Duplin	66.39%	61.11%	21.27%	27.68%	12.31%	11.21%

Durham	57.35%	53.94%	33.57%	36.46%	9.08%	9.60%
Edgecombe	49.36%	42.82%	48.31%	55.15%	2.33%	2.02%
Forsyth	73.69%	70.88%	20.99%	23.72%	5.33%	5.41%
Franklin	73.41%	67.82%	23.34%	28.64%	3.28%	3.54%
Gaston	86.61%	84.56%	10.46%	12.61%	2.93%	2.84%
Gates	65.33%	59.71%	32.12%	38.02%	2.55%	2.27%
Graham	91.08%	92.39%	0.00%	0.00%	8.92%	7.61%
Granville	69.03%	60.59%	26.48%	34.62%	4.52%	4.79%
Greene	60.84%	54.04%	33.01%	39.48%	6.14%	6.48%
Guilford	69.34%	66.79%	25.14%	27.57%	5.51%	5.64%
Halifax	53.88%	45.35%	42.13%	50.23%	3.99%	4.43%
Harnett	76.99%	73.50%	17.29%	20.73%	5.73%	5.76%
Haywood	97.07%	96.99%	1.12%	1.42%	1.81%	1.59%
Henderson	92.40%	93.03%	2.04%	2.61%	5.57%	4.36%
Hertford	47.74%	40.47%	49.94%	57.16%	2.39%	2.38%
Hoke	53.20%	46.72%	30.54%	36.87%	16.30%	16.42%
Hyde	77.18%	64.94%	20.47%	33.66%	2.12%	1.40%
Iredell	85.77%	83.78%	11.17%	12.95%	3.06%	3.28%
Jackson	87.85%	87.50%	1.02%	1.75%	11.13%	10.74%
Johnston	83.25%	79.55%	11.96%	14.77%	4.78%	5.68%
Jones	65.94%	62.97%	31.75%	35.07%	2.31%	1.96%
Lee	75.20%	72.13%	16.44%	19.85%	8.36%	8.02%
Lenoir	64.59%	58.61%	32.29%	38.61%	3.12%	2.78%
Lincoln	92.56%	91.39%	5.43%	6.24%	2.00%	2.37%
McDowell	93.44%	92.47%	3.69%	4.74%	2.86%	2.79%
Macon	97.43%	97.01%	0.53%	1.01%	2.04%	1.98%
Madison	98.49%	97.37%	0.24%	1.04%	1.27%	1.58%
Martin	63.69%	55.21%	35.06%	43.44%	1.25%	1.35%
Mecklenburg	69.35%	66.27%	23.26%	25.84%	7.39%	7.89%
Mitchell	96.73%	97.51%	0.37%	0.24%	2.97%	2.24%
Montgomery	77.79%	71.62%	14.05%	21.13%	8.16%	7.24%
Moore	83.05%	82.55%	13.07%	14.04%	3.90%	3.41%
Nash	69.15%	64.32%	27.48%	32.20%	3.36%	3.48%
New Hanover	85.21%	82.07%	11.51%	14.92%	3.27%	3.01%
Northampton	50.34%	41.80%	48.42%	56.83%	1.17%	1.37%
Onslow	76.11%	74.21%	16.36%	17.27%	7.53%	8.52%
Orange	81.91%	79.36%	11.03%	12.80%	7.06%	7.83%
Pamlico	81.92%	74.07%	15.67%	23.51%	2.30%	2.41%
Pasquotank	67.28%	58.66%	30.21%	38.67%	2.55%	2.67%
Pender	80.20%	74.17%	17.10%	22.69%	2.70%	3.13%
Perquimans	77.65%	72.83%	20.94%	26.13%	1.41%	1.04%
Person	74.90%	70.84%	22.68%	26.82%	2.45%	2.34%
Pitt	71.08%	65.30%	25.08%	30.91%	3.85%	3.79%
Polk	93.19%	92.80%	5.09%	5.09%	1.72%	2.11%
Randolph	91.15%	90.19%	4.47%	5.20%	4.37%	4.61%
Richmond	73.05%	67.36%	22.13%	28.14%	4.85%	4.50%
Robeson	39.38%	35.68%	19.20%	24.20%	41.43%	40.12%
Rockingham	81.53%	78.67%	15.70%	18.45%	2.78%	2.88%

Rowan	84.12%	81.39%	12.22%	14.88%	3.66%	3.73%
Rutherford	90.53%	88.35%	7.83%	10.21%	1.64%	1.44%
Sampson	67.45%	62.20%	24.17%	28.94%	8.40%	8.86%
Scotland	61.00%	55.35%	29.58%	34.91%	9.42%	9.73%
Stanly	88.92%	86.20%	8.08%	10.87%	3.00%	2.93%
Stokes	94.38%	93.73%	3.83%	4.78%	1.79%	1.49%
Surry	92.31%	91.70%	3.15%	3.62%	4.54%	4.68%
Swain	72.12%	70.90%	1.19%	2.73%	26.69%	26.36%
Transylvania	94.13%	94.00%	3.83%	4.15%	2.09%	1.85%
Tyrrell	70.45%	57.42%	23.71%	37.50%	5.84%	5.09%
Union	86.96%	84.21%	9.26%	11.65%	3.78%	4.14%
Vance	58.20%	51.51%	38.78%	45.68%	3.02%	2.81%
Wake	76.30%	73.66%	16.66%	18.70%	7.05%	7.65%
Warren	45.32%	41.40%	47.00%	52.14%	7.60%	6.46%
Washington	56.02%	51.27%	41.37%	46.75%	2.61%	1.98%
Watauga	96.89%	96.20%	0.97%	1.58%	2.13%	2.21%
Wayne	68.43%	63.35%	26.24%	31.70%	5.34%	4.95%
Wilkes	93.91%	93.10%	3.59%	4.16%	2.52%	2.74%
Wilson	65.13%	58.69%	30.26%	36.84%	4.63%	4.47%
Yadkin	94.79%	94.08%	2.44%	2.94%	2.77%	2.97%
Yancey	98.18%	98.17%	0.40%	0.46%	1.42%	1.37%

Appendix D: CTPP Driving Population Estimates versus Census 2000 Statistics (Age 16+) Comparison Based on Ethnicity

	Car Availability Percent Hispanic Driving	Percent Hispanic Population 16+	Car Availability Percent Non- Hispanic Driving	Percent Non- Hispanic Population 16+
North Carolina State Totals	4.18%	4.24%	95.82%	95.76%

County Name	Car Availability Percent Hispanic Driving	Percent Hispanic Population 16+	Car Availability Percent Non- Hispanic Driving	Percent Non- Hispanic Population 16+
Alamance	5.63%	5.94%	94.37%	94.06%
Alexander	1.77%	1.89%	98.23%	98.11%
Alleghany	4.90%	3.98%	95.10%	96.02%
Anson	0.43%	0.50%	99.57%	99.50%
Ashe	1.54%	1.93%	98.46%	98.07%
Avery	1.77%	2.23%	98.23%	97.77%
Beaufort	2.43%	2.34%	97.57%	97.66%
Bertie	1.02%	0.81%	98.91%	99.19%
Bladen	4.07%	3.25%	95.89%	96.75%
Brunswick	3.00%	2.61%	97.00%	97.39%
Buncombe	2.64%	2.37%	97.36%	97.63%
Burke	3.06%	3.08%	96.94%	96.92%
Cabarrus	3.79%	4.27%	96.21%	95.73%
Caldwell	2.31%	2.07%	97.69%	97.93%
Camden	1.62%	1.31%	98.22%	98.69%
Cateret	1.43%	1.39%	98.57%	98.61%
Caswell	1.30%	1.35%	98.70%	98.65%
Catawba	5.52%	5.20%	94.48%	94.80%
Chatham	9.04%	8.71%	90.96%	91.29%
Cherokee	1.08%	0.88%	98.92%	99.12%
Chowan	1.20%	1.26%	98.80%	98.74%
Clay	0.41%	0.65%	99.59%	99.35%
Cleveland	0.98%	0.96%	99.02%	99.04%
Columbus	1.87%	1.65%	98.16%	98.35%
Craven	3.70%	3.70%	96.30%	96.30%
Cumberland	6.15%	6.22%	93.86%	93.78%
Currituck	0.78%	1.04%	99.22%	98.96%
Dare	2.18%	1.74%	97.82%	98.26%
Davidson	2.83%	2.89%	97.17%	97.11%
Davie	3.45%	3.24%	96.55%	96.76%
Duplin	14.65%	13.25%	85.35%	86.75%
Durham	6.90%	7.40%	93.10%	92.60%
Edgecombe	2.40%	2.34%	97.60%	97.66%

Forsyth	5.59%	5.82%	94.41%	94.18%
Franklin	4.09%	3.85%	95.91%	96.15%
Gaston	2.49%	2.76%	97.51%	97.24%
Gates	0.10%	0.20%	100.00%	99.80%
Graham	2.23%	1.20%	97.77%	98.80%
Granville	3.76%	4.12%	96.24%	95.88%
Greene	6.08%	6.97%	93.92%	93.03%
Guilford	3.67%	3.62%	96.33%	96.38%
Halifax	0.54%	0.64%	99.46%	99.36%
Harnett	5.60%	5.14%	94.41%	94.86%
Haywood	1.01%	0.93%	98.99%	99.07%
Henderson	5.67%	4.55%	94.33%	95.45%
Hertford	2.20%	1.32%	97.80%	98.68%
Hoke	7.21%	6.68%	92.79%	93.32%
Hyde	3.06%	2.69%	96.94%	97.31%
Iredell	2.73%	3.04%	97.27%	96.96%
Jackson	0.95%	1.13%	99.05%	98.87%
Johnston	4.80%	6.53%	95.21%	93.47%
Jones	2.19%	2.07%	97.81%	97.93%
Lee	10.92%	10.38%	89.08%	89.62%
Lenoir	2.70%	2.68%	97.30%	97.32%
Lincoln	5.26%	4.76%	94.74%	95.24%
McDowell	2.01%	2.06%	97.99%	97.94%
Macon	1.31%	1.22%	98.69%	98.78%
Madison	1.21%	0.96%	98.79%	99.04%
Martin	1.60%	1.55%	98.40%	98.45%
Mecklenburg	5.66%	6.43%	94.34%	93.57%
Mitchell	2.01%	1.55%	97.99%	98.45%
Montgomery	9.07%	8.20%	90.89%	91.80%
Moore	3.64%	3.17%	96.36%	96.83%
Nash	2.40%	2.70%	97.60%	97.30%
New Hanover	2.22%	1.98%	97.78%	98.02%
Northampton	0.28%	0.51%	99.72%	99.49%
Onslow	5.64%	6.81%	94.36%	93.19%
Orange	4.42%	4.33%	95.58%	95.67%
Pamlico	1.67%	1.44%	98.33%	98.56%
Pasquotank	1.29%	0.97%	98.71%	99.03%
Pender	3.16%	3.24%	96.84%	96.76%
Perquimans	0.59%	0.61%	99.41%	99.39%
Person	1.49%	1.34%	98.51%	98.66%
Pitt	2.71%	2.74%	97.29%	97.26%
Polk	1.92%	2.66%	98.08%	97.34%
Randolph	5.45%	5.56%	94.55%	94.44%
Richmond	2.43%	2.26%	97.57%	97.74%
Robeson	4.60%	4.42%	95.40%	95.58%
Rockingham	2.47%	2.83%	97.53%	97.17%
Rowan	3.37%	3.36%	96.63%	96.64%
Rutherford	1.57%	1.35%	98.42%	98.65%

Sampson	8.62%	9.47%	91.38%	90.53%
Scotland	1.05%	0.75%	98.95%	99.25%
Stanly	2.24%	2.15%	97.76%	97.85%
Stokes	1.58%	1.59%	98.42%	98.41%
Surry	5.26%	5.11%	94.74%	94.89%
Swain	0.60%	0.94%	99.40%	99.06%
Transylvania	0.72%	0.69%	99.28%	99.31%
Tyrrell	5.50%	4.45%	94.50%	95.55%
Union	5.15%	5.87%	94.85%	94.13%
Vance	3.67%	3.75%	96.33%	96.25%
Wake	4.73%	5.23%	95.27%	94.77%
Warren	1.68%	1.64%	98.32%	98.36%
Washington	1.31%	1.20%	98.69%	98.80%
Watauga	1.05%	1.36%	98.97%	98.64%
Wayne	4.37%	4.11%	95.63%	95.89%
Wilkes	3.02%	2.81%	96.98%	97.19%
Wilson	5.79%	5.26%	94.21%	94.74%
Yadkin	5.65%	5.30%	94.35%	94.70%
Yancey	3.57%	2.48%	96.50%	97.52%

Appendix E: CTPP Driving Population Estimates versus Stop Percentages Comparison Based on Ethnicity

Counties where Non-Hispanic Stop Percentage was less than 2% below Non-Hispanic Population Estimate

County Names	Total Number of Stops All Drivers	Pop. Est. by Car Av. Non-Hisp. Drivers	Stop Percentage Non-Hisp. Drivers	Pop. Est Stop Per. Non-Hisp. Drivers
Alamance	4231	94.37%	93.38%	0.99%
Alexander	1610	98.23%	97.14%	1.08%
Ashe	1034	98.46%	97.10%	1.36%
Beaufort	4138	97.57%	95.60%	1.97%
Bertie	1522	98.91%	99.15%	-0.24%
Bladen	4587	95.89%	99.43%	-3.54%
Brunswick	3174	97.00%	96.53%	0.47%
Buncombe	6272	97.36%	98.07%	-0.71%
Burke	2419	96.94%	98.26%	-1.32%
Cabarrus	4953	96.21%	95.30%	0.91%
Caldwell	2621	97.69%	96.76%	0.93%
Camden	1210	98.22%	99.26%	-1.04%
Carteret	4525	98.57%	98.41%	0.16%
Caswell	1272	98.70%	98.11%	0.58%
Catawba	7714	94.48%	94.65%	-0.17%
Cherokee	520	98.92%	99.42%	-0.50%
Chowan	1517	98.80%	97.76%	1.04%
Clay	378	99.59%	99.74%	-0.15%
Columbus	4491	98.16%	99.80%	-1.64%
Craven	4654	96.30%	97.42%	-1.12%
Cumberland	8296	93.86%	95.56%	-1.71%
Currituck	1734	99.22%	99.48%	-0.26%
Dare	2122	97.82%	98.92%	-1.10%
Davie	4494	96.55%	96.62%	-0.06%
Duplin	4521	85.35%	83.59%	1.76%
Edgecombe	3774	97.60%	98.01%	-0.41%
Forsyth	8112	94.41%	92.75%	1.66%
Franklin	1914	95.91%	94.25%	1.66%
Gaston	7490	97.51%	97.17%	0.34%
Gates	1063	100.00%	99.06%	0.94%
Graham	360	97.77%	99.44%	-1.67%
Granville	3665	96.24%	95.44%	0.80%
Greene	1934	93.92%	94.11%	-0.19%
Guilford	10922	96.33%	95.43%	0.90%
Halifax	4096	99.46%	98.39%	1.07%
Harnett	4495	94.41%	94.26%	0.15%
Haywood	3771	98.99%	98.46%	0.52%

Hertford	2202	97.80%	98.23%	-0.43%
Hyde	789	96.94%	95.94%	1.00%
Iredell	5287	97.27%	96.08%	1.18%
Jackson	2280	99.05%	99.08%	-0.03%
Jones	1037	97.81%	98.17%	-0.36%
Lee	2013	89.08%	87.88%	1.20%
Lincoln	2703	94.74%	94.67%	0.07%
McDowell	3344	97.99%	97.16%	0.83%
Macon	938	98.69%	98.93%	-0.24%
Madison	1385	98.79%	97.47%	1.32%
Martin	1740	98.40%	97.41%	0.99%
Mecklenburg	7935	94.34%	94.97%	-0.64%
Mitchell	655	97.99%	96.34%	1.66%
Montgomery	1866	90.89%	91.59%	-0.70%
Moore	2848	96.36%	94.70%	1.66%
Nash	5836	97.60%	96.40%	1.20%
New Hanover	4120	97.78%	97.79%	-0.02%
Northampton	1784	99.72%	98.77%	0.96%
Onslow	7172	94.36%	96.82%	-2.47%
Orange	3460	95.58%	95.12%	0.46%
Pamlico	608	98.33%	96.71%	1.62%
Pasquotank	2346	98.71%	98.55%	0.16%
Pender	4925	96.84%	95.88%	0.96%
Perquimans	1673	99.41%	98.33%	1.09%
Person	2052	98.51%	98.25%	0.26%
Polk	1701	98.08%	97.59%	0.49%
Richmond	2655	97.57%	96.20%	1.38%
Rowan	4902	96.63%	94.98%	1.65%
Rutherford	1598	98.42%	97.87%	0.54%
Scotland	2366	98.95%	97.38%	1.57%
Stanly	2930	97.76%	98.63%	-0.87%
Stokes	2530	98.42%	97.39%	1.03%
Surry	2269	94.74%	92.82%	1.93%
Swain	556	99.40%	99.46%	-0.06%
Transylvania	1100	99.28%	98.55%	0.73%
Tyrrell	1014	94.50%	95.76%	-1.26%
Union	4300	94.85%	93.12%	1.74%
Vance	2535	96.33%	95.58%	0.75%
Wake	13046	95.27%	93.50%	1.77%
Warren	1585	98.32%	97.60%	0.72%
Watauga	2148	98.97%	98.70%	0.28%
Wilkes	3859	96.98%	97.15%	-0.17%
Wilson	3642	94.21%	92.94%	1.27%
Yadkin	2309	94.35%	94.20%	0.15%

Appendix F: Stop Percentages versus Search Percentages Comparison Based on Race

County Names	Total Number of Searches All Drivers	Stop Percentages White Drivers	Search Percentage White Drivers	Stop Per Search Per. White Drivers
Alexander	8	88.94%	87.50%	1.44%
Alleghany	1	88.82%	100.00%	-11.18%
Anson	33	48.16%	39.39%	8.76%
Ashe	1	95.94%	100.00%	-4.06%
Avery	5	94.86%	60.00%	34.86%
Bertie	9	44.15%	33.33%	10.82%
Bladen	4	56.64%	25.00%	31.64%
Brunswick	14	77.10%	85.71%	-8.62%
Buncombe	15	90.74%	93.33%	-2.60%
Burke	11	88.26%	81.82%	6.44%
Cabarrus	38	76.72%	68.42%	8.30%
Caldwell	5	92.18%	80.00%	12.18%
Camden	1	76.94%	100.00%	-23.06%
Carteret	29	85.10%	79.31%	5.79%
Caswell	5	59.51%	60.00%	-0.49%
Catawba	38	83.33%	81.58%	1.75%
Cherokee	0	96.35%	No Searches Done	No Searches Done
Chowan	7	63.61%	28.57%	35.04%
Clay	0	97.88%	No Searches Done	No Searches Done
Cleveland	64	70.71%	62.50%	8.21%
Columbus	2	68.78%	50.00%	18.78%
Cumberland	14	57.03%	57.14%	-0.12%
Currituck	8	87.77%	62.50%	25.27%
Dare	12	92.79%	100.00%	-7.21%
Forsyth	63	74.12%	66.67%	7.46%
Franklin	2	56.74%	0.00%	56.74%
Gaston	125	74.70%	72.80%	1.90%
Gates	6	51.08%	16.67%	34.42%
Graham	0	94.17%	No Searches Done	No Searches Done
Greene	2	54.71%	0.00%	54.71%
Guilford	223	65.76%	59.64%	6.12%
Haywood	29	90.19%	89.66%	0.53%
Henderson	8	85.08%	62.50%	22.58%
Hertford	18	43.87%	44.44%	-0.58%
Hoke	18	33.29%	44.44%	-11.16%
Hyde	5	69.96%	40.00%	29.96%
Jackson	5	91.27%	100.00%	-8.73%
Jones	7	74.73%	57.14%	17.59%
Lincoln	2	87.24%	50.00%	37.24%

Counties where White Search Percentage was less than 10% below White Stop Percentage and Counties that had less than 10 searches

McDowell	8	90.82%	62.50%	28.32%
Macon	0	93.60%	No Searches Done	No Searches Done
Madison	12	93.14%	83.33%	9.81%
Martin	6	58.28%	0.00%	58.28%
Mitchell	6	95.27%	100.00%	-4.73%
Moore	9	70.19%	66.67%	3.52%
Nash	247	60.33%	61.54%	-1.21%
New Hanover	27	81.80%	88.89%	-7.09%
Northampton	5	41.76%	40.00%	1.76%
Orange	6	62.80%	50.00%	12.80%
Pamlico	2	72.53%	0.00%	72.53%
Pasquotank	6	67.90%	50.00%	17.90%
Perquimans	3	66.17%	100.00%	-33.83%
Person	7	65.98%	57.14%	8.84%
Polk	13	85.24%	92.31%	-7.06%
Richmond	78	59.89%	51.28%	8.60%
Robeson	3	41.18%	0.00%	41.18%
Rutherford	2	84.86%	100.00%	-15.14%
Stanly	16	83.34%	75.00%	8.34%
Surry	11	87.09%	81.82%	5.27%
Swain	0	87.77%	No Searches Done	No Searches Done
Transylvania	0	93.36%	No Searches Done	No Searches Done
Vance	2	49.66%	50.00%	-0.34%
Warren	21	46.44%	52.38%	-5.95%
Watauga	6	96.42%	83.33%	13.08%
Wilkes	12	91.60%	83.33%	8.27%
Wilson	37	60.79%	56.76%	4.03%
Yancey	4	92.75%	100.00%	-7.25%

Appendix G: Stop Percentages versus Search Percentages Comparison Based on Ethnicity

County Names	Total Number of Searches All Drivers	Stop Percentages Non-Hisp. Drivers	Search Percentage Non-Hisp. Drivers	Stop Per Search Per. Non-Hisp. Drivers
Alexander	8	97.14%	100.00%	-2.86%
Alleghany	1	92.00%	100.00%	-8.00%
Anson	33	96.81%	93.94%	2.87%
Ashe	1	97.10%	100.00%	-2.90%
Avery	5	95.58%	60.00%	35.58%
Bertie	9	99.15%	100.00%	-0.85%
Bladen	4	99.43%	100.00%	-0.57%
Buncombe	15	98.07%	100.00%	-1.93%
Caldwell	5	96.76%	100.00%	-3.24%
Camden	1	99.26%	100.00%	-0.74%
Carteret	29	98.41%	100.00%	-1.59%
Caswell	5	98.11%	100.00%	-1.89%
Catawba	38	94.65%	92.11%	2.54%
Cherokee	0	99.42%	No Searches Done	No Searches Done
Chowan	7	97.76%	100.00%	-2.24%
Clay	0	99.74%	No Searches Done	No Searches Done
Cleveland	64	97.01%	96.88%	0.13%
Columbus	2	99.80%	100.00%	-0.20%
Craven	26	97.42%	92.31%	5.11%
Cumberland	14	95.56%	92.86%	2.71%
Currituck	8	99.48%	100.00%	-0.52%
Dare	12	98.92%	100.00%	-1.08%
Davidson	60	94.55%	86.67%	7.88%
Davie	19	96.62%	94.74%	1.88%
Edgecombe	28	98.01%	96.43%	1.58%
Franklin	2	94.25%	50.00%	44.25%
Gaston	125	97.17%	94.40%	2.77%
Gates	6	99.06%	100.00%	-0.94%
Graham	0	99.44%	No Searches Done	No Searches Done
Granville	25	95.44%	92.00%	3.44%
Greene	2	94.11%	100.00%	-5.89%
Halifax	15	98.39%	100.00%	-1.61%
Haywood	29	98.46%	96.55%	1.91%
Henderson	8	91.58%	87.50%	4.08%
Hertford	18	98.23%	100.00%	-1.77%
Hoke	18	87.75%	94.44%	-6.70%
Hyde	5	95.94%	80.00%	15.94%
Iredell	38	96.08%	86.84%	9.24%

Counties where Non-Hispanic Search Percentage was less than 10% below Non-Hispanic Stop Percentage and Counties that had less than 10 searches

Jackson	5	99.08%	100.00%	-0.92%
Johnston	227	90.15%	82.82%	7.33%
Jones	7	98.17%	100.00%	-1.83%
Lincoln	2	94.67%	50.00%	44.67%
McDowell	8	97.16%	87.50%	9.66%
Macon	0	98.93%	No Searches Done	No Searches Done
Madison	12	97.47%	91.67%	5.81%
Martin	6	97.41%	83.33%	14.08%
Mecklenburg	54	94.97%	94.44%	0.53%
Mitchell	6	96.34%	100.00%	-3.66%
Moore	9	94.70%	88.89%	5.81%
Nash	247	96.40%	89.07%	7.33%
New Hanover	27	97.79%	92.59%	5.20%
Northampton	5	98.77%	80.00%	18.77%
Onslow	134	96.82%	93.28%	3.54%
Orange	6	95.12%	100.00%	-4.88%
Pamlico	2	96.71%	100.00%	-3.29%
Pasquotank	6	98.55%	100.00%	-1.45%
Pender	42	95.88%	90.48%	5.40%
Perquimans	3	98.33%	100.00%	-1.67%
Person	7	98.25%	100.00%	-1.75%
Polk	13	97.59%	92.31%	5.28%
Richmond	78	96.20%	93.59%	2.61%
Robeson	3	93.26%	66.67%	26.59%
Rowan	23	94.98%	91.30%	3.68%
Rutherford	2	97.87%	100.00%	-2.13%
Scotland	112	97.38%	93.75%	3.63%
Stanly	16	98.63%	100.00%	-1.37%
Stokes	15	97.39%	100.00%	-2.61%
Surry	11	92.82%	90.91%	1.91%
Swain	0	99.46%	No Searches Done	No Searches Done
Transylvania	0	98.55%	No Searches Done	No Searches Done
Vance	2	95.58%	100.00%	-4.42%
Watauga	6	98.70%	83.33%	15.36%
Wilkes	12	97.15%	91.67%	5.48%
Yancey	4	93.97%	100.00%	-6.03%

Appendix H: Correlation Tables for Stop Percentage versus Search Percentage Correlations for both Race and Ethnicity

Correlations

		RDIFSTOP	RDIFSEAR
RDIFSTOP	Pearson Correlation	1.000	.145
	Sig. (2-tailed)		.151
	Ν	100	100
RDIFSEAR	Pearson Correlation	.145	1.000
	Sig. (2-tailed)	.151	
	Ν	100	100

RDIFSTOP = Difference between Driving Population Estimate and Stop Percentage based on Race

RDIFSEAR = Difference between Stop Percentage and Search Percentage based on Race

		EDIFSTOP	EDIFSEAR
EDIFSTOP	Pearson Correlation	1.000	.311*'
	Sig. (2-tailed)		.002
	Ν	100	100
EDIFSEAR	Pearson Correlation	.311**	1.000
	Sig. (2-tailed)	.002	
	Ν	100	100

Correlations

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

EDIFSTOP = Difference between Driving Population Estimate and Stop Percentage based on Ethnicity

EDIFSEAR = Difference between Stop Percentage and Search Percentage based on Ethnicity