Connecticut
RACIAL PROFILING
PROHIBITION PROJECT

STATE OF CONNECTICUT

TRAFFIC STOP DATA ANALYSIS AND FINDINGS, 2017

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This report was written by the Institute for Municipal and Regional Policy (IMRP) at Central Connecticut State University with the help of Matthew B. Ross and Jesse Kalinowski who applied the statistical tests known as the "Veil of Darkness", "Synthetic Control", "Stop Disposition", and "KPT Hit Rate."

TABLE OF CONTENTS

LIST OF TABLES

II: Characteristics of Traffic Stop Data

III: Analysis of Traffic Stops, Veil of Darkness

IV: Analysis of Traffic Stops, Synthetic Control

V: Analysis of Traffic Stops, Descriptive Statistics and Intuitive Measures

VI: Analysis of Stop Dispositions

VII: Analysis of Vehicular Searches

X: Derby Follow-Up Analysis

XI: Fairfield Follow-Up Analysis

LIST OF FIGURES

II: Characteristics of Traffic Stops

X: Derby Follow-Up Analysis

XI: Fairfield Follow-Up Analysis

PREAMBLE

This preamble was written by an ad-hoc committee of the Connecticut Racial Profiling Prohibition Project advisory board and endorsed unanimously by the board on December 6, 2018.

1. Racial Profiling has historically occurred, and continues to occur throughout America.
2. The Alvin W. Penn Racial Profiling Law enacted by the Connecticut General Assembly in 1999 required state and local police to collect traffic stop data and report the data to the state.
3. The 2011 federal investigation into the East Haven Police Department brought this issue to the forefront in Connecticut again and led to the Connecticut General Assembly updating the Profiling Legislation in 2012.
4. Disparities across racial and ethnic groups occur in traffic stops in Connecticut.
5. Enforcing the law's data reporting requirement and collecting and analyzing racial disparities in traffic stop records in the primary charge of the advisory board.
    a. A broader analysis, utilizing multiple methodologies in the preferred method for measuring for the presence of racial disparities in traffic enforcement;
    b. Although no measure is 100% accurate in measuring disparities, the analysis utilized in Connecticut is sufficient in determining the presence of disparities;
    c. We will continue to modify and refine our methodologies based on the best available research and accepted practices in the field.
6. We will take a proactive approach in understanding, explaining and addressing disparities found in the analysis by:
    a. Utilizing input from all stakeholders to understand the underlying causes for such disparities;
    b. Clearly explaining to the public and stakeholders if there are justifiable reasons for such disparities;
    c. Reporting to the Office of Policy and Management instances where the Connecticut Racial Profiling Prohibition Project Advisory Board believes that a police department is in violation of the Alvin W. Penn law.

EXECUTIVE SUMMARY OF FINDINGS

The Alvin W. Penn Racial Profiling Prohibition Act (Public Act 99-198) was first enacted in 1999 in the State of Connecticut. The law prohibits any law enforcement agency in the state from stopping, detaining, or searching motorists when the stop is motivated solely by considerations of the race, color, ethnicity, age, gender, or sexual orientation of that individual (Connecticut General Statutes Sections 54-1l and 54-1m). In 2012 and 2013, the Connecticut General Assembly made several major revisions to the law in an effort to ensure its effective implementation. In accordance with these changes, police agencies began collecting data pertaining to all traffic stops on October 1, 2013.

In 2012, the Racial Profiling Prohibition Project Advisory Board was established to advise the Office of Policy and Management (OPM) in adopting the law's standardized methods and guidelines. The Institute for Municipal and Regional Policy (IMRP) at Central Connecticut State University was tasked to help oversee the design, evaluation, and management of the racial profiling study mandated by Public Act No. 12-74 and Public Act No. 13-75, "An Act Concerning Traffic Stop Information." The project staff worked with the state's Criminal Justice Information System (CJIS) to develop a system to collect consistent and universal traffic stop information and submit it to CJIS electronically on a monthly basis.

In Connecticut, there are a total of 94 municipal police departments: 29 departments employing more than 50 officers, 50 employing between 20 and 50 officers, and 15 with fewer than 20 officers. State police are comprised of 11 distinct troops. Although there are an additional 80 jurisdictions that do not have organized police departments and are provided police services by the state police, either directly or through provision of resident troopers, these stops were categorized with their overarching state police troops. Additionally, a total of 13 special agencies have the authority to conduct traffic stops.

As per section 54-1m of the Connecticut General Statutes, the IMRP is required to submit an annual report analyzing traffic stops records for all police departments in Connecticut. This is the fourth annual report published by the IMRP and presents the results from an analysis of approximately 542,000 traffic stops conducted during the 12-month study period from January 1, 2017 through December 31, 2017.

This report is divided into two parts. Part I of this report serves as a screening tool, essentially highlighting areas where disparities between races and ethnicities are greatest in traffic enforcement throughout the state, thereby providing guidance as where to focus attention and resources for the next step of the process. It is important that readers understand the context of the initial findings in this report. There are many reasons for disparities to exist. Further analysis is presented in Part II on those specific departments identified with statistically significant disparities. By examining factors such as the location of accidents, call for service records, crime patterns, and areas of major traffic generators, readers will gain a better understanding of the nature of policing and the variety of factors that influence traffic enforcement in each identified community. It is during this part of the process that policymakers, citizens and law enforcement can best come together to understand and address the disparities present in those departments traffic stops.

Although Part II of this report only focuses attention and resources on specific departments identified with statistically significant disparities, all departments and communities would benefit from carefully reviewing the findings in this report. Addressing statewide racial and ethnic disparities will require a collective effort of all law enforcement and community stakeholders. An atmosphere of open-mindedness, empathy, and honesty from all stakeholders remains necessary to create sustained police legitimacy and a safer, more just society.

The authors of this report are hopeful that the information contained herein will be valuable to the citizens of Connecticut as they seek to fulfill the promise of the Alvin W. Penn Act. We are both humbled and grateful for the opportunity to be part of this important effort.

E.1: 2017 STATEWIDE TRAFFIC STOP ANALYSIS AND FINDINGS

Assessing racial disparities in policing data has been used for the last two decades as a policy tool to evaluate whether there exists the possibility that racial and ethnic bias is occurring within a given jurisdiction. The statistical evaluation of policing data in Connecticut is an important step towards developing a transparent dialogue between law enforcement and the public at large. As such, it is the goal of this report to present the results of that evaluation in the most transparent and unbiased manner possible. The report is organized to lead the reader through a host of descriptive and statistical tests that vary in their assumptions and level of scrutiny. The intent behind this approach is to apply multiple tests as a screening filter for the possibility that any one test (1) produces false positive results or (2) reports a false negative.

The research strategy underlying the statistical analysis presented in Part I of this report was developed with three guiding principles in mind. Each principle was considered throughout the research process and when selecting the appropriate results to display publicly. A better understanding of these principles helps to frame the results presented in the technical portions of the analysis. In addition, by presenting these principles at the onset of the report, readers have a better context to understand the overall framework of the approach.

> *Principle 1: Acknowledge that statistical evaluation is limited to finding racial and ethnic disparities that are indicative of racial and ethnic bias but that, in the absence of a formal procedural investigation, cannot be considered comprehensive evidence.*
>
> *Principle 2: Apply a holistic approach for assessing racial and ethnic disparities in Connecticut policing data by using a variety of approaches that rely on well-respected techniques from existing literature.*
>
> *Principle 3: Outline the assumptions and limitations of each approach transparently so that the public and policy makers can use their judgment in drawing conclusions from the analysis.*

Seven distinct analytical tools were used to evaluate whether racial and ethnic disparities are present in the Connecticut policing data. The first analytical tool researchers used was a method referred to as the *Veil of Darkness.* The *Veil of Darkness* is a statistical technique that was developed by Jeffery Grogger and Greg Ridgeway (2006) and published in the *Journal of the American Statistical Association*. The *Veil of Darkness* examines a restricted sample of stops occurring during the "inter-twilight window" and assesses relative differences in the ratio of minority to non-minority stops that occur in daylight as compared to darkness. The inter-twilight window restricts stops to a fixed window of time throughout the year when visibility varies due to seasonality as well as the discrete daylight savings time shift. This technique relies on the idea that, if police officers are profiling motorists, they are better able to do so during daylight hours when race and ethnicity is more easily observed. After restricting the sample of stops to the inter-twilight window and controlling for things like the time of day and day of week, any remaining difference in the likelihood a minority motorist is stopped during daylight is attributed to disparate treatment. This analytical approach is considered the most rigorous and broadly applicable of all the tests presented in this report.

The second analytical tool used in the analysis is the synthetic control where the number of minority traffic stops in a given department is evaluated against a benchmark constructed using stops made by all other departments in Connecticut. Since departments differ in terms of their enforcement activity (i.e. time of stops, reason for stops, etc.) and the underlying demographics of the population on the roadway, this analysis relies on the rich statistical literature on propensity scores. Here, a propensity score is a measure of how similar a stop made outside a given department is to a stop made by the department being analyzed. These measures of similarity are used to weight stops when constructing an individual benchmark for each department. This methodology ensures that there is an apples-to-apples comparison between the numbers of minorities stopped in a given town relative to their benchmark and allows for the interpretation of any remaining differences to be attributed to possible disparate treatment.

The three techniques contained in Part I, Section I.E are descriptive in nature and compare department-level data to three benchmarks (statewide average, estimated commuter driving populations, and resident population). These methods are referred to as population benchmarks and are commonly used to evaluate racial disparities in police data across the country. The statewide average comparison provides a simple and effective way to establish a baseline for all departments from which the relative differences between department stop numbers and the average for the state are compared. A comparison to the statewide average is presented alongside the context necessary to understand differences between local jurisdictions. Next, researchers adjust "static" residential census data to approximate the estimated driving demographics in a particular jurisdiction. Residential census data can be modified to create a reasonable estimate of the possible presence of many nonresidents likely to be driving in a given community because they work there and live elsewhere. This estimate is a composition of the driving population during typical commuting hours based on data provided by the U.S. Census Bureau. The final population benchmark comparison limits the analysis to stops involving only residents of the community and compares them to the community demographics based on the 2010 decennial census for residents age 16 and over. Although any one of these benchmarks cannot provide by itself a rigorous enough analysis to draw conclusions regarding racial disparities, if taken together with the more rigorous statistical methods they do serve as a useful tool.

The sixth analytical tool used in the analysis tests for disparities in the outcomes of traffic stops using a model that examines the distribution of dispositions conditional on race and the reason for the stop. Specifically, we test whether traffic stops made of minority motorists result in different outcomes relative to their white non-Hispanic peers. We provide one important cautionary note about interpreting this test as causal evidence of discrimination. Ideally, this test would be performed on data containing *all* violations observed by the police officer prior to making a traffic stop and where we would include a control for the number of total violations. In practice, data on traffic stops typically only contain the most severe reason that motivated the stop. In the absence of data on the full set of violations observed by police officers, we suggest that the reader interpret results from this test as providing descriptive evidence to be viewed in concert with other such empirical measures.

Lastly, an analysis of post-stop outcomes using a hit-rate approach following a technique published in the *Journal of Political Economy* by Knowles, Persico and Todd (2001). The hit-rate approach relies on the idea that motorists rationally adjust their propensity to carry contraband in response to their likelihood of being searched by police. Similarly, police officers rationally decide whether to search a motorist based on visible indicators of guilt and an expectation of the likelihood that a given motorist might have contraband. According to the model, a demographic group of motorists would be searched by police more often than white non-Hispanic motorists if they were more likely to carry contraband. However, the higher level of searches should be exactly proportional to the higher propensity for this group to carry contraband. Thus, in the absence of racial animus, we should expect the rate of successful searches (i.e. the hit-rate) to be equal across different demographic groups regardless of differences in their propensity to carry contraband. [1]

Finally, we emphasize the message that any statistical test is only truly capable of identifying racial and ethnic disparities. Such findings provide a mechanism to indicate possible racial profiling but they cannot, without further investigation, provide sufficient evidence that racial profiling exists.

E.1 (A): Findings from the Statewide Analysis

Across Connecticut's municipal departments and State Police troops, a total of 16 percent of motorists stopped during the analysis period were observed to be Black while 14 percent of stops were Hispanic motorists. Taken as a whole and relative to prior year's studies, the findings from the 2017 analysis of Connecticut's traffic stop data indicate that some progress has been made in terms of the decision to stop a minority motorist. Across the state, as well as in the analysis based on the aggregate municipal and State Police samples, the Veil of Darkness did not indicate that stopped motorists were any more likely to be from minority groups in daylight relative to darkness. Although we have identified one municipal police department and two state police troops where the Veil of Darkness indicated a statistically significant disparity, the lack of a disparity statewide and the lower number of identified departments is a promising sign.

However, the data show that large and statistically significant disparities remain in terms of how minorities are treated following a traffic stop. The new post-stop test for differential outcomes provides compelling evidence that minority motorists receive different dispositions (tickets, warnings, searches) after a stop is made, even after we condition on the basis for the stop and other potentially confounding factors. Similar evidence of adverse treatment was found statewide in terms of searches where the data suggests that the bar for searching a minority motorist is substantially lower than their white non-Hispanic counterparts. Finally, the statewide hit-rate analysis also found statistically significant evidence that the police were far less likely to be successful when searching a minority relative to a white non-Hispanic motorists.

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[1] Although some criticism has risen concerning the technique and extensions have suggested that more disaggregated groupings of searches be used in the test, the ability to implement such improvements is limited by the small overall sample of searches in a single year of traffic stops. Despite these limitations, the hit-rate analysis is still widely applied in practice and contributes to the overall understanding of post-stop police behavior in Connecticut.

Veil of Darkness Analysis Findings, 2017

In an effort to better identify racial and ethnic disparities at the department level, each analysis was repeated at the department level. The threshold for identifying individual departments was the presence of a disparity that was statistically significant at the 95 percent level in the Black or Hispanic alone categories. The departments that were identified as having a statistically significant disparity are, by nature, the largest contributors to the overall statewide results. [2] Here, the unit of analysis is a municipal department or State Police troops where disparities could be a function of a number of factors including institutional culture, departmental policy, or individual officers.[3]

The one municipal department and two State Police troops identified to exhibit a statistically significant racial or ethnic disparity include:

Fairfield

The Fairfield municipal police department was observed to have made 30.4 percent minority stops during the inter-twilight window of which 13.4 percent were Hispanic and 14.6 percent were Black motorists in 2017. The Veil of Darkness analysis indicated a statistically significant disparity in the rate that both Black and Hispanic motorists were stopped during daylight relative to darkness. Within the inter-twilight window, the odds that a stopped motorist was Black increased by 1.6 while the odds that a stopped motorist was Hispanic increased by 1.3 during daylight. These results were statistically significant at a level greater than 95 percent and robust to the inclusion of a variety of controls, officer fixed-effects, and a restricted sample of moving violations.

State Police Troop C

State Police Troop C was observed to have made 22.2 percent minority stops during the inter-twilight window of which 7.7 percent were Hispanic and 8.1 percent were Black motorists in 2017. The Veil of Darkness analysis indicated a statistically significant disparity in the rate that both Black and Hispanic motorists were stopped during daylight relative to darkness. Within the inter-twilight window, the odds that a stopped motorist was Black increased by 1.4 while the odds that a stopped motorist was Hispanic also increased by 1.4 during daylight. These results were statistically significant at a level greater than 95 percent and robust to the inclusion of a variety of controls, officer fixed-effects, and a restricted sample of moving violations.

State Police Troop K

State Police Troop C was observed to have made 21.5 percent minority stops during the inter-twilight window of which 10.5 percent were Hispanic and 7.9 percent were Black motorists

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[2] To identify departments, a disparity must have been estimated with at least a 95 percent level of statistical significance and have a false discovery rate of less than 10 percent. Put simply, there must have been at least a 95 percent chance that the motorists were more likely to be stopped at a higher rate relative to white Non-Hispanic motorists. The false discovery rate of 10 percent allows for there to be a less than 10 percent chance that one of our identified estimates misidentifies a department.

[3] Since department or state police barrack estimates represent an average effect of stops made by individual officers weighted by the number of stops that they made in 2017, it is possible that officer-level disparities exist in departments which were not identified.

in 2017. The Veil of Darkness analysis indicated a statistically significant disparity in the rate that both Black and Hispanic motorists were stopped during daylight relative to darkness. Within the inter-twilight window, the odds that a stopped motorist was Hispanic increased by 10.5 during daylight. This results was statistically significant at a level greater than 95 percent and robust to the inclusion of a variety of controls, officer fixed-effects, and a restricted sample of moving violations.

Other Statistical and Descriptive Measure Analysis Findings, 2017

In addition to the one municipal police department and two State Police troops identified to exhibit statistically significant racial or ethnic disparities in the Veil of Darkness analysis, a number of other departments were identified using either the synthetic control method, descriptive tests, stop disposition test or KPT hit-rate analysis. Identification in any one of these tests alone is not, in and of itself, sufficient to be identified for further analysis. However, these additional tests are designed as an additional screening tool to identify the jurisdictions where consistent disparities exceed certain thresholds that appear in the data. Although it is understood that certain assumptions have been made in the design of each of these measures, it is reasonable to believe that departments with consistent data disparities that separate them from the majority of other departments should be subject to further review and analysis with respect to the factors that may be causing these differences.

The results from estimating whether individual municipal departments stopped more minority motorists relative to their requisite synthetic control found six municipal police departments to have a disparity that was statistically significant at the 95 percent level in the Black or Hispanic alone categories. However, the disparities did not all persist through doubly robust estimation. In total, there were only three municipal police departments that withstood this more rigorous estimation procedure. Those departments are *Meriden, Watertown,* and *Wethersfield.*

The descriptive tests are designed as an additional tool to identify disparities that exceed certain thresholds that appear in a series of census-based benchmarks. Those three benchmarks are: (1) statewide average, (2) the estimated commuter driving population, and (3) resident-only stops. Although 59 municipal police departments were identified with racial and ethnic disparities when compared to one or more of the descriptive measures, only *Darien, Derby, East Hartford*, *Meriden, Stratford, Trumbull, Waterbury, Wethersfield, and Wolcott* exceeded the disparity threshold in more than half the benchmark areas.

The results from the Stop Disposition test shows minority motorists stopped by police departments were found to have a statistically different distribution of outcomes conditional on the basis for which they were stopped. In the departmental analysis, there were 40 of 94 total departments, one of nine special departments, and 10 of 12 State Police Troops found to have a disparity in the distribution of outcomes that was statistically significant at the 95 percent level in the Black or Hispanic alone categories. Although it does appear that minority motorists are treated differently in many of the same departments identified in other tests, we still caution the reader from drawing any conclusions based on these results. As noted before, our ideal analysis would include data on every reason that a stop was made and all requisite outcomes.

Finally, the results of this test, applied to the aggregate search data for all departments in Connecticut show that departments are less successful in motorist searches across all minority groups, which is a potential indicator of disparate treatment. There was a total of one municipal police department found to have a disparity in the hit-rate of minority motorists relative to white Non-Hispanic motorists, which was statistically significant at the 95 percent level but did not fall below the threshold of a 10 percent false discovery rate. The municipal departments identified to exhibit a statistically significant racial or ethnic disparity in searches was *Milford.*

E.1 (B): Conclusions from the Statewide Analysis

Part I of this report should be utilized as a screening tool by which researchers, law enforcement administrators, community members and other appropriate stakeholders focus resources on those departments displaying the greatest level of disparities in their respective stop data. As noted previously, racial and ethnic disparities in any traffic stop analysis do not, by themselves, provide conclusive evidence of racial profiling. Statistical disparities do, however, provide significant evidence of the presence of idiosyncratic data trends that warrant further analysis.

In order to determine if a departments racial and ethnic disparities warrant additional in-depth analysis, researchers review the results from the five analytical sections of the report (Veil of Darkness, Synthetic Control, Descriptive Statistics, Stop Disposition and KPT Hit-Rate). The threshold for identifying significant racial and ethnic disparities for departments is described in each section of the report (ex. departments with a disparity that was statistically significant at the 95 percent level in the black or Hispanic alone categories in the Veil of Darkness methodology were identified as statistically significant). A department is identified for a follow-up analysis if they meet any one of the following criteria:

1. A statistically significant disparity in the Veil of Darkness analysis
2. A statistically significant disparity in the synthetic control analyses and any one of the following analyses:
    a. Descriptive statistics
    b. Stop Disposition
    c. KPT-Hit Rate
3. A statistically significant disparity in the descriptive statistics, stop disposition, and KPT hit-rate analyses.

Based on the above listed criteria it was determined that an in-depth follow-up analysis should be considered for the following departments: **(1) Derby, (2) Fairfield, and (3) Troop K.** None of these two municipal departments or one state police troop have been identified in previous reports.

Meriden, **Wethersfield, and Troop C** were also identified with racial and ethnic disparities in this study as well as in previous annual reports. Meriden was identified in the Year 2 (Traffic Stop Data Analysis and Findings, 2014-15) and Year 3 (Traffic Stop Data Analysis and Findings, 2015-16) studies. Wethersfield has been identified in all four statewide studies conducted since the start of this project. Troop C was identified in the Year 1 (Traffic Stop Data Analysis and Findings, 2013-14) study. An in-depth follow-up analysis, with recommendations, was previously completed for both municipal agencies and Troop C. The racial and ethnic disparities have remained consistent in each of the annual studies for Wethersfield and it is the only municipal department that has been identified in all four annual studies. However, Meriden was identified with fewer racial and ethnic disparities in this report compared to prior years and the disparities were only marginally above the benchmarks. Based on the results of the previously published follow-up analyses and our further understanding of traffic stop enforcement in Meriden, Wethersfield, and Troop C, we do not believe another follow-up analysis for these departments would significantly add to the knowledge of factors that may have influenced these disparities already documented in the previous follow-up reports. The departments should continue to review and monitor traffic enforcement policies to evaluate the disproportionate effect they could be having on minority drivers. They should also continue to take steps to assure that their minority community is fully engaged in the process of understanding why the allocation of enforcement resources are made and what outcomes are being achieved.

Although further analysis is important, a major component of addressing concerns about the possibility of racial profiling in Connecticut is bringing law enforcement officials and community members together in an effort to build trust by discussing relationships between police and the community. Public forums should be held in each identified community to bring these groups together. They serve as an important tool to inform the public of the findings and outline steps for moving forward with additional analysis. The IMRP is committed to utilizing both data and dialogue to enhance relationships between the police and community.

E.2: 2017 FOLLOW-UP ANALYSIS AND FINDINGS

A total of four municipal police departments and two state police troops were identified as having a statistically significant disparity in the conditional probability of a minority motorist being stopped in each respective jurisdiction. As noted in Part I of the report, these four municipal departments were identified across multiple statistical and descriptive tests. Although it is impossible to draw any direct inference about racial bias itself, the findings present compelling statistical evidence that warranted further investigation. The agencies identified were: **Derby, Fairfield, Meriden, Wethersfield, Troop C and Troop K.** In Part II of this report researchers conducted an in-depth follow-up analysis for the Derby and Fairfield Police Departments. A follow-up analysis, with recommendations, was previously completed for the Meriden Police Department in Year 2 and for the Wethersfield Police Department in Year 1 and Year 2. The racial and ethnic disparities have remained consistent in each of the annual studies for Wethersfield and it is the only municipal department that has been identified in all four annual studies. However, Meriden was identified with fewer racial and ethnic disparities in this report compared to prior years and the disparities were only marginally above the benchmarks. Based on the results of the previously published follow-up analyses and our further understanding of traffic stop enforcement in Meriden and Wethersfield, we do not believe another follow-up analysis for these two departments would significantly add to the knowledge of factors that may have influenced these disparities already documented in the previous follow-up reports. We would refer readers to the follow-up analysis for Meriden published in *2014-15 Supplemental Traffic Stop Analysis and Findings report* and for Wethersfield in Part II of the *2014-15 Traffic Stop Analysis and Findings report* and in the *2014-15 Supplemental Traffic Stop Analysis and Findings report* for more specific information on these departments.

Although both Troop C and Troop K were identified with statistically significant racial and ethnic disparities, additional research and analysis aimed at devising a more effective way to assess the stop data for these troops is ongoing and no conclusions are being presented in this report. There are very different challenges associated with assessing the racial and ethnic disparities identified for the Connecticut State Police (CSP) compared to municipal police departments. CSP not only provides enforcement on Connecticut interstate highways and state roads, but is also responsible for local policing services for 80 towns and both staffing patterns and reporting procedures vary considerably from those followed by municipal departments. A follow-up analysis was previously completed for Troop C and the racial and ethnic disparities have remained consistent from past studies. However, this is the first time Troop K has been identified with statistically significant disparities. Researchers have met with CSP command staff to discuss the development of a more in-depth analysis specific to the different nature of CSP policing services for the Troop K analysis and have requested additional information about the nature of these policing services. We anticipate completing and publishing a separate analysis of the CSP data in the coming months.

By conducting additional in-depth analyses on the Derby and Fairfield Police Departments, the public can have a better understanding as to why and how disparities exist. This transparency is intended to assist in achieving the goal of increasing trust between the public and law enforcement. The follow-up analysis was designed to be a collaborative effort between research staff, the police department and the community. The analysis was tailored based on the department and community's unique characteristics. Traffic stop disparities can be influenced by many factors such as the location of accidents, high call for service volume areas, high crime rate areas, and areas with major traffic generators such as shopping and entertainment districts, to name a few.

The first part of the follow-up analysis outlines additional descriptive measures that were applied to department-level data for the two municipal departments. In order to understand the factors that might be contributing to traffic enforcement decisions in the identified departments, researchers sought to understand where their respective traffic enforcement patterns occurred and why. Mapping the traffic stops for each identified community was a primary means to begin this part of the analysis. (Due to the relatively low number of stops that could be adequately identify longitude and latitude coordinates for in the case of Derby, we decided to analyze data by roadway.)

After completing the mapping exercise for the Fairfield Police Department, researchers proceeded with a descriptive analysis of traffic stops at the census tract level. A census tract analysis not only provided a more nuanced understanding of population demographics, but also allowed researchers to focus on the unique attributes of a subsection of a community such as major traffic generators, accident rates, local crime problems, and calls for service. Due to the lack of detailed location information available in Derby for the majority of stops, the census tract-based analysis was replaced by a descriptive analysis of major corridors and roadways. The location information typically identified the road where the traffic stop took place, but not the specific point on the road. Although analyzing traffic stops by census tract is the preferred method, analyzing traffic stops by corridor proved just as effective an approach. The follow-up analysis for both departments also included a much more in-depth post-stop data review to examine differences in citation rates, contraband found as a result of a search, and stop reasons.

The final section of this report moves beyond examining disparities at the department level and examines individual officer information. The officer analysis was developed and utilized as a tool to better understand if disparities in data were driven by individual officers or groups of officers. A total of 102 unique officer identifiers were listed in the traffic stop database for the two municipal departments that were part of the follow-up analysis. After limiting the sample to officers with 50 or more traffic stops, a total of 41 officers were examined. Of the officers examined, 5 were identified as being statistically more likely to stop a minority motorist relative to their benchmark. These officers were then examined using a balancing test that directly compared the distribution of observable traffic stop characteristics with those of each officer's benchmark. The balancing test revealed that all 5 identified officers had a benchmark that convincingly captured the distribution of observable traffic stops. As part of this process, law enforcement administrators were requested to review the findings in conjunction with additional officer information not available to researchers.

To date, traffic stop studies in other states have primarily focused on statewide or department level trends. Aside from formal investigations, there is little precedence for a state to gain a more nuanced understanding of department level enforcement patterns with an eye towards racial and ethnic disparities contained therein. Yet researchers believes it imperative to the success of this project that the conversation not end at the identification of departments with significant racial and ethnic disparities. Indeed, the individual department follow-up proved enlightening for both researchers and departments. There is, however, always more to build upon in order to achieve the stated goals of the Alvin W. Penn Act. The follow up analysis should be viewed as a part of an ongoing process for the public, law enforcement and the law's implementing agency to gain an increasingly enhanced understanding of the factors contributing to racial and ethnic disparities in traffic stops.

BACKGROUND

First enacted in 1999, Connecticut's anti-racial profiling law entitled, the Alvin W. Penn Racial Profiling Prohibition Act (Public Act 99-198), prohibits any law enforcement agency from stopping, detaining, or searching any motorist when the stop is motivated solely by considerations of the race, color, ethnicity, age, gender or sexual orientation of that individual (Connecticut General Statutes Sections 54-1l and 54-1m). In 2012 and 2013, the Connecticut General Assembly made several changes to this law to create a system to address racial profiling concerns in Connecticut.

In 2012, the Racial Profiling Prohibition Project Advisory Board was established to advise OPM in adopting the law's standardized methods and guidelines. The Institute for Municipal and Regional Policy (IMRP) at Central Connecticut State University was tasked to help oversee the design, evaluation, and management of the racial profiling study mandated by PA 12-74 and PA 13-75, "An Act Concerning Traffic Stop Information." The IMRP worked with the advisory board and all appropriate parties to enhance the collection and analysis of traffic stop data in Connecticut.

Through September 30, 2013, police agencies collected traffic stop information based on requirements outlined in the original 1999 Alvin W. Penn law. Beginning October 1, 2013, police agencies had to submit traffic stop data for analysis under the new methods outlined by the Office of Policy and Management (OPM), as required by the amended racial profiling prohibition law. The law also authorized the OPM secretary to order appropriate penalties (i.e., the withholding of state funds) when municipal police departments, the Department of Emergency Services and Public Protection (DESPP), and other police departments fail to comply.

The National Highway Traffic and Safety Administration (NHTSA) provided resources for this project through a grant administered by the Connecticut Department of Transportation. The Racial Profiling Prohibition Project Advisory Board and the project staff have been meeting since May 2012 in an effort to outline a plan to successfully implement the requirements of the 2012 and 2013 legislation. The focus of the project's early phase was to better understand traffic stop data collection in other states. After an extensive review of best practices, working groups were formed and met monthly to discuss the different aspects of the project. These working groups included Data and System, Public Awareness, and Training work groups. The full advisory board held more than 20 meetings and the working groups met approximately 50 times.

The advisory board and IMRP also worked with law enforcement officials to create a data collection system that is efficient, not burdensome to the police collecting it, and provides information that is easy to work with when it is submitted. Police agencies in Connecticut vary in their levels of sophistication and technological capacity with respect to how they collect and report data. The project staff worked with the state's Criminal Justice Information System (CJIS) to develop a system to collect consistent and universal traffic stop information and submit it to CJIS electronically on a monthly basis.

The IMRP developed and maintains a project website (www.ctrp3.org) that informs the public of the advisory board's activities, statewide informational forums, and related news items on racial profiling. The website includes meeting agendas and minutes, press releases, and links to register for events. The website is updated weekly. In addition to the project website, the IMRP partnered with the Connecticut Data Collaborative to publish all traffic stop data on a quarterly basis. The public can download the information in its original form or view summary tables for easy use. A full set of analytical tools will be available for more advanced users who are interested in data analysis.

Although much of the initial focus of this project was to develop a standardized method for data collection and analysis, there are other important components. The initiatives include a public awareness and education campaign, effective training for officers and departments, and a rigorous complaint process. Information about all of these initiatives is provided on the project website. These initiatives collectively represent different tools available for education and the prevention of racial profiling in policing. These tools were implemented in the hope of building and enhancing trust between communities and law enforcement in Connecticut.

In February 2014, the U.S. Department of Justice, Community Oriented Policing Services Division, sponsored a train-the-trainer program in Connecticut on "Fair and Impartial Policing (FIP)." The FIP program was established to train police officers and supervisors on fair and impartial policing by understanding both conscious and unconscious bias. This program was offered to police agencies throughout the state over the next year.

Lastly, a major component of addressing concerns about the possibility of racial profiling in Connecticut is bringing law enforcement officials and community members together to discuss relationships between police and the community. The project staff has conducted several public forums throughout the state to bring these groups together and will continue these dialogues in the foreseeable future. They serve as an important tool to inform the public of their rights and the role of law enforcement in serving their communities.

PART I: 2017 TRAFFIC STOP ANALYSIS AND FINDINGS

I: METHODOLOGICAL APPROACH UNDERLYING THE ANALYSIS

Assessing racial disparities in policing data has been used for the last two decades as a policy tool to evaluate whether racial bias exists within a given jurisdiction. Although there has always been widespread public support for the equitable treatment of individuals of all races, recent national headlines have brought this issue to the forefront of American consciousness and prompted a contentious national debate about policing policy. The statistical evaluation of policing data in Connecticut is an important step towards developing a transparent dialogue between law enforcement and the public. As such, this report's goal is to present the results of that evaluation in a transparent and unbiased manner.

The research strategy underlying this statistical analysis was developed with consideration to three guiding principles. Each principle served as an important foundation for the research process, particularly when selecting the appropriate results to disseminate to the public. A better understanding of these principles helps to frame the results in the technical portions of the analysis. Further, presenting these principles at the outset of the report provides readers with the appropriate context to understand our overall approach.

> *Principle 1: Acknowledge that statistical evaluation is limited to finding racial and ethnic disparities that are indicative of racial and ethnic bias but that, in the absence of a formal procedural investigation, cannot be considered comprehensive evidence.*
>
> *Principle 2: Apply a holistic approach for assessing racial and ethnic disparities in Connecticut policing data by using a variety of approaches that rely on well-respected techniques from existing literature.*
>
> *Principle 3: Outline the assumptions and limitations of each approach transparently so that the public and policy-makers can use their judgment in drawing conclusions from the analysis.*

The report is organized to lead the reader through a host of descriptive and statistical tests that vary in their assumptions and level of scrutiny. The intent behind this approach is to apply multiple tests as a screening filter for the possibility that any one test (1) produces false positive results or (2) reports a false negative. Seven distinct analytical tools were used to evaluate whether racial and ethnic disparities are present in the Connecticut policing data. In the analysis, the demography of motorists was grouped into four overlapping categories to ensure a large enough sample size for the statistical analysis. Although much of the analysis focuses on stops made of black (Hispanic or non-Hispanic) and Hispanic motorists (any race), the analysis was also conducted for aggregated groupings of all non-white motorists (Hispanic or non-Hispanic) as well as a combined sample of black and Hispanic motorists. In terms of identifying departments or state police barracks in individual tests, the estimated disparity (i.e. the higher likelihood of stopping a minority motorist) must have been estimated with at least a 95 percent level of statistical significance for either black or Hispanic motorists alone. Put simply, under the rigorous conditions set by each test, there must have been at least a 95 percent chance that either black or Hispanic motorists were more likely to be stopped (or searched) at a higher rate relative to Caucasian non-Hispanic motorists.

The analysis begins by first presenting a method referred to as the Veil of Darkness was used to assess the existence of racial and ethnic disparities in stop data. The test is a statistical technique that was developed by Jeffery Grogger and Greg Ridgeway (2006) and published in the *Journal of the American Statistical Association*. The Veil of Darkness analysis examines a restricted sample of stops occurring during the "inter-twilight window" and assesses relative differences in the ratio of minority to non-minority stops that occur in daylight as compared to darkness. The inter-twilight window restricts stops to a fixed window of time throughout the year when visibility varies due to seasonality as well as the discrete daylight savings time shift. This technique relies on the idea that, if police officers are profiling motorists, they are better able to do so during daylight hours when race and ethnicity is more easily observed. After restricting the sample of stops to the inter-twilight window and controlling for things like the time of day and day of week, any remaining difference in the likelihood a minority motorist is stopped during daylight is attributed to disparate treatment. This analytical approach is considered the most rigorous and broadly applicable of all the tests presented in this report.

The second analytical tool used in the analysis is the synthetic control where the number of minority traffic stops in a given department is evaluated against a benchmark constructed using stops made by all other departments in Connecticut. Since departments differ in terms of their enforcement activity (i.e. time of stops, reason for stops, etc.) and the underlying demographics of the population on the roadway, this analysis relies on the rich statistical literature on propensity scores. Here, a propensity score is a measure of how similar a stop made outside a given department is to a stop made by the department being analyzed. These measures of similarity are used to weight stops when constructing an individual benchmark for each department. For example, if the department being analyzed has a high minority population and makes most of their stops on Friday nights at 7PM for speeding violations then stops made for speeding violations by departments with a similar residential population at this time and day will be given more weight when constructing the benchmark. This methodology ensures that there is an apples-to-apples comparison between the number of minorities stopped in a given town relative to their benchmark and allows for the interpretation of any remaining differences to be attributed to possible disparate treatment.

The three techniques contained in Chapter 5 are descriptive in nature and compare department-level data to three benchmarks (statewide average, estimated commuter driving populations, and resident population). These methods are referred to as population benchmarks and are commonly used to evaluate racial disparities in police data across the country. The statewide average comparison provides a simple and effective way to establish a baseline for all departments from which the relative differences between department stop numbers and the average for the state are compared. A comparison to the statewide average is presented alongside the context necessary to understand differences between local jurisdictions. Next, researchers adjust "static" residential census data to approximate the estimated driving demographics in a particular jurisdiction. Residential census data can be modified to create a reasonable estimate of the possible presence of many nonresidents likely to be driving in a given community because they work there and live elsewhere. This estimate is a composition of the driving population during typical commuting hours based on data provided by the U.S. Census Bureau. The final population benchmark comparison limits the analysis to stops involving only residents of the community and compares them to the community demographics based on the most recent decennial census for residents age 16 and over. Although any one of these benchmarks cannot provide by itself a rigorous enough analysis to draw conclusions regarding racial disparities, if taken together with the more rigorous statistical methods they do serve as a useful tool.

The sixth analytical tool used in the analysis tests for disparities in the outcomes of traffic stops using a model that examines the distribution of dispositions conditional on race and the reason for the stop. Specifically, we test whether traffic stops made of minority motorists result in different outcomes relative to their white non-Hispanic peers. We provide one important cautionary note about interpreting this test as causal evidence of discrimination. Ideally, this test would be performed on data containing *all* violations observed by the police officer prior to making a traffic stop and where we would include a control for the number of total violations. In practice, data on traffic stops typically only contain the most severe reason that motivated the stop. In the absence of data on the full set of violations observed by police officers, we suggest that the reader interpret results from this test as providing descriptive evidence to be viewed in concert with other such empirical measures.

Lastly, an analysis of post-stop outcomes using a hit-rate approach following a technique published in the *Journal of Political Economy* by Knowles, Persico and Todd (2001). The hit-rate approach relies on the idea that motorists rationally adjust their propensity to carry contraband in response to their likelihood of being searched by police. Similarly, police officers rationally decide whether to search a motorist based on visible indicators of guilt and an expectation of the likelihood that a given motorist might have contraband. According to the model, a demographic group of motorists would be searched by police more often than white non-Hispanic motorists if they were more likely to carry contraband. However, the higher level of searches should be exactly proportional to the higher propensity for this group to carry contraband. Thus, in the absence of racial animus, we should expect the rate of successful searches (i.e. the hit-rate) to be equal across different demographic groups regardless of differences in their propensity to carry contraband. [4] In this test, discrimination is interpreted as a preference for searching minority motorists that shows up statistically as a lower hit-rate relative to Caucasian motorists. Note that this test inherently says nothing about disparate treatment in the decision to stop motorists as it is limited in scope to vehicular searches.

In short, we move forward with the overall goal of identifying the statistically significant racial and ethnic disparities in Connecticut policing data. A variety of statistical tests are applied to the data in the hope of providing a comprehensive approach based on the lessons learned from academic and policy applications. Our explanations of the mechanisms and assumptions that underlie each of the tests are intended to provide policymakers and the public with enough information to assess the data and draw their own conclusions from the findings.

Finally, we emphasize the message that any statistical test is only truly capable of identifying racial and ethnic disparities. Such findings provide a mechanism to indicate possible racial profiling but they cannot, without further investigation, provide sufficient evidence that racial profiling exists.

[4] Although some criticism has risen concerning the technique and extensions have suggested that more disaggregated groupings of searches be used in the test, the ability to implement such improvements is limited by the small overall sample of searches in a single year of traffic stops. Despite these limitations, the hit-rate analysis is still widely applied in practice and contributes to the overall understanding of post-stop police behavior in Connecticut.

II: CHARACTERISTICS OF TRAFFIC STOP DATA

This section examines general patterns of traffic enforcement activities in Connecticut for the study period of January 1, 2017 to December 31, 2017. Statewide and agency activity information can be used to identify variations in traffic stop patterns to help law enforcement and local communities understand more about traffic enforcement. Although some comparisons can be made between similar communities, we caution against comparing agencies' data in this section of the report. Please note that the tables included in this report present information from only a limited number of departments. Complete tables for all agencies are included in the technical appendix.

In Connecticut, more than 540,000 traffic stops were conducted during the 12-month study period. Almost 67% of the total stops were conducted by the 94 municipal police departments, 31% of the total stops were conducted by state police, and the remaining 2% of stops were conducted by other miscellaneous policing agencies. Figure 2.1 shows the aggregate number of traffic stops by month along with each demographic category. As can be seen below, the volume of traffic stops has a seasonal variation pattern. However, the proportion of minority stops remained relatively consistent across the year.

Figure 2. 1: Aggregate Traffic Stops by Month of the Year

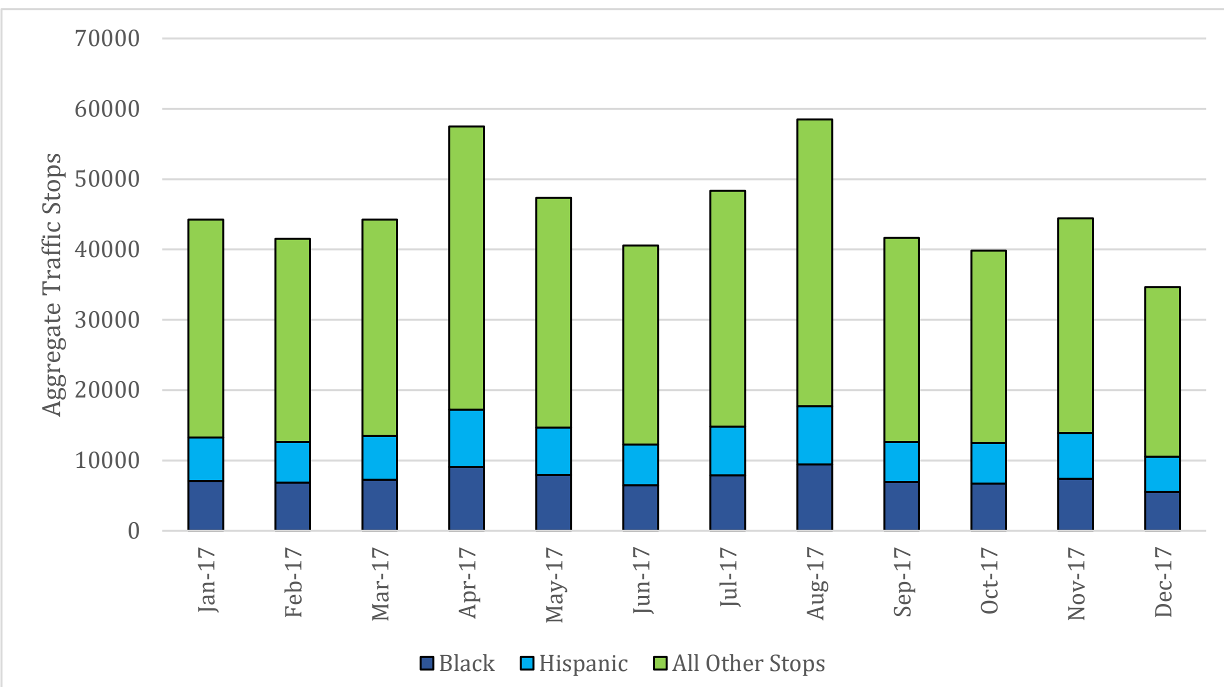


Figure 2.2 displays traffic stops by time of day for the entire analysis period. As can be seen from the figure, the total volume of traffic stops fluctuates significantly across different times of the day. The highest hourly volume of traffic stops in the sample occurred from five to six in the evening and accounted for 7.6% of all stops. It is not surprising that the volume of traffic stops increases between these hours as this is a peak commuting time in Connecticut. The lowest volume of traffic stops occurred between four and five in the morning and continued at a suppressed level during the morning commute. The low level of traffic stops during the morning commute is likely due to an

interest in maintaining a smooth flow of traffic during these hours. Discretionary traffic stops might be less likely to be made during these hours relative to others in the sample.

The evening commute, in contrast to the morning commute, represents a period when a significant proportion of traffic stops are made. The surge seen between the hours of four and seven at night represents the most significant period of traffic enforcement. In aggregate, stops occurring between these hours represented 20.3% of total stops. Interestingly, there seems to be a significant correlation between the proportion of minority stops and the overall volume of stops. In particular, the share of Hispanic and Black stops increase when the total volume of stops increase.

Figure 2. 2: Aggregate Traffic Stops by Time of Day

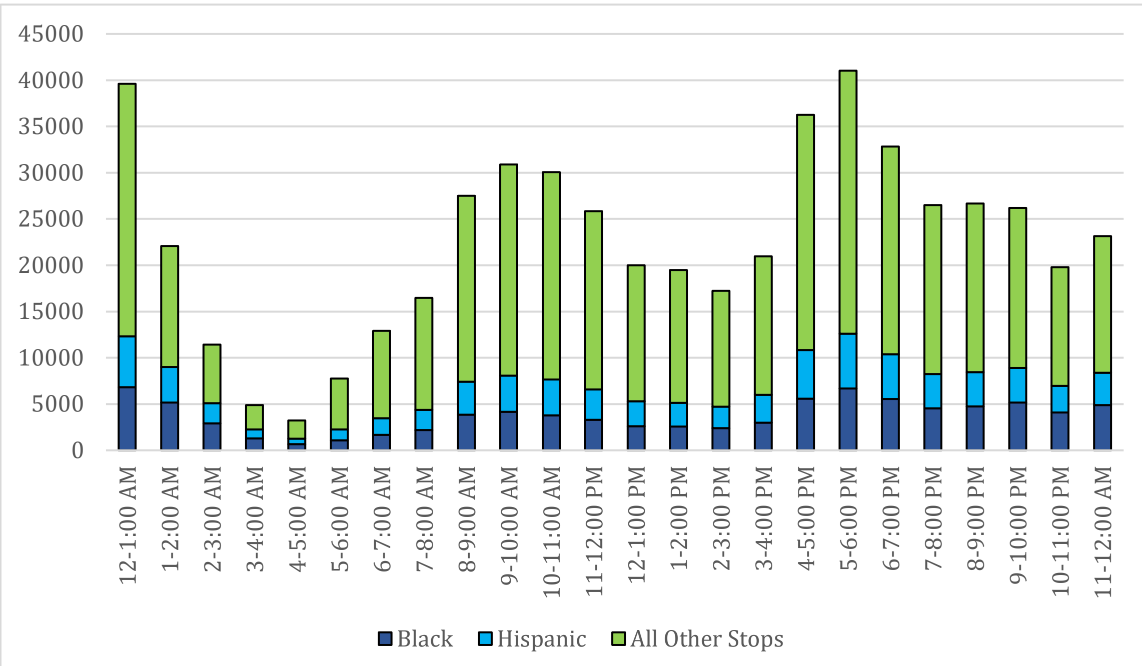
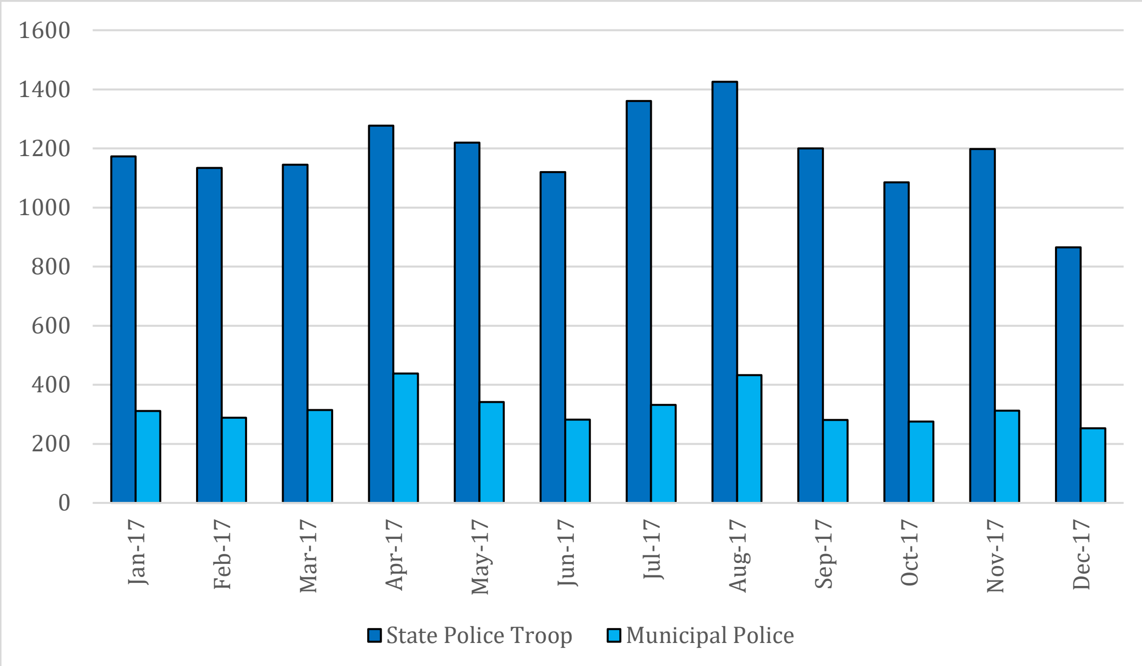


Figure 2.3 illustrates the average number of traffic stops by month for municipal police agencies and the state police. The data illustrates a fairly stable pattern of municipal traffic stop enforcement with the average number of traffic stops ranging from 253 to 438 each month for each agency. State police traffic stops are less stable by month relative to the municipal departments and range from a low of 865 to a high of 1426. This may be due to the nature of state police traffic enforcement activity that fluctuates for a variety of reasons including enforcement campaigns around the holidays.

Figure 2. 3: Average Number of Traffic Stops by Month for Police Agencies



The level of and reason for traffic stop enforcement varies greatly across agencies throughout the state for a number of reasons. For example, some enforcement is targeted to prevent accidents in dangerous areas, combat increased criminal activity, or respond to complaints from citizens. Those agencies with active traffic units produce a higher volume of traffic stops. The rate of traffic stops per 1,000 residents in the population helps to compare the stop activity between agencies. The five municipal police agencies with the highest stop rate per 1,000 residents are Wilton, New Canaan, Westport, Ridgefield, and Windsor. Conversely, Middlebury, Wolcott, Shelton, Bridgeport and Meriden have the lowest rate of stops per 1,000 residents. Table 2.1 shows the distribution of stops for the highest and lowest level of enforcement per 1,000 residents for police agencies. All department results are contained in the Table B.1 of Appendix B.

Table 2. 1: Municipal Police, Highest and Lowest Rates of Traffic Stops

Town Name	16+ Population*	Traffic Stops	Stops per 1,000 Residents
Connecticut	2,825,946	542,820	192
Municipal Departments with the Highest Rate of Traffic Stops			
Wilton	12,973	5,219	402
New Canaan	14,138	5,492	388
Westport	19,410	7,461	384
Ridgefield	18,111	6,733	372
Windsor	23,222	8,485	365
Municipal Departments with the Lowest Rate of Traffic Stops			
Middlebury	5,842	34	6
Wolcott	13,175	120	9
Shelton	32,010	561	18
Bridgeport**	109,401	2,262	21
Meriden	47,445	1,578	33

* The population 16 years of age and older was obtained from the United States Census Bureau 2010 Decennial Census.
**Bridgeport did not report an indeterminate number of traffic stops. Please see the note to the reader on page xvi.

Table 2.2 presents some basic demographic data on persons stopped in Connecticut between January 1, 2017 and December 31, 2017. Nearly two-thirds (63.1%) of drivers stopped were male and the vast majority of drivers (86%) were Connecticut residents. Of the stops conducted by police departments other than state police, 90% were Connecticut residents. Of the stops made by state police, 78% were Connecticut residents. About one-third (38%) of drivers stopped were under the age of 30 compared to 24% over 50. The vast majority of stops in Connecticut were White Non-Hispanic drivers (66%);16.3% were Black Non-Hispanic drivers; 14.2% were Hispanic drivers; and 3.0% were Asian/Pacific Islander Non-Hispanic and American Indian/Alaskan Native Non-Hispanic drivers.

Table 2. 2: Statewide Driver Characteristics

<table>
<tr><th colspan="2">Race and Ethnicity</th><th colspan="2">Gender</th><th colspan="2">Residency</th><th colspan="2">Age</th></tr>
<tr><td rowspan="2">White</td><td rowspan="2">66.4%</td><td rowspan="4">Male</td><td rowspan="4">63.1%</td><td rowspan="4">CT Resident</td><td rowspan="4">86.2%</td><td>16 to 20</td><td>8.5%</td></tr>
<tr><td>21 to 30</td><td>29.5%</td></tr>
<tr><td rowspan="2">Black</td><td rowspan="2">16.3%</td><td>31 to 40</td><td>21.2%</td></tr>
<tr><td>41 to 50</td><td>17.0%</td></tr>
<tr><td rowspan="2">Hispanic</td><td rowspan="2">14.2%</td><td rowspan="3">Female</td><td rowspan="3">36.9%</td><td rowspan="3">Non-Resident</td><td rowspan="3">13.8%</td><td>51 to 60</td><td>14.4%</td></tr>
<tr><td>Older than 61</td><td>9.4%</td></tr>
<tr><td>Other</td><td>3.1%</td><td colspan="2"></td></tr>
</table>

Table 2.3 presents data on the characteristics of the traffic stops in the state. Most traffic stops were made for a violation of the motor vehicle laws (88 percent) as opposed to a stop made for an investigatory purpose or motorist assist. The most common violation drivers were stopped for was speeding (28 percent). After a driver was stopped, over 42% were given a ticket while most of the remaining drivers received some kind of a warning (50%). Statewide, less than 1 percent of traffic stops resulted in the arrest of a driver and only 3 percent of stops resulted in a search being conducted.

Table 2. 3: Statewide Stop Characteristics

Classification of Stop		Basis for Stop	
Motor Vehicle Violation	88.4%	Speeding	28.2%
Equipment Violation	9.6%	Cell Phone	9.0%
Investigatory	2.0%	Defective Lights	8.9%
Outcome of Stop		Registration	8.8%
Uniform Arrest Report	0.8%	STC Violation	7.7%
Misdemeanor Summons	4.7%	Misc. Moving Violation	7.7%
Infraction Ticket	42.6%	Traffic Control Signal	7.2%
Written Warning	15.1%	Stop Sign	7.0%
Verbal Warning	35.4%	Seatbelt	3.5%
No Disposition	1.4%	Display of Plates	2.8%
Vehicles Searched	3.2%	All Other	9.2%

In addition to the difference in the volume of traffic stops across communities, agencies stopped drivers for a number of different reasons. Police record the statutory reason for stopping a motor vehicle for every stop. Those statutes are then sorted into 15 categories from speeding to registration violation to stop sign violation. For example, all statutory violations that are speed related are categorized as speeding. Although speeding is the most often cited reason for stopping a motor vehicle statewide, the results vary by jurisdiction.

The average municipal police department stops for speeding violations was 26% compared to the state police average of 33%. Due to the nature of state police highway operations, it is reasonable that its average for speeding is higher. In Ledyard, Ridgefield, Weston, Simsbury, Thomaston, Enfield, Guilford, Easton, Suffield, Newtown, Windsor Locks, Wolcott, New Milford, Redding, Bethel, and Southington, more than 50% of the traffic stops were for speeding violations. On the other hand, Eastern Connecticut State University, Orange, Yale University, the State Capitol Police and Western Connecticut State University stopped drivers for speeding less than 5% of the time. The four special police agencies (Yale, WCSU, ECSU, and State Capitol Police) have limited jurisdiction and it is reasonable that they are not stopping a high percentage of drivers for speeding violations. Table 2.4 shows the top 10 departments where speeding (as a percentage of all stops) was the most common reason for the traffic stop. All department results are contained in the Table B.2 of Appendix B.

Table 2. 4: Highest Speeding Stop Rates across All Departments

Department Name	Total Stops	Speeding Violations
Ledyard	2,191	63.5%
CSP Headquarters	14,090	58.8%
Ridgefield	6,733	57.9%
Weston	611	57.8%
Simsbury	3,356	57.4%
Thomaston	1,278	57.3%
Enfield	8,806	54.5%
Guilford	2,372	54.1%
Easton	1,203	53.5%
Suffield	665	53.2%

Registration violations have been cited as a low discretion reason for stopping a motor vehicle, particularly due to the increased use of license plate readers to detect registration violations. Statewide, 8.8% of all traffic stops are for a registration violation. Table 2.5 presents the top 10 departments with the highest percentage of stops for registration violations. All department results are contained in the Table B.3 of Appendix B.

Table 2. 5: Highest Registration Violation Rates across All Departments

Department Name	Total Stops	Registration Violations
Trumbull	2,749	23.9%
Troop L	8,981	22.0%
North Haven	2,633	21.2%
West Haven	8,790	20.6%
Redding	2,282	18.8%
Troop B	6,437	18.6%
North Branford	843	18.3%
Branford	5,271	18.1%
Newington	5,541	17.1%
Waterbury	3,052	16.6%

The Connecticut Department of Transportation and the National Highway Safety Administration work together every year to fund a variety of different driver safety campaigns. Some of the campaigns that we are most familiar with include: “Click it or Ticket,” “Drive Sober or get Pulled Over,” and “Move Over.” Each year law enforcement agencies receive federal grants to fund targeted traffic safety campaigns. Over the past few years there has been an increase in federal funding for distracted driver campaigns. This past year, Connecticut continued to see a significant increase in distracted driving related traffic stops. Stops as the result of a cell phone violation are the second most common reason for stopping a driver. Statewide, 9% of all stops were the result of a cell phone violation and this rate varies across departments. Table 2.6 presents the top 10 departments with the highest percentage of stops for cell phone violations. All department results are contained in the Table B.4 of Appendix B.

Table 2. 6: Highest Cell Phone Violation Rates across All Departments

Department Name	Total Stops	Cell Phone Violations
Danbury	6,160	34.9%
West Hartford	6,207	30.4%
Hamden	5,888	27.4%
Brookfield	2,187	23.4%
Bridgeport	2,262	23.3%
Trumbull	2,749	22.8%
Westport	7,461	22.4%
Stamford	13,399	21.8%
Plymouth	1,650	21.2%
Berlin	5,441	19.0%

Some Connecticut residents have expressed concern about the stops made for violations that are perceived as more discretionary in nature; therefore potentially making the driver more susceptible to possible police bias. Those stops are typically referred to as pretext stops and might include stops for defective lights, excessive window tint, or a display of plate violation each of which, though a possible violation of state law, leaves the police officer with considerable discretion with respect to actually making the stop. A statewide combined average for stopping drivers for any of these violations is 13.1%. Sixty municipal police departments exceeded that statewide average. The departments with the highest percentage of stops conducted for these violations are UCONN (33.8%), Torrington (32.2%), State Capitol Police (31.6%), West Haven (29.2%), and Middletown (26.8%).

In communities with a larger proportion of stops due to these violations, it is recommended that the departments be proactive in discussing the reasons for these stops with members of the community and examine for themselves whether or not such stops produce disparate enforcement patterns.

Many have argued that it is difficult for police to determine the defining characteristics about a driver prior to stopping and approaching the vehicle. Similar to variations found across departments for the reason for the traffic stop, there are variations that occur with the outcome of the stop. These variations illustrate the influence that local police departments have on the enforcement of state traffic laws. Some communities may view infraction tickets as the best method to increase traffic safety, while others may consider warnings to be more effective. This analysis should help police departments and local communities understand their level and type of traffic enforcement when compared to other communities.

Almost half (43%) of drivers stopped in Connecticut received an infraction ticket, while 50% received either a written or verbal warning. Individual jurisdictions varied in their post-stop enforcement actions. Danbury issued infraction tickets in 64% of all traffic stops, which is the highest in the state. Weston only issued infraction tickets in 3.3% of all traffic stops, which is the lowest rate in the state. For state police, officers not assigned to a troop issued the highest infractions (89%) and Troop L issued the lowest number of infractions (47%). Table 2.7 presents the highest infraction rates across all departments. All department results are contained in the Table B.5 of Appendix B.

Table 2. 7: Highest Infraction Rates across All Departments

Department Name	Total Stops	Infraction Ticket
Highest Municipal Departments		
Danbury	6,160	63.7%
Bridgeport	2,262	59.9%
New London	5,041	58.5%
DMV	1,575	58.3%
Trumbull	2,749	57.0%
Hamden	5,888	55.3%
Meriden	1,578	54.6%
East Hartford	7,475	54.5%
Norwalk	6,007	53.8%
Branford	5,271	53.8%
Highest State Police Troops		
CSP Headquarters	14,090	89.2%
Troop F	17,331	72.0%
Troop C	20,499	71.4%
Troop H	17,680	71.1%
Troop E	15,525	69.2%

On the other hand, Weston issued warnings 94% of the time (the highest rate) and East Hartford issued warnings 27% of the time (the lowest rate). For state police, Troop L issued the highest percentage of warnings (42%) and the group of officers not assigned to a troop issued the lowest percentage of warnings (6.1%). Table 2.8 presents the highest warning rates across all departments. All department results are contained in the Table B.6 of Appendix B.

Table 2. 8: Highest Warning Rates across All Departments

Department Name	Total Stops	Resulted in Warning
Highest Municipal Departments		
Weston	611	94.3%
Eastern CT State University	207	90.8%
Torrington	7,414	89.3%
Redding	2,282	88.6%
State Capitol Police	174	86.8%
Putnam	1,069	86.5%
Portland	358	86.3%
Seymour	3,883	85.8%
Western CT State University	7	85.7%
Avon	1,243	85.0%
Highest State Police Troops		
CSP Troop L	8,981	42.0%
CSP Troop B	6,437	39.1%
CSP Troop A	16,762	32.7%
CSP Troop K	15,428	32.4%
CSP Troop D	11,154	30.6%

Statewide, less than 1% of all traffic stops resulted in the driver being arrested. As with infraction tickets and warnings, municipal departments varied in the percentage of arrests associated with traffic stops. The Wallingford Police Department issued the most uniform arrest reports from a traffic stop, with 4.3% of all stops resulting in an arrest. East Haven arrested more than 3% of all drivers stopped. The variation in arrest rates for state police is much smaller across troop levels. Table 2.9 presents the highest arrest rates across all departments. All department results are contained in the Table B.7 of Appendix B.

Table 2. 9: Highest Arrest Rates across All Departments

Department Name	Total Stops	Arrests
Wallingford	7,909	4.3%
East Haven	2,503	3.2%
Putnam	1,069	2.8%
Middletown	3,247	2.6%
Stratford	3,697	2.5%
Vernon	3,378	2.5%
Hartford	8,243	2.4%
West Hartford	6,207	2.2%
Bloomfield	2,226	2.2%
Willimantic	2,331	2.1%

Rarely do traffic stops in Connecticut result in a vehicle being searched. During the study period, only 3.2% of all traffic stops resulted in a search. Although searches are rare in Connecticut, they do vary across jurisdictions and the data provides information about enforcement activity throughout the state. When they search a vehicle, officers must report the supporting legal authority, and whether contraband was found. Forty departments exceeded the statewide average for searches, but the largest disparity was found in Waterbury (17.8%), Stratford (15.9%), and Yale University (12.0%). Of the remaining departments, 23 searched vehicles more than 5% of the time, 14 searched vehicles between 3.2 % and 5% of the time, and the remaining departments searched vehicles less than 3% of the time. No state police troops exceeded the statewide average for searches. The highest search rate was in Troop G (2.8%). Table 10 presents the highest search rates across all departments. All department results are contained in the Table B.8 of Appendix B.

Table 2. 10: Highest Searches Rates across All Departments

Department Name	Total Stops	Resulted in Search
Highest Municipal Departments		
Waterbury	3,052	17.8%
Stratford	3,697	15.9%
Yale University	1,354	12.0%
Vernon	3,378	11.6%
Bridgeport	2,262	10.8%
Middletown	3,247	10.3%
Derby	2,347	10.0%
New Haven	19,038	8.8%
Wallingford	7,909	8.4%
Trumbull	2,749	8.0%

III: ANALYSIS OF TRAFFIC STOPS, VEIL OF DARKNESS

The Veil of Darkness test of racial and ethnic disparities in police traffic stop data operates under the key assumption that police officers are marginally better able to observe the race and ethnicity of motorists during daylight relative to darkness (Grogger and Ridgeway 2006; Ridgeway 2009; Horace and Rohlin 2017; Kalinowski et al. 2017).[5] The test relies on seasonal variation in the timing of sunset as well as the discrete daylight savings time shift to compare stops made at the same time in darkness vs. daylight. The advantage of this methodology, relative to population-based benchmarks, is that it does not require any assumptions about the underlying risk-set of motorists on the roadway. Rather, the test presumes that the composition of motorists, within a restricted sample of stops, does not vary in response to changes in visibility.[6] Here, the racial composition of stops in darkness serves as a counterfactual for those made in daylight, i.e. when officers can better observe race.

More specifically, the Veil of Darkness method evaluates whether there exist statistically significant disparities in the likelihood that a stopped motorist is a minority during daylight relative to darkness. As detailed explicitly in Appendix A.1, Grogger and Ridgeway (2006) illustrate that under certain conditions the odds-ratio of a stopped motorist being a minority in daylight vs. darkness is equivalent to the odds-ratio that a minority motorist is stopped during daylight vs. darkness. In a practical context, these assumptions are that variation in travel and enforcement patterns (abject of discrimination) do not change differentially by race in response to daylight. To ensure that these conditions are met, the estimates condition on time and day of week. To further control for inherent differences in daylight and darkness, the sample is restricted to the inter-twilight window, a period when Veil of Darkness varies throughout the year (i.e. between the earliest eastern sunset and the latest western end to civil twilight). Conveniently, this window of time falls within the evening commute where we might expect the risk-set of motorists to be less susceptible to seasonal variation.

III.A: AGGREGATE ANALYSIS WITH VEIL OF DARKNESS, 2017

Table 3.1 presents the results from the *Veil of Darkness* method applied at the state-level during the inter-twilight window. These results were estimated using Equation 4 of Appendix A.1 with the standard errors clustered by department. The estimates include controls for time of day, day of week, and department fixed-effects. The estimates rely on four definitions of minority status that are compared to white Non-Hispanics and annotated accordingly. The minority definitions across each specification are not mutually exclusive in that the first specification includes all non-White motorists (regardless of ethnicity) while the third includes all Hispanic motorists (regardless of race). The second specification is restricted to only Black motorists (regardless of ethnicity, i.e. a subset of the

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[5] Applications of the Veil of Darkness include: Grogger and Ridgeway (2006) in Oakland, CA; Ridgeway (2009) in Cincinnati, OH; Ritter and Bael (2009) and Ritter (2017) in Minneapolis, MN; Worden et al. (2010; 2012) in Syracuse, NY while Horace and Rohlin (2016) in Syracuse, NY; Renauer et al. (2009) in Portland, OR; Taniguchi et al. (2016a, 2016b, 2016c, 2016d) in Durham, Greensboro, Raleigh, and Fayetteville; Masher (2016) in New Orleans, LA; Chanin et al. (2016) in San Diego, CA; Ross et al. (2015; 2016; 2017a; 2017b) in Connecticut and Rhode Island; Criminal Justice Policy Research Institute (2017) in Corvallis PD, OR; Milyo (2017) in Columbia, MO; Smith et al. (2017) in San Jose, CA; and Wallace et al. (2017) in Maricopa, AZ.

[6] Note that this assumption allows for differential rates of traffic stops to exist across races and the potential for differences in guilt and driving behavior.

first specification) and the fourth specification includes both Black and Hispanic motorists (i.e. combines the second and third specifications). The control across all specifications includes only stops made of motorists who were observed to be white and Non-Hispanic.

As shown below, none of the coefficient estimates are statistically significant and all are relatively close to zero. Thus, we observe no change in the odds that a stopped motorist is a minority in daylight relative to darkness. As previously mentioned and discussed in detail in Appendix A.1, we should expect that (under the assumption of a constant relative risk-set) there will be a direct correspondence between changes to the odds-ratio for stopped motorists and that of motorists at risk of being stopped. In the presence of discrimination, we would have expected the coefficient estimates to be positive. Since these estimates are conducted at an aggregate level, however, they should be interpreted as a statewide average which does not necessarily rule out the possibility that underlying jurisdictions may display evidence of a disparity. Similar results were found through the application of several robustness checks including restricting the sample to moving violations (Table 3.4), officer rather than department fixed-effects (Appendix C, Table C.1), and the combination these alternative specifications (Appendix C, Table C.4).

Table 3. 1: Logistic Regression of Minority Status on Daylight with Department Fixed-Effects, All Traffic Stops 2017

LHS: Minority Status		Non-Caucasian	Black	Hispanic	Black or Hispanic
Daylight	Coefficient	-0.004	-0.004	0.001	0.002
	Standard Error	(0.032)	(0.030)	(0.032)	(0.027)
Sample Size		118082	113809	109543	132654
Pseudo R^2		0.136	0.167	0.107	0.138

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for time of the day, day of the week, analysis year, and department fixed-effects.
Note 3: Sample includes all traffic stops made during the inter-twilight window in 2017.

Table 3.2 presents the results estimated from the subsample of all municipal police departments during the inter-twilight window in 2017. Here again, we find no evidence of a statistically significant disparity in the aggregate subsample of municipal departments. Similar results were found through the application of several robustness checks including restricting the sample to moving violations (Table 3.5), officer rather than department fixed-effects (Appendix C, Table C.2), and the combination these alternative specifications (Appendix C, Table C.5). As before, these estimates are conducted at an aggregate level and do not rule out the possibility that underlying jurisdictions may display evidence of a disparity.

Table 3. 2: Logistic Regression of Minority Status on Daylight, Municipal Traffic Stops 2017

LHS: Minority Status		Non-Caucasian	Black	Hispanic	Black or Hispanic
Daylight	Coefficient	-0.041	-0.035	-0.048	-0.039
	Standard Error	(0.032)	(0.034)	(0.030)	(0.028)
Sample Size		82059	79609	75618	94132
Pseudo R^2		0.159	0.187	0.119	0.153

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for time of the day, day of the week, analysis year, and department fixed-effects.
Note 3: Sample includes all traffic stops made during the inter-twilight window in 2017.

Table 3.3 presents the results estimated from a subsample of all State Police troops during the inter-twilight window in 2017. As before, the results control for time of day, day of week, and department fixed-effects. Standard errors are clustered by troop. Here the coefficient estimates are positive and statistically significant at a level above 90 percent for the Black as well as the Black or Hispanic groupings. In the case of State Police, including officer fixed-effects had the effect of increasing statistical precision in both these categories as well as the two others that were not initially observed as significant. Results similar in magnitude but with smaller standard errors were found through the application of several robustness checks including restricting the sample to moving violations (Table 3.5), officer rather than department fixed-effects (Appendix C, Table C.3), and the combination these alternative specifications (Appendix C, Table C.6). Although the estimates from Table 3.3 provide strong evidence suggesting that there is a disparity in the rate that minority motorists are stopped by State Police, it does not necessarily imply that all State Police Troops exhibit a similar pattern of stops. The disparity could be the product of explicit or implicit police discrimination as well as changes to enforcement activity that are correlated with both race/ethnicity and daylight.

Table 3. 3: Logistic Regression of Minority Status on Daylight, State Police Traffic Stops 2017

LHS: Minority Status		Non-Caucasian	Black	Hispanic	Black or Hispanic
Daylight	Coefficient	0.079	0.078	0.141*	0.116**
	Standard Error	(0.070)	(0.064)	(0.075)	(0.056)
Sample Size		33842	32151	32113	36189
Pseudo R^2		0.046	0.056	0.050	0.059

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for time of the day, day of the week, analysis year, and department fixed-effects.
Note 3: Sample includes all traffic stops made during the inter-twilight window in 2017.

As mentioned, these estimates aggregate all traffic stops across multiple departments and should be considered an average effect. Although the results from this section, with respect to State Police, find a statistically significant disparity in the rate of minority traffic stops, they do not identify the geographic source of that disparity. The results of a department-level analysis are presented in a later section and better identify the source of specific department-wide disparities. However, the next section provides an additional set of robustness checks using a select sample of moving violations. As will be discussed subsequently, these robustness checks are necessary because certain types of stops (e.g. headlight, seatbelt, and cell phone violations) may be correlated with darkness and minority status. Indeed, we might expect that including these biases the coefficient estimates towards zero and makes it less likely that we would detect discrimination.

III.B: AGGREGATE ROBUSTNESS CHECKS WITH VEIL OF DARKNESS, 2017

This section presents robustness checks on the initial specifications using a more restrictive subsample of traffic stops. Analysis using all violations is potentially biased by specific violations that are correlated with visibility and minority status. To see why this might be a problem, imagine that minority motorists are more likely to have a headlight or taillight out and that these violations are only observable to police during darkness. In that instance, comingling equipment violations with other violations might make it more likely to observe more minorities stopped at night, thus biasing the results downward. In contrast, if minority motorists are more likely to talk on their cellphone or drive without a seatbelt and those violations are more easily observed during daylight, the results would be biased upwards. Since both of these scenarios seem reasonable and the net direction of the bias is unclear, a reasonable robustness check is to limit the sample of traffic stops to moving violations.

Table 3.4 presents the aggregate results estimated from a sample of moving violations made during the inter-twilight window in 2017. As before, these results were estimated with the standard errors clustered by department. The estimates include controls for time of day, day of week, and department fixed-effects. The coefficient estimates are statistically insignificant and close to zero. This finding indicates that there is a disparity, on average, for the state as whole. However, this does not indicate that some of the underlying departments do not have a disparity. Adding a high-dimensional set of officer fixed-effects, as shown in Appendix C, Table C.4, increases the precision of the estimates such that all of the specifications are highly significant. As before, we note that this disparity could be the product of explicit or implicit police discrimination as well as remaining unobserved changes to speed enforcement that are correlated with both race/ethnicity and daylight.

Table 3. 4: Logistic Regression of Minority Status on Daylight with Department Fixed-Effects, All Moving Violations 2017

LHS: Minority Status		Non-Caucasian	Black	Hispanic	Black or Hispanic
Daylight	Coefficient	0.037	0.032	-0.046	0.003
	Standard Error	(0.039)	(0.037)	(0.041)	(0.030)
Sample Size		67174	64247	62209	73032
Pseudo R^2		0.112	0.146	0.092	0.123

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for time of the day, day of the week, analysis year, and department fixed-effects.
Note 3: Sample includes all moving violations made during the inter-twilight window in 2017.

Table 3.5 presents the aggregate results estimated from a sample of municipal moving violations made during the inter-twilight window in 2017. As before, these results were estimated with the standard errors clustered by department. The estimates include controls for time of day, day of week, and department fixed-effects. The estimates only report a statistically significant disparity for Hispanic motorists but the coefficients are negative indicating that, on average, municipal departments stop more white Non-Caucasian motorists during daylight. Adding a high-dimensional set of officer fixed-effects, as shown in Appendix C, Table C.5, increases the precision of the estimates but the Hispanic specification is the only that is significant there as well. As before, we note that these are aggregate estimates and should be treated as such.

Table 3. 5: Logistic Regression of Minority Status on Daylight, Municipal Moving Violations 2017

LHS: Minority Status		Non-Caucasian	Black	Hispanic	Black or Hispanic
Daylight	Coefficient	-0.004	0.008	-0.114***	-0.043
	Standard Error	(0.037)	(0.041)	(0.039)	(0.028)
Sample Size		44009	42458	40743	48765
Pseudo R^2		0.146	0.181	0.115	0.150

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for time of the day, day of the week, analysis year, and department fixed-effects.
Note 3: Sample includes all moving violations made during the inter-twilight window in 2017.

Table 3.6 presents the results from the subsample of State Police moving violations during the inter-twilight window. As before, these results were estimated with the standard errors clustered by State Police troops. The estimates include controls for time of day, day of week, and department fixed-effects. The coefficient estimates are positive which indicates that the odds a stopped motorist is Black increases during daylight but are not statistically significant. However, we find that the precision across all specifications increases substantially when a high dimensional set of officer fixed-effects are added (see Appendix C, Table C.6). Since the patrol areas of State Police troopers varies widely even within individual troops, this finding is not entirely surprising and does indeed suggest the presence of a disparity. As before, we note that this disparity could be the product of explicit or implicit police discrimination as well as remaining unobserved changes to speed enforcement that are correlated with both race/ethnicity and daylight.

Table 3. 6: Logistic Regression of Minority Status on Daylight, State Police Moving Violations 2017

LHS: Minority Status		Non-Caucasian	Black	Hispanic	Black or Hispanic
Daylight	Coefficient	0.122	0.087	0.093	0.104
	Standard Error	(0.090)	(0.086)	(0.082)	(0.071)
Sample Size		22109	20796	20557	23120
Pseudo R^2		0.037	0.046	0.034	0.045

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for time of the day, day of the week, analysis year, and department fixed-effects.
Note 3: Sample includes all moving violations made during the inter-twilight window in 2017.

The results presented in the state-level analysis provide strong evidence that a disparity exists in the rate of minority traffic stops by State Police departments in 2017. Although restricting the sample to moving violations reduces out estimation power, we find significant disparities present across all minority groups when officer fixed-effects are included in the model. Thus, we conclude that minority motorists are disproportionately more likely to be stopped by State Police during periods of daylight suggesting possible adverse treatment. In the preceding section, the test will be applied to both individual municipal departments and State Police troops.

III.C: DEPARTMENT ANALYSIS WITH VEIL OF DARKNESS, 2017

The analysis presented at the state-level shows that the odds a stopped motorist is a minority increases in daylight relative to darkness. As noted in the introduction and detailed in Appendix A.1, we can directly attribute this disparity to a change in the odds that a minority motorist is stopped in daylight relative to darkness under reasonable conditions about the counterfactual. By construction, the aggregate analysis does not investigate the source of these disparities in terms of specific municipal police departments or State Police troops. The analysis presented in this section seeks to better identify the sources of that disparity by running the same test for individual departments and State Police troops.

In this section, we estimate Equation 4 of Appendix A.1 separately for each municipal department and State Police troops. Thus, each set of estimates includes a vector of town-specific controls for time of day, day of week, and department fixed-effects. We identify all departments and State Police troops found to have a disparity that is statistically significant at the 95 percent level in either of the Hispanic or Black alone minority groups. The full set of results are contained in Table C.7 of Appendix C. Although we do not include officer fixed or restrict the sample to moving violations here, Appendix C, Tables C.8, C.9 and C.10 contain results with these more rigorous specifications. As discussed in detail below, we annotate those departments that do not withstand the scrutiny of the robustness checks.

Table 3.7 presents the results from estimating the Veil of Darkness test statistic for individual departments using the 2017 sample. There were two municipal departments and three State Police troops found to have a disparity that was statistically significant at the 95 percent level in the Black or Hispanic categories and which had a false discovery rate below 10 percent. As annotated below, the disparity for one municipal department and one State Police troop did not persist through all of the robustness checks that included officer fixed-effects, the moving violation subsample, and the combination of these specifications. In total, the disparities persisted through these robustness checks for two municipal departments and two State Police troops: Fairfield, Troop K, and Troop C. The disparity for Troop C and Fairfield was present for all racial and ethnic groups but only present for the Hispanic group for Troop K.

Table 3. 7: Logistic Regression of Minority Status on Daylight, Select Department Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Bristol+	Coefficient	0.275	0.321	-0.168	0.004
	Standard Error	(0.244)	(0.252)	(0.224)	(0.180)
	P-Value	0.259	0.201	0.449	0.984
	Q-Value	0.680	0.640	N/A	0.987
	Effective Sample	1180	1173	1233	1354
	Pseudo R2	0.035	0.032	0.024	0.014
CSP Troop A+	Coefficient	0.264++	0.277++	0.400***	0.305***
	Standard Error	(0.118)	(0.131)	(0.120)	(0.098)
	P-Value	0.025	0.035	0.001	0.002
	Q-Value	0.233	0.268	0.001	0.035
	Effective Sample	3056	2925	3098	3551
	Pseudo R2	0.014	0.014	0.012	0.010
CSP Troop C	Coefficient	0.340***	0.312++	0.370***	0.349***
	Standard Error	(0.096)	(0.127)	(0.123)	(0.093)
	P-Value	0.001	0.014	0.003	0.001
	Q-Value	0.001	0.152	0.045	0.001
	Effective Sample	5454	5049	5026	5476
	Pseudo R2	0.009	0.013	0.021	0.016
CSP Troop K	Coefficient	0.059	-0.085	0.612***	0.324++
	Standard Error	(0.162)	(0.195)	(0.166)	(0.131)
	P-Value	0.712	0.665	0.001	0.014
	Q-Value	0.855	N/A	0.001	0.152
	Effective Sample	2820	2711	2793	3032
	Pseudo R2	0.012	0.013	0.023	0.009
Fairfield	Coefficient	0.456***	0.483***	0.261++	0.379***
	Standard Error	(0.115)	(0.126)	(0.128)	(0.097)
	P-Value	0.001	0.001	0.039	0.001
	Q-Value	0.001	0.001	0.282	0.001
	Effective Sample	2724	2628	2592	3030
	Pseudo R2	0.014	0.018	0.028	0.019

Note 1: The coefficients are presented along with robust standard errors. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for time of the day and day of the week.
Note 3: Sample includes all traffic stops made during the inter-twilight window in 2017.
Note 4: Q-Values were estimated using a false discovery rate procedure following Simes (1986) and later refined by Benjamini and Hochberg (1995) and Benjamini and Yekutieli (2001).
+ Results are not robust across subsequent specifications.
++ Results are significant for the moving violation sample only.

As noted previously, only a select one of two municipal departments and two of the three State Police troops in Table 3.7 persisted through the additional robustness checks contained in the Appendix. For these departments and State Police troop, we conclude that there is strong evidence that a disparity exists in the rate of minority traffic stops made during high visibility conditions. For the two departments where the disparity did not persist through the robustness checks, it is impossible to say if the more restrictive specifications invalidated the initial findings or whether the power was diminished by reducing the sample size. Thus, we annotate the results for those departments but caution against any undue interpretation about the fact that these results did not withstand more rigorous estimation. One overarching observation is that the largest and most persistent disparities driving the results for the aggregate State Police are likely coming from these particular troops. However, it is impossible to clearly link these observed disparities to racial profiling as the differences could be driven by any combination of policing policy, heterogeneous enforcement patterns, or individual bad actors.

IV: ANALYSIS OF TRAFFIC STOPS, SYNTHETIC CONTROL

Traditional approaches that rely on population-based benchmarks to evaluate policing data must make a variety of very strong assumptions about the underlying risk-set of motorists. These approaches, despite their flaws, are intuitively appealing because they offer tangible descriptive measures of racial and ethnic disparities. This section presents the results of a synthetic control analysis that has the same intuition as traditional population-based benchmarks but remains grounded in rigorous statistical theory. A synthetic control is a unique benchmark constructed for each individual department using various stop-specific and town-level demographic characteristics as captured through inverse propensity score weighting. The synthetic control is then used to assess the effect of treatment on an outcome variable(s). In the present context, treatment is defined as a traffic stop made by a specific municipal police department and the outcome variable(s) indicates whether a motorist is a racial or ethnic minority.[7]

Put simply, departments differ in terms of their enforcement activity (i.e. timing of stops and types of violations etc.) and the underlying demographics of the population on the roadway. This analysis accounts for these differences by estimating a measure of similarity called a propensity score. Here, a propensity score is a measure of how similar a stop made outside a given department is to a stop made by the department being analyzed. These measures of similarity are used to weight stops when constructing an individual benchmark for each department. For example, if the department being analyzed has a high minority population and makes most of their stops on Friday nights at 7PM for speeding violations then stops made for speeding by departments with a similar residential population at this time and day will be given more weight when constructing the benchmark. This methodology ensures that there is an apples-to-apples comparison between the numbers of minorities stopped in a given town relative to their benchmark and allows for the interpretation of any remaining differences to be attributed to possible disparate treatment.

Weighting the observations by the inverse of the propensity score ensures that the distribution of observable characteristics is consistent between department of interest and the so-called "synthetic control". As long as these observed variables fully capture selection into treatment, inverse propensity score weighting allows for an unbiased estimate of the effect of treatment on the outcome of interest. In the present context, constructing a synthetic control using inverse propensity score weights allows for an assessment of whether specific departments are disproportionately stopping minority motorists. A detailed description of the mechanics underlining this methodology as well as the current application can be found in Appendix A.2. Generally speaking, the synthetic control approach follows a rich and extensive literature spanning the fields of statistics, economics, and public policy. The application of similar methodologies to policing data have recently entered the criminal justice literature through notable applications by McCaffrey et al. (2004), Ridgeway (2006), and Ridgeway and MacDonald (2009).

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[7] In the proceeding methodological discussion, the details of the estimation procedure are presented as if a single treatment effect were estimated using a single outcome variable. However, the estimates were constructed for each municipal department using four different outcome variables.

IV.A: AGGREGATE ANALYSIS WITH SYNTHETIC CONTROL, 2017

Each individual municipal police department was examined independently by weighting observations with inverse propensity scores estimated using Equation 7 of Appendix A.2. The variables used to estimate the propensity scores are detailed in Table A.2 (1) of Appendix A.2. Treatment effects were estimated using Equation 8 of Appendix A.2 for individual departments and State Police troops across four demographic subgroups relative to white Non-Hispanics. As before, we identify all departments found to have a disparity that is statistically significant at the 95 percent level in either the Hispanic or Black alone minority group. The full set of results for all departments can be found in Table D.1 of Appendix D. Although we do not use doubly-robust estimation here, Table D.2 of Appendix D contains results with this more rigorous modeling specification. Note that significantly more departments are identified in these estimates than those using doubly-robust estimation which indicates that in some departments, the results fail on balance. Thus, we present results here for departments identified using the less rigorous specification but only confidently identify those that withstand the more rigorous approach.

Table 4.1 presents the results from estimating treatment effects of individual departments relative to their requisite synthetic control using the 2017 sample. There were 6 municipal departments found to have a disparity that was statistically significant at the 95 percent level in the Black or Hispanic categories and which had a false discovery rate below 10 percent. The disparities in all of these departments did not persist through the more restrictive modeling specifications with doubly-robust estimation. In total, there were four municipal departments that withstood this more rigorous estimation procedure which accounted for innate differences in the construction of a synthetic control. In particular, the departments that persisted through our primary specification and robustness checks included: Meriden, Wallingford, Watertown, and Wethersfield.

Table 4. 1: Inverse Propensity Score Weighted Logistic Regression of Minority Status on Treatment, Select Department Traffic Stops 2017 Department

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Derby+	Coefficient	-0.004	0.061	1.184***	-0.123+++
	Standard Error	(0.056)	(0.057)	(0.054)	(0.048)
	P-Value	0.949	0.287	0.001	0.008
	Q-Value	N/A	1	0.046	N/A
	Effective Sample	89080	89080	89080	89080
	Pseudo R2	N/A	N/A	N/A	N/A
Meriden	Coefficient	-0.532+++	-0.522+++	0.892***	0.317***
	Standard Error	(0.064)	(0.065)	(0.054)	(0.052)
	P-Value	0.001	0.001	0.001	0.001
	Q-Value	N/A	0.001	0.046	0.001
	Effective Sample	98683	98683	98683	98683
	Pseudo R2	N/A	N/A	N/A	N/A

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Middletown+	Coefficient	0.488***	0.523***	-0.360+++	0.232***
	Standard Error	(0.043)	(0.043)	(0.061)	(0.039)
	P-Value	0.001	0.001	0.001	0.001
	Q-Value	0.046	0.046	0.001	0.001
	Effective Sample	63744	63744	63744	63744
	Pseudo R2	N/A	N/A	N/A	N/A
Wallingford+	Coefficient	-0.616	-0.760	2.266+++	0.199
	Standard Error	(0.563)	(0.564)	(0.818)	(0.538)
	P-Value	0.273	0.177	0.006	0.712
	Q-Value	N/A	N/A	0.232	1
	Effective Sample	38711	38711	38711	38711
	Pseudo R2	N/A	N/A	N/A	N/A
Watertown	Coefficient	N/A	6.209+++	0.421***	4.302+++
	Standard Error	(0.081)	(0.083)	(0.092)	(0.065)
	P-Value	0.001	0.001	0.001	0.001
	Q-Value	N/A	N/A	0.001	N/A
	Effective Sample	82660	82660	82660	82660
	Pseudo R2	N/A	N/A	N/A	N/A
Wethersfield	Coefficient	7.094+++	N/A	1.123***	0.165***
	Standard Error	(0.046)	(0.048)	(0.046)	(0.039)
	P-Value	0.001	0.001	0.001	0.001
	Q-Value	N/A	N/A	0.046	0.001
	Effective Sample	79077	79077	79077	79077
	Pseudo R2	N/A	N/A	N/A	N/A

Note 1: The coefficients are presented along with robust standard errors. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: Propensity scores were estimated using principal components analysis of traffic stop characteristics as well as Census data selected using the Kaiser-Guttman stopping rule. Traffic stop characteristics include time of the day, day of the week, month, department traffic stop volume, officer traffic stop volume, and type of traffic stop. Census demographics for both the primary and border towns include retail employment, entertainment employment, commuting population, vacant housing, rental housing, median earnings, population density, gender, age, race, and ethnicity.
Note 3: Sample includes all traffic stops made by the primary department and an inverse propensity score weighted sample of all other departments from October 2013 to September 2017.
Note 4: Q-Values were estimated using a false discovery rate procedure following Simes (1986) and later refined by Benjamini and Hochberg (1995) and Benjamini and Yekutieli (2001).
+ Results are not robust across subsequent specifications.

As noted previously, only a select number of these persisted through the additional robustness check contained in the Table D.2 of Appendix D. Although it is impossible to determine whether these robustness checks invalidated the findings in Table 4.1 or whether a balanced synthetic control is simply not able to be created given the data in other departments, we annotate the results for those departments and caution against any undue interpretation. As before, the cautionary note here is due to the fact that it is impossible to clearly link the observed disparities to racial profiling as these differences may be driven by any combination of policing policy, heterogeneous enforcement patterns, or individual bad actors.

V: ANALYSIS OF TRAFFIC STOPS, DESCRIPTIVE STATISTICS AND INTUITIVE MEASURES

The descriptive statistics and benchmarks presented in this section help to understand patterns in Connecticut policing data. Although these simple statistics present an intriguing story, conclusions should not be drawn from any one measure alone. The two previously applied statistical tests of racial and ethnic disparities in the policing data are based solely on the policing data itself and rely on the construction of a theoretically derived identification strategy and a natural experiment. These results have been applied by academic and police researchers in numerous areas across the country and are generally considered to be the most current and relevant approaches to assessing policing data.

In all the benchmark analysis, the demography of motorists was grouped into three overlapping categories to ensure a large enough sample size for the analysis. Much of the analysis focuses on stops made of black (Hispanic or non-Hispanic) and Hispanic motorists (any race), the analysis also was conducted for aggregated groupings of all non-white motorists (Hispanic or non-Hispanic).

V.A: STATEWIDE AVERAGE COMPARISON

Comparing town data to statewide average data is frequently the first thing the public does when trying to understand and assess how a police department may be conducting traffic stops. In this section, a comparison to the statewide average is presented alongside the context necessary to understand the information. This benchmark does provide a simple and effective way to establish a baseline for all towns from which the relative differences between town stop numbers become more apparent. A detailed explanation of the methodology can be found in Appendix A.4. The analysis presented in this report only identified the departments for which the statewide average comparison indicated the largest distances between the net stop percentage and net resident population using 10 or more points as a threshold. Tables showing the calculations for all departments, rather than just those showing distance measures of more than 10 points, can be found in Appendix E of this report. Readers should note that this section focuses entirely on departments that exceeded the statewide average for stops in these racial groups.

Comparison of Minority Drivers to the State Average

The Minority category includes all racial classifications except for white drivers. Specifically it covers Blacks, Hispanics, Asian/Pacific Islander, American Indian/Alaskan Native, and Other Race classifications included in the census data.

For the study period from January 1, 2017 through December 31, 2017, the statewide percentage of drivers stopped by police who were identified as Minority was 30.6%. A total of 34 departments stopped a higher percentage of Minority drivers than the state average, 18 of which exceeded the statewide average by more than 10 percentage points. The statewide average for Minority residents (16+) is 25.2%. Of the 34 towns that exceeded the statewide average for Minority drivers stopped, 22 also have Minority resident populations (16+) that exceeded the statewide average.

After the stop resident population percentages were adjusted using the method described in Appendix A.3 (2), a total of 23 departments were found to have a relative distance between their net Minority driver stop percentage and net Minority driving age population percentage of more than 10 points. Table 5.1 shows the data for these 23 towns. All department results are contained in the Table E.1 of Appendix E.

Table 5. 1: Statewide Average Comparisons for Minority Drivers for Selected Towns

Municipal Department	Minority Stops	Difference Between Town and State Average	Minority Residents Age 16+	Difference Between Town and State Average	Distance Between Net Differences
Wethersfield	52.8%	22.2%	12.5%	-12.8%	34.9%
Stratford	57.5%	26.9%	27.2%	2.0%	24.9%
Darien	36.0%	5.4%	7.2%	-18.1%	23.5%
Trumbull	37.7%	7.1%	11.9%	-13.3%	20.4%
Newington	40.1%	9.5%	14.5%	-10.7%	20.2%
Wolcott	30.8%	0.2%	5.4%	-19.8%	20.0%
Berlin	29.8%	-0.8%	5.8%	-19.5%	18.6%
Woodbridge	35.9%	5.3%	12.8%	-12.4%	17.7%
Fairfield	31.5%	0.9%	10.0%	-15.2%	16.1%
Wilton	29.3%	-1.3%	8.1%	-17.1%	15.9%
Meriden	56.0%	25.4%	34.9%	9.6%	15.8%
North Haven	30.8%	0.2%	10.5%	-14.7%	14.9%
West Hartford	39.9%	9.3%	21.8%	-3.4%	12.8%
Waterford	27.9%	-2.7%	9.8%	-15.4%	12.7%
Windsor Locks	30.7%	0.1%	12.7%	-12.5%	12.6%
Derby	38.5%	7.9%	20.6%	-4.7%	12.6%
Redding	21.8%	-8.8%	4.4%	-20.9%	12.0%
Wallingford	27.8%	-2.8%	11.1%	-14.1%	11.3%
Greenwich	34.4%	3.8%	18.0%	-7.3%	11.1%
East Hartford	68.1%	37.5%	51.6%	26.4%	11.1%
New Canaan	22.9%	-7.7%	7.2%	-18.1%	10.4%
East Haven	29.3%	-1.3%	14.0%	-11.3%	10.0%
Vernon	29.4%	-1.2%	14.1%	-11.2%	10.0%
Connecticut	30.6%	0.0%	25.2%	0.0%	NA

Comparison of Black Drivers to the State Average

For the study period, the statewide percentage of motorists stopped by police who were identified as Black was 16.3 percent. A total of 27 departments stopped a higher percentage of Black motorists than the state average, 10 of which exceeded the statewide average by more than 10 percentage points. The statewide average for black residents (16+) is 9.1%. Of the 27 towns that exceeded the statewide average for black drivers stopped, 17 also have black resident populations (16+) that exceeded the statewide average.

After the resident population stop percentages were adjusted using the method described in Appendix A.3 (2), a total of three departments were found to have a relative distance between their net black driver stop percentage and net black driving age population percentage of more than 10 points. Table 5.2 shows the data for these three towns. All department results are contained in the Table E.2 of Appendix E.

Table 5. 2: Statewide Average Comparisons for Black Drivers for Selected Towns

Municipal Department	Black Stops	Difference Between Town and State Average	Black Residents Age 16+	Difference Between Town and State Average	Distance Between Net Differences
Stratford	35.4%	19.1%	12.8%	3.6%	15.4%
Woodbridge	23.6%	7.3%	1.9%	-7.2%	14.4%
Trumbull	21.2%	4.9%	2.9%	-6.2%	11.2%
Connecticut	16.3%	0.0%	9.1%	0.0%	NA

Comparison of Hispanic Drivers to the Statewide Average

For the study period, the statewide percentage of drivers stopped by police who were identified as Hispanic was 14.2%. A total of 27 towns stopped a higher percentage of Hispanic drivers than the state average, nine of which exceeded the statewide average by more than 10 percentage points. Four of the 30 departments exceeded the statewide average by 1.5 percentage points of less. The statewide Hispanic resident population (16+) is 11.9%. The ratio of stopped Hispanic drivers to Hispanic residents (16+) on a statewide basis was slightly higher (14.2% Hispanic drivers' stopped/11.9% Hispanic residents). Of the 27 towns that exceeded the statewide average for Hispanic drivers stopped, 14 also have Hispanic resident populations (16+) that exceeded the statewide average.

After the stop and resident population percentages were adjusted using the method described in Appendix A.3 (2), a total of five towns were found to have a relative distance between their net Hispanic driver stop percentage and net Hispanic population percentage of more than 10 points. The five towns were Wethersfield, Darien, Newington, Wolcott, and Berlin. The Meriden Police Department fell just below the 10-point threshold. Table 5.3 shows the data for the towns named above. All department results are contained in the Table E.3 of Appendix E.

Table 5. 3: Statewide Average Comparisons for Hispanic Drivers for Selected Towns

Municipal Department	Hispanic Stops	Difference Between Town and State Average	Hispanic Residents Age 16+	Difference Between Town and State Average	Distance Between Net Differences
Wethersfield	32.7%	18.47%	7.1%	-4.8%	23.27%
Darien	19.3%	5.08%	3.5%	-8.4%	13.50%
Newington	20.6%	6.43%	6.4%	-5.5%	11.95%
Wolcott	16.7%	2.47%	2.8%	-9.1%	11.55%
Berlin	16.3%	2.07%	2.7%	-9.2%	11.30%
Connecticut	14.2%	0.0%	11.9%	0.0%	NA

V.B: ESTIMATED DRIVING POPULATION COMPARISON

The EDP analysis was confined to the 94 municipal police departments in Connecticut. There are 80 municipalities in Connecticut that either (1) do not have their own departments and rely upon the state police for their law and traffic enforcement services or (2) have one or more resident state troopers who either provide their police services or supervise local constables or law enforcement officers. Most of these communities are smaller and located in Connecticut's more rural areas. Once the state police stops made on limited access highways were removed from the data, we found that these towns generally had too few stops during the 6am to 10am and 3pm to 7pm periods to yield meaningful comparisons. Consequently, these towns were not considered appropriate candidates for the EDP analysis.

The only traffic stops included in this analysis were stops conducted Monday through Friday from 6:00am to 10:00am and 3:00pm to 7:00pm (peak commuting hours). Overall, when compared to their respective EDP, 79 departments had a disparity between the Minorities stopped and the proportion of non-whites estimated to be in the EDP. For many of these departments (27) the disparity was very small (less than five percentage points). In the remaining 15 communities, the disparity was negative, meaning that more whites were stopped than expected in the EDP numbers. However, the negative disparities were also very small in most communities. There were 92 departments with a disparity for Black drivers stopped and 75 departments with a disparity for Hispanic drivers stopped when compared to the respective EDPs.

Due to the margins of error inherent in the EDP estimates, we established a reasonable set of thresholds for determining if a department shows a disparity in its stops when compared to its EDP percentages. Departments that exceed their EDP percentages by greater than 10 percentage points in any of the three categories: (1) Minority (all race/ethnicity), (2) Black non-Hispanic, and (3) Hispanic, were identified in our tier one group. Table 5.4 shows the data for the departments meeting the tier one criteria. In addition, departments that exceeded their EDP percentage by more than five but less than 10 percentage points were identified in our tier two group for this benchmark if the ratio of the percentage of stops for the target group compared to the baseline measure for that group also was 1.75 or above (percentage of stops divided by benchmark percentage equals 1.75 or more) in any of the three categories: (1) Minority (all race/ethnicity), (2) Black non-Hispanic, or (3) Hispanic. Table 5.5 shows the data for the departments meeting the tier two criteria. Results for all departments are available in Tables E.4, E.5, and E.6 of Appendix E.

Table 5. 4: Highest Ratio of Stops to EDP (Tier I)

Department Name	Number of Stops	Stops	EDP	Absolute Difference	Ratio
Minority (All Non-White)					
Wethersfield	730	45.3%	16.6%	28.7%	2.73
East Hartford	3,156	67.7%	40.0%	27.6%	1.69
Wolcott	46	34.8%	8.2%	26.6%	4.25
Meriden	634	56.2%	31.4%	24.7%	1.79
Stratford	1,036	51.2%	27.9%	23.3%	1.84
Waterbury	894	62.5%	40.1%	22.4%	1.56
Darien	1,323	36.8%	15.9%	20.9%	2.31
New Haven	8,353	65.8%	46.3%	19.5%	1.42
Windsor	3,610	52.4%	33.2%	19.2%	1.58
New Britain	2,766	55.1%	38.9%	16.2%	1.42
Hartford	3,091	66.2%	50.1%	16.2%	1.32
Middlebury*	11	27.3%	11.4%	15.9%	2.40
Bloomfield	741	57.6%	42.7%	14.9%	1.35
West Hartford	2,263	38.5%	24.1%	14.4%	1.60
Newington	1,471	33.3%	19.0%	14.3%	1.75
Derby	612	35.0%	21.1%	13.8%	1.65
North Haven	888	30.9%	17.5%	13.3%	1.76
Willimantic	432	42.6%	29.3%	13.3%	1.45
Trumbull	833	31.2%	18.2%	13.0%	1.71

Department Name	Number of Stops	Stops	EDP	Absolute Difference	Ratio
Redding	959	20.0%	7.6%	12.4%	2.65
Berlin	2,026	24.8%	12.9%	11.9%	1.92
West Haven	2,210	47.3%	35.6%	11.7%	1.33
Fairfield	3,954	29.2%	17.5%	11.7%	1.67
Woodbridge	783	28.7%	17.3%	11.4%	1.66
Manchester	4,817	38.1%	26.7%	11.4%	1.43
Easton	456	18.4%	7.5%	10.9%	2.45
Orange	90	30.0%	19.5%	10.5%	1.54
Norwich	1,314	34.8%	24.7%	10.1%	1.41
Black					
East Hartford	3,156	38.2%	17.0%	21.3%	2.26
Stratford	1,036	31.3%	12.1%	19.2%	2.58
New Haven	8,353	41.5%	22.6%	18.9%	1.83
Hartford	3,091	39.5%	21.6%	17.9%	1.83
Bloomfield	741	48.7%	31.1%	17.6%	1.56
Windsor	3,610	35.3%	20.1%	15.2%	1.76
Waterbury	894	29.2%	14.3%	14.9%	2.04
Woodbridge	783	18.3%	4.8%	13.5%	3.83
Manchester	4,817	22.3%	9.9%	12.4%	2.25
Hamden	2,910	28.3%	16.1%	12.2%	1.76
Bridgeport	728	38.3%	26.5%	11.9%	1.45
Darien	1,323	15.3%	3.6%	11.7%	4.28
Middletown	733	20.2%	9.7%	10.5%	2.08
Ledyard	612	14.7%	4.3%	10.4%	3.45
Derby	612	16.8%	6.7%	10.1%	2.51
Hispanic					
Wethersfield	730	29.7%	8.7%	21.1%	3.43
Meriden	634	40.5%	21.1%	19.4%	1.92
Willimantic	432	36.1%	23.1%	13.0%	1.56
New Britain	2,766	38.1%	26.0%	12.1%	1.46
Darien	1,323	19.0%	8.0%	11.1%	2.38
Wolcott	46	15.2%	4.3%	10.9%	3.51
Waterbury	894	32.9%	22.7%	10.2%	1.45

Table 5. 5: High Ratio of Stops to EDP (Tier II)

Department Name	Number of Stops	Stops	EDP	Absolute Difference	Ratio
Minority (All Non-White)					
Plymouth	327	11.0%	4.6%	6.4%	2.39
Black					
Wethersfield	730	14.7%	4.9%	9.8%	2.99
Norwich	1,314	17.2%	7.5%	9.7%	2.29
North Haven	888	15.9%	6.3%	9.6%	2.52
Orange	90	15.6%	6.3%	9.3%	2.49
Windsor Locks	324	15.7%	7.1%	8.6%	2.20
West Hartford	2,263	16.1%	7.6%	8.4%	2.10
Wolcott	46	10.9%	2.5%	8.3%	4.29
Trumbull	833	13.9%	5.9%	8.1%	2.37
Fairfield	3,954	13.1%	5.3%	7.9%	2.49
Newington	1,471	12.8%	5.5%	7.3%	2.32

Department Name	Number of Stops	Stops	EDP	Absolute Difference	Ratio
Waterford	1,282	10.8%	3.9%	6.9%	2.76
Meriden	634	14.5%	7.7%	6.8%	1.87
Middlebury*	11	9.1%	2.6%	6.5%	3.46
Groton Town	990	11.6%	5.5%	6.1%	2.12
Cheshire	928	9.8%	3.9%	5.9%	2.49
Berlin	2,026	9.3%	3.5%	5.8%	2.67
Westport	3,079	11.0%	5.3%	5.7%	2.08
Vernon	517	10.8%	5.3%	5.5%	2.04
Wallingford	2,645	9.0%	3.8%	5.3%	2.39
Enfield	2,163	9.3%	4.1%	5.2%	2.25
Avon	324	8.6%	3.5%	5.2%	2.49
Portland	90	7.8%	2.7%	5.1%	2.91
Hispanic					
Newington	1,471	17.7%	8.9%	8.8%	1.99
Redding	959	12.6%	4.0%	8.6%	3.16
Easton	456	11.0%	3.5%	7.5%	3.14
Berlin	2,026	13.9%	6.6%	7.3%	2.11
East Haven	708	16.1%	9.1%	7.0%	1.77
Trumbull	833	14.6%	8.3%	6.3%	1.76
Ridgefield	2,862	12.1%	6.7%	5.4%	1.81
New Canaan	1,892	11.7%	6.4%	5.3%	1.83
New Milford	802	11.2%	6.2%	5.0%	1.80

V.C: RESIDENT ONLY STOP COMPARISON

Overall, when compared to the census, 79 departments stopped more Minority resident drivers than white drivers. Again, the disparity for many of these departments was very small. In the remaining 15 communities, the disparity was negative, meaning that more whites were stopped than expected based on the population numbers. However, the negative disparities were also very small in most communities. Almost all departments (90 of 94) had a disparity for Black drivers stopped and 65 departments had a disparity for Hispanic drivers stopped when compared to the resident driving age population.

Departments with a difference of 10 percentage points or more between the resident stops and the 16+ resident population in any of the three categories: (1) Minority (all race/ethnicity), (2) Black non-Hispanic, and (3) Hispanic, were identified in our tier one group. Table 5.6 shows the data for the departments meeting the tier one criteria. In addition, departments that exceeded their resident population percentage by more than five but less than 10 percentage points were identified in our tier two group for this benchmark if the ratio of the percentage of resident stops for the target group compared to the baseline measure for that group also was 1.75 or above (percentage of stopped residents divided by resident benchmark percentage equals 1.75 or more) in any of three categories: (1) Minority (all race/ethnicity), (2) Black non-Hispanic, and (3) Hispanic. Table 5.7 shows the data for the departments meeting the tier two criteria. Results for all departments are available in Tables E.7, E.8, and E.9 of Appendix E.

Table 5. 6: Highest Ratio of Resident Population to Resident Stops (Tier I)

Department Name	Number of Residents	Residents	Resident Stops	Minority Resident Stops	Difference	Ratio
Minority (All Non-White)						
Stratford	40,980	27.2%	1,272	54.2%	27.0%	1.99
Meriden	47,445	34.9%	1,086	61.5%	26.7%	1.76
Derby	10,391	20.6%	416	46.4%	25.8%	2.26
Willimantic	20,176	34.6%	1,172	59.0%	24.5%	1.71
Waterbury	83,964	48.1%	1,888	70.7%	22.6%	1.47
East Hartford	40,229	51.6%	3,485	73.1%	21.5%	1.42
New Britain	57,164	45.0%	4,731	66.3%	21.3%	1.47
Windsor	23,222	43.9%	2,677	65.1%	21.2%	1.48
Norwich	31,638	29.1%	3,384	49.3%	20.2%	1.70
New Haven	100,702	62.8%	11,897	82.8%	19.9%	1.32
Bloomfield	16,982	61.5%	701	81.0%	19.5%	1.32
Groton City*	7,960	26.9%	437	43.7%	16.8%	1.62
Hamden	50,012	30.9%	1,814	46.1%	15.2%	1.49
New London	21,835	43.6%	1,811	58.0%	14.5%	1.33
Middletown	38,747	23.5%	3,027	37.8%	14.3%	1.61
Vernon	23,800	14.1%	1,262	28.2%	14.2%	2.01
Manchester	46,667	27.9%	4,551	41.9%	14.0%	1.50
Bristol	48,439	12.7%	1,648	26.3%	13.6%	2.07
Norwalk	68,034	40.8%	2,373	54.2%	13.4%	1.33
Danbury	64,361	38.6%	1,386	51.9%	13.2%	1.34
Wethersfield	21,607	12.5%	652	25.3%	12.8%	2.03
Black						
Stratford	40,980	12.76%	1,272	35.8%	23.0%	2.80
New Haven	100,702	32.16%	11,897	54.6%	22.5%	1.70
Bloomfield	16,982	54.76%	701	76.9%	22.1%	1.40
Windsor	23,222	32.20%	2,677	53.0%	20.8%	1.65
Waterbury	83,964	17.37%	1,888	36.7%	19.3%	2.11
East Hartford	40,229	22.52%	3,485	40.5%	17.9%	1.80
Norwich	31,638	8.96%	3,384	26.3%	17.3%	2.93
Derby	10,391	6.03%	416	23.3%	17.3%	3.86
Hamden	50,012	18.28%	1,814	35.4%	17.2%	1.94
Middletown	38,747	11.68%	3,027	25.9%	14.2%	2.22
Manchester	46,667	10.15%	4,551	23.9%	13.7%	2.35
Norwalk	68,034	13.13%	2,373	26.2%	13.1%	2.00
New London	21,835	15.18%	1,811	27.1%	11.9%	1.78
Vernon	23,800	4.70%	1,262	16.4%	11.7%	3.49
Groton City*	7,960	7.70%	437	19.0%	11.3%	2.47
Hartford	93,669	35.80%	7,190	46.6%	10.8%	1.30
Meriden	47,445	7.80%	1,086	18.0%	10.3%	2.31
Hispanic						
Willimantic	20,176	28.88%	1,172	52.0%	23.1%	1.80
Meriden	47,445	24.86%	1,086	42.5%	17.7%	1.71
New Britain	57,164	31.75%	4,731	48.5%	16.7%	1.53
Danbury	64,361	23.25%	1,386	39.5%	16.3%	1.70

Table 5. 7: High Ratio of Resident Population to Resident Stops (Tier II)

Department Name	Number of Residents	Residents	Resident Stops	Minority Resident Stops	Difference	Ratio
Minority (All Non-White)						
Cheshire	21,049	8.6%	1,188	17.6%	9.0%	2.04
New Milford	21,891	9.7%	1,210	18.2%	8.5%	1.88
Clinton	10,540	6.1%	1,420	13.8%	7.7%	2.26
Enfield	33,218	8.7%	3,645	15.8%	7.1%	1.83
Old Saybrook	8,330	5.2%	696	10.6%	5.5%	2.06
Portland	7,480	4.6%	146	9.6%	5.0%	2.07
Black						
Ledyard	11,527	3.10%	556	12.6%	9.5%	4.06
Ansonia	14,979	9.74%	1,458	18.7%	8.9%	1.92
Windsor Locks	10,117	4.27%	288	12.8%	8.6%	3.01
Bristol	48,439	3.24%	1,648	11.3%	8.0%	3.49
Groton Town	31,520	6.07%	1,461	13.9%	7.8%	2.29
Cheshire	21,049	1.27%	1,188	8.8%	7.5%	6.87
East Windsor	9,164	5.96%	401	12.7%	6.8%	2.13
Trumbull	27,678	2.90%	477	8.6%	5.7%	2.97
Shelton	32,010	2.07%	272	7.7%	5.7%	3.73
Hispanic						
Groton City*	7,960	11.80%	437	21.5%	9.7%	1.82
Wethersfield	21,607	7.10%	652	16.7%	9.6%	2.35
Norwich	31,638	10.59%	3,384	18.6%	8.1%	1.76
Wolcott	13,175	2.83%	54	9.3%	6.4%	3.27
Bristol	48,439	7.65%	1,648	13.9%	6.2%	1.82
New Milford	21,891	5.46%	1,210	11.7%	6.2%	2.13

V.D: CONCLUSIONS FROM THE DESCRIPTIVE COMPARISONS

The descriptive tests outlined in the above sections are designed to be used as a screening tool to identify those jurisdictions with consistent data disparities that exceed certain thresholds. The tests compare stop data to three different benchmarks: (1) statewide average, (2) the estimated driving population, and (3) resident-only stops that each cover three driver categories: Black, Hispanic, and Minority. Department data is then measured against the resulting total of nine descriptive measures for evaluation purposes.

In order to classify the disparities within the descriptive benchmarks, any disparity greater than 10 percentage points for a measure was given a weight of one (1) point. Any disparity of more than five, but less than 10 percentage points accompanied by a disparity ratio of 1.75 or above was given a weight of 0.5 points. Therefore, a department could score no more than nine (9) total points.

Table 5.8 identifies the nine departments with significant disparities. A department was identified if the stop data was found to exceed the disparity threshold level in at least two of the three benchmark areas and a weighted total score of 4.5 or more. All department results are contained in Table E.10 of Appendix E.

Table 5. 8: Departments with the Greatest Number of Disparities Relative to Descriptive Benchmarks

Department Name	Statewide Average			Estimated Driving Population			Resident Population			Point Total
	M	B	H	M	B	H	M	B	H	
Meriden	15.8%			24.7%	6.8%	19.4%	26.7%	10.3%	17.7%	6.5
Stratford	24.9%	15.4%		23.3%	19.2%		27.0%	23.0%		6.0
Wethersfield	34.9%		23.3%	28.7%	9.8%	21.1%	12.8%		9.6%	6.0
Darien	23.5%		13.5%	20.9%	11.7%	11.1%				5.0
Derby	12.6%			13.8%	10.1%		25.8%	17.3%		5.0
East Hartford	11.1%			27.6%	21.3%		21.5%	17.9%		5.0
Waterbury				22.4%	14.9%	10.2%	22.6%	19.3%		5.0
Wolcott	20.0%		11.6%	26.6%	8.3%	10.9%			6.4%	5.0
Trumbull	20.4%	11.2%		13.0%	8.1%	6.3%		5.7%		4.5

VI. ANALYSIS OF STOP DISPOSITIONS

In this section, we test for disparities in the outcomes of traffic stops using a model that examines the distribution of outcomes conditional on race and the reason for the stop. Following the model outlined in Equation 9 of Appendix A.4, we test whether traffic stops made of minority motorists result in different outcomes relative to their white non-Hispanic peers. It is unclear whether we should expect police discrimination to result in more or less citations relative to warnings and searches. If we discovered that minority motorists receive more citations conditional on the reason that they are stopped, we might interpret this as evidence adverse treatment. On the other hand, we could draw the same conclusion if minorities receive less citations and more warnings since these could represent pretextual stops. Thus, we proceed by simply testing for equality in the distribution of outcomes across different demographic groups conditional on the motivating reason for the stop. The intuition is similar to hit-rate style tests but where we are unable to predict the direction that we expect bias to take. We implement the test by applying a multinomial logistic regression on the four possible stop outcomes and condition on race and the reason for the stop. We then conduct a joint hypothesis test on the interaction between an indicator of race and the reason for the stop across all outcomes.

We account for differences in outcomes not related to this interaction term by including additional controls for age, gender, time of day, day of week, week of year, and officer fixed-effects. Unlike previous sections where our main specification omits officer fixed-effects, here we only estimate models that include this key set of granular control. The reason behind this key difference is because, in the case of stop disposition, it seems very likely that officer heterogeneity (in terms of geography and assignment) might have a large impact on the relationship between race, basis for a stop, and the subsequent outcome. We provide one important cautionary note about interpreting our test as causal evidence of discrimination. Ideally, this test would be performed on data containing *all* violations observed by the police officer prior to making a traffic stop and where we would include a control for the number of total violations. In practice, data on traffic stops typically only contain the most severe reason that motivated the stop. In the absence of data on the full set of violations observed by police officers, we suggest that the reader interpret results from this test as providing descriptive evidence to be viewed in concert with other such empirical measures.

VI.A: AGGREGATE ANALYSIS OF STOP DISPOSITION, 2017

Table 6.1 presents the results of applying a multinomial logit to a sample of all traffic stops with six distinct stop outcomes regressed on race, stop basis, and their interaction. We present only the coefficient estimates on the interaction between race and the stop basis for each outcome relative to the omitted category, i.e. no search- ticket or misdemeanor issued. In terms of stop-basis, we omit speed-related offenses and present only the interaction between the remaining four categories and the respective demographic indicator. Across all specifications, we find strong evidence suggesting that minority motorists are treated differently than their White Non-Hispanic counterparts even when they are stopped for the same reason. Interestingly, minority drivers are more frequently given a warning for our broadest category of stop-basis (all other) but less likely to receive a warning for equipment violations. In contrast, minority motorists are most likely to be searched for registration or license violations as well as seatbelt or cellphone violations but less likely than their peers across the other categories. A joint hypothesis test across all the interaction terms and all outcomes indicates that the difference in outcomes are statistically significant at the 99 percent level for each demographic group relative to White Non-Hispanic motorists.

Table 6. 1: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop, All Traffic Stops 2017

	Non-White		Black		Hispanic		Black or Hispanic	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
No Search, Warning or No Action								
All other	0.433**	(0.189)	0.386*	(0.208)	0.224	(0.174)	0.287	(0.184)
Equipment	-0.127	(0.101)	-0.297**	(0.122)	-0.167	(0.13)	-0.392***	(0.118)
SB or Cell	0.006	(0.083)	-0.086	(0.093)	0.021	(0.068)	-0.061	(0.071)
Reg. or Lic.	0.256**	(0.114)	0.213*	(0.127)	0.014	(0.084)	0.113	(0.104)
No Search, Arrest								
All other	-0.017	(0.211)	-0.001	(0.234)	-0.418**	(0.163)	-0.162	(0.183)
Equipment	0.001	(0.201)	-0.08	(0.215)	0.052	(0.268)	-0.212	(0.201)
SB or Cell	0.8***	(0.232)	0.881***	(0.251)	0.122	(0.316)	0.507**	(0.24)
Reg. or Lic.	0.43	(0.289)	0.457	(0.296)	0.358	(0.252)	0.487**	(0.229)
Search								
All other	0.062	(0.102)	-0.199*	(0.109)	-0.06	(0.129)	-0.292***	(0.108)
Equipment	0.022	(0.126)	-0.383***	(0.139)	0.163	(0.177)	-0.496***	(0.136)
SB or Cell	0.437***	(0.12)	0.235*	(0.124)	0.212	(0.147)	0.086	(0.118)
Reg. or Lic.	0.233**	(0.111)	-0.027	(0.117)	0.324***	(0.121)	-0.033	(0.098)
Chi^2	97.85		104.57		57.05		87.35	
P-Value	0.001		0.001		0.001		0.001	
Sample Size	467288		450436		435741		524234	

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for gender, age, time of the day, day of the week, week of year, and officer fixed-effects.

Table 6.2 presents the results of applying a multinomial logit to a subset of traffic stops made by municipal police departments. As before, we test for differences across four distinct stop outcomes for motorists of different races but who were stopped for the same reason. Across all specifications, we again find strong evidence suggesting that minority motorists are treated differently than their White Non-Hispanic counterparts even when they are stopped for the same reason. Again, a joint hypothesis test across all the interaction terms and all outcomes indicates that the difference in outcomes are statistically significant at the 99 percent level for each demographic group relative to White Non-Hispanic motorists.

Table 6. 2: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop, Municipal Traffic Stops 2017

	Non-White		Black		Hispanic		Black or Hispanic	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
No Search, Warning or No Action								
All other	0.571**	(0.229)	0.586**	(0.238)	0.415*	(0.212)	0.482**	(0.217)
Equipment	-0.123	(0.143)	-0.096	(0.16)	-0.375**	(0.146)	-0.302**	(0.15)
SB or Cell	-0.014	(0.084)	-0.029	(0.095)	0.076	(0.066)	-0.007	(0.07)
Reg. or Lic.	0.401**	(0.162)	0.425**	(0.176)	0.178*	(0.108)	0.299**	(0.138)

	Non-White		Black		Hispanic		Black or Hispanic	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
No Search, Arrest								
All other	0.189	(0.268)	0.072	(0.289)	-0.097	(0.211)	-0.075	(0.225)
Equipment	0.101	(0.242)	0.207	(0.267)	-0.131	(0.29)	-0.029	(0.248)
SB or Cell	1.226***	(0.246)	1.359***	(0.266)	0.703**	(0.287)	0.959***	(0.223)
Reg. or Lic.	0.761**	(0.336)	0.844**	(0.342)	0.59**	(0.272)	0.7***	(0.256)
Search								
All other	0.086	(0.132)	0.138	(0.138)	-0.178	(0.158)	-0.147	(0.141)
Equipment	-0.064	(0.154)	0.039	(0.169)	-0.508***	(0.167)	-0.41**	(0.162)
SB or Cell	0.32***	(0.111)	0.422***	(0.124)	-0.047	(0.134)	0.092	(0.111)
Reg. or Lic.	0.169	(0.129)	0.236*	(0.141)	0.155	(0.114)	0.073	(0.103)
Chi^2	117.98		123.19		69.09		105.33	
P-Value	0.001		0.001		0.001		0.001	
Sample Size	308712		299951		89323		352558	

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for gender, age, time of the day, day of the week, week of year, and officer fixed-effects.

Table 6.3 presents the results of applying a multinomial logit to a subset of traffic stops made by State Police departments. Again, our goal is to test for differences across four distinct stop outcomes for motorists of different races but who were stopped for the same reason. Across all specifications, we again find evidence suggesting that minority motorists are treated differently than their White Non-Hispanic counterparts. A joint hypothesis test across all the interaction terms and all outcomes indicates that the difference in outcomes are only statistically significant at the 95 percent level for the combined Black and Hispanic group relative to White Non-Hispanic motorists.

Table 6. 3: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop, State Police Traffic Stops 2017

	Non-White		Black		Hispanic		Black or Hispanic	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
No Search, Warning or No Action								
All other	0.162**	(0.076)	0.056	(0.08)	-0.142	(0.13)	-0.053	(0.096)
Equipment	-0.12	(0.148)	-0.264*	(0.149)	-0.203*	(0.114)	-0.255**	(0.111)
SB or Cell	-0.141	(0.156)	-0.341**	(0.161)	-0.231**	(0.112)	-0.3**	(0.128)
Reg. or Lic.	0.077	(0.07)	-0.024	(0.065)	-0.173*	(0.097)	-0.101	(0.075)
No Search, Arrest								
All other	-0.131	(0.327)	-0.01	(0.327)	-0.591**	(0.279)	-0.315	(0.31)
Equipment	-1.826*	(1.035)	-1.714	(1.065)	-1.029**	(0.501)	-1.177**	(0.495)
SB or Cell	-1.233**	(0.486)	-1.853***	(0.711)	-1.287**	(0.573)	-1.421***	(0.468)
Reg. or Lic.	-0.272	(0.461)	-0.401	(0.484)	0.281	(0.505)	0.166	(0.444)
Search								
All other	-0.15	(0.101)	-0.251**	(0.104)	-0.578***	(0.173)	-0.408***	(0.104)
Equipment	-0.12	(0.168)	-0.292*	(0.166)	-0.624***	(0.186)	-0.421***	(0.139)
SB or Cell	0.582**	(0.225)	0.42	(0.259)	0.232	(0.232)	0.294	(0.248)
Reg. or Lic.	0.344	(0.235)	0.203	(0.26)	-0.017	(0.228)	0.071	(0.224)
Chi^2	1437.87		142437		139280		162605	
P-Value	0.001		0.001		0.001		0.001	
Sample Size	150037		156.15		321.44		590.41	

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for gender, age, time of the day, day of the week, week of year, and officer fixed-effects.

The previous set of estimates aggregate all traffic stops across multiple departments and should be considered an average effect. Although the results from this section find a statistically significant disparity in the rate of minority traffic stops made by municipal police departments in Connecticut, these results do not identify the geographic source of that disparity. The results of a department-level analysis are presented in the next section and better identify the source of specific department-wide disparities.

VI.B: DEPARTMENT ANALYSIS OF STOP DISPOSITION, 2017

The analysis presented at the state-level shows that minority motorists are treated differently, in terms of disposition, relative to their white non-Hispanic counterparts, even when they are stopped for the same reason. By construction, the aggregate analysis does not investigate the source of these disparities in terms of specific municipal police departments or State Police barracks. The analysis presented in this section seeks to better identify the sources of that disparity by running the same test for individual municipal departments and State Police barracks. In this section, we estimate Equation 9 of Appendix A.4 separately for each municipal department and State Police barracks. Thus, each set of estimates includes a vector of town-specific controls for time of day, day of week, and department fixed-effects. We identify all departments and State Police barracks found to have a disparity that is statistically significant at the 95 percent level in either of the Hispanic or Black alone minority groups and with a false discovery rate under the ten percent threshold. The full set of results are contained in Table F.1 of Appendix F.

Table 6.4 presents the results from estimating the test of equality in stop dispositions for minority motorists relative to their white non-Hispanic peers. As before, our test statistic is generated from a joint hypothesis test on the interaction between race and the basis for a traffic stop across all possible outcomes. For parsimony, we omit the coefficient estimates on these interaction terms and present only the chi-squared and level of significance for the joint hypothesis test. As shown below, we find that 40 of the total 94 municipal departments, one of nine special departments, and 10 of 12 State Police Troops tested had a statistically significant difference disparity in the distribution of stop outcomes for minority motorists. Although it does appear that minority motorists are treated differently in many of the same departments identified in other tests, we still caution the reader from drawing any conclusions based on these results. As noted before, our ideal analysis would include data on every reason that a stop was made and all requisite outcomes.

Table 6. 4: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop by Department, All Traffic Stops 2017

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Municipal Police Departments					
Berlin	Chi^2	17.615+	24.714***	23.618***	19.957**
	Observations	4564	4436	4700	5307
	P-Value	0.061	0.006	0.008	0.029
	Pseudo R2	0.365	0.37	0.368	0.344
	Q-Value	0.162	0.019	0.028	0.081
Bristol	Chi^2	2,774.594***	N/A	577.804***	7.697
	Observations	3279	3237	3330	3741
	P-Value	0.001	N/A	0.001	0.657
	Pseudo R2	0.368	0.368	0.37	0.354
	Q-Value	0.003	1	0.004	1
Canton	Chi^2	255.126***	988.195***	1,918.026***	397.235***
	Observations	897	877	870	908
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.573	0.58	0.587	0.587
	Q-Value	0.003	0.003	0.004	0.003
Clinton	Chi^2	N/A	856.469***	819.812***	462.223***
	Observations	1369	1347	1428	1479
	P-Value	N/A	0.001	0.001	0.001
	Pseudo R2	0.358	0.356	0.347	0.335
	Q-Value	N/A	0.001	0.001	0.001
Coventry	Chi^2	N/A	1,483.626***	N/A	186.326***
	Observations	1290	1250	1270	1345
	P-Value	N/A	0.001	N/A	0.001
	Pseudo R2	0.349	0.356	0.321	0.317
	Q-Value	N/A	0.001	N/A	0.001
Cromwell	Chi^2	N/A	N/A	847.026***	1,184.446***
	Observations	1471	1442	1338	1530
	P-Value	N/A	N/A	0.001	0.001
	Pseudo R2	0.462	0.453	0.467	0.453
	Q-Value	N/A	N/A	0.001	0.001
Danbury	Chi^2	920.606***	637.987***	21.393++	20.860+
	Observations	4475	4332	5519	6007
	P-Value	0.001	0.001	0.045	0.052
	Pseudo R2	0.368	0.374	0.333	0.328
	Q-Value	0.003	0.003	0.128	0.141
Derby	Chi^2	140.572***	136.464***	116.481***	171.647***
	Observations	1953	1917	1821	2298
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.277	0.275	0.282	0.263
	Q-Value	0.003	0.003	0.004	0.003

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
East Lyme	Chi^2	408.009***	N/A	197.897***	556.616***
	Observations	353	340	343	364
	P-Value	0.001	N/A	0.001	0.001
	Pseudo R2	0.985	0.999	0.953	0.925
	Q-Value	0.003	1	0.004	0.003
East Windsor	Chi^2	1,380.093***	1,216.500***	457.910***	N/A
	Observations	1572	1549	1480	1724
	P-Value	0.001	0.001	0.001	N/A
	Pseudo R2	0.54	0.541	0.546	0.517
	Q-Value	0.003	0.003	0.004	1
Enfield	Chi^2	N/A	N/A	19.197**	103.695***
	Observations	8044	7872	7647	8614
	P-Value	N/A	N/A	0.014	0.001
	Pseudo R2	0.328	0.328	0.34	0.328
	Q-Value	N/A	N/A	0.014	0.001
Fairfield	Chi^2	N/A	N/A	2,241.333***	N/A
	Observations	7182	6974	6859	8104
	P-Value	N/A	N/A	0.001	N/A
	Pseudo R2	0.305	0.305	0.305	0.301
	Q-Value	N/A	N/A	0.001	N/A
Granby	Chi^2	771.041***	907.010***	957.921***	842.554***
	Observations	527	519	510	539
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.497	0.505	0.488	0.476
	Q-Value	0.003	0.003	0.004	0.003
Groton City	Chi^2	N/A	N/A	531.318***	N/A
	Observations	1339	1285	1266	1493
	P-Value	N/A	N/A	0.001	N/A
	Pseudo R2	0.351	0.363	0.368	0.337
	Q-Value	N/A	N/A	0.001	N/A
Groton Town	Chi^2	1,315.665***	910.671***	566.166***	220.212***
	Observations	3932	3780	3580	4234
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.241	0.248	0.261	0.23
	Q-Value	0.003	0.003	0.004	0.003
Hamden	Chi^2	31.688***	27.815***	N/A	18.233**
	Observations	5370	5293	3947	5799
	P-Value	0.001	0.001	N/A	0.019
	Pseudo R2	0.601	0.602	0.611	0.545
	Q-Value	0.003	0.003	1	0.056
Hartford	Chi^2	21.045+	N/A	438.897***	23.090**
	Observations	5994	5897	4324	8129
	P-Value	0.05	N/A	0.001	0.027
	Pseudo R2	0.602	0.603	0.614	0.56
	Q-Value	0.136	1	0.004	0.076

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Madison	Chi^2	9,942.966***	3,852.464***	1,537.336***	2,161.687***
	Observations	2941	2888	2917	3016
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.261	0.263	0.28	0.279
	Q-Value	0.003	0.003	0.004	0.003
Manchester	Chi^2	92.561***	18.284	304.295***	25.854***
	Observations	9075	8789	7696	10297
	P-Value	0.001	0.107	0.001	0.01
	Pseudo R2	0.395	0.379	0.405	0.377
	Q-Value	0.003	0.328	0.004	0.03
New Britain	Chi^2	19.738++	24.569***	21.531**	534.539***
	Observations	4472	4385	5914	7238
	P-Value	0.048	0.01	0.017	0.001
	Pseudo R2	0.421	0.442	0.407	0.372
	Q-Value	0.134	0.032	0.052	0.003
New Canaan	Chi^2	483.434***	537.471***	N/A	N/A
	Observations	4877	4704	4843	5312
	P-Value	0.001	0.001	N/A	N/A
	Pseudo R2	0.223	0.224	0.214	0.215
	Q-Value	0.003	0.003	1	1
New Haven	Chi^2	9.63	286.713***	24.711**	14.833
	Observations	14907	14652	10031	18761
	P-Value	0.564	0.001	0.016	0.25
	Pseudo R2	0.451	0.451	0.458	0.425
	Q-Value	1	0.003	0.05	0.635
New London	Chi^2	232.539***	309.697***	23.634**	16.597
	Observations	4208	4124	4121	4955
	P-Value	0.001	0.001	0.014	0.119
	Pseudo R2	0.289	0.291	0.298	0.273
	Q-Value	0.003	0.003	0.045	0.316
North Branford	Chi^2	1,632.006***	1,802.219***	448.098***	1,479.582***
	Observations	817	808	797	831
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.347	0.349	0.347	0.34
	Q-Value	0.003	0.003	0.004	0.003
North Haven	Chi^2	1,743.107***	N/A	670.976***	2,124.779***
	Observations	2335	2275	2116	2563
	P-Value	0.001	N/A	0.001	0.001
	Pseudo R2	0.277	0.279	0.301	0.28
	Q-Value	0.003	1	0.004	0.003
Norwalk	Chi^2	65.842***	62.159***	N/A	159.123***
	Observations	4668	4543	4584	5866
	P-Value	0.001	0.001	N/A	0.001
	Pseudo R2	0.328	0.33	0.316	0.31
	Q-Value	0.003	0.003	1	0.003

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Portland	Chi^2	70.794***	726.703***	N/A	N/A
	Observations	348	338	328	348
	P-Value	0.001	0.001	N/A	N/A
	Pseudo R2	0.805	0.996	0.759	0.74
	Q-Value	0.003	0.003	1	1
Ridgefield	Chi^2	18.016***	335.648***	1.797	584.844***
	Observations	5958	5732	6112	6492
	P-Value	0.006	0.001	0.773	0.001
	Pseudo R2	0.275	0.272	0.279	0.273
	Q-Value	0.017	0.003	1	0.003
Rocky Hill	Chi^2	400.536***	297.726***	10.947	870.463***
	Observations	3760	3624	3476	3913
	P-Value	0.001	0.001	0.204	0.001
	Pseudo R2	0.321	0.321	0.333	0.317
	Q-Value	0.003	0.003	0.568	0.003
Stonington	Chi^2	2,475.531***	6,684.526***	4,082.468***	4,133.728***
	Observations	4864	4755	4663	4857
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.31	0.314	0.31	0.312
	Q-Value	0.003	0.003	0.004	0.003
Suffield	Chi^2	461.660***	404.778***	233.462***	227.511***
	Observations	621	611	609	654
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.663	0.663	0.654	0.642
	Q-Value	0.003	0.003	0.004	0.003
Wallingford	Chi^2	504.684***	N/A	40.793***	N/A
	Observations	6684	6563	6924	7777
	P-Value	0.001	N/A	0.001	N/A
	Pseudo R2	0.298	0.303	0.293	0.277
	Q-Value	0.003	1	0.004	1
West Hartford	Chi^2	1,104.332***	975.797***	1,930.178***	3,142.916***
	Observations	5185	4764	4750	5766
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.279	0.282	0.296	0.277
	Q-Value	0.003	0.003	0.004	0.003
West Haven	Chi^2	423.938***	105.415***	283.785***	495.888***
	Observations	6907	6794	6116	8662
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.264	0.263	0.266	0.241
	Q-Value	0.003	0.003	0.004	0.003
Westport	Chi^2	200.955***	303.157***	302.269***	200.869***
	Observations	6741	6582	6482	7289
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.268	0.268	0.264	0.259
	Q-Value	0.003	0.003	0.004	0.003

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Willimantic	Chi^2	N/A	12.668	209.365***	57.570***
	Observations	1529	1503	2132	2297
	P-Value	N/A	0.123	0.001	0.001
	Pseudo R2	0.405	0.407	0.365	0.351
	Q-Value	N/A	0.123	0.001	0.001
Wilton	Chi^2	N/A	656.392***	N/A	N/A
	Observations	4481	4208	4411	4935
	P-Value	N/A	0.001	N/A	N/A
	Pseudo R2	0.275	0.286	0.296	0.277
	Q-Value	N/A	0.001	N/A	N/A
Windsor Locks	Chi^2	2,497.678***	1,965.234***	N/A	2,750.147***
	Observations	1030	1008	867	1098
	P-Value	0.001	0.001	N/A	0.001
	Pseudo R2	0.526	0.536	0.561	0.531
	Q-Value	0.003	0.003	1	0.003
Winsted	Chi^2	N/A	N/A	461.205***	N/A
	Observations	825	817	787	831
	P-Value	N/A	N/A	0.001	N/A
	Pseudo R2	0.545	0.541	0.61	0.537
	Q-Value	N/A	N/A	0.001	N/A
Woodbridge	Chi^2	2,613.989***	2,405.135***	740.164***	3,871.762***
	Observations	1859	1778	1460	1936
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.202	0.207	0.216	0.209
	Q-Value	0.003	0.003	0.004	0.003
State Police Troops					
Troop A	Chi^2	1,699.104***	830.054***	793.068***	1,179.629***
	Observations	14098	13521	13969	16168
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.209	0.211	0.204	0.201
	Q-Value	0.003	0.003	0.004	0.003
Troop C	Chi^2	833.474***	N/A	287.898***	266.756***
	Observations	18750	17328	17025	19048
	P-Value	0.001	N/A	0.001	0.001
	Pseudo R2	0.232	0.232	0.241	0.234
	Q-Value	0.003	1	0.004	0.003
Troop D	Chi^2	852.833***	744.942***	1,124.583***	1,776.163***
	Observations	10438	10011	10110	10719
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.18	0.18	0.184	0.182
	Q-Value	0.003	0.003	0.004	0.003
Troop E	Chi^2	655.073***	1,210.104***	3,183.506***	754.943***
	Observations	14171	13319	12820	14651
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.179	0.182	0.182	0.18
	Q-Value	0.003	0.003	0.004	0.003

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Troop F	Chi^2	1,122.364***	11.248	5,137.013***	3,845.933***
	Observations	15716	15047	15001	16620
	P-Value	0.001	0.259	0.001	0.001
	Pseudo R2	0.317	0.321	0.323	0.317
	Q-Value	0.003	0.739	0.004	0.003
Troop G	Chi^2	337.295***	315.859***	33.604***	24.065**
	Observations	11099	10319	9625	13200
	P-Value	0.001	0.001	0.001	0.019
	Pseudo R2	0.188	0.188	0.2	0.187
	Q-Value	0.003	0.003	0.004	0.056
Troop H	Chi^2	1,248.609***	1,189.729***	19.562++	N/A
	Observations	14740	13870	12586	16801
	P-Value	0.001	0.001	0.034	N/A
	Pseudo R2	0.231	0.233	0.241	0.224
	Q-Value	0.003	0.003	0.101	1
Troop I	Chi^2	1,087.854***	1,237.550***	1,100.081***	1,465.916***
	Observations	10606	10069	9385	11989
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.182	0.187	0.197	0.182
	Q-Value	0.003	0.003	0.004	0.003
Troop K	Chi^2	408.062***	650.309***	11.001	451.023***
	Observations	14003	13449	13425	14849
	P-Value	0.001	0.001	0.275	0.001
	Pseudo R2	0.303	0.305	0.31	0.303
	Q-Value	0.003	0.003	0.748	0.003
Troop L	Chi^2	299.820***	N/A	245.468***	282.535***
	Observations	8241	8077	8198	8808
	P-Value	0.001	N/A	0.001	0.001
	Pseudo R2	0.221	0.224	0.223	0.218
	Q-Value	0.003	1	0.004	0.003
Special Police Departments					
Southern CT State University	Chi^2	29.523***	740.838***	N/A	12,924.452***
	Observations	448	441	255	509
	P-Value	0.001	0.001	N/A	0.001
	Pseudo R2	0.551	0.568	0.764	0.589

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for gender, age, time of the day, day of the week, week of year, and officer fixed-effects.
Note 3: Q-Values were estimated using a false discovery rate procedure following Simes (1986) and later refined by Benjamini and Hochberg (1995) as well as Benjamini and Yekutieli (2001).

VII: ANALYSIS OF VEHICULAR SEARCHES

This section contains the results of an analysis of post-stop outcomes using a hit-rate approach following Knowles, Persico and Todd (2001). The hit-rate approach relies on the idea that motorists rationally adjust their propensity to carry contraband in response to their likelihood of being searched by police. Similarly, police officers rationally decide whether to search a motorist based on visible indicators of guilt and an expectation of the likelihood that a given motorist might have contraband. According to the model, a demographic group of motorists would be searched by police more often than Whites if they were more likely to carry contraband. However, the higher level of searches should be exactly proportional to the higher propensity for this group to carry contraband. Thus, in the absence of racial animus, we should expect the rate of successful searches (i.e. the hit-rate) to be equal across different demographic groups regardless of differences in their propensity to carry contraband. [8]

In this test, discrimination is interpreted as a preference for searching minority motorists that shows up in the data as a statistically lower hit-rate relative to white motorists. In more technical terms, the testable implication derived from this model is that the equilibrium search strategy, in the absence of group bias, will result in an equalization of the rate of contraband that is found relative to the total number of searches (i.e. the hit-rate) across motorist groups. In our application, we test for the presence of a disparity in the rate of successful searches using a nonparametric test, the Pearson X^2 test. Note that this test inherently says nothing about disparate treatment in the decision to stop motorists as it is limited in scope to vehicular searches. We limit our analysis to discretionary searches which are defined as those characterized as probable cause.

VII.A: AGGEGATE ANALYSIS WITH HIT-RATES, 2017

The analysis begins by aggregating all search data for Connecticut by demography and performing the non-parametric test of hit-rates. The rate that discretionary searches end in contraband being found for white Non-Hispanic motorists is compared to each minority subgroup. The results of this test, applied to the aggregate search data for all departments in Connecticut, can be seen in Table 7.1. As seen below, the rate of successful searches for white Non-Hispanic motorists was 28.9 percent in 2017. Relative to white Non-Hispanic motorists, the hit-rate for each of the four minority subgroups was lower and ranged from 19.2 to 19.8 percent. The difference in hit-rates for each group was statistically significant at the 99 percent level. In aggregate, Connecticut police departments are less successful in motorist searches across all minority groups, which is a potential indicator of disparate treatment.

[8] Although some criticism has risen concerning the technique and extensions have suggested that more disaggregated groupings of searches be used in the test, the ability to implement such improvements is limited by the small overall sample of searches in a single year of traffic stops. Despite these limitations, the hit-rate analysis is still widely applied in practice and contributes to the overall understanding of post-stop police behavior in Connecticut.

Table 7. 1: Chi-Square Test of Hit-Rate, All Discretionary Searches 2017

Variable	Caucasian	Non-Caucasian	Black	Hispanic	Black or Hispanic
Hit Rate	28.943%	19.861%***	19.688%***	19.216%***	19.440%***
Contraband	791	404	393	275	654
Searches	2733	2034	1996	1431	3364
Chi2	N/A	51.186	52.624	46.638	75.279
P-Value	N/A	0.001	0.001	0.001	0.001

Note 1: The coefficients are presented along with robust standard errors. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: Sample includes all discretionary searches in 2017.

Table 7.2 provides the results of a hit-rate analysis for discretionary searches made in aggregate by municipal departments in 2017. The hit-rate in municipal departments for white Non-Hispanic motorists was 27.4 percent. Relative to white Non-Hispanic motorists, the hit-rate for each of the four minority subgroups was lower and ranged from 17.6 to 17.9 percent. Each of these differences were also statistically significant at the 99 percent level. Our interpretation of these coefficient estimates is that municipal departments in Connecticut may be disproportionately searching minority motorists relative to their Caucasian counterparts.

Table 7. 2: Chi-Square Test of Hit-Rate, Municipal Police Discretionary Searches 2017

Variable	Caucasian	Non-Caucasian	Black	Hispanic	Black or Hispanic
Hit Rate	27.361%	17.878%***	17.611%***	17.794%***	17.798%***
Contraband	527	295	286	200	482
Searches	1926	1650	1624	1124	2708
Chi2	N/A	45.148	47.451	35.798	60.432
P-Value	N/A	0.001	0.001	0.001	0.001

Note 1: The coefficients are presented along with robust standard errors. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance
Note 2: Sample includes all discretionary searches made by municipal departments in 2017.

Table 7.3 provides the results of a hit-rate analysis for discretionary searches made in aggregate by State Police in 2017. The hit-rate for all State Police was 31.6 percent for white Non-Hispanic motorist. Relative to white Non-Hispanic motorists, the hit-rate for each of the four minority subgroups was lower and ranged from 23.9 to 25.6 percent. The hit-rate for minority groups were smaller than that of White Non-Hispanics and this difference was statistically different from zero. In particular, the results were statistically significant at a 95 percent level or greater depending on the specification. As before, our interpretation of these coefficient estimates is that State Police in Connecticut may be disproportionately searching minority motorists relative to their Caucasian counterparts.

Table 7. 3: Chi-Square Test of Hit-Rate, State Police Discretionary Searches 2017

Variable	Caucasian	Non-Caucasian	Black	Hispanic	Black or Hispanic
Hit Rate	31.565%	25.142%**	25.663%**	23.875%**	24.256%***
Contraband	244	88	87	69	147
Searches	773	350	339	289	606
Chi2	N/A	4.771	3.926	5.984	8.930
P-Value	N/A	0.028	0.048	0.014	0.003

Note 1: The coefficients are presented along with robust standard errors. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance
Note 2: Sample includes all discretionary searches made by State Police in 2017.

VII.B: DEPARTMENT ANALYSIS WITH HIT-RATES, 2017

In this subsection, differences in hit-rates are estimated independently for each municipal department and State Police troop. Here, we identify and present only those departments found to have a disparity that is statistically significant at the 95 percent level in either the Hispanic or Black alone minority groupings. The full set of results can be found in Table G.1 of Appendix G. Table 7.4 presents the results from estimating the hit-rate test for individual departments using the 2017 sample. There was only one municipal departments found to have a disparity in the hit-rate for the combined Black or Hispanic category. Although the disparity in this department was statistically significant at the 95 percent level, it did not have a false discovery rate less than 10 percent, or a sample size of greater than 30 in the Black or Hispanic alone categories.

Table 7. 4: Chi-Square Test of Hit-Rate, Select Department Discretionary Searches 2017

Department	Variable	Caucasian	Non-Caucasian	Black	Hispanic	Black or Hispanic
Milford+	Chi2	N/A	N/A	N/A	N/A	13.215
	Searches	62	N/A	N/A	N/A	40
	Hit Rate	9.677%	N/A	N/A	N/A	40%***
	Q-Value	N/A	N/A	N/A	N/A	0.001
	Contraband	6	N/A	N/A	N/A	16
	P-Value	N/A	N/A	N/A	N/A	0.001

Note 1: The coefficients are presented along with robust standard errors. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance
Note 2: Sample includes all discretionary searches made by municipal departments and State Police in 2017.
Note 3: The test was only estimated when the combined sample of Caucasian and minority motorists exceeded 30 searches.
Note 4: Q-Values were estimated using a false discovery rate procedure following Simes (1986) and later refined by Benjamini and Hochberg (1995) and Benjamini and Yekutieli (2001).

VIII: FINDINGS FROM THE 2017 ANALYSIS

This section represents a summary of the findings from the one year analysis of traffic stops conducted January 1, 2017 to December 31, 2017.

VIII.A: AGGREGATE FINDINGS FOR CONNECTICUT, 2017

Across Connecticut's municipal departments and State Police troops, a total of 16 percent of motorists stopped during the analysis period were observed to be Black while 14 percent of stops were Hispanic motorists. Taken as a whole and relative to prior year's studies, the findings from the 2017 analysis of Connecticut's traffic stop data indicate that some progress has been made in terms of the decision to stop a minority motorist. Across the state, as well as in the analysis based on the aggregate municipal and State Police samples, the Veil of Darkness did not indicate that stopped motorists were any more likely to be from minority groups in daylight relative to darkness. Although we have identified one municipal police department and two state police troops where the Veil of Darkness indicated a statistically significant disparity, the lack of a disparity statewide and the lower number of identified departments is a promising sign.

However, the data show that large and statistically significant disparities remain in terms of how minorities are treated following a traffic stop. The new post-stop test for differential outcomes provides compelling evidence that minority motorists receive different dispositions (tickets, warnings, searches) after a stop is made, even after we condition on the basis for the stop and other potentially confounding factors. Similar evidence of adverse treatment was found statewide in terms of searches where the data suggests that the bar for searching a minority motorist is substantially lower than their white non-Hispanic counterparts. Finally, the statewide hit-rate analysis also found statistically significant evidence that the police were far less likely to be successful when searching a minority relative to a white non-Hispanic motorists.

VIII.B: VEIL OF DARKNESS ANALYSIS FINDINGS, 2017

In an effort to better identify racial and ethnic disparities at the department level, each analysis was repeated at the department level. The threshold for identifying individual departments was the presence of a disparity that was statistically significant at the 95 percent level in the Black or Hispanic alone categories. The departments that were identified as having a statistically significant disparity are, by nature, the largest contributors to the overall statewide results. [9] Here, the unit of analysis is

[9] To identify departments, a disparity must have been estimated with at least a 95 percent level of statistical significance and have a false discovery rate of less than 10 percent. Put simply, there must have been at least a 95 percent chance that the motorists were more likely to be stopped at a higher rate relative to white Non-Hispanic motorists. The false discovery rate of 10 percent allows for there to be a less than 10 percent chance that one of our identified estimates misidentifies a department.

a municipal department or State Police troops where disparities could be a function of a number of factors including institutional culture, departmental policy, or individual officers.[10]

The one municipal departments and two State Police troops identified to exhibit a statistically significant racial or ethnic disparity include:

Fairfield

The Fairfield municipal police department was observed to have made 30.4 percent minority stops during the inter-twilight window of which 13.4 percent were Hispanic and 14.6 percent were Black motorists in 2017. The Veil of Darkness analysis indicated a statistically significant disparity in the rate that both Black and Hispanic motorists were stopped during daylight relative to darkness. Within the inter-twilight window, the odds that a stopped motorist was Black increased by 1.6 while the odds that a stopped motorist was Hispanic increased by 1.3 during daylight. These results were statistically significant at a level greater than 95 percent and robust to the inclusion of a variety of controls, officer fixed-effects, and a restricted sample of moving violations.

State Police Troop C

State Police Troop C was observed to have made 22.2 percent minority stops during the inter-twilight window of which 7.7 percent were Hispanic and 8.1 percent were Black motorists in 2017. The Veil of Darkness analysis indicated a statistically significant disparity in the rate that both Black and Hispanic motorists were stopped during daylight relative to darkness. Within the inter-twilight window, the odds that a stopped motorist was Black increased by 1.4 while the odds that a stopped motorist was Hispanic also increased by 1.4 during daylight. These results were statistically significant at a level greater than 95 percent and robust to the inclusion of a variety of controls, officer fixed-effects, and a restricted sample of moving violations.

State Police Troop K

State Police Troop C was observed to have made 21.5 percent minority stops during the inter-twilight window of which 10.5 percent were Hispanic and 7.9 percent were Black motorists in 2017. The Veil of Darkness analysis indicated a statistically significant disparity in the rate that both Black and Hispanic motorists were stopped during daylight relative to darkness. Within the inter-twilight window, the odds that a stopped motorist was Hispanic increased by 10.5 during daylight. This results was statistically significant at a level greater than 95 percent and robust to the inclusion of a variety of controls, officer fixed-effects, and a restricted sample of moving violations.

VIII.C: OTHER STATISTICAL AND DESCRIPTIVE MEASURE FINDINGS, 2017

In addition to the one municipal police departments and two State Police troops identified to exhibit statistically significant racial or ethnic disparities in the Veil of Darkness analysis, a number of other

[10] Since department or state police barrack estimates represent an average effect of stops made by individual officers weighted by the number of stops that they made in 2017, it is possible that officer-level disparities exist in departments which were not identified.

departments were identified using either the synthetic control method, descriptive tests, stop disposition test or KPT hit-rate analysis. Identification in any one of these tests alone is not, in and of itself, sufficient to be identified for further analysis. However, these additional tests are designed as an additional screening tool to identify the jurisdictions where consistent disparities exceed certain thresholds that appear in the data. Although it is understood that certain assumptions have been made in the design of each of these measures, it is reasonable to believe that departments with consistent data disparities that separate them from the majority of other departments should be subject to further review and analysis with respect to the factors that may be causing these differences.

Synthetic Control Analysis

The results from estimating whether individual municipal departments stopped more minority motorists relative to their requisite synthetic control found six municipal police departments to have a disparity that was statistically significant at the 95 percent level in the Black or Hispanic alone categories. However, the disparities did not all persist through doubly robust estimation. In total, there were only three municipal police departments that withstood this more rigorous estimation procedure. Those departments are *Meriden, Watertown,* and *Wethersfield.*

Descriptive Statistics Analysis:

The descriptive tests are designed as an additional tool to identify disparities that exceed certain thresholds that appear in a series of census-based benchmarks. Those three benchmarks are: (1) statewide average, (2) the estimated commuter driving population, and (3) resident-only stops. Although 59 municipal police departments were identified with racial and ethnic disparities when compared to one or more of the descriptive measures, only *Darien, Derby, East Hartford*, *Meriden, Stratford, Trumbull, Waterbury, Wethersfield, and Wolcott* exceeded the disparity threshold in more than half the benchmark areas.

Stop Disposition Analysis:

In aggregate, minority motorists stopped by police departments were found to have a statistically different distribution of outcomes conditional on the basis for which they were stopped. In the departmental analysis, there were 40 of 94 total departments, one of nine special departments, and 10 of 12 State Police Troops found to have a disparity in the distribution of outcomes that was statistically significant at the 95 percent level in the Black or Hispanic alone categories. Although it does appear that minority motorists are treated differently in many of the same departments identified in other tests, we still caution the reader from drawing any conclusions based on these results. As noted before, our ideal analysis would include data on every reason that a stop was made and all requisite outcomes.

KPT Hit-Rate Analysis:

The results of this test, applied to the aggregate search data for all departments in Connecticut show that departments are less successful in motorist searches across all minority groups, which is a potential indicator of disparate treatment. There was a total of one municipal police department found to have a disparity in the hit-rate of minority motorists relative to white Non-Hispanic motorists, which was statistically significant at the 95 percent level but did not fall below the threshold of a 10 percent false discovery rate. The municipal departments identified to exhibit a statistically significant racial or ethnic disparity in searches was *Milford.*

VIII.D: FOLLOW-UP ANALYSIS

The entirety of Part I of this report should be utilized as a screening tool by which researchers, law enforcement administrators, community members and other appropriate stakeholders focus resources on those departments displaying the greatest level of disparities in their respective stop data. As noted previously, racial and ethnic disparities in any traffic stop analysis do not, by themselves, provide conclusive evidence of racial profiling. Statistical disparities do, however, provide significant evidence of the presence of idiosyncratic data trends that warrant further analysis.

In order to determine if a departments racial and ethnic disparities warrant additional in-depth analysis, researchers review the results from the five analytical sections of the report (Veil of Darkness, Synthetic Control, Descriptive Statistics, Stop Disposition and KPT Hit-Rate). The threshold for identifying significant racial and ethnic disparities for departments is described in each section of the report (ex. departments with a disparity that was statistically significant at the 95 percent level in the black or Hispanic alone categories in the Veil of Darkness methodology were identified as statistically significant). A department is identified for a follow-up analysis if they meet any one of the following criteria:

1. A statistically significant disparity in the Veil of Darkness analysis
2. A statistically significant disparity in the synthetic control analyses and any one of the following analyses:
    a. Descriptive statistics
    b. Stop Disposition
    c. KPT-Hit Rate
3. A statistically significant disparity in the descriptive statistics, stop disposition, and KPT hit-rate analyses.

Based on the above listed criteria it was recommended that an in-depth follow-up analysis should be conducted for the following departments: **(1) Derby, (2) Fairfield, and (3) Troop K.** None of these two municipal departments or one state police troop have been identified in previous reports.

Meriden, **Wethersfield, and Troop C** were also identified with racial and ethnic disparities in this study as well as in previous annual reports. Meriden was identified in the Year 2 (Traffic Stop Data Analysis and Findings, 2014-15) and Year 3 (Traffic Stop Data Analysis and Findings, 2015-16) studies. Wethersfield has been identified in all four statewide studies conducted since the start of this project. Troop C was identified in the Year 1 (Traffic Stop Data Analysis and Findings, 2013-14) study. An in-depth follow-up analysis, with recommendations, was previously completed for both municipal agencies and Troop C. The racial and ethnic disparities have remained consistent in each of the annual studies for Wethersfield and it is the only municipal department that has been identified in all four annual studies. However, Meriden was identified with fewer racial and ethnic disparities in this report compared to prior years and the disparities were only marginally above the benchmarks. Based on the results of the previously published follow-up analyses and our further understanding of traffic stop enforcement in Meriden, Wethersfield, and Troop C, we do not believe another follow-up analysis for these departments would significantly add to the knowledge of factors that may have influenced these disparities already documented in the previous follow-up reports. The departments should continue to review and monitor traffic enforcement policies to evaluate the disproportionate effect they could be having on minority drivers. They should also continue to take steps to assure that their minority community is fully engaged in the process of understanding why the allocation of enforcement resources are made and what outcomes are being achieved.

Although further analysis is important, a major component of addressing concerns about the possibility of racial profiling in Connecticut is bringing law enforcement officials and community members together in an effort to build trust by discussing relationships between police and the community. Public forums should be held in each identified community to bring these groups together. They serve as an important tool to inform the public of the findings and outline steps for moving forward with additional analysis. The IMRP is committed to utilizing both data and dialogue to enhance relationships between the police and community.

PART II: 2017 FOLLOW-UP ANALYSIS

IX: FOLLOW-UP ANALYSIS INTRODUCTION

The information presented in the subsequent sections consists of two follow-up reports, one conducted for each department that warranted further analysis (Derby and Fairfield). Although Troop K was identified with statistically significant racial and ethnic disparities, additional research and analysis aimed at devising a more effective way to assess the stop data for this troop is ongoing and no conclusions are being presented in this report.

The goal of an enhanced analysis is to better understand the reasons for racial and ethnic disparities in traffic stop data. Disparities can be the result of the interplay of a variety of factors that can be identified and further explored through a more in-depth examination of the data. Although there are some factors common to policing in general, the true nature of policing can differ from one community to another based on a variety of unique factors. Police administrators must deal with a variety of crime and disorder problems. Traffic stop disparities can be influenced by factors such as the location and frequency of accidents, high call for service volume areas, high crime rate areas, and areas with major traffic generators such as shopping and entertainment districts, to name a few. Police administrators frequently make decisions about how to effectively deploy police resources based on their perception of the needs of the community.

In order to understand the factors that might be contributing to traffic enforcement decisions, we first sought an understanding of where traffic enforcement occurs in the community. The best way to complete this task is to map traffic stops for each identified community. Police officers are required to report the location of a traffic stop in a manner that would allow the stop to be identified on a map. In some cases, technology allows the officer to capture the specific longitude and latitude coordinates for the stop. In other cases, the officer enters a descriptive location such as the number and street or street and nearest cross street.

The project staff worked with both of the municipal police departments identified to map traffic stops during the study period. The Fairfield Police Department was able to provide researchers with longitude and latitude information**.** Unfortunately, specific longitude and latitude information wasn't available for the Derby Police Department. Researchers determined that a descriptive analysis of traffic stops at the census tract level was the most appropriate method to use in Fairfield. On the other hand, due to the lack of latitude and longitude coordinates in Derby, researchers decided to conduct a descriptive analysis of traffic stops by major traffic corridors.

In Fairfield, where we had a significant percentage of location coordinates, we mapped the stops by census tract. Each community is broken up into census tracts to help understand the different makeup of a community. According to the United States Census Bureau, a census tract is "a small, relatively permanent statistical subdivision of a county or equivalent entity that are updated by local participants prior to each decennial census as part of the Census Bureau's Participant Statistical Areas Program." Census tract boundaries generally follow visible and identifiable features. Also, census tracts generally have a population size between 1,200 and 8,000 people, with an optimum size of about 4,000 people. Each census tract is identified by a unique number.

Researchers have the ability to better understand the demographics of a subsection of a community by breaking down traffic stops into census tracts. A census tract analysis not only provides a better understanding of population demographics, but also allows researchers to focus on the unique attributes of a subsection of a community such as major traffic generators, accident rates, local crime problems, and calls for service. Neighborhoods can vary greatly within a community and a more detailed analysis will help to better understand the information presented in the initial analysis.

In Derby, researchers conducted a descriptive analysis of traffic stops by major corridors. The location information typically identified the road where the traffic stop was conducted, but not the specific point on the road. Although analyzing traffic stops by census tract is the preferred method, analyzing traffic stops by corridor can also be an effective approach. Presented in the subsequent sections are our findings from the department level descriptive analysis for both the Derby and Fairfield police departments.

The final section of this report outlines a methodology that moves us beyond examining disparities at the department level and examining individual officers. It is important to realize that the analysis only identifies if the driver demographics of an officer's traffic stops showed a statistically significant difference relative to their individualized internal benchmark and not whether officers are engaged in discriminatory policing. If any of the officers identified in this analysis were engaged in a particular activity that was not captured by the data, such as having been tasked with a specialized assignment, it could provide a reasonable explanation for the disparity. It is important that these results be viewed as the starting point of a dialogue and not as conclusive evidence of wrongdoing on the part of the officer. The officer analysis is meant to be an internal tool for law enforcement administrators to review in conjunction with additional officer information not available to researchers.

X: DERBY FOLLOW-UP ANALYSIS SUMMARY

Racial and ethnic disparities in any traffic stop analysis do not, by themselves, provide conclusive evidence of racial profiling. Statistical disparities do, however, provide significant evidence of the presence of idiosyncratic data trends that warrant further analysis. Based on the pre-established criteria for identifying racial and ethnic disparities in traffic stops, the Racial Profiling Prohibition Project staff conducted an in-depth analysis for the Derby Police Department.

The Derby Police Department was identified as having a racial and ethnic disparity using the three descriptive measures presented in Part I of the report. Derby exceeded the threshold in all three descriptive benchmarks used and five of the nine possible measures. Derby received a disparity score of five out of a possible nine points. The synthetic control test also revealed a disparity in the rate for stopping Hispanic motorists that was statistically significant at the 99 percent level respectively, but there was a marginal change in the results during a robustness check. Additionally, the results from the Stop Disposition test shows minority motorists stopped were found to have a statistically different distribution of outcomes conditional on the basis for which they were stopped. Although researchers made certain assumptions in the design of each methodology, it is reasonable to conclude that departments with consistent data disparities separating them from the majority of other departments should be subject to further review and analysis with respect to the factors that may have caused these differences. It is worth noting that identifying Derby for additional analysis was a judgement made by researchers based on the marginal disparities identified in both this study and previous studies.

During the 2017 calendar year, the Derby Police Department made 2,347 traffic stops. Of these, 39% were minority stops (17% Hispanic and 20% black). Table 10.1 below summarizes traffic stops reported by the Derby Police Department over a three-year period.

Table 10. 1: Derby Traffic Stops – 2015 - 2017

	2015 Stops		2016 Stops		2017 Stops	
White	1,940	70%	2,086	68%	1,443	61%
Black	440	16%	497	16%	478	20%
AsPac*	20	1%	27	1%	31	1%
AI/AN**	3	0%	0	0%	5	0%
Hispanic	353	13%	472	15%	390	17%
Total	**2,756**		**3,082**		**2,347**	

*Asian Pacific Non-Hispanic
** American Indian/Alaska Native Non-Hispanic

X.A: Descriptive Analysis of the 2017 Traffic Stop Data

Researchers studied the racial and ethnic disparities in the Derby Police Department data using a more detailed review of traffic stops during the study period. Part of this analysis involved mapping all stops, if possible, using the location data provided by the department and any enhancements we were able to make. Unfortunately, the descriptive information on stop locations was not specific enough to allow accurate mapping of the traffic stops reported. Due to the lack of detailed location information available in Derby, a census tract-based analysis was replaced by a descriptive analysis of major corridors and roadways. The location information typically identified the road where the traffic stop was made, but not the specific point on the road. Although analyzing traffic stops by census tract is the preferred method, analyzing traffic stops by corridor proved just as effective an approach because 87% of traffic stops in Derby are made on 11 roadways. More specifically, stops on one roadway (Route 34), which goes by multiple local names, account for 58% of all stops.

According to the 2010 census, Derby is a city with approximately 10,391 residents over the age of 16. Approximately 21% of the driving age population in Derby is identified as a minority. However, according to the 2017 five-year American Community Survey[11] estimate counts provided by the U.S. Census Bureau, Derby's Hispanic driving age population has increased by approximately 57% since 2010. Other groups appear to have remained the same or seen a small decrease in population. We reference the 2010 census data in the table below because this information is the most detailed and complete data available. However, it is worth noting that the Hispanic population is more likely to be approximately 18%, as opposed to the 12.4% reported in 2010. Table 10.2 outlines the basic demographic information for Derby residents over age 16 according to the 2010 decennial census.

Table 10. 2: Derby Population

Race/Ethnicity	16+ Population Total	% Population Total
White Non-Hispanic	8,255	79.4%
Black Non-Hispanic	627	6.0%
AsPac Non-Hispanic	224	2.2%
Hispanic	1,285	12.4%
Other	0	0.0%
Total	**10,391**	

Derby is approximately five square miles in area, making it the smallest city in Connecticut. It is bisected by the Naugatuck River, which runs parallel to the east of Route 8. The city is bordered by Ansonia to the northeast, Seymour to the northwest, and Shelton to the southwest across the Housatonic River and Orange to the southeast. Orange, Shelton, and Seymour are predominantly white demographically, with an average white driving age population of 90% (compared to Derby's white driving age population of 79%). Ansonia's 79% white driving age population is comparable to Derby's. Of the drivers stopped in Derby, only 18% were residents of the city.

Route 8 (General Samuel Jaskilka Highway) is the city's only major expressway, running north to south through the center of town. There are six on-ramps and four off-ramps along Route 8 in Derby. One of the city's major off-ramps exits onto Pershing Drive, which is a high commercial activity roadway in the center of the city. Route 34 is also a main roadway that runs along the Housatonic River on Derby's southern border. Route 34 runs from the northwest corner of Derby, bordering Seymour, to the southeast corner of Derby, bordering Orange.

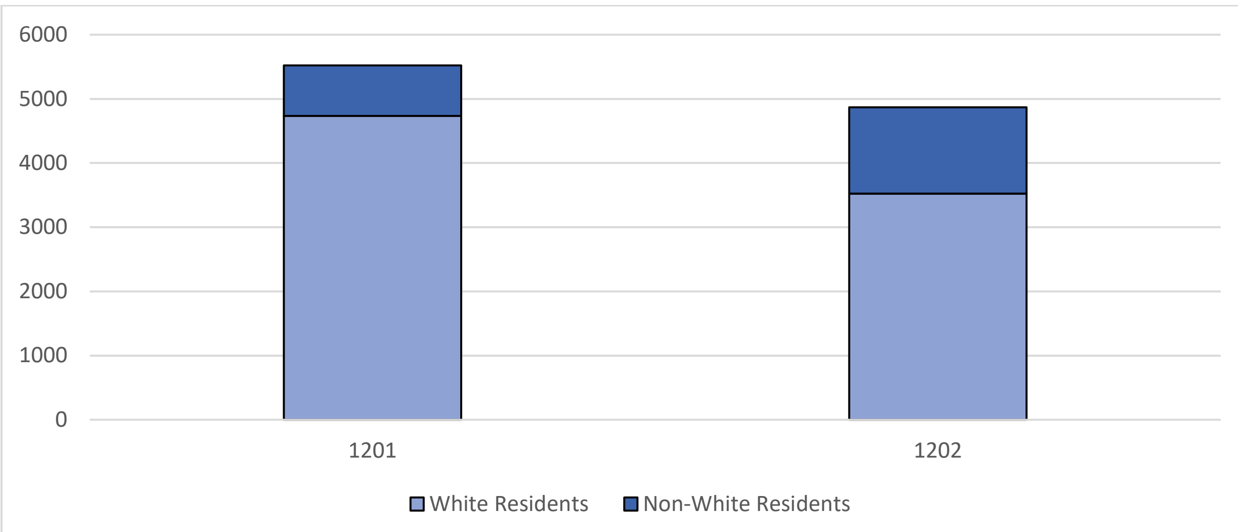
Derby is largely residential with the two main commercial areas located off of Route 8 on the west side of the Naugatuck River, and in the southeast corner of the city bordering Orange. Located in the Pershing Drive area are two supermarkets, multiple shopping plazas, a Planet Fitness, and several food establishments. The New Haven Avenue section of Route 34 is another major commercial corridor with shopping, food establishments, and other major traffic generators. City Hall is located

[11] The American Community Survey is a survey conducted by the U.S. Census Bureau to gather vital information on a yearly basis about our nation and its people. This helps to supplement information collected between the decennial censuses.

along Main Street and the Derby Police Department is located on Water Street, directly off Main Street. Another major traffic generator for the area is Griffin Hospital, which is located on the west side of Division Street along the border of Ansonia.

Although we do not conduct an analysis by census tract, it is still helpful to understand the racial make-up of different sections of the town, as evidenced in the census tract data. The U.S. Census Bureau divides Derby into two census tracts, using the Naugatuck River to divide the two tracts. The resident driving age population in each census tract varies only minimally with about 5,500 people living in tract 1201 (east of the Naugatuck River) and 4,900 living in tract 1202 (west of the Naugatuck River). Census tract 1202 has almost twice as many minority residents at 28%, while tract 1201 has approximately 14% minority residents. Figure 10.1 shows the distribution for each census tract in terms of the white and non-white driving age populations.

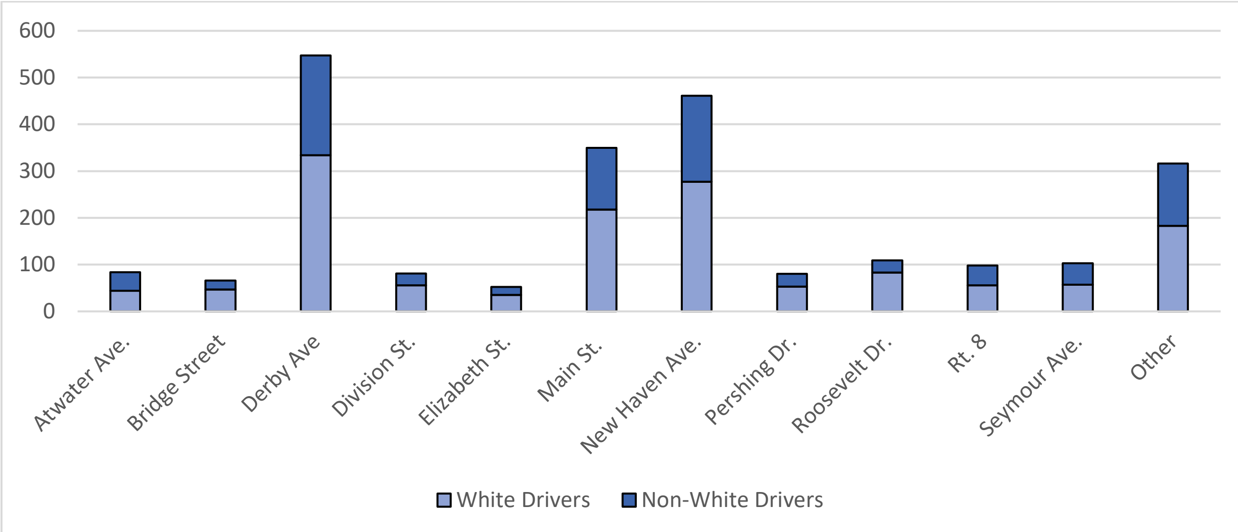
Figure 10. 1: Age 16 and Older Resident Population by Census Tract



Researchers identified 11 roadways in Derby that account for 87% of traffic stop locations. More than 50 stops were conducted on each of these 11 roadways; all other roads in the city contributed fewer than 50 traffic stops each. In particular, Derby Avenue, New Haven Avenue, and the Main Street corridors account for 58% of all traffic enforcement in the city. Therefore, this analysis of traffic stops in Derby will largely focus more on these roadways rather than on census tracts, although some references to the census tract data are included.

Figure 10.2 illustrates the volume of traffic stops that occur on each of the 11 identified roadways. The Route 34 corridor accounted for at least 39% of Derby traffic stops, excluding any stops on Derby Avenue. The Derby Avenue corridor is part of Route 34 for approximately one-quarter of a mile, but then continues north into Ansonia as Route 34 continues west towards Seymour. Derby Avenue accounts for 23% of all traffic stops. Unfortunately, we are unable to differentiate between the stops that occurred on the section of Derby Avenue that is a part of Route 34 and the section of Derby Avenue that is not. It is important to note that according to department officials, most of the stops reported on Derby Avenue likely occurred on the section that overlaps with Route 34. Due to the large volume of traffic stops on Route 34 and Derby Avenue, the following analysis focuses primarily on those corridors.

Figure 10. 2: Traffic Stops by Major Roadway



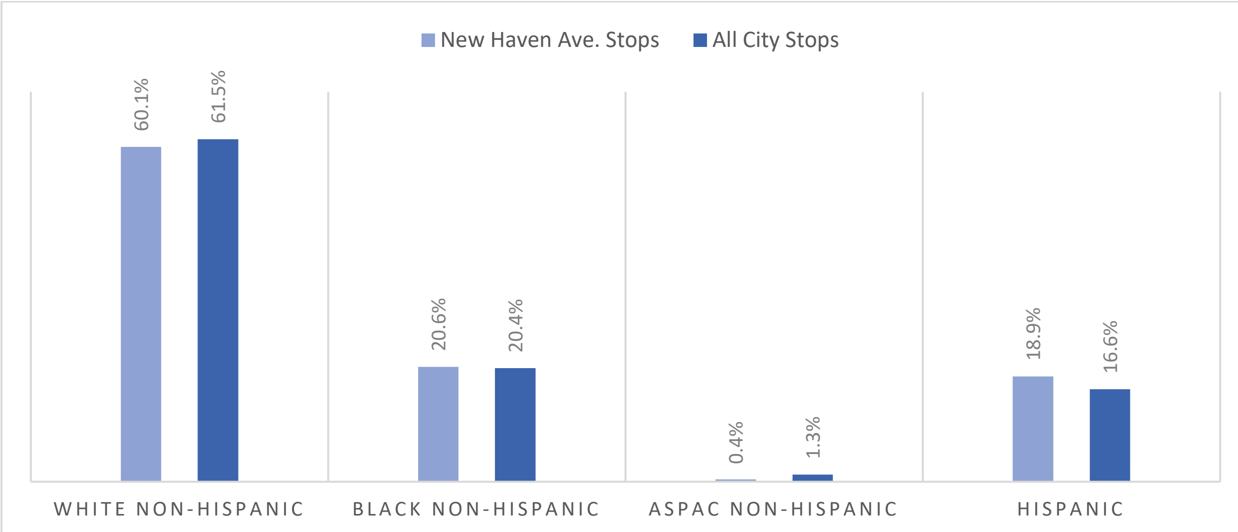
X.B: Traffic Stop Breakdown on Route 34 (Excluding Derby Avenue)

Route 34 is a primary state highway, approximately 25 miles long, that extends from Newtown to New Haven. Five of the 25-mile roadway runs through Derby and parts of it are a high commercial activity area for the city. From the west, Route 34 enters Derby at the border of Seymour and from the east, it crosses into Derby from Orange. Route 34 is known as Roosevelt Drive as it crosses into Derby from Seymour. It is mostly a two-lane road that runs parallel to the Housatonic River until it crosses Bridge Street. As Route 34 crosses Bridge Street it becomes Main Street for about one-half mile and is a main thoroughfare which includes City Hall, shopping and restaurants. Main Street ends at the Naugatuck River and the intersection with Derby Avenue. Route 34 then continues east as a four-lane divided highway for about two miles until it crosses into Orange. This section of Route 34 is locally known by two names, New Haven Avenue and Derby Avenue. Because Derby Avenue is not exclusively part of Route 34, we will consider those stops separately.

Thirty-nine percent of all traffic stops in Derby occurred on New Haven Avenue (20%), Main Street (15%), and Roosevelt Drive (5%). To explain how traffic enforcement varies along Route 34, the analysis considered each segment of the roadway independently.

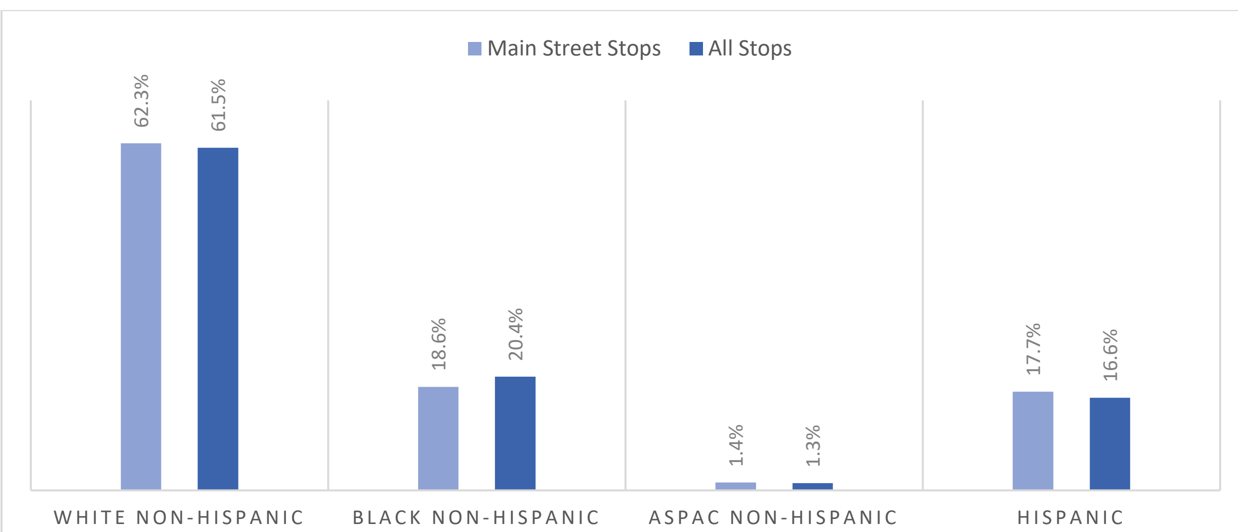
A total of 461 traffic stops were made during the study year along New Haven Avenue, which is a four-lane divided highway with heavy commercial activity and is the busiest section of Route 34 in the city. The overall percentage of traffic stops involving minority drivers on New Haven Avenue was 40%, almost equivalent to the 38.5% city average for all minority drivers stopped. Approximately 19% of drivers stopped were Hispanic and 21% were black. Of the more than 460 traffic stops on New Haven Avenue, 87% of the drivers were not residents of Derby (which is higher than the city-wide average of non-resident drivers stopped at 82%). Hispanic drivers were 19% of all Derby residents stopped on New Haven Avenue and 19% of all non-residents. Black drivers were 27% of all Derby residents stopped on New Haven Avenue and 20% of all non-residents. Figure 10.3 shows the proportion of traffic stops on New Haven Avenue by race and ethnicity compared to the city-wide average for all stops.

Figure 10. 3: New Haven Avenue Traffic Stops by Race/Ethnicity



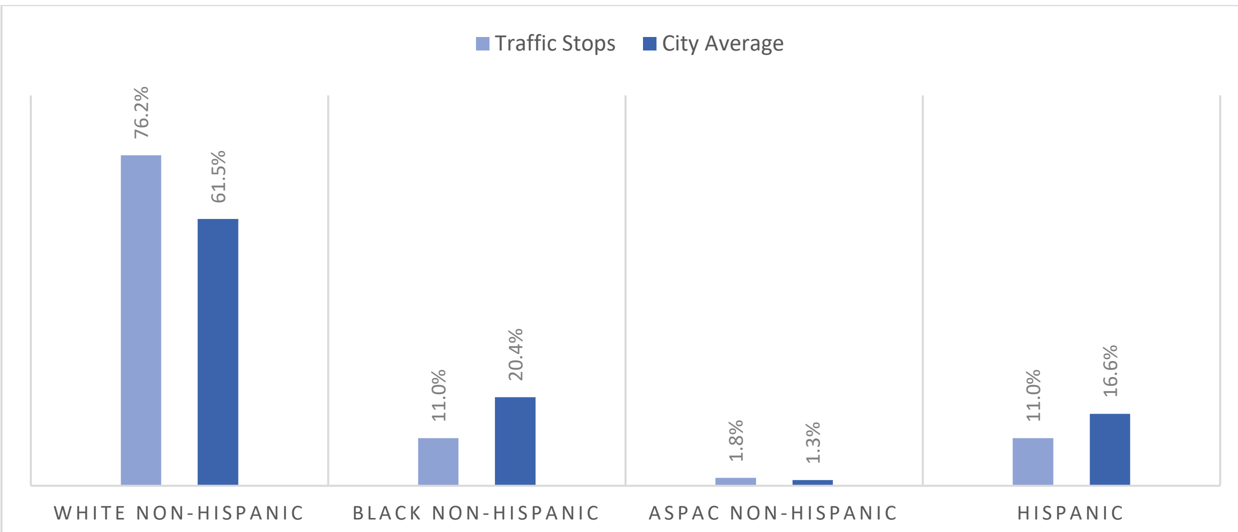
A total of 350 traffic stops were made during the study year along the half-mile stretch of Route 34 known as Main Street. This is a small but busy section of roadway that includes government offices, shopping, and restaurants and is used as a major entry and exit point for Route 8 in Derby. The overall percentage of traffic stops involving minority drivers on Main Street was 38%, equivalent to the city average. Approximately 18% of drivers stopped were Hispanic and 19% were black. Of the more than 350 traffic stops on Main Street, 85% of the drivers stopped were not residents of Derby (which is higher than the city-wide average of non-resident drivers stopped at 82%). Hispanic drivers were 33% of all Derby residents stopped on Main Street and 15% of all non-residents. Black drivers were 23% of all Derby residents stopped on Main Street and 18% of all non-residents. Figure 10.4 shows the proportion of traffic stops on Main Street by race and ethnicity compared to the city-wide average for all stops.

Figure 10. 4: Main Street Traffic Stops by Race/Ethnicity



Lastly, Roosevelt Drive has the smallest number of traffic stops along the Route 34 corridor with only 109 stops made during the study period. Roosevelt Drive is approximately two miles long, but is mostly a two-lane rural roadway that runs parallel to the Housatonic River. This stretch of Route 34 connects Derby to neighboring Seymour and Oxford. The overall percentage of traffic stops involving minority drivers on Roosevelt Drive was 24%. Approximately 11% of drivers stopped were Hispanic and 11% were black. Of the more than 100 traffic stops on Roosevelt Drive, 89% of the drivers stopped were not residents of Derby (which is higher than the city-wide average of non-resident drivers stopped at 82%). Hispanic drivers were 8% of all Derby residents stopped on Roosevelt Drive and 11% of all non-residents. Black drivers were 8% of all Derby residents stopped on Roosevelt Drive and 11% of all non-residents. Figure 10.5 shows the proportion of traffic stops on Roosevelt Drive by race and ethnicity compared to the city-wide average for all stops.

Figure 10. 5: Roosevelt Drive Traffic Stops by Race/Ethnicity



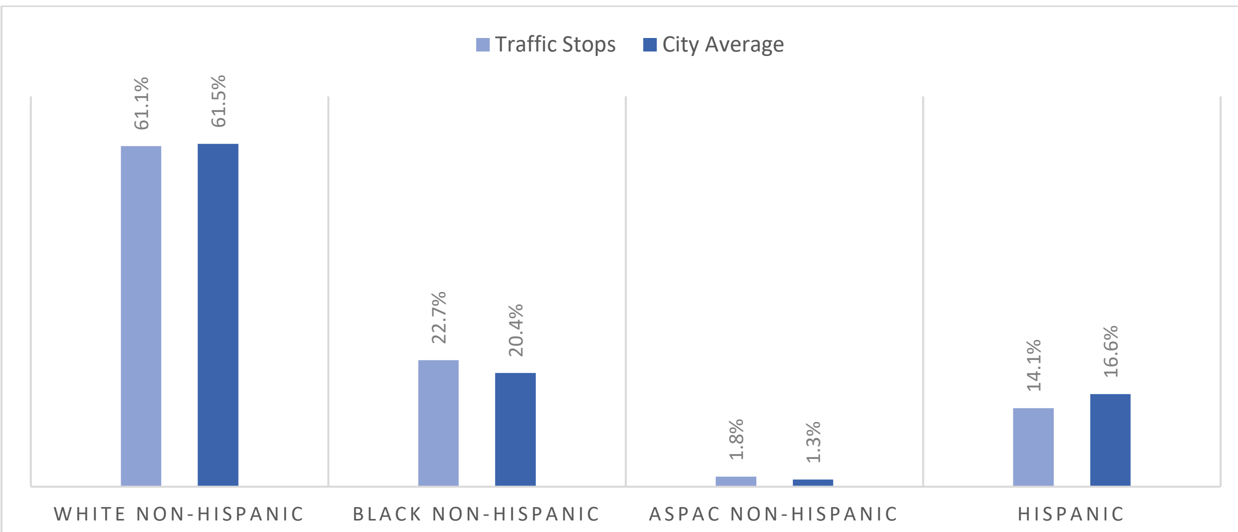
It is clear that the level of stop activity is greatest along the eastern portion of Route 34 and decreases as you travel west towards Roosevelt Drive. To help understand traffic flow on Route 34, the analysis looked at the average daily traffic (ADT) records that are reported by the Connecticut Department of Transportation (DOT). DOT is responsible for collecting traffic volume information for state and local roads throughout the state by placing counting stations at different points along the roadway for a period to count the cars that drive through that point. According to the ADT information along Route 34, there are approximately 36,000 vehicles a day that cross into Derby from Orange. On the other hand, there are only about 12,000 vehicles a day that cross into Derby from Seymour. Traffic volume peaks at 46,000 vehicles a day where Main Street intersects with Derby Avenue. The traffic volume decreases by over 50%, to 22,000 vehicles per day, west of Route 8 on Main Street. The smallest number of vehicles, at approximately 12,000 a day, drive along Roosevelt Drive, west of Bridge Street towards Seymour. Based on the volume of traffic along Route 34, it is logical that there would be greater enforcement along the eastern and central portions of Route 34.

X.C: Traffic Stop Breakdown on Derby Avenue

The greatest percentage of stops on any roadway in Derby, 23percent, occurred on Derby Avenue. A small, but very busy section of Route 34 overlaps with Derby Avenue. This section of Derby Avenue is east of Main Street as you travel towards Orange. This portion of Derby Avenue is a four-lane divided highway with significant commercial activity. Derby Avenue turns into a two-lane roadway traveling north past Main Street and runs parallel to the Naugatuck River. It continues for approximately one mile where the road intersects with Division Street, which is the border between Derby and Ansonia.

A total of 547 traffic stops were made during the study year along Derby Avenue. The overall percentage of traffic stops involving minority drivers on Derby Avenue was 39%. Approximately 14% of drivers stopped were Hispanic and 23% were black. Of the 547 traffic stops on Derby Avenue, 84% of the drivers stopped were not residents of Derby (which is higher than the city-wide average of non-resident drivers stopped at 82%). Hispanic drivers were 15% of all Derby residents stopped on Derby Avenue and 14% of all non-residents. Black drivers were 23% of all Derby residents stopped on Derby Avenue and 22% of all non-residents. Figure 10.6 shows the proportion of traffic stops on Derby Avenue by race and ethnicity compared to the city-wide average for all stops.

Figure 10. 6: Derby Avenue Traffic Stops by Race/Ethnicity



It is likely that the vast majority of stops on Derby Avenue occurred on the section that overlaps with Route 34, according to the department. This would be consistent with our assessment that traffic enforcement is greatest along the eastern portion of Route 34 where traffic volume is significantly higher. According to the ADT information, traffic is greatest in Derby along the Derby Avenue section of Route 34 with approximately 46,000 vehicles a day. Based on the volume of traffic along Derby Avenue, it is logical that this would be an area with the greatest level of enforcement in the city.

X.D: Special Enforcement Campaigns

Derby participated in a Distracted Driving special enforcement campaign, that was sponsored by the Connecticut DOT through funds made available by the National Highway Traffic Safety Administration (NHTSA). The Derby Police Department identified the dates the department participated in the special enforcement campaign, but not the case numbers for stops made as part of the campaign. The department reported that 178 stops or 8% of all their enforcement during the study period was a result of its participation in the special enforcement campaign. All of these stops occurred over eight days in August 2017. There were 321 stops conducted during the month of August and 55% were the result of the Distracted Driving enforcement campaign. Included in the eight days that the department participated in the special campaign were five days when the department conducted spot checks at areas along the Route 34 corridor including, the intersection of Main Street and Derby Avenue, Main Street and Elizabeth Street, Main Street and Caroline Street, and Derby Avenue and Bank Street. On one day in August, officers conducted a roving patrol; and during the remaining two days, officers conducted spot checks near the Shoprite Plaza on Pershing Drive.

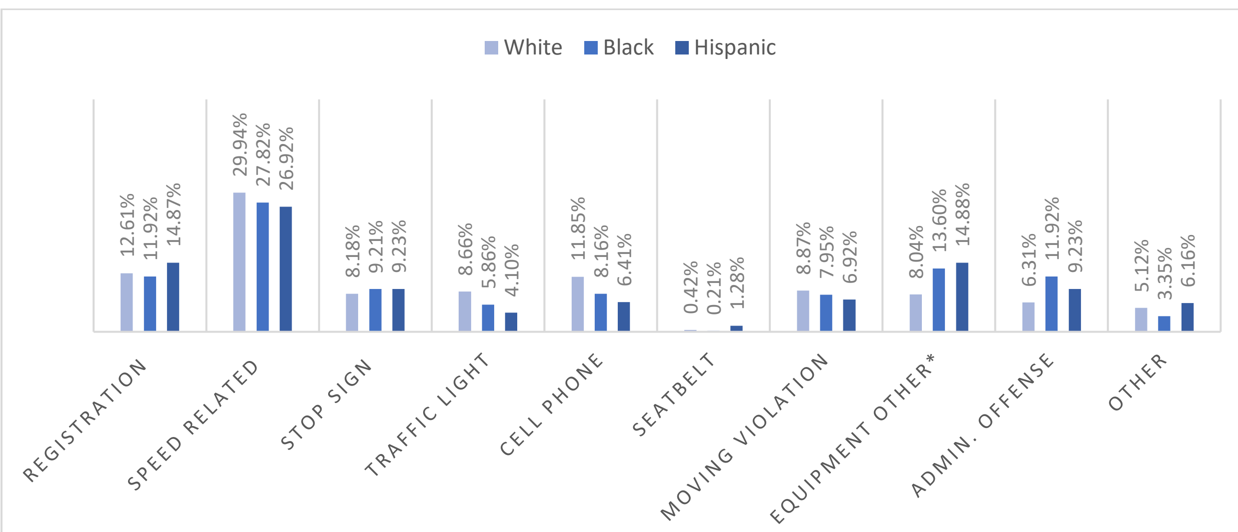
X.E: Traffic Stop Distribution for Derby Officers

Derby's total 2,347 traffic stops were reported for 28 officers, an average of 84 per officer. Of the 28 officers reporting stops, half made fewer than 50 stops, three made between 50 and 100 stops, eight made between 100 and 200 stops, and three made over 200 stops. The three most active officers making more than 200 stops collectively accounted for 32% of Derby stops. While these three officers clearly had the greatest impact on Derby's total stop numbers, the average number of stops per officer is still substantial and not greatly impacted by any one officer.

X.F: Post-Stop Outcome Review

The reasons police stop a motor vehicle can vary significantly from department to department. Researchers reviewed the statutory authority that Derby officers reported as the reason for stopping motor vehicles. The three most common reasons cited for stopping a motorist in Derby cover 52% of the total stops. The three largest stop categories were for speeding violations (29%), registration violations (13%), and cell phone violations (10%). Figure 10.7 illustrates the reason officers used to stop a motor vehicle by race and ethnicity.

Figure 10. 7: Reason for Traffic Stop



*Equipment Other includes violations for defective lights, excessive window tint, or display of plate violations.

The data shows that the reason for stopping vehicles can vary by roadway. For example, in five of the 11 roadways where the majority of traffic stops occurred, more than 30% of the traffic stops were for speed-related violations. On the other hand, the proportion of speed-related traffic stops on the remaining seven roadways varied from 2% of the stops to 28%. Stops for equipment-related violations and administrative offenses also varied by roadway. A significantly higher proportion of these stops were made along the Main Street and New Haven Avenue compared to the other high enforcement roadways.

Speed-related motor vehicle enforcement appears to have had a significant impact on overall traffic enforcement in Derby. Over 67% of the speed-related stops occurred on the three high-enforcement roadways (Derby Avenue, New Haven Avenue, and Main Street). More specifically, 32% of all speed enforcement occurred on Derby Avenue, 21% occurred on New Haven Avenue, and 14% occurred on Main Street. Over 65% of the white drivers stopped for speeding were stopped on one of the three high-enforcement roadways compared to 70% of black drivers and 70% of Hispanic drivers.

Another important factor is that officers reported 68% of speed-related stops as "blind." This means an officer reported using a blind enforcement technique like radar, laser, license plate recognition device, or other similar technology or method. The speed-related stops recorded as "blind" were likely the result of an officer using radar or laser technology. Of the speed-related stops recorded as "blind," the racial demographics were 61% white, 20% black, and 16% Hispanic, which almost mirrored the racial demographics for all stops. For all other speed-related stops, the racial demographics were 67% white, 17% black and 14% Hispanic. The demographics of "blind" speeding stops is an indication that the racial demographics of drivers on Derby roadways was reflected in its stop activity.

While white drivers were stopped more frequently than black or Hispanic drivers for more hazardous driving violations as a percentage of their total stops, black and Hispanic drivers were stopped more frequently for equipment-related violations, and administrative offenses than white drivers as a percentage of their total stops. The data shows that, with respect to the racial and ethnic demographics of those stopped, equipment-related violations (defective, improper, or inoperative lighting; display of plates; or window tinting) and administrative offenses are closely related to the frequency and location of where the stops are made. When these types of stops are made more frequently in locations where there are higher concentrations of minority drivers, they tend to result in higher proportions of minority drivers being stopped than white drivers. However, in many places, the data also shows that when these same types of stops are made in areas with a higher concentration of white drivers, the stop demographics shift toward white drivers, suggesting that the likelihood of finding violators may be more dependent on location than race.

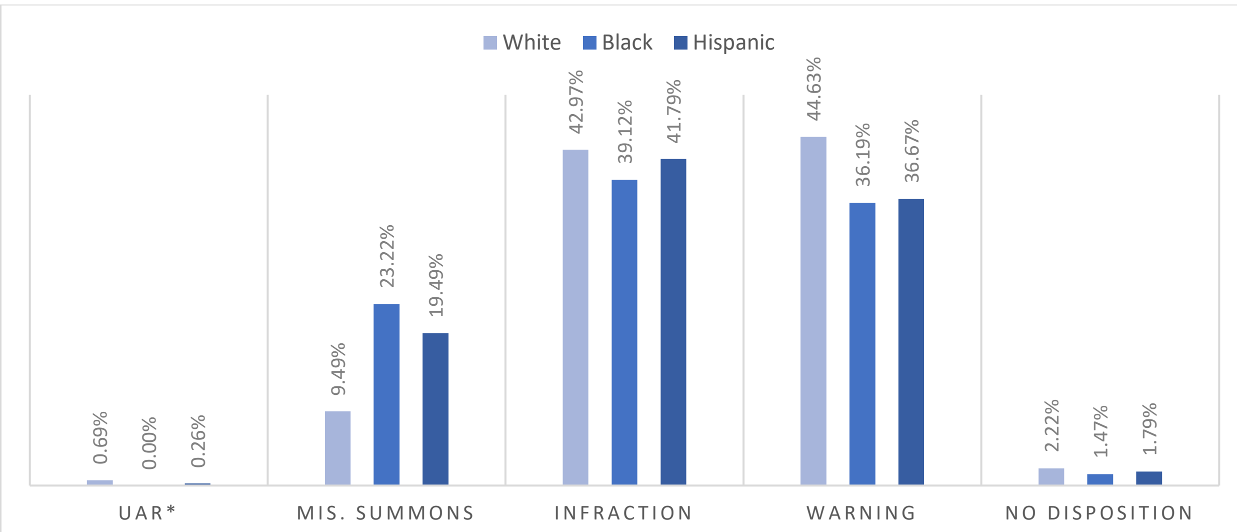
The Derby data tends to confirm these observations. It appears that a greater number of stops for equipment-related and administrative violations occurred on the three high enforcement roadways (Derby Avenue, Main Street, and New Haven Avenue), where a higher percentage of minority drivers are stopped. These three roadways also appear to have a higher percentage of minority drivers traversing them. Over 52% of all equipment- and administrative-related stops occurred on the three high enforcement roadways where 59% of the black and Hispanic drivers were stopped. The remaining 48% of these stops occurred on all other roadways in the city, where 41% of the black and Hispanic drivers were stopped. Of the stops on the three high-enforcement roadways, the racial breakdown for these stops shows 31% black drivers, 23% Hispanic drivers, and 46% white drivers. The racial demographics for all other equipment and administrative stops shows 26% black drivers, 21% Hispanic drivers, and 51% white drivers. This proportion appears to have been due more to the frequency and location of where such stops were made than an inherently higher violation rate by Hispanic or black drivers.

It is worth noting that the equipment and administrative violation traffic stops appear to be driven by a small portion of the officer force. Twenty-one of the 28 officers reported making at least one equipment or administrative violation traffic stop. The average number of traffic stops per officer for these violations was 20. Six officers exceeded the town average of 20 such stops and accounted for 74% of all these stops. One officer made over 100 of these stops and accounted for 25% of all equipment and administrative violation traffic stops.

Outcome of Stops

The majority of motor vehicle stops in Derby resulted in the driver receiving either a ticket (42%) or a warning (41%). Black and Hispanic drivers were more likely to receive a misdemeanor summons as a percentage of their total stops. Black drivers were less likely to be charged with an infraction compared to white and Hispanic drivers. Figure 10.8 shows the outcome of motor vehicle stops by race and ethnicity.

Figure 10. 8: Outcome of Traffic Stop



*Uniform Arrest Report

Most violations of the motor vehicle laws are designated as infractions, but some are not. The more serious violations can be reckless driving, operating under suspension, operating under the influence of alcohol or drugs, and operating an uninsured or underinsured vehicle. The system for collecting and reporting traffic stop data requires officers to record the statutory citation for the violation that was the basis for the stop as well as any subsequent charges that differed from and were more significant that the initial charge. This provides the data on the initial cause for making a stop as well as any subsequent, more serious charge. For example, if someone was initially stopped for a lesser reason such as not wearing a seat belt or rolling through a stop sign, the officer might subsequently determine that the driver was operating with a suspended license. If this information is properly recorded, researchers are able to distinguish those stops from the ones that begin and end with the same charge.

In Derby, 326 of the stops made resulted in the issuance of a misdemeanor summons (14%), which is significantly more than the state average. Black and Hispanic drivers were more than twice as likely to be issued a misdemeanor summons following a stop than were white drivers (23% of black drivers stopped and 19% of Hispanic drivers stopped compared to 9% of all white drivers). Of the misdemeanor violation stops, 171 were initiated for a reason that was not a misdemeanor violation (e.g., speeding, stop sign violation, defective or improper lighting, etc.) However, once the officer interacted with the operator of the vehicle a misdemeanor violation should have been identified. The vast majority of these stops (83%) resulted in a misdemeanor summons for a license- or registration-related issue. Unlike many infraction violations, officers have limited discretion in the issuance of a misdemeanor summons when a misdemeanor violation is identified. Officers did not report the misdemeanor violation in at least 18 of the stops where the data indicated a misdemeanor violation occurred.

Search Information

Police officers have the legal authority to search a motor vehicle under several circumstances. One of those circumstances is for the purpose of taking inventory of the items in a motor vehicle prior to taking custody of the vehicle. Connecticut General Statute requires motor vehicles to be impounded when certain violations occur such as driving an unregistered vehicle. According to the Derby Police Department standard operating procedures, "It is the practice of the Derby Police Department that an inventory be conducted any time a vehicle is towed at the request of the Derby Police Department…"

A review of the Derby department's search information shows that 10% (234) of the drivers stopped in Derby were subjected to a motor vehicle search. This rate of motor vehicle searches is significantly above the state's 3% average. Moreover, black and Hispanic drivers were searched at almost twice the rate of white drivers. Of the 234 vehicles searched, 69% were subjected to an inventory search (compared to 21% statewide), 8% were subjected to a consent search (compared to 36% statewide), and 23% were subjected to a search for some other reason (compared to 43% statewide). Further analysis of the Derby search data has revealed that the department's inventory search policy clearly affected its overall search numbers. Of the 2,347 traffic stops made in the study year, 182 (8%) vehicles were towed. However, the department only reported searching 162 towed vehicles, of which 153 were reported as inventory searches. This discrepancy is most likely the result of errors in data entry by police officers. Almost 70% of car searches were reported as inventory searches and contraband was found only 1% of the time (known as the "hit rate"). Consent and other searches made up 30% of the searches and contraband was found 22% of the time. Since inventory searches tend to produce contraband hits less frequently than other types of searches, the greater prevalence of inventory searches influences the overall search hit rate for Derby to some degree. Figure 10.9 illustrates the motor vehicle search rate and the hit rate for all searches. Figure 10.10 illustrates the motor vehicle search rate and the rate at which contraband was found for searches excluding inventory searches.

Figure 10. 9: Search and Hit Rate (All Searches)

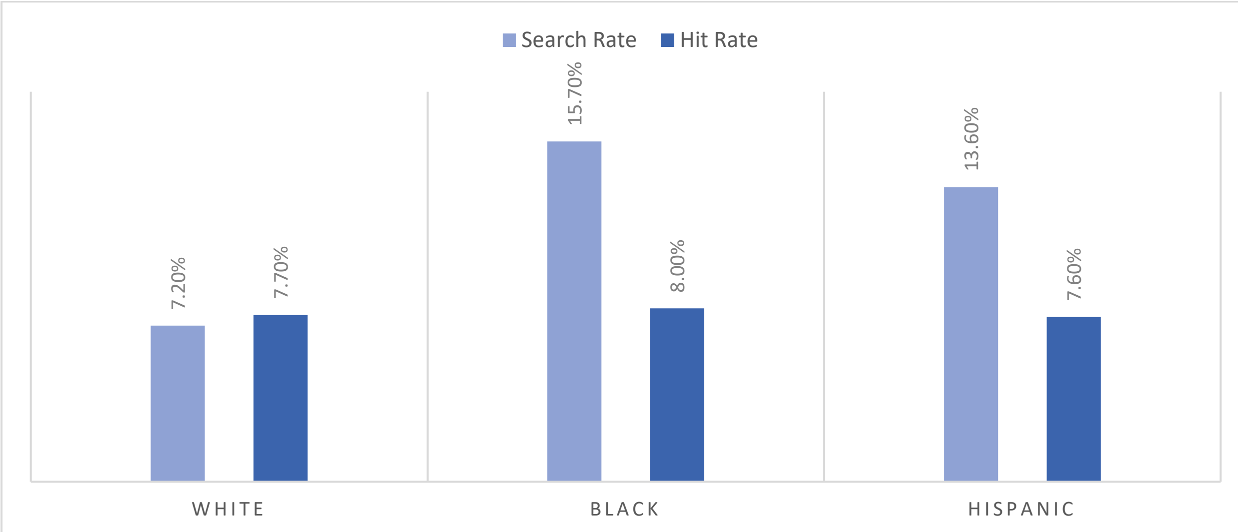
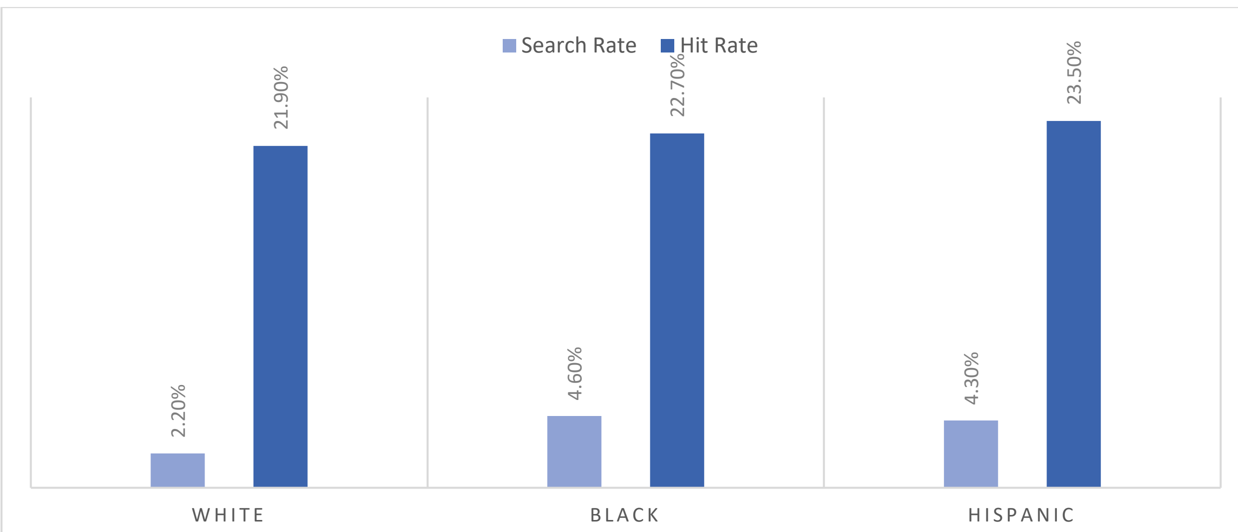


Figure 10. 10: Search and Hit Rate (Excluding inventory searches)



X.G: Additional Contributing Factors

Law enforcement administrators choose to deploy police resources within a community based on a number of different factors, including where calls for service are more prevalent. The department provided researchers with the calls for service log, which included calls for service and officer initiated actions that were called into police dispatch. The logs report approximately 11,000 entries from January 1, 2017 through December 31, 2017, exclusive of traffic stops. The top reasons for calling dispatch were for a medical emergency (8%), suspicious activity (6.5%), or a response to an alarm (6%). These top three reasons account for about 20.5% of all calls.

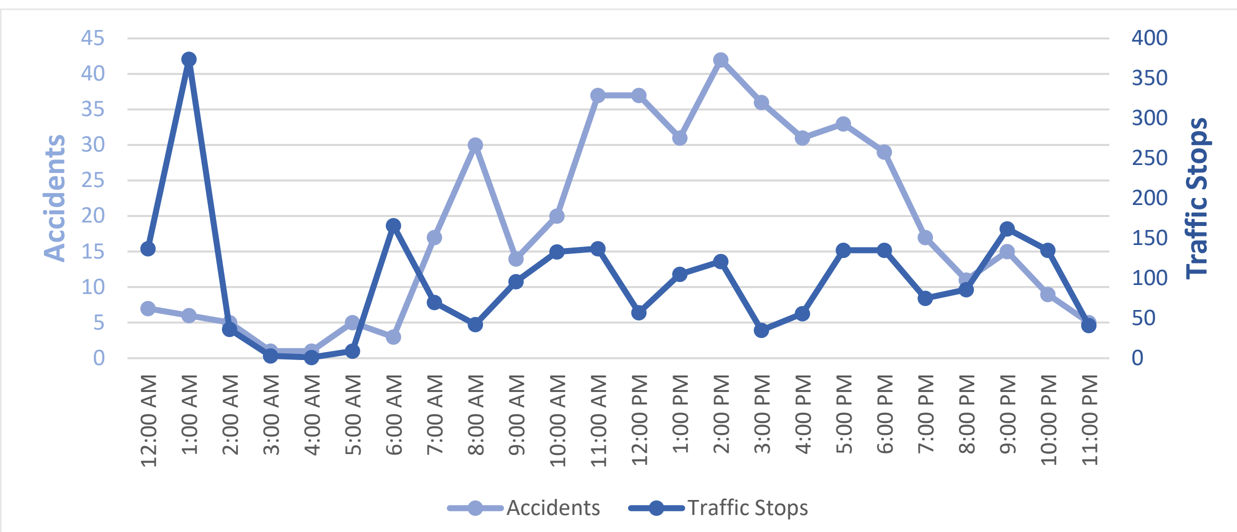
In addition to calls for service, law enforcement administrators also distribute police resources within a community based on accident rates or where crime rates are higher. In addition to these factors, police presence may be greater where traffic volume is higher as the result of common factors that draw people into a community such as employment and entertainment. Traffic enforcement actions are likely to be more prevalent in locations that attract greater police presence due to any of these factors. Basic information on crime, accidents, and other economic factors associated with Derby are important considerations that provide a context to potentially explain the rational for police deployments.

According to the Connecticut Economic Resource Center (CERC) town profiles, approximately 4,733 people work in Derby and its major employers include Griffin Hospital, Home Depot, City of Derby, Shop Rite, and Lowes. The vast majority of commuters traveling into Derby for employment are from Ansonia, Shelton, Seymour, New Haven, and Naugatuck. The overall unemployment rate is 6.4%, which is above the unemployment rate for both New Haven County and the state.

During the study period, approximately 442 motor vehicle accidents occurred on roads patrolled by the Derby Police Department. Accidents were reported as occurring on 60 roads. The roadways with the highest number of accidents were New Haven Avenue (99 accidents), Main Street (80 accidents), Division Street (38 accidents), and Roosevelt Drive (36 accidents). There were only eight roads with 10 or more accidents and those roads account for 76% of all accidents in Derby. New Haven Avenue accounted for 22% of all accidents in the town.

Figure 10.11 illustrates the time of day when traffic accidents were reported and the number of traffic stops that occurred during that same period. This shows how traffic enforcement is correlated with traffic accidents in Derby. While the vehicle crash rate in town tends to build steadily throughout the day, it peaks during the afternoon period from 12:00 p.m. to 5:00 p.m. However, traffic enforcement peaks between midnight and 2:00 a.m.

Figure 10.11: Accidents Compared to Traffic Stops by Time of Day



Crime data and pattern activity are an integral component of a department's crime control and reduction strategy. The department provided information on the location of index crimes, which are eight crimes the FBI combines to produce its annual crime index. The offenses include homicide, forcible rape, robbery, burglary, aggravated assault, larceny over $50, motor vehicle theft, and arson. In 2017, the crime rate in Derby was reported to be 267 per 10,000 residents, compared to the state crime rate of 200 per 10,000 residents. According to the 2017 Connecticut Uniform Crime Report[12], there were 348 reported crimes in Derby in 2017, 68% of which were larcenies. The three most reported crimes were larceny (238), burglary (35), and motor vehicle theft (33).

There were only 10 roadways in town where more than 10 crimes were reported. Crime was reported at the highest levels on New Haven Avenue (40 crimes), Pershing Drive (27 crimes), Main Street (23 crimes), and Derby Avenue (18 crimes). Crimes were reported as more likely having occurred in areas either on Route 34 or close to Route 34. A more detailed review of the location of Derby's overall index crimes helps to provide a better understanding of what may cause Derby officers to be more active in some areas of the city than in others.

X.H: Summary of Findings

The Derby Police Department identified factors they believe contributed to the disparity identified in the initial traffic stop analysis. In particular, the department identified areas with the highest levels of traffic as some of the same areas with the highest levels of motor vehicle enforcement. They also indicated the impact that reported incidents of crime and accidents along Route 34 have had on the deployment of departmental resources. It is evident from the volume of traffic stops made along Route 34 that the department concentrates its resources primarily in and around this roadway and that Route 34 makes up the city's high-enforcement area.

On 11 roadways 50 or more traffic stops occurred and these account for 87% of all stops. However, a single major roadway, Route 34, is where significant traffic enforcement occurred. Almost 58% of all traffic stops in Derby occurred on the Route 34 corridor, of which 21% of the stops involved black drivers and 17% of the stops involved Hispanic drivers. Route 34 is a primary state highway that extends from Newtown to New Haven. Five miles of the roadway run through Derby and significant parts of it are a high commercial activity area. Route 34 is broken up into four segments, each with its own local road name. This includes Roosevelt Drive, a two-lane road that runs parallel to the Housatonic River until it crosses Bridge Street. After crossing Bridge Street the roadway becomes Main Street, a major thoroughfare which includes City Hall, shopping, and restaurants. As Route 34 crosses the Naugatuck River, it intersects with Derby Avenue, the busiest section of the corridor. Route 34 then continues east as a four-lane divided highway for about two miles and is a major destination for shopping, local business, and other activities. Route 34 also provides access to Route 8 in Derby and Route 15 when drivers cross into Orange.

Based on the average daily traffic counts provided by the Connecticut Department of Transportation, the level of stop activity is greatest along the eastern portion of Route 34 and decreases as toward the west. Approximately 36,000 vehicles a day drive into Derby on the eastern portion of Route 34 (the Orange border), but only 12,000 vehicles a day cross into Derby from the western portion of Route 34 (the Seymour border). Traffic volume peaks at 46,000 vehicles a day where Main Street intersects with Derby Avenue. Based on the volume of traffic along Route 34, it is reasonable that there would be greater enforcement along the eastern and central portions of the corridor.

The majority (82%) of stops in Derby involved out-of-town drivers. The race and ethnicity of those stopped differed between town residents and out-of-town drivers. In particular, almost 47% of

[12] The Uniform Crime Report is an index for gauging fluctuations in the overall volume and rate of crime. The crime index includes seven offenses: the violent crimes of murder, rape, robbery, and aggravated assault and the property crimes of burglary, larceny-theft, and motor vehicle theft.

residents stopped were minority drivers compared to 37% of out-of-town drivers. Some of the disparity in resident driver stops may be attributed to the fact that on Route 34, minority residents were more likely than non-minority residents to be stopped (18% of minority drivers stopped were residents of Derby compared to only 12% of white drivers.) Additionally, according to the 2017 five-year American Community Survey[13] estimate counts by the Census Bureau, the Hispanic population in Derby increased by approximately 57% since 2010. However, even after accounting for the increase in the Hispanic resident population and out-of-town drivers, a disparity still remained.

Derby has 28 officers who made at least one traffic stop during the study period. The average stops made per officer was 84, but three officers (11% of the officer force) who made over 200 stops each accounted for 32% of all the traffic stops. When a relatively small portion of the officer force makes a significant portion of all the stops, the specific duties, patrol areas, and shifts of these officers might have a significant impact on overall stop demographics.

Traffic Stop Outcomes

In Derby, the three most common reasons for stopping a motorist make up 52% of the total stops. The three largest stop categories were for speeding violations (29%), registration violations (13%), and cell phone violations (10%). While white drivers were stopped more frequently than black or Hispanic drivers for more hazardous driving violations, black and Hispanic drivers were stopped at a higher rate for equipment-related and administrative offenses. However, the total percentage of equipment-related and administrative stops is below the state average.

Speed-related motor vehicle enforcement on Route 34 appears to have had a significant impact on overall traffic stop disparities for black and Hispanic drivers in Derby. Over 67% of the speed-related stops occurred on Route 34. Over 65% of the white drivers stopped for speeding were stopped on Route 34, compared to 70% of black and Hispanic drivers. Officers reported 68% of speed-related stops as "blind," meaning officers report using a blind enforcement technique like radar, a laser, license plate recognition device, or other similar technology or method. The speed-related stops recorded as "blind" were likely the result of an officer using radar or laser technology. Of the speed-related stops recorded as "blind," the racial demographics were 61% white, 20% black, and 16% Hispanic, which almost mirrored the racial demographics for all stops.

In Derby, over 52% of the equipment-related and administrative stops were made on Route 34, where a higher percentage of minority drivers are stopped. When equipment-related and administrative stops occur with greater frequency in areas with higher minority drivers than they do in areas where the driving populations are predominantly white, there is the potential for racial disparities to appear in the data even though violation rates for these offenses could be similar across racial categories. The demographics for equipment-related and administrative stops on Route 34 were 23% Hispanic drivers, 31% black drivers, and 46% white drivers. However, on all other roadways in the city, the stop demographics for the same offenses were 21% Hispanic, 26% black drivers, and 51% white drivers. This proportion suggests that the frequency with which these enforcement choices occurred and, more importantly, where they occurred, had a greater impact on

[13] The American Community Survey is a survey conducted by the U.S. Census Bureau to gather vital information on a yearly basis about our nation and its people. This helps to supplement information collected between the decennial censuses.

the overall stop demographics, particularly for black and Hispanic drivers, than racially inherent differences in the overall likelihood of violation.

Regarding stop outcomes, the majority of motor vehicle stops in Derby resulted in the driver receiving either an infraction (42%) or a warning (41%). Minority drivers were more likely to receive a misdemeanor summons. Stops involving black drivers were less likely to result in an infraction citation than either white or Hispanic drivers. The proportion of Derby's traffic stops that resulted in a misdemeanor summons (14%) was significantly greater than the state average of 5%. The majority of the stops that resulted in a misdemeanor charge were initiated for a reason that was not initially a misdemeanor violation. However, once the officer interacted with the operator, a misdemeanor violation was identified. Most of the misdemeanor charges were for a license- or registration-related issue. Unlike many infraction violations, officers do not have discretion in the issuance of a misdemeanor summons when such a violation is identified.

Derby police searched 10% of drivers they stopped, which was above the state average of 3%. Black and Hispanic drivers were searched at almost twice the rate of white drivers. The Derby Police Department inventory search policy appeared to affect its overall search numbers. The purpose of an inventory search is for officers to take inventory of the items in a motor vehicle prior to taking custody of the vehicle. Over 69% of all Derby department searches were the result of an inventory search. Since inventory searches tend to produce contraband at a lower rate, the greater prevalence of inventory searches for drivers influenced the overall demographics of the search-hit rate. Contraband was found at a similar rate for all drivers, even after accounting for inventory searches.

Conclusion

Taken as a whole, the Derby traffic stop data reflects the influence of the Route 34 corridor where drivers are somewhat more diverse than the predominantly white local driving age population. Route 34 appears to have a relatively high level of enforcement and a relatively higher proportion of non-resident minority drivers travelling it. It is a significant traffic magnet for business, shopping, and entertainment and is a major thoroughfare between New Haven and Newtown. Access to Route 8 is available from Route 34 and this also has a significant impact on traffic volume along the corridor. Based on the volume of traffic along Route 34, it seems reasonable that there would be greater traffic enforcement along the corridor. However, the department would benefit by reviewing its enforcement practices along Route 34 to assure that the disparate impact these policies have on its minority residents are reasonable in terms of policy outcomes. When disparities result from policies and practices established to meet community and policing goals and objectives, even when profiling is not a direct result, minority communities can feel disadvantaged unless they can clearly recognize the overall benefits of this approach. It is important that the department assure that Derby's minority community fully understands what benefits come from this enforcement presence.

In addition, speed-, equipment- and administrative-related enforcement on Route 34 influenced the overall racial disparity in the city's traffic stops. In most of the speed-related stops, officers made the determination to stop the driver using speed enforcement technology and this had a greater impact on minority drivers. The racial demographics for speed-related stops almost mirrored the racial demographics for all stops. Black and Hispanic drivers were also more likely to be stopped for vehicle equipment or administrative violations. Our analysis indicates that this difference could be due more to the greater frequency with which these stops were made within the high enforcement areas of Derby where minority drivers are more likely to be present in the driving population in greater numbers, rather than an inherently greater likelihood that minority drivers violate these laws with greater frequency than white drivers.

After a full review it is recommended that the department:

(1) review its traffic enforcement policies along Route 34 to evaluate the extent to which they may have a disproportionate effect on minority drivers and

(2) take steps to assure that its minority community is fully engaged in the process of understanding why the allocation of enforcement resources are made and what outcomes are being achieved.

X.I: Department Response

Below on page 72 is a response provided by the Derby Police Department.

Derby Police Department

125 Water Street
Derby, Connecticut 06418
Tel. (203) 735-7811

Ken Barone
Project Manager
Institute for Municipal and Regional Policy
Central Connecticut State University

June 12, 2019

Mr. Barone,

Thank you for the opportunity for our organization to comment on the Follow-up Analysis Summary for the Derby Police Department. The sharing of information between your organization and ours was very beneficial to both sides to understand some of the minutiae that may skew an interpretation of raw data.

First and foremost, racial bias has no place in policing. **Fairness** is the first of our organization's core values which call for *"impartial and ethical enforcement of the law"* as well as *"consistent treatment of all persons tempered with reason and equity"*. We were concerned when your organization identified our department for in-depth analysis and we openly met and shared information to identify and/or correct any issues.

The Follow-up Analysis Summary is detailed and lengthy. I would like to reiterate parts of the documents as well as address some disparities. I have policed this community for over thirty years and have watched the demographics and crime trends change significantly. Derby is a small community with a population density of nearly 2 times that of New Haven County and 3.5 times that of Connecticut. Additionally, Derby has a much greater poverty rate and significantly lower median household income than New Haven County and the entire state. This is reflected in our high crime rate and, more specifically, a high violent crime rate. Aggressive proactive policing and community engagement are some of the policing strategies our department is using to keep our community safe. While our criminal offenders are multimodal in their means of travel, the vast majority travel via motor vehicle. Hence, aggressive and lawful motor vehicle enforcement goes hand in hand with crime prevention and enforcement.

A concern our organization had with the initial data was the 2010 race/ethnicity breakdown of the estimated driving population is based on census data that is nearly a decade old. Your staff acknowledged our concerns and also considered more recent 2017 estimates by the American Community Survey that reflects an increase of Derby's Hispanic driving population by 57% from the 2010 data. Considering census data, city-level data, and other local experiences **our city and our police department believe that Derby's Hispanic driving population is significantly higher than the data used in the study.**

As your findings show, the bulk of our department's motor vehicle enforcement occurs on Route 34. Your findings also indicate that in this area of enforcement *"minority drivers are more likely to be present in the driving population in greater numbers"*. The Route 34 and Route 8 exchange is a key route between the urban areas of New Haven, Danbury, Bridgeport, and Waterbury. This higher minority rate coupled with a much greater city Hispanic driving population helps explain some disparities. Additionally, in your review of the data, your agency confirmed that none of our officers were identified as being statistically more likely to stop a minority than their benchmark.

Our mission is to protect life and property, provide professional police services, and improve the quality of life in our community. We do this by partnering with the community and through aggressive and constitutional policing to prevent crime and enforce the law. At times some policies may have unintended consequences. A review of the Follow-up Analysis Summary shed light on some record keeping and reporting strategies we will improve. We are sharing the report with our staff and key stakeholders and will continue to review policies and procedures to see if they may have any potential unintended disparate results. This document will assist us to address any policy or practices that could be improved to ensure that we continue to police our community fairly and impartially.

Respectfully,

Gerald D. Narowski

Chief of Police,
Derby Police Department

XI: FAIRFIELD FOLLOW-UP ANALYSIS SUMMARY

Racial and ethnic disparities in any traffic stop analysis do not, by themselves, provide conclusive evidence of racial profiling. Statistical disparities do, however, provide significant evidence of the presence of idiosyncratic data trends that warrant further analysis. Based on the pre-established criteria for identifying racial and ethnic disparities in traffic stops, Part I of this report recommended that the Racial Profiling Prohibition Project staff conduct an in-depth analysis for the Fairfield Police Department.

According to the results from the "Veil of Darkness" analysis, the Fairfield Police Department indicated a statistically significant disparity in the rates that both black and Hispanic motorists were stopped during daylight relative to darkness. Within the inter-twilight window, the odds that a stopped motorist was black increased by 1.6 while the odds that a stopped motorist was Hispanic increased by 1.3 during daylight. These results were statistically significant at a level greater than 95 percent and robust to the inclusion of a variety of controls, officer- fixed effects, and a restricted sample of moving violations. Although certain assumptions have been made in the design of each methodology, it is reasonable to conclude that departments with consistent data disparities separating them from the majority of other departments should be subject to further review and analysis with respect to the factors that may have caused these differences.

During the 2017 calendar year, the Fairfield Police Department made 8,320 traffic stops. Of these, 31.5% were minority stops (14% Hispanic and 15% black). Table 11.1 below compares summary racial data for reported traffic stops in Fairfield over a three-year period.

Table 11. 1: Fairfield Traffic Stops – 2015 - 2017

	2015 Stops		2016 Stops		2017 Stops	
White	5,357	67.9%	5,903	69.2%	5,701	68.5%
Black	1,169	14.8%	1,198	14.0%	1,246	15.0%
AsPac*	106	1.3%	138	1.6%	136	1.6%
AI/AN**	49	0.6%	87	1.0%	70	0.8%
Hispanic	1,206	15.3%	1,205	14.1%	1,167	14.0%
Total	**7,887**		**8,531**		**8,320**	

*Asian Pacific

** American Indian/Alaska Native

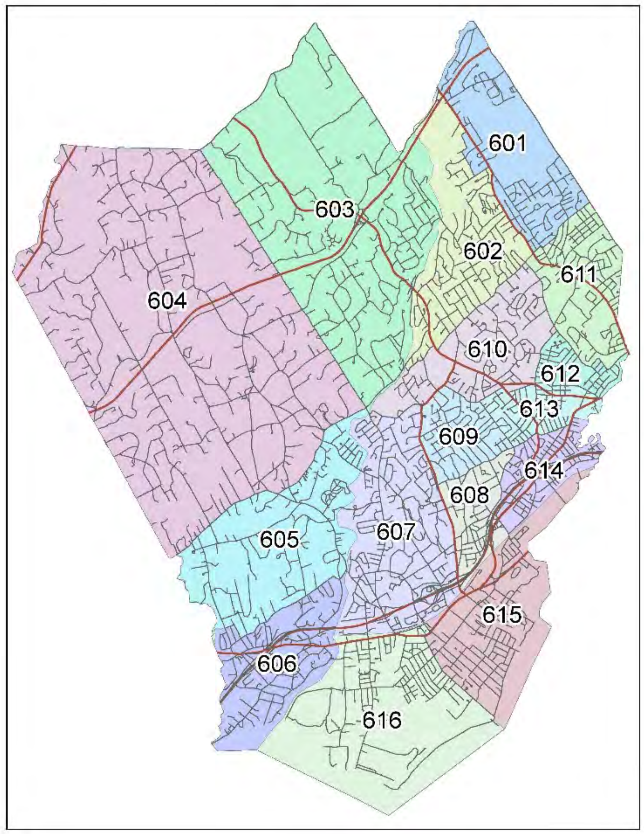
XI.A: Descriptive Analysis of the 2017 Traffic Stop Data

Researchers studied the racial and ethnic disparities in the Fairfield Police Department data using a more detailed review of traffic enforcement during the study period. Part of the analysis involved mapping all the stops; if possible, using the location data provided by the department and any enhancements we were able to make. Fairfield provided detailed location descriptions that allowed accurate mapping of 88% of their stops. The mapping allowed researchers to analyze the location of stops by census tract or major corridor. The U.S. Census Bureau has divided Fairfield into sixteen census tracts. Figure 11.1 is a map that outlines the boundaries of Fairfield census tracts. According to the 2010 census, Fairfield is a town with approximately 45,567 residents over the age of 16. Approximately 10% of the driving age population in Fairfield is identified as a minority. Table 11.2 outlines the basic demographic information for Fairfield residents over age 16.

Table 11. 2: Fairfield Population

Race/Ethnicity	16+ Population Total	% Population Total
White Non-Hispanic	41,010	90.0%
Black Non-Hispanic	790	1.7%
AsPac Non-Hispanic	1,592	3.5%
Hispanic	2,057	4.5%
Other	118	0.3%
Total	**45,567**	

Figure 11. 1: Fairfield Census Tract Map



Fairfield is approximately 31 square miles in area with five miles of coastline to its south on the Long Island Sound. Fairfield is a coastline community off Interstate 95 (I-95). The town has seven exits on the northbound side of I-95 (exits 19 to 25) and six exits on the southbound side (exits 24 to 19). The Merritt Parkway is situated in the northern part of town, with two exits in both directions. US Route 1 also runs east-west through the southern portion of town, running almost parallel with I-95.

Fairfield has three train stations along the Metro-North New Haven line, which runs parallel to Interstate 95 (south of the interstate) along the southern part of the town. Moving east to west, the first station is located just north of the Black Rock neighborhood near Bridgeport, the second is south of Fairfield University in the center of town, and the third is in Southport – a census location but technically a borough of Fairfield in the southwest corner of the town bordering Westport.

Fairfield hosts two universities. Sacred Heart has its main campus in the northeast corner of the town, south of the Merritt Parkway (in Census Tract 601). Its west campus is located in the same area, separated by Easton Turnpike (in Census Tract 602). Fairfield University is located in the central part of town, just north of I-95 (in Census Tract 607). Fairfield University has a graduate and undergraduate enrollment of about 5,000 students, and Sacred Heart has a combined enrollment of roughly 8,500.

Five other municipalities border Fairfield: Weston and Easton to its north, Trumbull and Bridgeport to its east, and Westport to its west. Four of the five border towns are predominantly white demographically (Easton, Trumbull, Weston, and Westport), with an average white driving age population of 92% (compared to Fairfield's white driving age population of 90%). The fifth border community, Bridgeport, has a white driving age population of only 27%. Of the drivers stopped in Fairfield overall, only 16% were Fairfield residents and 85% lived elsewhere.

The Fairfield Police Department identified both its patrol division and traffic unit as the entities responsible for the majority of the traffic enforcement in town. The patrol division is structured with eight districts that operates three shifts per day (days, evening, and mid-shift). A minimum of eight patrol officers and two supervisors are assigned to each shift, with at least one officer patrolling each district. The patrol division is responsible for responding to calls for service, apprehending criminals, enforcing motor vehicle laws, and working with the public to prevent crime. The traffic unit consists of four officers and one supervisor who are deployed at least six days a week, usually operating from 9:00 a.m. to 9:00 p.m. The traffic unit focuses on DUI enforcement on Thursdays, Fridays, and Saturdays between 5:00 p.m. and 9:00 p.m. There are no set districts where the traffic unit must operate.

The U.S. Census Bureau has divided Fairfield into sixteen census tracts. The resident driving age population in each census tract varies from about 1,500 to about 6,000 people, with the largest concentration of people (14% of the total population) in tract 607. The racial breakdown in each census tract varies, from a high of over 27% minority driving age residents in census tract 614 to none in tracts 608 and 609. Figure 11.2 shows the distribution for each census tract in terms of white and non-white driving age population.

Figure 11. 2: Age 16 and Older Resident Population by Census Tract

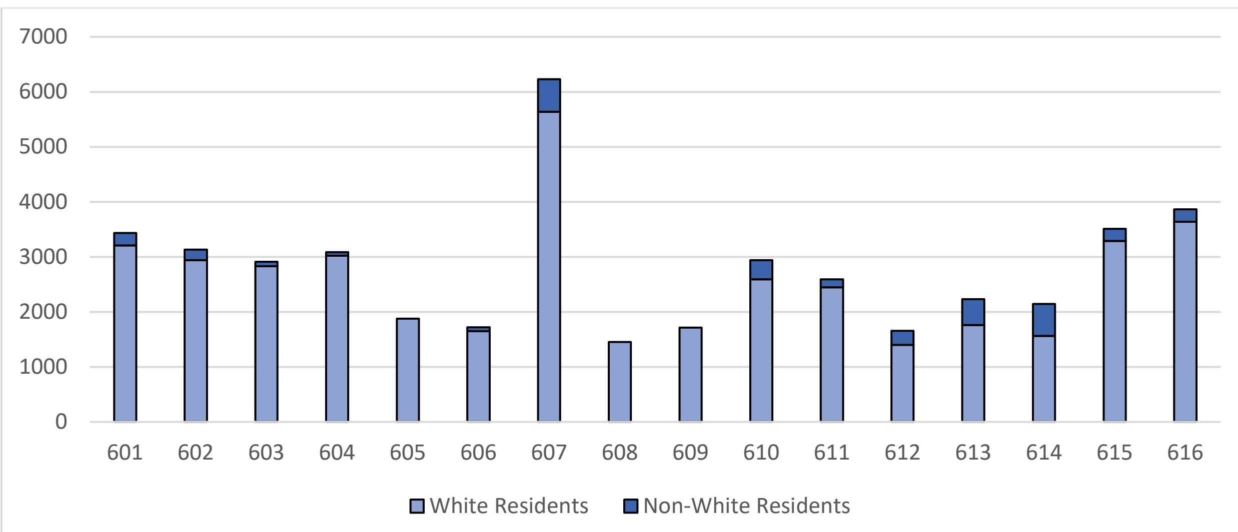
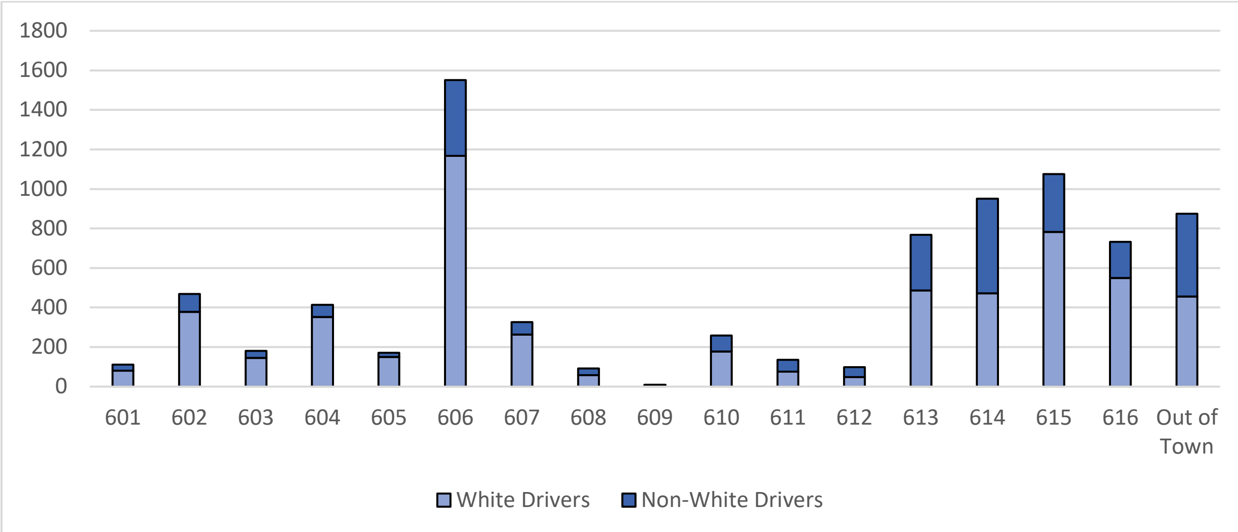


Figure 11.3 illustrates the volume of traffic enforcement that occurred in each Fairfield census tract during the study period. A large percentage of traffic enforcement activity (61%) occurred in a relatively small geographical area encompassing five census tracts (606, 613, 614, 615, and 616) in the southern portions of town along the I-95 and Route 1 corridors. Census tract 606 has the largest percentage of traffic enforcement with 19% of the town's traffic stops. This tract borders Westport to the west and is situated on the Long Island Sound. In addition, there were 103 stops that could not be mapped. These are not considered in our analysis, for purposes of discussing traffic stops by census tract.

Figure 11. 3: Traffic Stops by Census Tract



Fairfield's overall resident population is 10% minority and 10.6% of all Fairfield residents who were stopped were minority. Resident minority drivers were stopped at a similar rate as the proportion of the town population. Thirty percent of the town's resident driving age population live in the five census tracts that account for 61% of the traffic enforcement activity. Tract 616 is the largest of these five tracts with 9% of the town population. The most heavily populated census tract in Fairfield (607) is located just outside of this high enforcement activity core. Approximately 35% of non-resident drivers stopped in Fairfield were minority. The five census tracts with the highest enforcement account for 62% of all stops of non-residents in Fairfield. This is most likely because I-95 and Route 1 are major traffic routes for surrounding communities. It is clear that non-residents contribute to the overall racial disparity in Fairfield stop data.

XI.B: Traffic Stop Breakdown by Race/Ethnicity

In Fairfield, 31% of all drivers stopped were minority drivers, classified as all non-white drivers, but predominantly black or Hispanic drivers. Fairfield's resident population age 16 and older is 10% minority. On its face, this might suggest a wide disparity in the proportion of minority drivers stopped during the study period. In one sense, this is true, considering that about 10% of the population is minority but close to 31% of the drivers stopped were minority. However, the racial and ethnic makeup of different areas of Fairfield varies by census tract, so the disparities were more pronounced in some areas compared to others.

Figure 11.4 shows the difference between the local black resident population (located in three census tracts 607, 613, and 614) and the black drivers stopped by census tract (in all but tract 609) . The overall percentage of Fairfield traffic stops involving black drivers was 15%. The percentage of black drivers stopped exceeded the town average of 15% in five census tracts (608, 611, 612, 613, and 614). However, the percentage of black drivers stopped in tract 608 was only slightly above the town average. There was a positive disparity above the resident black driving age population in all census tracts, with the largest disparity in tract 614. Over 96% of all black drivers stopped were not Fairfield residents.

Figure 11. 4: Black Population Compared to Black Drivers Stopped by Census Tract[14]

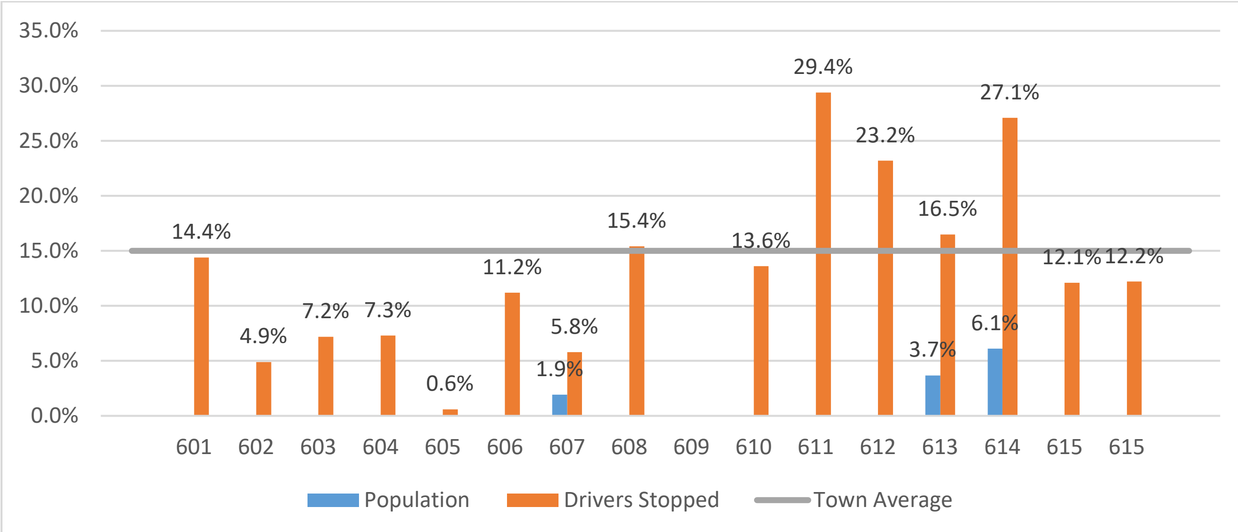
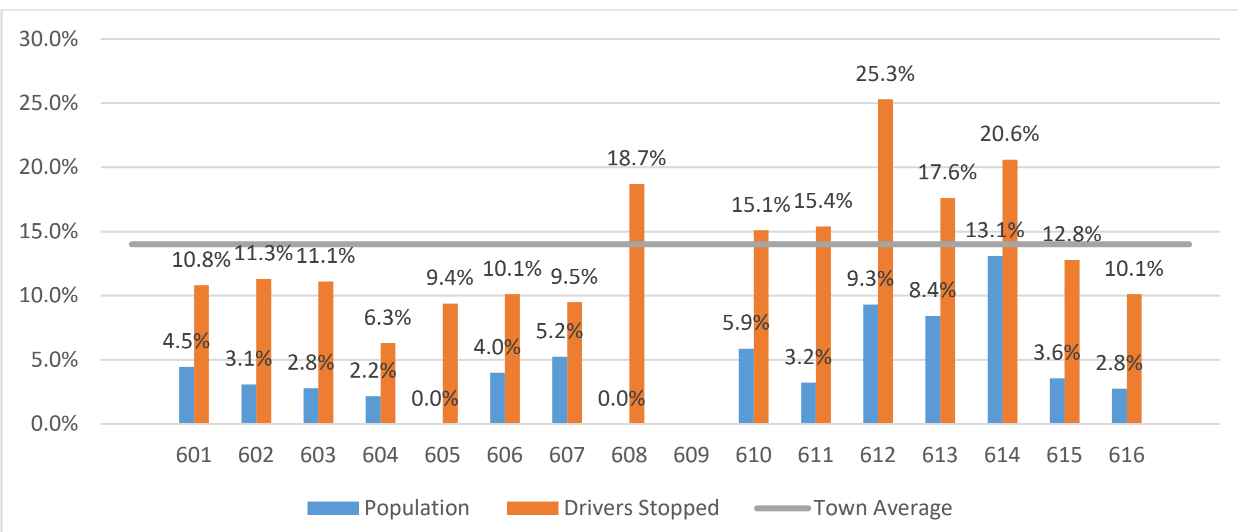


Figure 11.5 shows the difference between the local Hispanic resident population and the Hispanic drivers stopped by census tract. The overall percentage of traffic stops involving Hispanic drivers was 14%. The percentage of Hispanic drivers stopped exceeded the town average of 14% in six census tracts (608, 610, 611, 612, 613, and 614). However, the percentage of Hispanic drivers stopped in tracts 610 and 611 was only slightly above the town average. There was a positive disparity above the resident Hispanic driving age population in all census tracts. Over 94% of all Hispanic drivers stopped were not Fairfield residents.

Figure 11. 5: Hispanic Population Compared to Hispanic Drivers Stopped by Census Tract



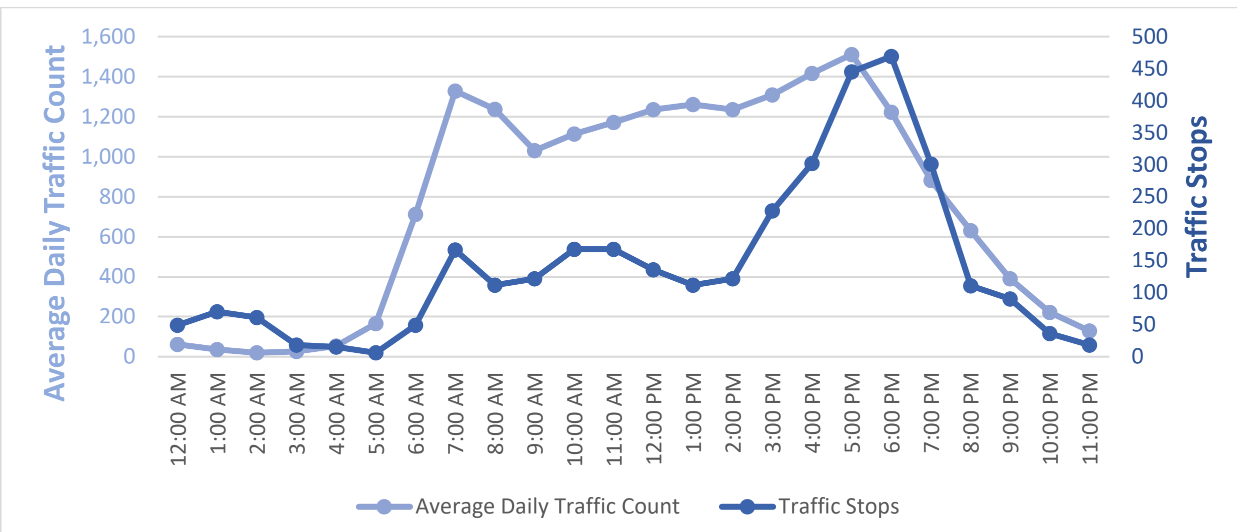
[14] Demographic information is only available for race/ethnic groups over 50 people reported as living in a census tract. According to the 2010 U.S. Census, there were not more than 50 black residents living in thirteen census tracts in Fairfield.

XI.C: Traffic Stop Breakdown on Route 1

Forty-one percent of all traffic stops in Fairfield occurred on U.S. Route 1. Route 1 is locally known as the Boston Post Road or the Post Road and runs approximately five miles from east to west through the southern portion of town. The Post Road is a four-lane, divided road that carries Route 1 from the Westport border to the Bridgeport border. Route 1 acts as one of Fairfield's main thoroughfares where a significant portion of the town's business and commercial activity is located. Route 1 in Fairfield runs through five census tracts (606, 613, 614, 615, and 616). Approximately 37% of traffic stops on Route 1 occurred in tract 606, 6% occurred in tract 613, 12% occurred in 614, 23% occurred in tract 615, and 15% occurred in tract 616.

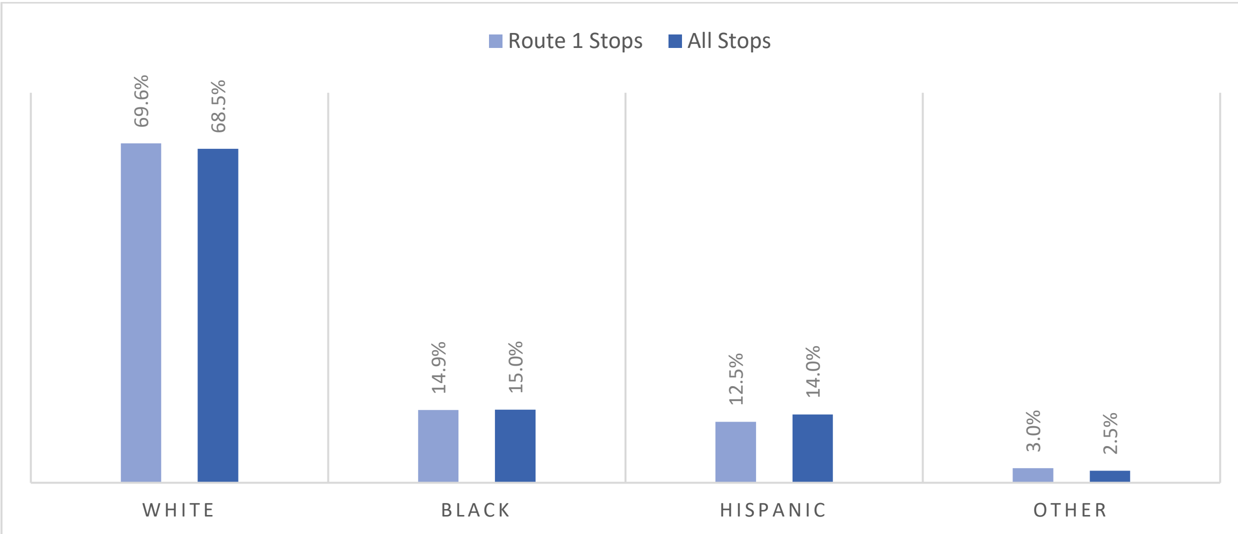
To help understand traffic flow on Route 1, researchers analyzed the average daily traffic (ADT) records that the Connecticut Department of Transportation (DOT) reports. DOT is responsible for collecting traffic volume information for state and local roads throughout the state by placing counting stations at different points along the roadway for a period to count the cars that drive through that point. According to the ADT information for Route 1, the traffic volume begins to build starting at 5:00 a.m. It peaks in the morning around 7:00 a.m. and traffic volume remains high through the afternoon and evening commuting hours. Traffic volume starts to decrease around 6:00 p.m. and is at its lowest levels during the overnight hours. Traffic enforcement peaks were offset somewhat from the commuter peaks, with enforcement peaks at 6:00 a.m. to 8:00 p.m. and 4:00 p.m. to 7:00 p.m. Figure 11.6 is a graph of traffic flow compared to traffic enforcement on Route 1.

Figure 11. 6: Route 1 Traffic Flow Compared to Traffic Enforcement



The overall percentage of traffic stops involving minority drivers on Route 1 was 39%, equivalent to the town average. Approximately 12% of drivers stopped were Hispanic and 15% were black. Of the more than 3,375 traffic stops on Route 1, 87% of the drivers stopped were not residents of Fairfield. Hispanic drivers were 5% of all Fairfield residents stopped on Route 1 and 14% of all non-residents. Black drivers were 3% of all Fairfield residents stopped on Route 1 and 17% of all non-residents. Figure 11.7 shows the percentage of traffic stops on Route 1 by race and ethnicity.

Figure 11. 7: Percent of Route 1 Traffic Stops by Race/Ethnicity Compared to All Stops



XI.D: Non-Resident Component of Fairfield Traffic Stops

To a great degree, Fairfield's traffic stop data tended to reflect two basic influences: (1) an extremely low non-white driving age resident population and (2) a relatively large proportion of non-Fairfield residents who make up the majority of people who were stopped in town. Fairfield's resident driving age population is estimated as 90% white, 4.5% Hispanic, 1.7% black and 3.5% Asian/Pacific Islander. The demographics of the Fairfield residents who were stopped during the study year showed only a small disparity for both Hispanic and black drivers. The disparity was most significant for non-Fairfield resident stops. Since 84% of all drivers stopped in Fairfield were not residents, out-of-town drivers clearly had an impact on the stop data. The non-resident component of four of the 16 Fairfield census tracts (601, 606, 613, and 614) were greater than the town wide average of 84%. However, there were fewer non-residents stopped than the town wide average in the other 12 census tracts. It is worth noting that Route 1 runs through tracts 606, 613, and 614. Additionally, tracts 613 and 614 border the city of Bridgeport, which has a population significantly more diverse than Fairfield. Drivers stopped in census tracts 606, 613, and 614 were approximately 89% non-residents. Although census tract 601 had a greater percentage of non-residents stopped than the town average, only 1% of all stops occurred there.

The racial breakdown of drivers stopped who were not Fairfield residents was as follows: 64% white, 16% Hispanic, 17% black, 2% Asian/Pacific Islander, and 1% Indian American. Approximately 95% of the black and Hispanic drivers stopped were not residents, compared to 79% of white drivers.

The Route 1 corridor appears to have had the greatest influence on the non-Fairfield resident component of the stop demographics, with 87% of the drivers stopped on Route 1 not living in Fairfield. Non-resident drivers were more likely to be stopped on Route 1 than they were on any other roadways in town (87% compared to 82%).

XI.E: Special Enforcement Campaigns

Fairfield participated in special enforcement campaigns that were sponsored by the Connecticut Department of Transportation through funds made available by the National Highway Traffic Safety

Administration (NHTSA). Fairfield reported a total of 1,453 stops as part of the NHTSA-funded campaigns. The Special Enforcement campaigns in which Fairfield participated focused on (1) seatbelt safety ("Click-It or Ticket") and (2) distracted driving (DDHVE). The Fairfield Police Department was able to identify only the dates, times, and basic stop information for special enforcement campaigns. They provided the locations for all check-points established during the campaign. The case numbers for each stop were not available to match to the traffic stop database.

Of the 1,453 stops made as part of the special enforcement campaigns, 1,179 (81%) were reported as part of distracted driving campaigns and 274 (19%) were part of "Click-It or Ticket" campaigns. Total stops made during special enforcement campaigns accounted for 17.5% of all stops made in Fairfield during the study period. When a town has participated in these enforcement campaigns and made a significant portion of its total traffic stops as part of them, it can add an additional dimension to analysis of the town's stop data because they can affect the overall data for the town in several ways. For example, stop outcomes for stops made during selective enforcement campaigns can, and usually do, result in a high proportion of penalty outcomes rather than warnings compared to stops made during regular routine patrol activities where officers may have more discretion in deciding whether or not to ticket the violator. Imposition of penalty-based outcomes is one of the tenets for participation in these federally-funded programs. Stop demographics can also differ, particularly with respect to distracted driving campaigns which focus primarily, though not exclusively, on cell phone use. In general, cell phone stop demographics statistically tend to show higher proportions of female violators and lower proportions of minority drivers than is typical for other types of motor vehicle violations. Finally, the criteria for selection of locations to conduct selective enforcement could differ in some ways from the way stops are generally conducted. For example, effective distracted driving enforcement requires officers to be able to observe drivers in their vehicles without being observed themselves, which can make some locations for this type of enforcement more suitable than others even though the less suitable locations might have as many drivers potentially violating the targeted laws than the more suitable enforcement locations.

Distracted driving campaigns (DDHVE) took place in April and August of 2017. In April 2017, special enforcement for distracted driving was conducted on 13 separate days. The focused patrols were at six different locations (based on the April DDHVE data but not August). The most frequent stops for the DDHVE campaign in April occurred at the Route 1 traffic circle (245 stops). Officers conducted 155 stops on King's Highway, 94 stops on the Post Road, 51 stops on Black Rock Turnpike, and 38 stops on Villa Avenue. Police reported 583 stops for the April DDHVE patrols, 314 of which were for cell phone violations. These stops accounted for 54% of all DDHVE stops conducted in April. There were also 183 stops conducted for seatbelt violations, accounting for 31% of all DDHVE stops in April. During the August campaign, there were focused patrols on 14 separate days. Location data for the August campaign were not available. Police reported 596 stops for the August campaign, 322 of which were for cell phone violations. These stops accounted for 54% of all stops conducted during the August campaign. Unlike the April campaign, in August police segmented texting infractions from regular cell phone violations. Of the 322 stops made, 256 (80%) were for texting. There were also147 stops for seatbelt violations, accounting for 25% of all stops during the August campaign.

The "Click-It or Ticket" campaign took place over three days in May and three days in November of 2017. Seven officers participated in the May campaign and eight participated in November. During the May campaign police made a total of 47 stops, of which 13 were for seatbelt violations or 28%. There were 27 stops for cell phone violations, accounting for 57% of all stops in the May seatbelt campaign. In the November seatbelt campaign, police made a total of 227 stops, 126 (56%) of which were for seatbelt violations and 37 (16%) were for cell phone violations. Location data for "Click-It or Ticket" was only available for the May campaign, and police conducted stops in two locations: (1) King's Highway and (2) Post Road. Over 57% of the stops were made on King's Highway and 43% were made on the Post Road.

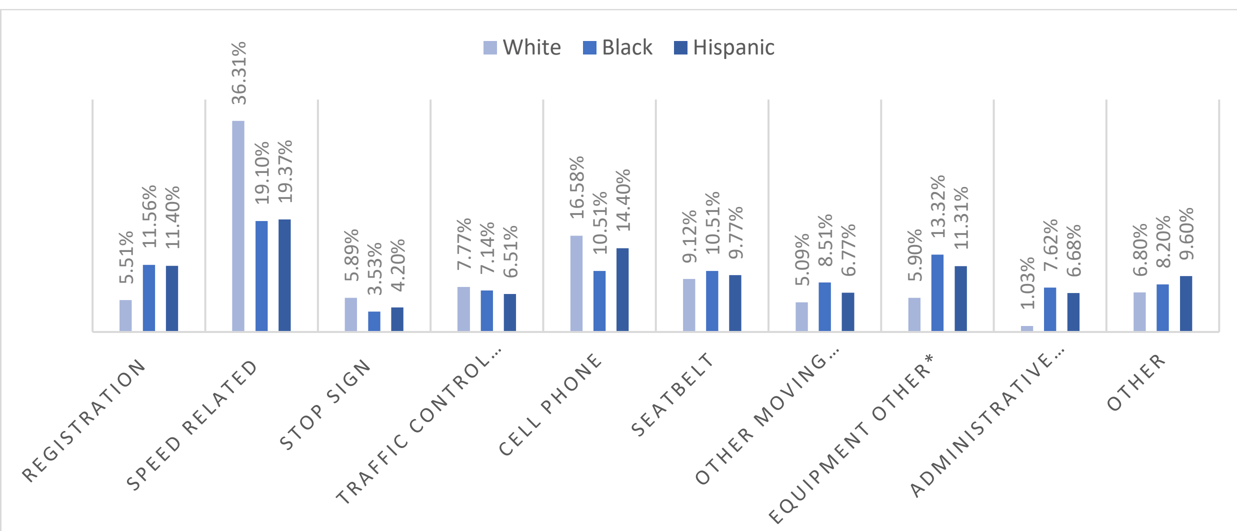
XI.F: Traffic Stop Distribution for Fairfield Officers

Fairfield's 8,320 traffic stops were reported by 74 officers. The average number of stops made per officer was 112. Of the 74 officers reporting stops, 47 made fewer than 50 stops, 10 made between 50 and 100 stops, six made between 100 and 200 stops, four made between 200 and 500 stops, six made between 500 and 1,000 stops and one officer made over 1,000 stops. The most active officer conducted 1,282 stops or 15% of all stops for the town. The seven most active officers making more than 500 stops collectively accounted for 58% of Fairfield stops. While these seven officers clearly had the greatest impact on Fairfield's total stop numbers, the overall average number of stops per officer for the entire department is higher than the averages found in a number of similar departments.

XI.G: Post-Stop Outcome Review

The reasons police use to stop a motor vehicle can vary significantly from department to department. Our review of the statutory authority Fairfield officers reported as the reasons for stopping motor vehicles showed that the three most common reasons motorists were stopped were for speed-related violations (31%); cell phone violations (15%); and seatbelt violations (9%). These three reasons accounted for 56% of all the stops in Fairfield. While white drivers were stopped more frequently than black or Hispanic drivers for more hazardous driving violations as a percentage of their total stops, black and Hispanic drivers were stopped more frequently for registration violations, equipment-related violations, and administrative offenses than white drivers as a percentage of their total stops. Figure 11.8 illustrates by race and ethnicity the reason officers cited to stop a motor vehicle.

Figure 11. 8: Reasons for Traffic Stops by Race and Ethnicity



*Equipment Other includes violations for defective lights, excessive window tint, or display of plate violations.

The data shows that the reason for stopping vehicles can vary by census tract. For example, in four of the 16 census tracts (601, 604, 605, and 606) more than half of the traffic stops were for speed-related violations. On the other hand, the proportion of speed-related traffic stops in the remaining 12 census tracts varied from 2% to 45% of the stops. Stops for equipment-related violations, registration violations and administrative offenses also varied by census tract. These stops accounted for 23% of all the stops made in the three census tracts bordering Bridgeport (613, 614, and 615) but only 15% of the stops made in the other 13 census tracts.

Speed enforcement appeared to be more heavily concentrated in the western part of town, with more than 58% of the stops in the three most western census tracts (604, 605, and 606). Speed-related stops in the seven census tracts in the center of town accounted for 28% of the speed stops and the remaining six census tracts along the eastern part of town accounted for only 14% of speed-related stops. It is worth noting that over 39% of all speed-related stops occurred in one census tract (606). Speed-related motor vehicle enforcement on Route 1 appears to have had an impact on overall traffic stop trends in Fairfield with speed-related stops occurring there at a higher rate than on other roadways in town. Of the 2,228 speed-related traffic stops that could be mapped, 43% occurred on Route 1. Census tracts 606 and 616, which cover almost half of Route 1, accounted for 94% of all speed-related stops on Route 1. More than half of all the black drivers stopped for speeding in Fairfield were stopped on Route 1. This compares to one out of every three white and Hispanic drivers stopped for speeding in Fairfield.

Another factor researchers considered was that officers reported 267 of speed-related stops as "blind." This means officers report using a blind enforcement technique like radar, a laser, or other similar technology or method when conducting the stop. The speed-related stops recorded as "blind" were likely the result of an officer using radar or laser technology. It is likely that significantly more speed-related stops should have been recorded as blind, but were not. "Blind" speed enforcement can be viewed as a reasonable benchmark for the racial demographics of drivers on a given roadway. Based on this assumption, the racial demographics of drivers stopped for blind speed-related offenses was less diverse. The racial demographics for speed-related stops recorded as "blind" were 77% white, 10% black, and 9% Hispanic compared to the racial demographics for all other stops which were 68% white, 15% black, and 14% Hispanic.

While white drivers were stopped more frequently than black or Hispanic drivers for more hazardous driving violations as a percentage of their total stops, black and Hispanic drivers were stopped more frequently for equipment-related violations, registration violations and administrative offenses than white drivers as a percentage of their total stops. The data shows that, with respect to the racial and ethnic demographics of those stopped, equipment-related violations (defective, improper, or inoperative lighting; display of plates; or window tinting), registration and administrative offenses are closely related to the frequency and location of where the stops are made. When these types of stops are made more frequently in locations where there are higher concentrations of minority drivers, they tend to result in higher proportions of minority drivers being stopped than white drivers. However, in many places, the data also shows that when these same types of stops are made in areas with a higher concentration of white drivers, the stop demographics shift toward white drivers, suggesting that the likelihood of finding violators may be more dependent on location than race.

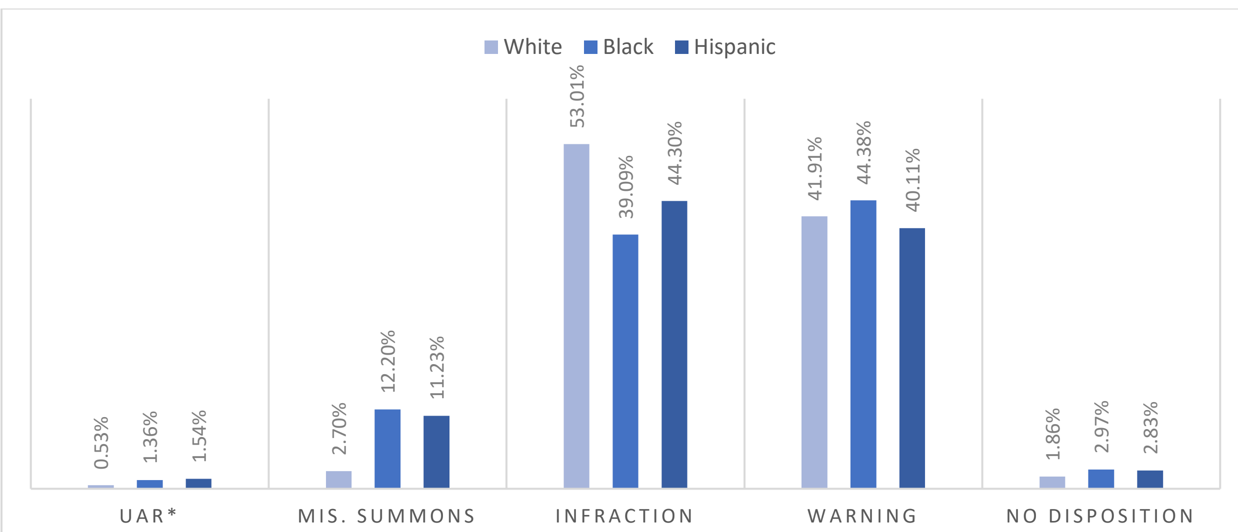
The Fairfield data illustrates that the reasons for motor vehicle stops in the census tracts that border Bridgeport, where a higher percentage of minority drivers are stopped, are different from the reasons frequently cited in other areas of town. Speed-related traffic violations accounted for 8% of the stops in the five census tracts bordering Bridgeport (611, 612, 613, 614, and 615) compared to 46% of the stops in the other 11 census tracts. Additionally, equipment, registration, and administrative violations accounted for 24% of the stops in the five tracts bordering Bridgeport compared to 10% of the stops in the remaining census tracts. Of all the equipment-related violations, registration violations, or administrative offense stops, 63% occurred in these same five census tracts. These census tracts also account for 56% of all black and Hispanic stops. These patterns seem to suggest that *where* these types of stops are made is an important factor in the stop demographics.

It is also worth noting that the equipment, registration and administrative violation traffic stops appear to be driven by a small portion of the officer force. The average number of traffic stops per officer for these violations was 29. Sixteen officers exceeded the town average of 29 such stops and accounted for 79% of all these stops. Four officers made over 100 of these stops each and accounted for 39% of all equipment, registration and administrative violation traffic stops.

Outcome of Stops

The majority of motor vehicle stops in Fairfield resulted in the driver receiving either a ticket for an infraction (50%) or a warning (42%). Black and Hispanic drivers were more likely to receive a misdemeanor summons as a percentage of their total stops. Black and Hispanic drivers were less likely to be charged with an infraction compared to white drivers. Figure 11.9 shows the outcome of motor vehicle stops by race and ethnicity.

Figure 11. 9: Outcome of Traffic Stops



*Uniform Arrest Report

Most violations of the motor vehicle laws are designated as infractions but some are not. The more serious violations can be reckless driving, operating under a license suspension, operating under the influence of alcohol or drugs, and operating an uninsured or underinsured vehicle, among others. The system for collecting and reporting traffic stop data requires officers to record the statutory citation for the violation that was the basis for the stop as well as any subsequent charges that differed from and were more significant that the initial charge. This provides the data on the initial cause for making a stop as well as any subsequent, more serious charge that may have been discovered after the stop was made. For example, if someone was initially stopped for a lesser reason such as not wearing a seat belt or rolling through a stop sign, the officer might subsequently determine that the driver was operating with a suspended license. If this information is properly recorded, it is possible to distinguish those stops from the ones that begin and end with the same charge.

In Fairfield, 440 stops resulted in the issuance of a misdemeanor summons (5.3% of all stops made). This was slightly above the statewide average of 4.7% for stops resulting in misdemeanor charges. Of the drivers charged with a misdemeanor, 35% were identified as white, 34.5% were identified as black, and 30% were identified as Hispanic. While this demographic distribution is relatively close, the proportion of all Hispanic drivers stopped in Fairfield who were charged with misdemeanors was 11% compared to only 3% of all of the white drivers stopped. Even though the actual number of black drivers and white drivers charged with misdemeanors was nearly identical (152 to 154), the 152 black drivers represented 12% of all the black drivers stopped in the town, a proportion that was four times larger than the proportion of white drivers charged with misdemeanors.

Almost 41% of the misdemeanor summonses issued by Fairfield police officers were for operation with a suspended or revoked driver's license or vehicle registration. The second largest category (31% of misdemeanors) was for misuse of motor vehicle plates or vehicle registration. The third largest category (21% of misdemeanors) was for violations of minimum motor vehicle insurance requirements. Together, these three categories accounted for over 92% of the misdemeanors. The remaining 8% of misdemeanors were for a variety of other offenses ranging from reckless driving, driving under the influence of alcohol or drugs, evading responsibility, possession of drugs or drug paraphernalia, and various offenses punishable under the Criminal Code.

The misdemeanor stops were heavily concentrated with respect to the type of enforcement action that led to the stop. Although operating with a suspended license or registration, misuse of plates, and failure to maintain adequate motor vehicle insurance were the three largest categories of misdemeanor charges for both white and minority drivers in Fairfield, there were significant distributional differences among them. White drivers were more frequently charged with operating under suspension than either black or Hispanic drivers (47% of white drivers, 30% of black drivers, and 37% of Hispanic drivers). Conversely, black and Hispanic drivers were significantly more likely to have been charged with misuse of plates than were white drivers (43% of black drivers, 32% of Hispanic drivers, and 11% of white drivers). Percentages for insurance violations were about the same for white drivers (11%) and Hispanic drivers (11.9%) and lowest for black drivers (6.9%).

While researchers analyzed the nature of the disparities in misdemeanor outcomes in the Fairfield stop data to some extent, the analysis was hampered to a degree by some of the shortcomings of the data collection and reporting for these stops. A significant number of the stops made for infraction violations but resulting in misdemeanor charges were missing the secondary citations necessary to determine the misdemeanor charge involved. In some other cases, the citations listed as the reason for the stop, although misdemeanors, were not the types of offenses that typically can form the basis for stopping a motor vehicle, but were much more likely to have come as a result of the stop. Some examples of these types of recording errors were things like drug possession, unlicensed motor vehicle operation, criminal trespass, creating a public disturbance, and larceny not involving a motor vehicle. It is worth noting that unlike many infraction violations, officers do not have discretion in the issuance of a misdemeanor summons when such a violation is identified.

Location information for stops involving misdemeanor charges was also problematic. Of the 440 stops involving a misdemeanor outcome, 113(26%) lacked precise location descriptions. While these stops could be used effectively to analyze driver demographic distribution, they were less useful for the geographic analysis.

Generally speaking, there appeared to be a strong geographic component to the misdemeanor stops. Census tracts 613, 614, and 615 accounted for a total of 163 (49%) of the misdemeanor stops that could be accurately mapped. Census tracts 606 and 616 accounted for 80 (24.5%) of the stops that could be mapped (although almost three-quarters of the 80 stops were made in census tract 606, which is the westernmost portion of Route 1 in Fairfield). With respect to the three census tracts bordering Bridgeport (613, 614, and 615) which accounted for 49% of the misdemeanor stops that could be mapped, 64 were made for administrative offenses (39%), 32 were made for registration violations (19.6%) and only three were made for speed-related violations (1.8%). The misdemeanor stops made in census tracts 606 and 616 reflect an entirely different enforcement pattern. For the 80 stops that could be mapped in these two tracts, 44% were made for speed-related violations, 15% were made for administrative offenses, and 10% were made for registration violations.

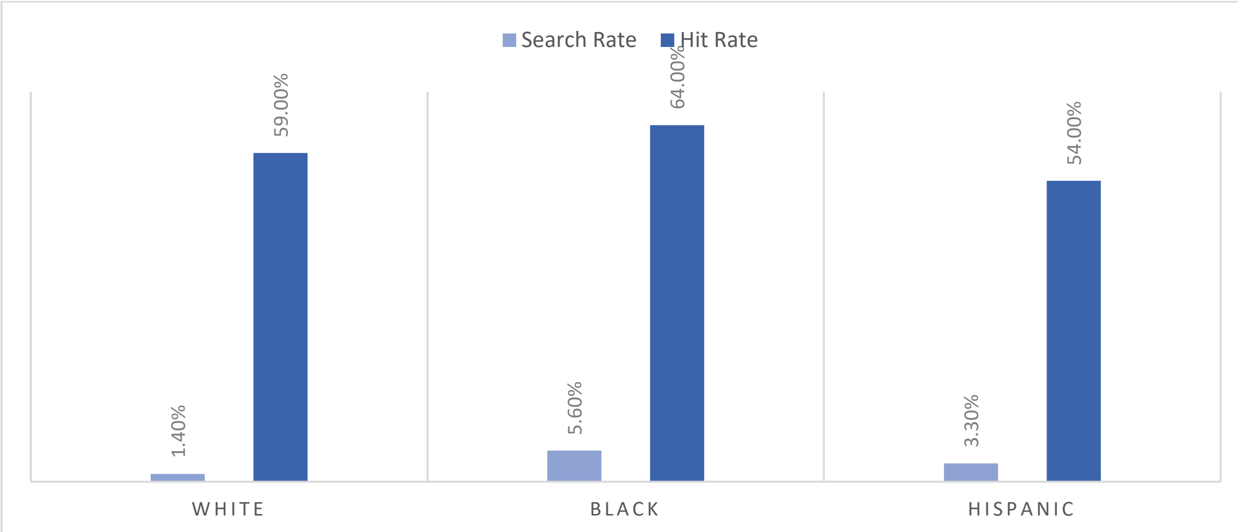
The distribution for the 113 stops that were not mapped conforms more closely to that for census tracts 613, 614, and 615 than it does to census tracts 606 and 616. Specifically, 56 were made for administrative offenses (50%), 27 for registration violations (24%), and four were made for speed-related violations (3.5%). This provides a strong indication than many of these stops were occurring in the three census tracts bordering Bridgeport. In fact, the location descriptive information for these stops indicates that, at a minimum, 43% of them were made at or near the Bridgeport border.

Although the issues with the clarity of the misdemeanor stop data do not allow determining a precise conclusion, the analysis provides substantial indications that the disparities with respect to misdemeanor outcomes for black and Hispanic drivers compared to white drivers are most likely related to differential exposure based primarily on geography and the enforcement choices made by officers patrolling different areas of the town.

Search Information

A review of department search information shows that 2.3% (192) of the drivers stopped in Fairfield were subjected to a motor vehicle search. This rate of motor vehicle searches is less than the state's 3% average. Black and Hispanic drivers were searched at a rate higher than white drivers were. Of the 192 vehicles searched, 2% were subjected to an inventory search (compared to 21% statewide), 38% were subjected to a consent search (compared to 36% statewide), and 61% were subjected to a search for some other reason (compared to 43% statewide). Contraband was found at a lower rate for Hispanic drivers, but a higher rate for black drivers compared to white drivers. However, the overall rate at which contraband was found is almost twice the statewide average (60% compared to 34%). Figure 11.10 illustrates the motor vehicle search rate and the rate at which contraband was found (the "hit rate").

Figure 11. 10: Search and Hit Rate



XI.H: Additional Contributing Factors

Law enforcement administrators choose to deploy police resources within a community based on a number of different factors, including where calls for service are more prevalent. The Fairfield department provided researchers with the calls for service log, which included calls for service and officer initiated actions that were called in to police dispatch. The logs report approximately 40,000 entries from January 1, 2017 through December 31, 2017, exclusive of traffic stops. The top reasons for calling dispatch were for a business or location check (33%), a medical response call (11%), or a response to an alarm (8%). These top three reasons account for about 52% of all calls.

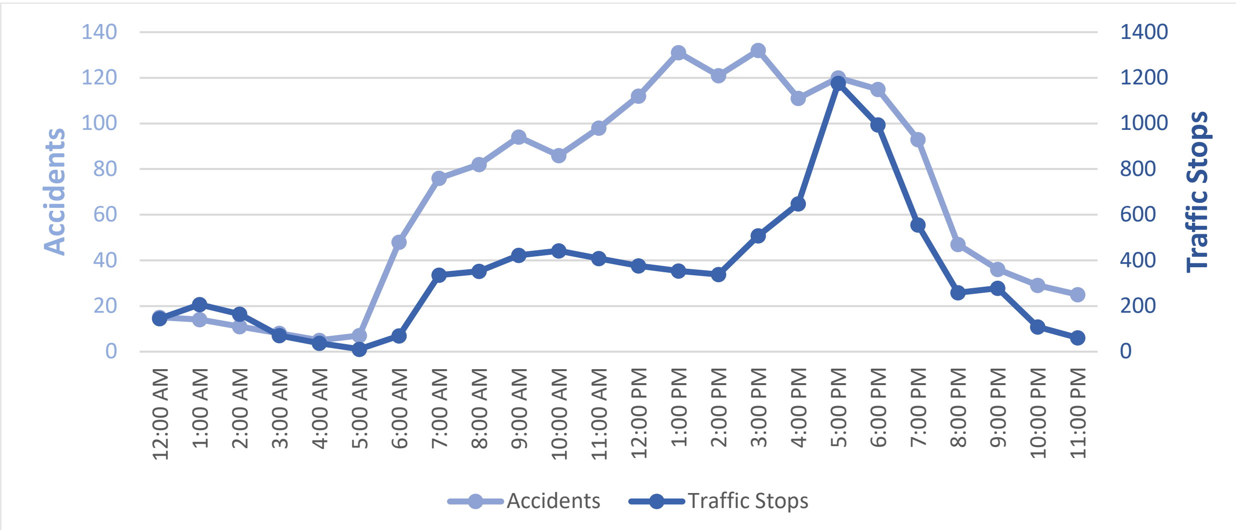
In addition to calls for service, law enforcement administrators also distribute police resources within a community based on accident rates, or where crime rates are higher. In addition to these factors, police presence may be greater where traffic volume is higher as the result of common factors that draw people into a community such as employment and entertainment. Traffic enforcement actions are likely to be more prevalent in locations that attract greater police presence due to some of these factors. Basic information on crime, accidents, and other economic factors associated with Fairfield provide a context to potentially explain the rational for police deployments that are important considerations.

According to the Connecticut Economic Resource Center (CERC) town profiles, approximately 26,417 people work in Fairfield and its major employers include Fairfield University, Sacred Heart University, and the Town of Fairfield. The vast majority of commuters traveling into Fairfield for employment are from Bridgeport, Stratford, Trumbull, Shelton, and Norwalk. The overall unemployment rate is 4.3%, which is below the unemployment rates for Fairfield County and the state.

During our study period, there were approximately 1,616 motor vehicle accidents on roads patrolled by the Fairfield Police Department. Accidents were reported as occurring on 193 roads. The roadways with the highest number of accidents were Route 1 (416 accidents), Black Rock Turnpike (194 accidents), Mills Plain Road (45 accidents), and North Benson Road (43 accidents). There were only 33 roads with 10 or more accidents and those roads account for 77% of all accidents in Fairfield. Route 1 accounted for 26% of all accidents in the town.

Figure 11.11 illustrates the time of day when traffic accidents were reported and the number of traffic stops that occurred during that same period. This shows how closely traffic enforcement is correlated with traffic accidents in Fairfield. While the vehicle crash rate tends to build steadily throughout the day in town, it peaks during the afternoon period from 12:00 p.m. to 5:00 p.m.

Figure 11. 11: Accidents Compared to Traffic Stops by Time of Day



The department also provided information on the location of index crimes, which are eight crimes the FBI combines to produce its annual crime index. The offenses include homicide, forcible rape, robbery, burglary, aggravated assault, larceny over $50, motor vehicle theft, and arson. In 2017, the crime rate in Fairfield was reported to be 157 per 10,000 residents, compared to the state crime rate of 200 per 10,000 residents. According to the 2017 Connecticut Uniform Crime Report[15], there were 945 reported crimes in Fairfield in 2017, 75% of which were larcenies. The three most reported crimes were larceny (710), burglary (110), and motor vehicle theft (102).

There were only 14 roadways in town where more than 10 crimes were reported. Crime was reported at the highest levels on the Post Road (74 crimes), Kings Highway Cut Off (70 crimes), Villa Avenue (61 crimes), and Black Rock Turnpike (57 crimes). Crimes were reported as more likely to have occurred on the eastern side of town, closer to Bridgeport, and in areas either on Route 1 or close to Route 1. Crime data and pattern activity is an integral component of a department's crime control and reduction strategy. Taking into consideration the location of Fairfield's overall index crimes in more detail helps to provide a better understanding of what may be leading Fairfield officers to be more active in some areas of the town than in others.

[15] The Uniform Crime Report is an index for gauging fluctuations in the overall volume and rate of crime. The crime index includes seven offenses: the violent crimes of murder, rape, robbery, and aggravated assault and the property crimes of burglary, larceny-theft, and motor vehicle theft.

XI.I: Summary of Findings

The Fairfield Police Department identified factors they believe contributed to the disparity identified in the initial analysis of traffic stops. In particular, the department identified Route 1 as a major traffic generator for the town. Route 1 is a four-lane, divided road that connects Bridgeport to Westport. There are a number of on-ramps and off-ramps from I-95 to Route 1 that significantly increase the number of out-of-town drivers travelling in the area. Route 1 is also where the majority of shopping, dining, and entertainment is located. In addition to having high traffic volume, Route 1 also had the highest number of both calls for service and accidents of any roadway in town. Over 41% of all traffic stops occurred on Route 1, with 15% of the stops involving black drivers and 12% of the stops involving Hispanic drivers. It is evident by the number of traffic stops made on Route 1 that more departmental resources are concentrated there. It makes sense that the highest levels of motor vehicle enforcement would be in the same area that has the highest levels of traffic volume, calls for service, and motor vehicle accidents.

Fairfield's traffic stop data also reflects an extremely low non-white driving age resident population and the relatively large proportion of non-Fairfield residents who make up the majority of people who were stopped in Fairfield. Since 84% of all drivers stopped in Fairfield were non-residents, the overall impact out-of-town drivers had on the stop data is fairly clear. Approximately 95% of black and Hispanic drivers stopped were not residents of Fairfield, compared to 79% of white drivers who were non-residents. The non-resident component of the stop demographics appeared to have its greatest impact on Route 1, with 87% of the drivers stopped on Route 1 not living in Fairfield. Route 1 was where 36% of the non-resident Hispanic drivers were stopped in Fairfield and 41% of the non-resident black drivers were stopped, compared to 43% of the non-resident white drivers stopped. Non-resident drivers were more likely to be stopped on Route 1 than they were on all other roadways in town. The driving population in the border city of Bridgeport, to the east of Fairfield and connected by Route 1, is significantly more diverse than the driving population in Fairfield.

Fairfield has 74 officers who made at least one traffic stop during the study period. The average stops made per officer was 112. Seven officers (9% of the officer force) made over 500 stops each and accounted for 58% of all the traffic stops. When a relatively small portion of the officer force makes a significant portion of all the stops, the specific duties, patrol areas, and shifts of these officers might have a great deal to do with the overall stop demographics.

Traffic Stop Outcomes

Stops for speeding violations was the largest category of stops made in Fairfield (31%). The next largest category of stops was for cell phone violations (15%), and the third largest stop category was for seatbelt violations (9%). Black and Hispanic drivers were more likely than white drivers to be stopped for a registration violation, equipment-related violation, or administrative offense. In contrast, white drivers were more likely to be stopped for a moving or speeding violation. The reasons for stopping a vehicle also varied by census tract throughout the town. Speed enforcement was more heavily concentrated in the census tracts along the western part of town (bordering Westport), while stops for equipment, registration, and administrative offenses occurred at a higher rate in the eastern part of town (bordering Bridgeport).

Just over 18% of Fairfield's stops were made for violations involving registration, equipment, or other administrative offenses. Hispanic drivers were stopped 29% of the time for equipment registration-, and administrative-related violations, and black drivers were stopped 33% of the time compared to 12% of the time for white drivers. Conversely, 72% of all the white drivers stopped in Fairfield were stopped for hazardous driving behaviors compared to 49% of black drivers and 51% of Hispanic drivers. Just over 56% of the equipment-, registration-, and administrative-related violations resulted in a warning. This was a significantly higher warning rate than for all other types of violations, which was only 39%. These stops occurred more frequently in the five census tracts that border Bridgeport, with over 63% of all equipment-, registration-, and administrative-related stops occurring in these five census tracts. The frequency and location of these stops along the western part of town appears to have been an important factor in the Fairfield disparity involving black and Hispanic drivers.

Overall, almost 50% of all drivers stopped received an infraction and 42% received a warning. The proportion of Fairfield's traffic stops that resulted in a misdemeanor summons (5.3%) exceeds the state average of 4.7%. Black and Hispanic drivers were more than four times as likely as white drivers to receive a misdemeanor summons as the result of a stop. White drivers were more likely to receive an infraction ticket. The majority of the stops that resulted in a misdemeanor charge were initiated for a reason that was not initially a misdemeanor violation. However, once the officer interacted with the operator, a misdemeanor violation was identified. Unlike many infraction violations, officers do not have discretion on whether to issue a misdemeanor summons when such a violation is identified. Although the issues with the clarity of the misdemeanor stop data preclude a precise conclusion, the analysis provides substantial indications that the disparities with respect to misdemeanor outcomes for black and Hispanic drivers compared to white drivers are most likely related to differential exposure based primarily on geography and the enforcement choices made by officers patrolling different areas of the town.

Fairfield police searched 2.3% of the vehicles they stopped, which is lower than the 3% state average. Black drivers were searched four times more often than white drivers were and Hispanic drivers were searched more than twice as often as white drivers were. Compared to white drivers, the rate of contraband found was lower for Hispanic drivers and higher for black drivers. However, the overall rate at which contraband was found is almost twice the statewide average. Given the relatively small number of searches conducted and the successful hit-rate, the search disparities are not significant.

Conclusion

Taken as a whole, the Fairfield traffic stop data reflects the influence of the Route 1 corridor where drivers are somewhat more diverse than the predominantly white local driving age population. Route 1 appears to have a relatively high level of enforcement and a relatively higher proportion of non-resident minority drivers travelling it. It is a significant traffic magnet in town for business, shopping and entertainment and is a major thoroughfare between Bridgeport and Westport. I-95 runs parallel to the roadway and has a significant impact on traffic volume along the corridor, as there are a total of five on-ramps and off-ramps along I-95 in Fairfield.

While white drivers are more likely to be stopped in Fairfield than black or Hispanic drivers for most types of hazardous driving behaviors, black and Hispanic drivers are more likely to be stopped for vehicle equipment, registration, and administrative violations. Our analysis indicates that this difference could be due more to the greater frequency with which these stops were made in census tracts bordering Bridgeport, where minority drivers are more likely to be among the driving population, rather than to an inherently greater likelihood that minority drivers violate these laws more frequently than white drivers.

Researchers identified two shortcomings in the data collection conducted by the department. These included a misunderstanding in how officers defined "blind enforcement[16]" as well as how officers reported the statutory outcome of a stop (only in some cases). It is not uncommon for similar data collection problems to be identified during this part of the analysis. However, we consider it an opportunity to correct any data collection problems and are pleased that the department promptly addressed these issues following our initial meeting with police administrators in January 2019.

Based on the overall follow-up analysis of the Fairfield data, it is recommended that the Fairfield Police Department:

(1) review its traffic enforcement policies along Route 1 in order to evaluate the extent to which they may have a disproportionate effect on black and Hispanic drivers;

(2) evaluate both the location and frequency of stops that involve equipment-, registration-, and administrative-related motor vehicle violations, to better understand the impact they may be having on minority drivers; and

(3) continue to provide refresher training for officers on the procedures for recording information for misdemeanor-related stops and the definition of blind enforcement.

XI.J: Department Response

Below on page 92 is a response provided by Fairfield Police Department.

[16] Officers must report whether a stop was made using general, blind, or spot check enforcement techniques. "Blind enforcement" is defined as a traffic stop that results from the use of technology such as a radar unit, laser unit, or license plate reader.

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Christopher Lyddy
Chief of Police

ORGANIZED
1930

Wednesday, June 19, 2019

Ken Barone
Project Manager
Institute for Municipal and Regional Policy
Central Connecticut State University
New Britain, Connecticut 06050

Dear Mr. Barone:

Thank you for the several meetings we have had, and the continual dialogue you have afforded us related to motor vehicle stops in the Town of Fairfield, as it relates to the statistical breakdown of Fairfield's 8320 Motor Vehicle stops during 2017.

Fairfield is a robust and complex community. We are a town, located adjacent to a major city, with two large universities, and two major thorough fares, I-95 and Route 15, that bifurcate our community. We are a community that actively recruits, publicizes, and invites others to enjoy the shopping, dining, beaches, and cultural experiences Fairfield has to offer.

In an effort to deploy our resources in the most efficient manner, we consider the times and locations that our data shows a propensity for accidents, criminal activity and citizen complaints. As noted in your report, "police presence may be greater where traffic volume is higher as the result of common factors that draw people into a community such as employment and entertainment. Traffic enforcement actions are likely to be more prevalent in locations that attract greater police presence due to some of these factors."

One role of law enforcement is to make every effort to keep our roadways safe. In addition to reducing hazardous driving behaviors, it is also important to ensure vehicles traveling on our roadways meet applicable equipment requirements, are appropriately registered and have adequate insurance.

As discussed in several meetings and noted in your draft report, this agency believes that the actual driving population of Fairfield was not accurately depicted throughout your report. As mentioned in your report, "Route 1 acts as one of Fairfield's main thoroughfares where a significant portion of the town's business and commercial activity is located." Additionally, Black Rock Turnpike and areas near the City of Bridgeport also contain many of Fairfield's commercial businesses. These areas significantly impact the demographics of the driving population, which is substantially different than shown in the 2010 census data utilized in the report.

In reviewing your report, we found value to the information provided as it relates to the data received from our officers collected during traffic stops. This has prompted us to take advantage of training opportunities to ensure we are recording the most accurate data possible.

The men and women of the Fairfield Police Department remain dedicated to maintaining a safe community and strives to achieve that mission through professionalism, honor and excellence. The insight you provided in your report will allow us to continue this mission and we look forward to working with your agency and community stakeholders in order to maintain transparency and accountability in the community we serve.

Sincerely,

Chris Lyddy, Chief of Police
Fairfield Police Department
203-254-4828

XII: OFFICER LEVEL ANALYSIS

Racial bias in policing has been brought to the forefront of American consciousness by recent national headlines of disparate treatment across racial and ethnic divides. These news stories have sparked a contentious and impassioned debate about fair and impartial policing. Although unbeknownst to most Americans, there is a longstanding debate among economists and statisticians about this very topic. Researchers in these fields have developed new and increasingly sophisticated analytical techniques for assessing the extent of racial and ethnic disparities in policing data. Much of the initial research in this field focused on assessing racial and ethnic disparities at the department-level.[17] Although important in their own right, analyses that focus on institutional bias are unable to identify disparities at the officer-level. Recent work by Ridgeway et al. (2006; 2007; 2009) utilizes propensity score methods to evaluate officer-level data. These techniques are quite attractive to policymakers as they have the potential to provide the basis for creating accurate early intervention systems.

The results in Part I identify statistical disparities at the department level. Profiling, however, may not be an aggregate problem. Since individual officers are the decision makers in the traffic stop process, it makes sense to test for statistical evidence that the minority status of the driver impacts this decision. In this section, an internal-benchmark approach developed by Ridgeway et al. (2006; 2007; 2009) is applied to the Derby and Fairfield police departments as part of our follow-up analysis. The hypothesis underlying this test is similar to the synthetic control methodology, but at a micro-level. That is, the racial distribution of stopped motorists should be identical when comparing an individual officer's stops to a benchmark officer whose stops are drawn from similar time, places, and contexts. Put simply, the comparison is between an individual officer and other officers who make stops at the same places and times. Thus, the internal-benchmark is unique to each officer, since patrol patterns and stop timing are fairly idiosyncratic.

A test for individual officers has several important benefits. First, it can function as an "early warning" system, allowing decision makers to identify potential issues before they become widespread. Second, it may confirm that aggregate statistical disparities can be traced back to just a few individuals. Finally, it may help answer questions related to these disparities. By looking at individual officers' benchmarking test results and stop patterns, a qualitative assessment becomes easier.

XII.A: ANALYTICAL RESULTS BY DEPARTMENT

The officer level analysis was conducted using the methodology outlined in Appendix H. As mentioned, the propensity score for each stop was generated iteratively for each officer using a boosted logistic regression.[18] The propensity scores were generated using binary indicator variables for clock time, reason for stop controls, state and town resident controls, day of the week controls,

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[17] Prominent work that focuses on assessment at the department-level includes: Knowles, Persico, and Todd (2001); Antonovics and Knight (2004); Anwar and Fang (2004); Dharmapalam and Ross (2004); Grogger and Ridgeway (2006); and Ritter (2013)

[18] The code used was from a user written R package titled "GBM" by Greg Ridgeway with contributions by Daniel Edwards, Brian Kriegler, Stefan Schroedl and Harry Southworth.

and season controls.[19] Additionally, latitude and longitude enter as continuous variables to control for location. The probability of a racial or ethnic minority conditional on their being stopped by the officer of interest (i.e. the treatment effect) was estimated using a doubly-robust logistic regression with inverse propensity score weights having been applied to the control group.

The doubly-robust regression included each of the covariates from the propensity score regression. The results for each department are presented sequentially along with a narrative describing the details of the analysis. It is important to realize that the analysis only identifies officers that stopped more motorists relative to their internal benchmark and not whether officers are engaged in discriminatory policing. If any of the officers identified in this analysis were engaged in a particular activity that was not captured by the data, such as having been tasked with a specialized assignment, it could provide a reasonable explanation for the disparity. It is important that these results be viewed as the starting point of a dialogue and not as conclusive evidence of wrongdoing on the part of the officer. A detailed presentation of each officer's traffic stops and requisite internal benchmark is contained in the supplemental appendix.[20]

A total of 102 unique officer identifiers were listed in the traffic stop database for the two municipal departments where researchers conducted a follow-up report. After limiting the sample to officers with 50 or more traffic stops, a total of 41 officers were examined. Of the officers examined, 5 were identified as being statistically more likely to stop a minority motorist relative to their benchmark. These officers were then examined using a balancing test that directly compared the distribution of observable traffic stop characteristics with those of each officer's benchmark. The balancing test revealed that all five identified officers had a benchmark that convincingly captured the distribution of observable traffic stops. A summary of the results of the analysis for each individual department is presented below.

Department: Derby

The Derby Police Department had a total of 28 unique officer identifiers in the traffic stop database from January through December 2017. These officers made 2,347 traffic stops during this window. After limiting the sample to officers with 50 or more traffic stops, a total of 14 officers were examined. None of these officers were identified as having been statistically more likely to stop a minority motorist than their benchmark. It should be noted that the stop data for Derby did not contain location data. The resulting synthetic benchmark for each officer may not have been representative of the officer in question. Proper comparisons are difficult in these situations.

Department: Fairfield

The Fairfield Police Department contained a total of 74 unique officer identifiers in the traffic stop database from January through December 2017. These officers made 8,320 traffic stops during this window. There were 104 stops removed due to bad location data, leaving a total of 8,216 for the

[19] Stop controls were aggregated into six distinct categories consisting of "safety" defined as cell phone and seatbelt violations; "equipment" defined as defective lights, display of plate, equipment, or window tint violations; "moving" defined as moving, stop sign, or traffic signal violations; "speeding" defined as speeding violations; "paperwork" defined as suspended license or registration violations; and "other" defined as stops coded as other, administrative offense, or unlicensed operation.

[20] As mentioned, estimation of treatment effects was conducted using doubly-robust logistic regression. The comparison tables contained in the appendix were constructed to conduct a balancing test and are presented only for descriptive purposes.

officer analysis. After limiting the sample to officers with 50 or more traffic stops, a total of 27 officers were examined. A total of five officers were identified as being statistically more likely to stop a minority motorist relative to their benchmark. These officers were then examined using a balancing test that directly compared the distribution of observable traffic stop characteristics with those of each officer's benchmark. All five of these officers were found to have benchmarks that convincingly captured the distribution of observable traffic stops.

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TECHNICAL APPENDICES

All tables in the technical appendix are identified by the section and table number where they can be found in the report. A complete listing is provided below.

APPENDIX A

A.1: METHODOLOGY FOR THE VEIL OF DARKNESS TEST

Let the parameter K_{ideal} capture the true level of disparate treatment for minority group m relative to majority group w:

$$K_{ideal} = \frac{P(S|V', m)P(S|V, m)}{P(S|V', w)P(S|V, w)} \quad (1)$$

The parameter captures the odds that a minority motorist is stopped during perfect visibility (V') relative to those in complete darkness (V). The parameter $K_{ideal} = 1$ in the absence of discrimination and $K_{ideal} > 1$ when minority motorists face adverse treatment.

Applying Baye's rule to Equation 1 such that:

$$K_{ideal} = \frac{P(m|V', S)P(w|V, S)}{P(w|V', S)P(m|V, S)} * \frac{P(m|V)P(w|V')}{P(w|V)P(m|V')} \quad (2)$$

The first term in K_{ideal} is the ratio of the odds that a stopped motorist is a minority during daylight relative to the same odds in darkness. Unlike Equation 1 which would detailed data on roadway demography, the odds ratio in Equation 2 can be estimated using data on stop outcomes. The second term in K_{ideal} is a measure of the relative risk-set of motorists on the roadway which captures any differences in the demographic composition of motorists associated with visibility. The second term will be equal unity if the composition of motorists is uncorrelated with solar visibility.

Assuming that the risk-set of motorists is uncorrelated with variation in solar visibility, a test statistic for K_{ideal} is then simply:

$$K_{vod} = \frac{P(m|S, \delta = 1)P(w|S, \delta = 0)}{P(w|S, \delta = 1)P(m|S, \delta = 0)} \quad (3)$$

Since we do not have continuous data on visibility, the variable δ is a binary indicator representing daylight.

The test statistic K_{vod} will be greater than or equal to the parameter K_{ideal} and exceed unity if the following conditions hold:

1) $K_{ideal} > 1$; The true parameter shows that there is a racial or ethnic disparity in the rate of minority police stops.
2) $P(V|\delta = 0) < P(V|\delta = 1)$; Darkness reduces the ability of officers to discern the race and ethnicity of motorists.
3) $\frac{P(m|V)P(w|V')}{P(w|V)P(m|V')} = 1$; The relative risk-set is constant across the analysis window.

Estimating the test statistic K_{vod} does not provide a quantitative measure for evaluating disparate treatment in policing data but does qualitatively identify the presence of disparate treatment. More concretely, the test identifies the presence of a racial or ethnic disparity if the test statistic K_{vod} is greater than one. Given the restrictive nature of the test statistic, it is reasonable (but not conclusive) to attribute the existence of this disparity to racially biased policing practices.

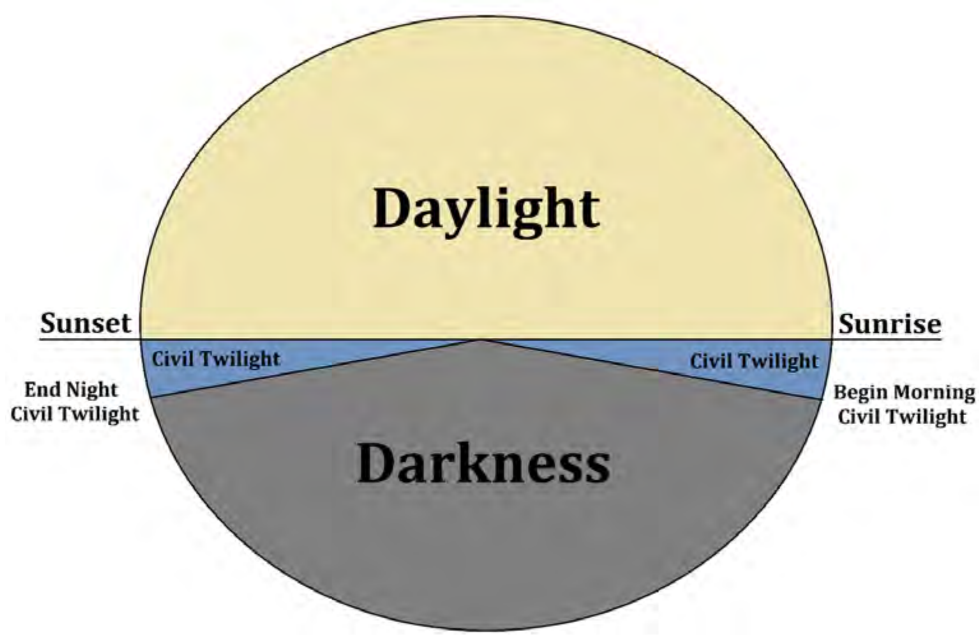
Assuming that the assumptions outlined above hold, Equation 4 can be estimated using a logistic regression in the following form:

$$ln\left(\frac{P(m|\delta)}{1-P(m|\delta)}\right) = \beta_0 + \delta + \mu \tag{4}$$

In practice, it is unlikely that the third assumption (a constant relative risk-set) will hold without including additional controls in Equation 4. Thus, we amend Equation 4 by including controls for time of day (indicators capturing 15 minute intervals), day of week, and statewide daily traffic stop volume. In estimates using data from all departments across the state, we also include department fixed-effects. The aggregate three-year sample also allows for the inclusion of officer fixed-effects.

The analysis requires that periods of darkness and daylight be properly identified. Following Grogger and Ridgeway (2006), the analysis is restricted to stops made within the inter-twilight window- that is, the time between the earliest sunset and latest end to civil twilight. As is shown in Figure A.2 (1), civil twilight is defined as the period when the sun is between zero and six degrees below the horizon and where its luminosity is transitioning from daylight to darkness. The motivation for limiting the analysis to the inter-twilight window is to help control for possible differences in the driving population.

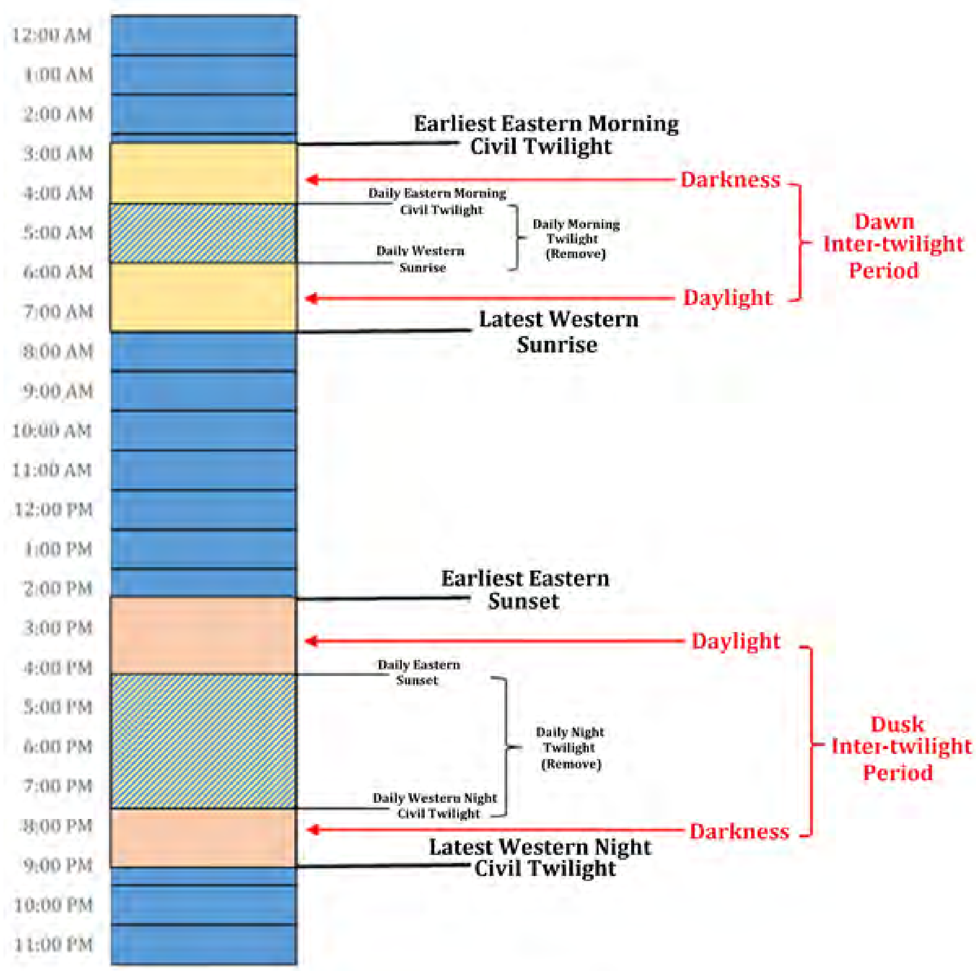
Figure A.2 (1): Diagram of Civil Twilight and Solar Variation



In this analysis, we rely primarily on a combined inter-twilight window that includes traffic stops made at both dawn and dusk. The dawn inter-twilight window is constructed from astronomical data and occurs in the morning hours. The dusk inter-twilight window, on the other hand, is constructed from the same astronomical data but occurs in the evening hours. The combined inter-twilight window relies on a sample that is created by pooling these timeframes and including an additional control variable that identifies the period. The inter-twilight window was identified by attaching astronomical data from the United States Naval Observatory (USNO) to the traffic stop data. As discussed previously, past applications of this method have focused on single large urban geographies and have had no need to consider the possibilities of differential astronomical impacts. The definition for both the dawn and dusk inter-twilight windows was amended to accommodate cross-municipal variation by utilizing data from the easternmost (Newport, RI) and westernmost (Westerly, RI) points available in the USNO data.

The USNO data was merged with the policing data and used to identify the presence of darkness. Again, the presence of darkness was the primary explanatory variable used to identify the presence of racial disparities in the Connecticut policing data. As a result, any observation in the data that occurred during twilight on any given day were dropped. The twilight period varied on a daily basis throughout the year and was identified using the USNO data. Twilight was defined in the dawn inter-twilight window as the time between the daily eastern start of civil twilight and western sunrise. Similarly, twilight was defined in the dusk inter-twilight window as the time between the daily eastern sunset and western end to civil twilight. The full delineation of the policing data is displayed graphically in Figure A.2 (2).

Figure A.2 (2): Delineation of Inter-twilight windows



A.2: METHODOLOGY FOR THE SYNTHETIC CONTROL TEST

Rosenbaum and Rubin (1983) characterize the propensity score as the probability of assignment to treatment conditional on pretreatment variables. The key insight is that conditional on this scalar function, assignment to treatment will be independent of the outcome variable. Simply put, given some *observed* pretreatment variables, it is possible to identify the conditional probability of treatment. Correctly adjusting for this conditional probability allows for the bias associated with *observed* covariates to be statistically controlled. If these observed covariates are correlated with unobserved variables, these confounding factors will also be controlled for statistically. This methodology allows for a causal interpretation of the difference between outcomes associated with treatment and control.

Hirano et al. (2003) note that a useful adjustment is to weight observations according to their propensity scores. This adjustment effectively creates a balanced sample among treatment and control observations. Conveniently, when the estimate of interest is the treatment effect on the treated, only potential control observations need to be weighted. In this context, the weight that balances the sample and removes bias associated with pretreatment confounding factors is exactly the inverse of the propensity score. Ridgeway and MacDonald (2009) apply this technique in the context of policing data by matching the joint distribution of a particular officer's stop features to those by other officers. The analysis proceeds by extending this technique for the purposes of developing synthetic controls of municipal police departments using microdata on police stops in combination with U.S. Census Bureau data on demographic and employment characteristics.

We begin using the dataset of k demographic and employment characteristics for county subdivision j in Connecticut. This set of variables also contains characteristics including: the racial and ethnic composition of the town, age and gender demographics, population size, land area, population density, housing characteristics, commuter patterns, employment in retail and entertainment sectors, and the aggregate racial and ethnic composition of all contiguous towns. A detailed list of the stop-specific and town-level characteristics can be found in Appendix C, Table 28a. We then applied principal components analysis to reduce dimensionality and assure orthogonality. Components were selected using Guttman-Kaiser's stopping rule, which suggests only keeping those with an Eigen value of 1.2 or larger.

Formally, the *i'th* loading factor is simply:

$$w_{(i)} = \underset{\|w\| = 1}{\arg max} \left\{\textstyle\sum_k \left[w \cdot x_j\right]^2\right\}. \tag{5}$$

Indices were then constructed for each component satisfying Guttman-Kaiser's stopping rule where:

$$y_{j,(i)} = \sum_k w_{(i)} x_j \tag{6}$$

Next, we attach the components capturing residential demographic and economic characteristics to the traffic stop data. We then conduct a second principal components analysis using variables from the traffic stop data itself, again to reduce dimensionality and ensure orthogonality. Traffic stop characteristics include time of the day, day of the week, month, department traffic stop volume, officer traffic stop volume, and type of traffic stop.

We then estimate propensity scores for each j department using a logistic regression of the form:

$$ln\left(\frac{F(j)}{1-F(j)}\right) = \beta_0 + \sum_i y_{j,(i)} \tag{7}$$

Propensity score p_j are used to construct weights $w_i = 1$for the department of interest (i.e. the treatment group) and equal to $w_i = p_j/(1-p_j)$ for stops made in all other departments. Applying a propensity score weight to stops made by other departments in the state creates a synthetic control group with a comparable distribution of stop-specific and town-level characteristics. The propensity score and resulting weight for those stops with characteristics that are drastically different than stops made by the department of interest will approach zero. As a result, the synthetic control will consist of the stops that are similar, in terms of stop-specific and town-level characteristics, to those made by the department of interest. The construction of a synthetic control group using propensity scores allows the comparison to reflect the average treatment effect on the treated and abstract from potential bias in so far as the observable covariates control for selection into treatment.

Hirano and Imbens (2001) extend the weighting framework to what Robins and Ritov (1997) refer to as doubly robust estimation. That is, including additional covariates to a semi-parametric least-squares regression model enables capture of a more precise estimate of the treatment effect. It is shown in both of these discussions that such an estimator is consistent if either of the models is specified correctly. Ridgeway and MacDonald (2009) further extend the doubly robust propensity score framework to policing data. Specifically, the authors look at whether the department of interest deviates from the synthetic control along the outcome dimension. Here, we provide estimates with and without so called doubly-robust estimation of treatment effects.

Treatment effects are estimated using a logistic regression of the form:

$$ln\left(\frac{F(m)}{1-F(m)}\right) = w_i\left(\beta_0 + t(j) + \sum_i y_{j,(i)}\right) \tag{8}$$

Where $t(j)$ is an indicator of treatment and $\sum_i y_{j,(i)}$ is a series of covariates included in the propensity score where the dimensionality has been reduced using principle components. If a particular department is designated as a treatment to a group of stops, it follows that the outcome of interest would be motorist race. The question is then simply, does the intervention by a particular department result in a relatively higher stop rate of minority motorists, controlling for all observable factors? Combining inverse propensity score weighting with regression analysis allows for a more precise answer to this question. In the circumstance where the synthetic control and individual department do not perfectly match along all dimensions of stop features, there is potential for bias in any comparison, especially if those features by which they differentiate relate to a motorist's race. Doubly robust estimation helps to remove this source of potential bias by controlling for these features, resulting in a much more accurate department effect. The share of minority motorists stopped within a department was evaluated through a direct comparison with a unique synthetic control.

Table A.3: Variables Included in Synthetic Control Methodology

Variable	Primary Town		Border Town	
	Percent	Count	Percent	Count
Male 18 to 24	X			
Male 25 to 34	X			
Male 35 to 54	X			
Male 55 to 64	X			
Male > 65	X			
Female 18 to 24	X			
Female 25 to 34	X			
Female 35 to 54	X			
Female 55 to 64	X			
Female 65+	X			
Total Population		X		X
White Population		X		X
Hispanic Population		X		X
Black Population		X		X
Asian + P.I. + N.A. Population		X		X
Other Population		X		X
Labor Force Participation	X			
Employment Rate	X			
Commute Alone	X			
Commute Carpool	X			
Commute Public Transit	X			
Commute Walk	X			
Income < 25k	X			
Income 26k to 50k	X			
Income 51k to 75k	X			
Income 76k to 100k	X			
Income 101k to 150k	X			
Income > 150k	X			
Employment Retail		X		
Employment Entertainment		X		
Vacant Housing		X		
Land Area		X		
Population Density		X		

Note 1: The source of all variables is the Census Bureau's 2016 American Community Survey 5 year estimates.
Note 2: Composite variables for border towns are constructed as weighted means where the weights are the length of each border segment.

A.3: DESCRIPTIVE STATISTICS METHODOLOGY

This section presents the methodology used to compare department-level data and three population based benchmarks commonly used across the country: (1) statewide average, (2) estimated commuter driving population, and (3) resident population. Although any one of these benchmarks cannot provide by itself a rigorous enough analysis to draw conclusions regarding racial profiling, if taken together with the more rigorous statistical methods, they do help to highlight those jurisdictions where disparities are significant and may justify further analysis. Any benchmark approach contains implicit assumptions that must be recognized and understood. The implicit assumptions are outlined in an effort to provide transparency to this research process.

A.3 (1): Problems with Approaches Using Traditional Benchmarks

A traditional approach to evaluating racial and ethnic disparities in policing data has been to apply population-based benchmarks. Although these benchmarks vary in their construction, the general methodology is consistent. Typically, the approach amounts to using residential data from the U.S Census Bureau to compare with the rate of minority traffic stops in a given geographic jurisdiction. In recent years, researchers have refined this approach by adjusting the residential census data to account for things like commuter sheds, access to vehicles, and differences over time. The population-based benchmark is an appealing approach for researchers and policymakers both because of its ease of implementation and intuitive interpretation. There are, however, numerous implicit assumptions that underlie the application of these benchmarks and are seldom presented in a transparent manner.

The goal of this analysis is to evaluate racial and ethnic disparities in the Connecticut policing data using (1) intuitive measures that compare the data against uniformly applied benchmarks and (2) sophisticated econometric techniques that compare the data against itself without relying on benchmarks. The goal of this section is to clearly outline the assumptions that often accompany traditional benchmarks. We do, however, present two nontraditional benchmarks in this chapter that develop a more convincing approximation and can be used to descriptively assess the data. By presenting these benchmarks alongside our more econometric methods, we provide the context for our findings. In addition, the descriptive data presents jurisdictional information in cases where samples may be too small to provide statistically meaningful results from the more stringent tests.

Although there are a number of examples, the most prominent application of a population-based benchmark is a study by the San Jose Police Department (2002) that received a great deal of criticism. A more recent example is a report by researchers from Northeastern University (McDevitt et al. 2014) using Connecticut policing data. Although adjusted and unadjusted population-based benchmarks can be intuitively appealing, they have drawn serious criticism from academics and policymakers alike because of the extent to which they are unable to account for all of the possible unobserved variables that may affect the driving population in a geography at any given time (Walker 2001; Fridell 2004; Persico and Todd 2004; Grogger and Ridgeway 2006; Mosher and Pickerill 2012). In an effort to clarify the implicit assumptions that underlie these approaches, an informal discussion of each is presented.

The implicit assumption that must be made when comparing the rate of minority stops in policing data to a population-based (or otherwise constructed) benchmark include the following.

Destination Commuter Traffic

The application of population-based benchmarks does not account for motorists who work but do not live in a given geography. Again, the application of population-based benchmarks implicitly assumes that the demographic distribution of destination commuter traffic, on average, matches the population-based benchmark. This assumption is trivial for geographies with low levels of industrial or commercial development where destination commuter traffic is small. On the other hand, areas with a high level of industrial or commercial development attract workers from neighboring geographies and this assumption becomes more tenuous. This differential impact creates a non-random distribution of error across geographies. While this shortcoming is impossible to avoid using population-based analysis, McDevitt et al. (2004) made a notable effort to adjust static residential population demographics by creating an "estimated driving populations" for jurisdictions in Connecticut.

Pass-through Commuter Traffic

A small but not insubstantial amount of traffic also comes from pass-through commuters. Although most commuter traffic likely occurs via major highways that form the link between origin and destination geographies, the commuter traffic in some towns likely contains a component of motorists who do not live or work in a given geography but must travel through the area on their way to work. As in the previous case, the application of a population-based benchmark must implicitly assume that the demographic distribution of these motorists matches the population-based benchmark. The distribution of error associated with this assumption is, again, very likely non-random. Specifically, it seems likely that a town's proximity to a major highway may impact the level of pass-through commuter traffic from geographies further away from the major highway and, as a result, affect the magnitude of the potential error. Unfortunately, little useful data exists to quantify the extent to which this affects any particular jurisdiction. Alternatives that survey actual traffic streams are prohibitively expensive and time-consuming to conduct on a statewide basis and, unfortunately, are subject to their own set of implicit assumptions that can affect distribution of error.

Recreational Traffic

Surges in recreational traffic are not accounted for in evaluation methods that utilize population-based benchmarks. In order to apply population-based benchmarks as a test statistic, it must be implicitly assumed that the demographic distribution of recreational traffic, on average, matches the population-based benchmark. Although these assumptions are not disaggregated as with commuter traffic above, this assumption must apply to both destination and pass-through commuter traffic. Although the assumption is troublesome on its face, it becomes more concerning when considering the distribution of the associated error during specific seasons of the year. Specifically, recreational traffic likely has a differential effect across both geographic locations and over time.

Differential Exposure Rates

The exposure rate can be defined as the cumulative driving time of an individual on the road. The application of a population-based benchmark must implicitly assume that exposure rates are, on average, equivalent across demographic groups. Although exposure rates may differ based on cultural factors like driving behavior, there are also many more factors that play an important role. An example might be the differences in age distribution across racial demographics. If a specific minority population is, on average, younger, and younger motorists have a greater exposure rate than older motorists; then one might falsely attribute a racial or ethnic disparity across these groups when there is simply a different exposure to law enforcement. Although census-based estimation methods exist to apply these demographically based exposure differences to a given population, they are best suited to situations where a single or very limited number of jurisdictions must be analyzed.

Temporal Controls

The lack of temporal controls in population-based benchmarks does not account for differences in the rate of stops across different times and days in the week. Assuming, that the above four assumptions hold and the population-based benchmark is representative of the demographic distribution of the driving population, then temporal controls are not an issue. However, if any of these assumptions do not hold, the lack of temporal controls may further magnify potential bias. Imagine that we believe the only assumption pertaining to exposure rates is invalid. It seems plausible that younger motorists are more likely to drive on weekend evenings than older motorists. If more stops were being made on weekend evenings than during the week and, as described above, minority groups were more prevalent in younger segments of the population, we might observe a racial or ethnic disparity simply because population-based benchmarks do not control for these temporal differences in policing patterns.

When one or more of the implicit assumptions associated with a population-based benchmark is violated, it can become a biased test statistic of racial disparities in policing data. Furthermore, since the source and direction of any such bias are unknown, it is impossible to determine if the bias is positive or negative, thus creating the potential for both type one (false positive) and two error (false negative). Further, the bias also is likely to be non-random across different geographies within the state. It might be that the bias disproportionately impacts urban areas compared to rural areas, tourist destinations compared to non-tourist destinations, geographies closer to highways, or based on similar policing patterns.

The question then becomes: If the assumptions inherent in population-based benchmarks make them less than ideal as indicators of possible bias, why include them in a statewide analysis of policing data? One answer is that excluding them as part of a multi-level analysis guarantees only that when others inevitably use these measures as a way to interpret the data, it is highly likely to be done inappropriately. Comparing a town's stop percentages to its residential population may not be a good way to draw conclusions about its performance but, in the absence of better alternatives, it inevitably becomes the default method for making comparisons. Providing an enhanced way to estimate the impact commuters have on the driving population and primarily analyzing the stops made during the periods of the day when those commuters are the most likely to be a significant component of the driving population improves that comparison.

Another answer to the question is that the population-based and other benchmarks are not used as indicators of bias, but rather as descriptive indicators for understanding each town's data. Since the purpose of this study is to uniformly apply a set of descriptive measures and statistical tests to all towns in order to identify possible candidates for more targeted analysis, having a broad array of possible applicable measures enhances the robustness of the screening process. Relying solely on benchmarking to accomplish this would not be effective, but using these non-statistical methods to complement and enhance the more technical evaluation results in a report that examines the data from many possible angles.

The third answer to the question is that the benchmarks and intuitive measures developed for this study can be useful in cases where an insufficient sample size make it difficult to draw meaningful conclusions from the formal statistical tests. The descriptive measures can serve a supportive role in this regard.

A.3 (2): Statewide Average Comparison

Although it is relatively easy to compare individual town stop data to the statewide average, this can be misleading if done without regard to differences in town characteristics. If, for example, the statewide average for a particular racial category of drivers stopped was 10% and the individual data for two towns was 18% and 38% respectively, a superficial comparison of both towns to the statewide average might suggest that the latter town, at 38%, could be performing less satisfactorily. However, that might not actually be the case if the town with the higher stop percentage also had a significantly higher resident population of driving age people than the statewide average. It is important to establish a context within which to make the comparisons when using the statewide average as a descriptive benchmark.

Comparing town data to statewide average data is frequently the first thing the public does when trying to understand and assess how a police department may be conducting traffic stops. Although these comparisons are inevitable and have a significant intuitive appeal, the reader is cautioned against basing any conclusions about the data exclusively upon this measure. In this section, a comparison to the statewide average is presented alongside the context necessary to understand the pitfall of interpreting these statistics on face value.

The method chosen to make the statewide average comparison is as follows:

- The towns that exceeded the statewide average for the three racial categories being compared to the state average were selected.
- The amount that each town's stop percentage exceeded the state average stop percentage was determined.
- The amount that each town's resident driving age population exceeded the state average for the racial group being measured was determined.
- The net differences in these two measures were determined and used to assess orders of magnitude differences in these factors.

While it is clear that a town's relative proportion of driving age residents in a racial group is not, in and of itself, capable of explaining differences in stop percentages between towns, it does provide a simple and effective way to establish a baseline for all towns from which the relative differences between town stop numbers become more apparent. To provide additional context, two additional factors were identified: (1) if the town shares a border with one or more towns whose age 16 and over resident population for that racial group exceeds the state average and (2) the percentage of nonresident drivers stopped for that racial group, in that town.

A.3 (3): Estimated Driving Population Comparison

Adjusting "static" residential census data to approximate the estimated driving demographics in a particular jurisdiction provides a more accurate benchmark method than previous census-based approaches. At any given time, nonresidents may use any road to commute to work or travel to and from entertainment venues, retail centers, tourist destinations, etc. in a particular town. It is impossible to account for all driving in a community at any given time, particularly for the random, itinerant driving trips sometimes made for entertainment or recreational purposes. However, residential census data can be modified to create a reasonable estimate of the possible presence of many nonresidents likely to be driving in a given community because they work there and live elsewhere. This methodology is an estimate of the composition of the driving population during typical commuting hours.

Previously, the most significant effort to modify census data was conducted by Northeastern University's Institute on Race and Justice. The institute created the estimated driving population (EDP) model for traffic stop analyses in Connecticut and Massachusetts. A summary of the steps used in the analysis is shown below in Table A.3 (1).

Table A.3 (1): Northeastern University Institute on Race and Justice Methodology for EDP Models in Rhode Island and Massachusetts

Step 1	Identify all the communities falling within a 30 mile distance of a given target community. Determine the racial and ethnic breakdown of the resident population of each of the communities in the contributing pool.
Step 2	Modify the potentially eligible contributing population of each contributing community by factoring in (a) vehicle ownership within the demographic, (b) numbers of persons within the demographic commuting more than 10 miles to work, and (c) commuting time in minutes. The modified number becomes the working estimate of those in each contributing community who may possibly be traveling to the target community for employment.
Step 3	Using four factors, (a) percentage of state employment, (b) percentage of state retail trade, (c) percentage of state food and accommodation sales, and (d) percentage of average daily road volume, rank order all communities in the state. Based on the average of all four ranking factors, place all communities in one of four groups thus approximating their ability to draw persons from the eligible nonresident pool of contributing communities.
Step 4	Determine driving population estimate for each community by combining resident and nonresident populations in proportions determined by which group the community falls into as determined in Step 3. (Range: 60% resident/40% nonresident for highest category communities to 90% resident/10% nonresident for lowest ranking communities)

Although the EDP model created for Rhode Island and Massachusetts is a significant improvement in creating an effective benchmark, limitations of the census data at the time required certain assumptions to be made about the estimated driving population. They used information culled from certain transportation planning studies to set a limit to the towns they would include in their potential pool of nonresident commuters. Only those towns located within a 30 minute driving time of a target town were included in the nonresident portion of the EDP model. This approach assumed only those who potentially could be drawn to a community for employment, and did not account for how many people actually commute. Retail, entertainment, and other economic indicators were used to rank order communities into groups to determine the percentage of nonresident drivers to be included in the EDP. A higher rank would lead to a higher percentage of nonresidents being included in the EDP.

Since development of the Rhode Island and Massachusetts model, significant enhancements were made to the U.S. Census Bureau data. It is now possible to get more nuanced estimates of those who identify their employment location as somewhere other than where they live. Since the 2004 effort by Northeastern University to benchmark Rhode Island and Massachusetts' data, the Census Bureau has developed new tools that can provide more targeted information that can be used to create a more useful estimated driving population for analyzing weekday daytime traffic stops.

The source of this improved data is a database known as the LEHD Origin-Destination Employer Statistics (LODES). LEHD is an acronym for "Local Employer Household Dynamics" and is a partnership between the U.S. Census Bureau and its partner states. LODES data is available through an online application called *OnTheMap* operated by the Census Bureau. The data estimates where people work and where workers live. The partnership's main purpose is to merge data from workers with data from employers to produce a collection of synthetic and partially synthetic labor market statistics including LODES and the Quarterly Workforce Indicators.

Under the LEHD Partnership, states agree to share Unemployment Insurance earnings data and the Quarterly Census of Employment and Wages data with the Census Bureau. The LEHD program combines the administrative data, additional administrative data, and data from censuses and surveys. From these data, the program creates statistics on employment, earnings, and job flows at detailed levels of geography and industry. In addition, the LEHD program uses this data to create workers' residential patterns. The LEHD program is part of the Center for Economic Studies at the U.S. Census Bureau.

It was determined that the data available through LODES, used in conjunction with data available in the 2010 census, could provide the tools necessary to create an advanced EDP model. The result was the creation of an individualized EDP for each of the 169 towns in Connecticut that reflects, to a certain extent, the estimated racial and ethnic demographic makeup of all persons identified in the data as working in the community but residing elsewhere. Table A.3 (2) shows the steps in this procedure.

Table A.3 (2): Central Connecticut State University Institute for Municipal and Regional Policy Methodology for EDP Model in Connecticut

Step 1	For each town, LODES data was used to identify all those employed in the town but residing in some other location regardless of how far away they lived from the target community.
Step 2	ACS* five-year average estimated data was used to adjust for individuals commuting by some means other than driving, such as those using public transportation.
Step 3	For all Connecticut towns contributing commuters, racial and ethnic characteristics of the commuting population were determined by using the jurisdictions' 2010 census demographics.
Step 4	For communities contributing more than 10 commuters who live outside of Connecticut, racial and ethnic characteristics of the commuting population were determined using the jurisdictions' 2010 census demographics.

Step 5	For communities contributing fewer than 10 commuters who live outside of Connecticut, racial and ethnic characteristics of the commuting population were determined using the demographic data for the county in which they live.
Step 6	The numbers for all commuters from the contributing towns were totaled and represent the nonresident portion of the given town's EDP. This was combined with the town's resident driving age population. The combined nonresident and resident numbers form the town's complete EDP.
Step 7	To avoid double counting, those both living and working in the target town were counted as part of the town's resident population and not its commuting population.

*American Community Survey, U.S. Census Bureau

Structured in this way, each town's EDP should reflect an improved estimate of the racial and ethnic makeup of the driving population who might be on a municipality's streets at some time during a typical weekday/daytime period. The more sophisticated methodology central to the LODES data should make this EDP, even with its inherent limitations, superior to previous uses of an EDP model. To an extent, it mirrors the process used by the Census Bureau to develop from ACS estimates the commuter-adjusted daytime populations (estimates of changes to daytime populations based on travel for employment) for minor civil divisions in several states, including Connecticut. This type of data is subject to a margin of error based on differing sample sizes and other factors. For the estimated daytime populations the Census Bureau calculated for 132 Connecticut communities, it reported margins of error ranging from 1.1% (Bridgeport) to 9.6% (East Granby). The average margin of error for all 132 towns was 3.7%.

It is important to understand that the EDPs used in this report are a first attempt to use this tool in assessing traffic stop data. Much of the data used to create the EDPs comes from the same sources the Census Bureau used to create its commuter-adjusted daytime population estimates so it is reasonable to expect a similar range in the margins of error in the EDP. While the limitations of the model must be recognized, its value as a new tool to help understand some of the traffic stop data should not be dismissed. It represents a significant improvement over the use of resident census demographics as an elementary analytical tool and can hopefully be improved as the process of analyzing stop data progresses.

It was determined that a limited application of the EDP can be used to assess stops that occur during typical morning and evening commuting periods, when the nonresident workers have the highest probability of actually being on the road. Traffic volume and populations can change significantly during peak commuting hours. For example, Bloomfield has a predominately Minority resident population (61.5%). According to *OnTheMap*, 17,007 people work in Bloomfield, but live somewhere else and we are estimating that about 73% of those people are likely to be white. The total working population exceeds the driving age resident population of 16,982 and it is reasonable to assume that the daytime driver population would change significantly due to workers in Bloomfield. According to the ACS Journey to Work survey, 73% of Connecticut residents travel to work between 6:00am and 10:00am. The census currently does not have complete state level data on residents' travel from work to home. In the areas where evening commute information is available, it is consistently between the hours of 3:00pm and 7:00pm. In addition to looking at census information to understand peak commuting hours, the volume of nonresident traffic stops in several Connecticut communities was also reviewed, based on our theory that the proportion of nonresidents stopped should increase during peak commuting hours.

The only traffic stops included in this analysis were stops conducted Monday through Friday from 6:00am to 10:00am and 3:00pm to 7:00pm (peak commuting hours). Due to the margins of error inherent in the EDP estimates, we established a reasonable set of thresholds for determining if a department shows a disparity in its stops when compared to its EDP percentages. Departments that exceed their EDP percentages by greater than 10 percentage points in any of the three categories: (1) Minority (all race/ethnicity), (2) Black non-Hispanic, and (3) Hispanic, were identified in our tier one group. In addition, departments that exceeded their EDP percentage by more than five but less than 10 percentage points were identified in our tier two group for this benchmark if the ratio of the percentage of stops for the target group compared to the baseline measure for that group also was 1.75 or above (percentage of stops divided by benchmark percentage equals 1.75 or more) in any of the three categories: (1) Minority (all race/ethnicity), (2) Black non-Hispanic, or (3) Hispanic.

A.3 (4): Resident Only Stop Comparison

Some questioned the accuracy of the estimated driving population. As a result, we have limited the next part of the analysis to stops involving only residents of the community and compared them to the community demographics based on the 2010 decennial census for residents age 16 and over.

While comparing resident-only stops to resident driving age population eliminates the influence out-of-town drivers on the roads at any given time may be having on a town's stop data, the mere existence of a disparity is not in and of itself significant unless it does so by a significant amount. Such disparities may exist for several reasons including high police presence on high crime areas.

Therefore, we established a reasonable set of thresholds for determining if a department shows a significant enough disparity in its resident stops compared to its resident population to be identified. Departments with a difference of 10 percentage points or more between the resident stops and the 16+ resident population in any of the three categories: (1) Minority (all race/ethnicity), (2) Black non-Hispanic, and (3) Hispanic, were identified in our tier one group. In addition, departments that exceeded their resident population percentage by more than five but less than 10 percentage points were identified in our tier two group for this benchmark if the ratio of the percentage of resident stops for the target group compared to the baseline measure for that group also was 1.75 or above(percentage of stopped residents divided by resident benchmark percentage equals 1.75 or more) in any of three categories: (1) Minority (all race/ethnicity), (2) Black non-Hispanic, and (3) Hispanic.

A.4: METHODOLOGY FOR THE EQUALITY OF DISPOSITION TEST

We propose a simple test of equality in the distribution of outcomes for motorists of different races conditional on the reason that they were stopped. Specifically, we test whether traffic stops made of minority motorists result in different outcomes relative to their White Non-Hispanic peers. Since ex-ante it is unclear whether discrimination would create more or less severe traffic stop outcomes in the data, we simply tests for equality in the distribution of outcomes across demography conditional on the motivating reason for the stop. To illustrate this point, imagine a simplified case where there are only two outcomes for a traffic stop- one resulting in a violation and the other resulting in a warning. On the one hand, discriminatory police officers might treat minority motorists more harshly conditional on the reason they were stopped. However, discriminatory police might also make more pretextual traffic stops for lower level offenses motivated by the fact that they may observe evidence of a more severe crime once the vehicle is stopped. In this case, we would expect that discriminatory police officers issue more warnings to minority motorists as a result of pretextual traffic stops and racial profiling. Rather than making unreasonable assumptions about the net-effect of such countervailing forces, we simply assume that the overall distribution of outcomes will not be equal across race in the presence of discrimination. The intuition is similar to hit-rate style tests but where we are unable to ex-ante sign the direction that we expect bias to take.

Here, we aggregate all search and arrest data (driver, passenger, and vehicle) into a singular aggregate statistic for whether a traffic stop resulted in these outcomes. In cases where a traffic stop resulted in a combination of outcomes, say an arrest and a ticket or where one individual in the car was searcher but others were not, we aggregate to the more severe outcome i.e. arrest in the first case and search in the latter. Since we have combined data on driver and passenger outcomes, we also amend the race variable to represent whether there was any minority person in the vehicle at the time of the stop. For example, unlike in other sections where the Hispanic category represents the demography of the driver, here it represents whether any individual in the vehicle was observed to be Hispanic.

We also aggregate the detailed outcome data into six categories, which include: (1) no search, ticket or misdemeanor, (2) no search, warning or no action, (3) no search, arrest, (4) search, ticker or misdemeanor, (5) search, warning or no action, and (6) search, arrest. Thus, we estimate the full set of *J-1* outcomes relative to a baseline outcome using multinomial logit. We assume that the log odds $\eta_{j,i}$ that a traffic stop *i* has an outcome *j* relative to the omitted baseline category (no search, ticket or misdemeanor) follows a linear model of the form

$$\eta_{j,i} = \beta_{j,0} + \beta_{\mathrm{j},1}^{T} reason_i + \beta_{\mathrm{j},2} m_i + \beta_{\mathrm{j},3}^{T} [reason_i * m_i] \tag{9}$$

where m_i is an indicator equal to one if anyone in the vehicle is a minority and zero if the vehicle contains only White Non-Hispanic motorists. The variable $reason_i$ is a vector of indicators constructed by aggregating the detailed reason for stop data into six categories which include: (1) speed or moving, (2) equipment, (3) seatbelt or cellphone, (4) registration or license, (5) warrant or criminal activity, and (6) all other. Although omitted from Equation 10 for parsimony, we also control for potential compositional differences across demographic groups by including gender and age.

Similarly, we include a series of controls for day of week, time of day, week of year, and depending on the specification either department or officer fixed-effects.

The key variable of interest in Equation 9 is the interaction term between minority status and the motivating reason for the traffic stop. As noted, we assume only that these coefficient estimates will be statistically different than zero in the presence of discrimination and do not put any emphasis on a particular sign. To identify discrimination in context of our empirical framework, we test whether the interaction between the reason a stop was made and minority status is statistically different from zero across all six of the outcomes modeled. Thus, we operationalize our test by performing a joint chi-squared hypothesis test on the 25 interaction terms across all non-omitted outcomes and possible reasons for the stop.

We provide one important cautionary note about interpreting our test as causal evidence of discrimination. Ideally, this test would be performed on data containing *all* violations observed by the police officer prior to making a traffic stop and where we would include a control for the number of total violations. In practice, data on traffic stops typically only contain the most severe reason that motivated the stop. Imagining that minority motorists were more likely to be stopped based on police observing multiple violations, the data might show that they receive worse outcomes conditional on the primary motivating reason for the stop. However, this might be a function of the unobserved variable (i.e. number and type of secondary violation) rather than a disparity. Intuitively, it seems reasonable that motorists with multiple violations are treated differently by police relative to those with a single violation and that there might be differences across race in the probability of having multiple violations conditional on being stopped. In the absence of data on the full set of violations observed by police officers, we suggest that the reader interpret results from this test as providing descriptive evidence to be viewed in concert with other such empirical measures.

A.5: METHODOLOGY FOR THE HIT-RATE TEST

The logic of the hit-rate test follows from a simplified game theoretic exposition. In the absence of disparate treatment, the costs of searching different groups of motorists are equal. Police officers make decisions to search in an effort to maximize their expectations of finding contraband. The implication being that police will be more likely to search a group that has a higher probability of carrying contraband, i.e. participate in statistical discrimination. In turn, motorists from the targeted demography understand this aspect of police behavior and respond by lowering their rate of carrying contraband. This iterative process continues within demographic groups until, in equilibrium, it is expected that an equalization of hit-rates across groups is found.

Knowles et al. introduce disparate treatment via search costs incurred by officers that differ across demographic groups. An officer with a lower search cost for a specific demographic group will be more likely to search motorists from that group. The result of this action will be an observable increase in the number of targeted searches for that group. As above, the targeted group will respond rationally and reduce their exposure by carrying less contraband. Eventually, the added benefit associated with a higher probability of finding contraband in the non-targeted group will offset the lower cost of search for that group. As a result, one would expect the hit-rates to differ across demographic groups in the presence of disparate treatment.

Knowles et al. (2001) developed a theoretical model with testable implications that can be used to evaluate statistical disparities in the rate of searches across demographic groups. Following Knowles et al. an empirical test of the null hypothesis (that no racial or ethnic disparity exists) in Equation 10 is presented.

$$P(H = 1 \mid m, S) = P(H = 1 | S) \ \forall \, r, c \tag{10}$$

Equation 10 computes the probability of a search resulting in a hit across different demographic groups. If the null hypothesis was true and there was no racial or ethnic disparity across these groups, one would expect the hit-rates across minority and non-minority groups to reach equilibrium. As discussed previously, this expectation stems from a game-theoretic model where officers and motorists optimize their behaviors based on knowledge of the other party's actions. In more concrete terms, one would expect motorists to lower their propensity to carry contraband as searches increase while officers would raise their propensity to search vehicles that are more likely to have contraband. Essentially, the model allows for statistical discrimination but finds if there is bias-based discrimination.

An important cautionary note about hit-rate tests related to an implicit infra-marginality assumption. Specifically, several papers have explored generalizations and extensions of the framework and found that, in certain circumstances, empirical testing using hit-rate tests can suffer from the infra-marginality problem as well as differences in the direction of bias across officers (see Antonovics and Knight 2004; Anwar and Fang 2006; Dharmapala and Ross 2003). Knowles and his colleagues responded to these critiques with further refinements of their model that provide additional evidence of its validity (Persico and Todd 2004). Although the results from a hit-rate analysis help contextualize post-stop activity within departments, the results should only be considered as supplementary evidence.

APPENDIX B

Table B.1: Rate of Traffic Stops per 1,000 Residents (Sorted Alphabetically)

Town Name	2010 16 and Over Census Pop.	2017 Traffic Stops	Stops per Resident	Stops per 1,000 Residents
State of CT	2,825,946	542,820	0.19	192
Ansonia	14,979	3,569	0.24	238
Avon	13,855	1,243	0.09	90
Berlin	16,083	5,441	0.34	338
Bethel	14,675	3,107	0.21	212
Bloomfield	16,982	2,226	0.13	131
Branford	23,532	5,271	0.22	224
Bridgeport	109,401	2,262	0.02	21
Bristol	48,439	3,791	0.08	78
Brookfield	12,847	2,187	0.17	170
Canton	7,992	931	0.12	116
Cheshire	21,049	2,313	0.11	110
Clinton	10,540	1,504	0.14	143
Coventry	9,779	1,389	0.14	142
Cromwell	11,357	1,561	0.14	137
Danbury	64,361	6,160	0.10	96
Darien	14,004	3,568	0.25	255
Derby	10,391	2,347	0.23	226
East Hampton	10,255	769	0.07	75
East Hartford	40,229	7,475	0.19	186
East Haven	24,114	2,503	0.10	104
East Lyme*	13,816	379	0.03	27
East Windsor	9,164	1,752	0.19	191
Easton	5,553	1,203	0.22	217
Enfield	33,218	8,806	0.27	265
Fairfield	45,567	8,320	0.18	183
Farmington	20,318	5,212	0.26	257
Glastonbury	26,217	4,166	0.16	159
Granby	8,716	548	0.06	63
Greenwich	46,370	7,546	0.16	163
Groton*	31,520	6,009	0.19	191
Guilford	17,672	2,372	0.13	134
Hamden	50,012	5,888	0.12	118
Hartford	93,669	8,243	0.09	88
Ledyard*	11,527	2,191	0.19	190
Madison	14,073	3,077	0.22	219
Manchester	46,667	10,589	0.23	227
Meriden	47,445	1,578	0.03	33
Middlebury	5,843	34	0.01	6
Middletown	38,747	3,247	0.08	84
Milford	43,135	4,462	0.10	103
Monroe	14,918	4,241	0.28	284
Naugatuck	25,099	4,753	0.19	189
New Britain	57,164	7,328	0.13	128
New Canaan	14,138	5,492	0.39	388
New Haven	100,702	19,038	0.19	189
New London	21,835	5,041	0.23	231
New Milford	21,891	2,318	0.11	106

Table B.1: Rate of Traffic Stops per 1,000 Residents (Sorted Alphabetically)

Town Name	2010 16 and Over Census Pop.	2017 Traffic Stops	Stops per Resident	Stops per 1,000 Residents
Newington	24,978	5,541	0.22	222
Newtown	20,171	3,547	0.18	176
North Branford	11,549	843	0.07	73
North Haven	19,608	2,633	0.13	134
Norwalk	68,034	6,007	0.09	88
Norwich	31,638	6,596	0.21	208
Old Saybrook	8,330	2,388	0.29	287
Orange	11,017	2,821	0.26	256
Plainfield	11,918	1,669	0.14	140
Plainville	14,605	3,450	0.24	236
Plymouth	9,660	1,650	0.17	171
Portland	7,480	358	0.05	48
Putnam	7,507	1,069	0.14	142
Redding	6,955	2,282	0.33	328
Ridgefield	18,111	6,733	0.37	372
Rocky Hill	16,224	4,055	0.25	250
Seymour	13,260	3,883	0.29	293
Shelton	32,010	561	0.02	18
Simsbury	17,773	3,356	0.19	189
South Windsor	20,162	3,850	0.19	191
Southington	34,301	5,123	0.15	149
Stamford	98,070	13,399	0.14	137
Stonington	15,078	4,976	0.33	330
Stratford	40,980	3,697	0.09	90
Suffield	10,782	665	0.06	62
Thomaston	6,224	1,278	0.21	205
Torrington	29,251	7,414	0.25	253
Trumbull	27,678	2,749	0.10	99
Vernon	23,800	3,378	0.14	142
Wallingford	36,530	7,909	0.22	217
Waterbury	83,964	3,052	0.04	36
Waterford	15,760	4,502	0.29	286
Watertown	18,154	1,665	0.09	92
West Hartford	49,650	6,207	0.13	125
West Haven	44,518	8,790	0.20	197
Weston	7,255	611	0.08	84
Westport	19,410	7,461	0.38	384
Wethersfield	21,607	2,899	0.13	134
Wilton	12,973	5,219	0.40	402
Winchester	9,133	842	0.09	92
Windham	20,176	2,331	0.12	116
Windsor	23,222	8,485	0.37	365
Windsor Locks	10,117	1,124	0.11	111
Wolcott	13,175	120	0.01	9
Woodbridge	7,119	2,020	0.28	284

Table B.2: Basis for Stop (Sorted by % Speeding)

Department Name	Total	Speed Related	Cell Phone	Registration	Defective Lights	Display of Plates	Equipment Violation	Moving Violation	Other	Seatbelt	Stop Sign	Administrative Offense	STC Violation	Traffic Control Signal	Unlicensed Operation	Window Tint
Ledyard	2,191	63.5%	0.8%	2.1%	13.7%	2.0%	0.1%	7.1%	3.8%	0.2%	1.1%	1.3%	0.0%	1.2%	0.6%	2.3%
CSP Headquarters	14,090	58.8%	11.9%	2.0%	0.3%	0.2%	0.0%	5.1%	1.4%	14.6%	0.2%	0.7%	3.8%	0.6%	0.3%	0.2%
Ridgefield	6,733	57.9%	11.9%	6.9%	7.6%	0.1%	0.0%	1.5%	1.6%	1.8%	5.7%	0.1%	1.3%	2.7%	0.2%	0.6%
Weston	611	57.8%	1.5%	0.8%	7.9%	0.5%	0.0%	4.9%	5.2%	0.2%	19.5%	0.2%	0.2%	1.3%	0.2%	0.0%
Simsbury	3,356	57.4%	9.8%	1.0%	9.6%	0.8%	0.1%	4.5%	1.6%	1.5%	6.2%	0.1%	0.1%	6.9%	0.1%	0.2%
Thomaston	1,278	57.3%	1.0%	1.8%	13.3%	1.6%	0.3%	6.1%	4.7%	1.8%	5.6%	1.6%	0.2%	4.2%	0.2%	0.4%
Enfield	8,806	54.5%	2.6%	5.0%	7.4%	2.2%	0.4%	6.7%	1.6%	4.5%	2.9%	1.1%	0.5%	9.7%	0.3%	0.6%
Guilford	2,372	54.1%	11.6%	1.0%	9.3%	0.2%	0.0%	2.7%	1.5%	2.7%	9.0%	0.1%	0.1%	7.4%	0.3%	0.0%
Easton	1,203	53.5%	1.7%	13.4%	3.2%	0.8%	0.2%	2.2%	4.0%	2.4%	13.9%	0.6%	2.0%	0.7%	1.1%	0.2%
Suffield	665	53.2%	1.1%	1.2%	15.9%	0.8%	0.0%	19.1%	1.4%	0.2%	2.9%	0.5%	0.2%	3.0%	0.8%	0.0%
Newtown	3,547	53.2%	5.3%	6.3%	6.6%	1.8%	0.2%	11.0%	1.9%	0.9%	6.0%	0.5%	1.9%	3.9%	0.4%	0.1%
Windsor Locks	1,124	52.6%	6.3%	2.7%	7.4%	1.6%	0.3%	4.9%	2.8%	4.9%	5.2%	1.2%	0.2%	9.0%	0.3%	0.9%
Wolcott	120	51.7%	2.5%	1.7%	5.0%	0.8%	0.0%	5.8%	6.7%	1.7%	11.7%	3.3%	0.0%	4.2%	0.8%	4.2%
New Milford	2,318	51.5%	3.6%	5.0%	12.4%	1.1%	0.9%	6.8%	3.5%	0.6%	4.3%	0.7%	0.3%	8.8%	0.3%	0.2%
Redding	2,282	51.3%	2.0%	18.8%	8.2%	0.3%	0.0%	6.5%	2.8%	2.5%	5.7%	0.6%	0.4%	0.4%	0.4%	0.2%
Bethel	3,107	50.9%	11.5%	2.1%	7.4%	0.8%	0.1%	2.0%	1.5%	3.6%	13.4%	0.3%	0.3%	4.1%	0.1%	1.9%
Southington	5,123	50.4%	7.0%	3.5%	15.9%	1.3%	0.1%	5.0%	1.2%	1.9%	4.3%	0.4%	1.6%	6.6%	0.3%	0.5%
Portland	358	48.9%	1.4%	2.8%	8.1%	0.6%	0.0%	6.1%	2.0%	0.0%	12.8%	0.3%	0.0%	16.8%	0.3%	0.0%
Waterford	4,502	44.2%	5.7%	0.7%	14.1%	7.1%	0.1%	10.3%	2.6%	2.5%	1.1%	0.4%	0.3%	9.9%	0.1%	1.0%
Old Saybrook	2,388	43.2%	8.3%	3.9%	14.2%	0.4%	0.1%	6.1%	2.9%	1.2%	10.2%	0.7%	1.1%	7.0%	0.3%	0.4%
Avon	1,243	42.5%	3.3%	5.5%	9.5%	0.8%	0.0%	14.0%	5.5%	0.1%	11.5%	0.5%	0.1%	6.4%	0.3%	0.1%
East Hampton	769	39.8%	6.8%	7.0%	7.7%	1.4%	0.7%	10.7%	3.5%	2.0%	4.9%	0.7%	0.0%	14.3%	0.0%	0.7%
Coventry	1,389	38.4%	6.8%	7.6%	15.2%	1.8%	0.5%	6.0%	3.5%	3.3%	3.7%	2.0%	6.9%	3.6%	0.5%	0.2%
Windsor	8,485	38.1%	5.5%	2.7%	18.4%	2.5%	0.0%	2.9%	0.9%	2.8%	8.9%	0.4%	0.4%	15.5%	0.2%	0.7%
Stonington	4,976	38.0%	6.4%	4.6%	12.5%	0.2%	0.1%	10.2%	6.0%	1.5%	8.2%	1.1%	4.3%	6.3%	0.6%	0.1%
Putnam	1,069	37.0%	13.0%	1.3%	16.2%	7.2%	0.3%	7.8%	2.6%	2.1%	2.7%	1.2%	0.0%	7.9%	0.5%	0.3%
Madison	3,077	36.5%	6.9%	10.8%	10.9%	1.9%	0.4%	9.2%	2.1%	2.3%	9.2%	0.7%	6.1%	2.7%	0.3%	0.2%
New London	5,041	36.2%	9.7%	0.7%	6.9%	0.5%	0.1%	4.4%	3.7%	5.1%	12.6%	0.5%	1.9%	17.4%	0.2%	0.2%
New Canaan	5,492	35.7%	14.1%	8.7%	16.4%	3.1%	0.2%	5.7%	1.6%	1.1%	6.6%	0.2%	0.2%	4.4%	0.3%	1.7%
Department of Motor Vehicle	1,575	35.4%	9.3%	7.4%	2.2%	2.3%	2.0%	15.3%	5.9%	1.6%	1.7%	0.7%	4.9%	4.9%	1.4%	5.1%
Bristol	3,791	35.3%	9.0%	9.3%	5.4%	1.7%	0.2%	8.3%	2.9%	5.3%	8.0%	2.1%	0.2%	11.2%	0.8%	0.3%
East Windsor	1,752	35.3%	12.6%	5.1%	18.4%	1.4%	0.3%	7.2%	3.2%	0.6%	7.5%	1.9%	0.9%	4.9%	0.5%	0.2%
Granby	548	35.0%	19.0%	3.1%	12.0%	1.8%	0.2%	8.2%	1.8%	5.7%	6.6%	0.4%	0.2%	5.5%	0.4%	0.2%
Central CT State University	1,848	34.7%	6.5%	5.5%	10.4%	2.1%	0.1%	9.0%	3.9%	4.2%	6.4%	0.5%	4.2%	11.8%	0.5%	0.2%
CSP Troop C	20,499	34.4%	2.4%	9.3%	4.4%	1.4%	0.2%	6.1%	4.2%	2.6%	2.3%	0.8%	30.0%	1.0%	0.5%	0.6%
CSP Troop L	8,981	33.2%	1.9%	22.0%	5.3%	4.5%	0.9%	7.5%	3.9%	1.7%	2.5%	3.4%	10.6%	0.6%	1.1%	1.0%
Branford	5,271	32.3%	12.5%	18.1%	3.5%	0.5%	0.2%	3.5%	4.5%	0.4%	7.5%	1.5%	0.6%	13.7%	0.4%	0.7%
CSP Troop A	16,762	32.1%	3.4%	15.5%	3.1%	2.5%	0.1%	11.7%	6.1%	2.9%	2.1%	1.9%	14.5%	1.8%	1.8%	0.5%
Seymour	3,883	32.0%	8.4%	1.6%	15.9%	2.3%	0.5%	6.8%	2.6%	3.8%	16.7%	0.3%	1.2%	7.0%	0.1%	0.8%
Clinton	1,504	31.8%	7.0%	2.3%	12.8%	2.1%	0.9%	13.2%	2.5%	5.7%	10.1%	0.3%	2.4%	7.3%	0.5%	1.1%
Fairfield	8,320	31.4%	15.4%	7.2%	4.7%	2.0%	0.2%	5.8%	3.8%	9.3%	5.3%	2.8%	2.8%	7.6%	0.7%	0.9%
CSP Troop B	6,437	31.4%	1.4%	18.6%	6.2%	1.5%	0.2%	6.0%	3.8%	2.4%	4.6%	1.4%	19.9%	1.3%	0.7%	0.6%
CSP Troop E	15,525	31.1%	3.2%	10.2%	3.6%	1.2%	0.1%	9.8%	4.8%	2.0%	1.7%	1.6%	27.4%	2.1%	1.0%	0.3%
Wilton	5,219	30.9%	8.0%	7.2%	19.3%	1.8%	0.2%	10.8%	2.5%	0.8%	6.4%	0.2%	0.6%	8.9%	0.3%	2.2%
East Lyme	379	30.3%	2.4%	4.7%	21.6%	1.3%	0.0%	10.3%	4.7%	3.2%	5.5%	3.2%	6.9%	5.3%	0.5%	0.0%
Groton Long Point	66	30.3%	9.1%	0.0%	4.5%	0.0%	1.5%	0.0%	4.5%	12.1%	33.3%	1.5%	0.0%	0.0%	3.0%	0.0%

Table B.2: Basis for Stop (Sorted by % Speeding)

Department Name	Total	Speed Related	Cell Phone	Registration	Defective Lights	Display of Plates	Equipment Violation	Moving Violation	Other	Seatbelt	Stop Sign	Administrative Offense	STC Violation	Traffic Control Signal	Unlicensed Operation	Window Tint
North Branford	843	30.2%	3.9%	18.3%	2.3%	0.6%	0.4%	12.8%	7.0%	0.6%	5.3%	1.8%	11.9%	4.4%	0.5%	0.1%
CSP Troop G	13,997	29.9%	4.5%	15.7%	2.6%	1.3%	0.0%	20.1%	5.1%	2.1%	0.3%	2.1%	12.2%	1.8%	1.8%	0.6%
CSP Troop D	11,154	29.8%	1.3%	11.0%	3.0%	1.9%	0.2%	6.9%	8.9%	0.7%	2.1%	2.4%	28.5%	1.7%	1.0%	0.4%
CSP Troop I	12,551	29.6%	4.4%	11.3%	3.7%	1.9%	0.1%	14.9%	4.5%	2.5%	1.5%	1.8%	20.2%	1.6%	1.3%	0.8%
CSP Troop H	17,680	29.5%	3.6%	13.1%	2.4%	1.1%	0.1%	12.3%	9.9%	1.4%	1.6%	2.0%	19.4%	1.7%	1.2%	0.6%
Derby	2,347	29.3%	10.0%	12.8%	5.4%	2.7%	0.2%	8.4%	2.5%	0.5%	8.7%	7.9%	1.9%	7.3%	0.5%	1.9%
Woodbridge	2,020	29.1%	17.2%	9.7%	7.0%	4.6%	0.1%	3.7%	4.3%	2.4%	5.0%	3.0%	6.0%	7.0%	0.8%	0.1%
Norwich	6,596	28.8%	7.4%	2.0%	18.1%	2.4%	0.2%	10.3%	4.9%	1.6%	7.3%	1.0%	0.7%	14.4%	0.5%	0.3%
Groton City	1,547	28.7%	16.1%	0.8%	11.8%	0.6%	0.1%	5.1%	2.5%	3.6%	17.0%	0.6%	0.5%	12.1%	0.6%	0.0%
Naugatuck	4,753	28.4%	11.0%	9.6%	12.8%	1.8%	0.1%	4.8%	4.5%	6.7%	8.6%	0.9%	0.5%	9.0%	0.3%	0.9%
Canton	931	28.1%	18.8%	1.1%	7.8%	0.5%	0.3%	8.8%	3.8%	1.3%	18.4%	0.6%	0.5%	8.7%	0.5%	0.6%
CSP Troop K	15,428	27.3%	2.8%	12.7%	2.6%	3.0%	0.1%	4.8%	5.7%	2.2%	3.3%	1.4%	31.6%	1.1%	0.9%	0.3%
Shelton	561	27.3%	2.3%	12.5%	10.0%	2.1%	0.5%	12.1%	4.5%	0.4%	11.1%	0.9%	2.5%	12.7%	0.2%	1.1%
Rocky Hill	4,055	27.1%	15.1%	5.4%	19.3%	2.0%	0.1%	5.6%	1.1%	0.8%	14.9%	0.5%	0.9%	6.8%	0.2%	0.0%
Watertown	1,665	26.8%	15.5%	13.0%	6.4%	5.2%	0.1%	6.2%	2.1%	5.5%	10.4%	1.1%	1.3%	4.7%	0.5%	1.1%
Winsted	842	26.6%	2.5%	3.4%	15.6%	9.9%	0.8%	11.3%	4.6%	6.1%	6.5%	2.9%	2.7%	6.2%	0.8%	0.1%
CSP Troop F	17,331	26.3%	4.1%	12.1%	3.7%	0.8%	0.5%	8.3%	5.7%	3.4%	2.3%	0.8%	29.8%	1.1%	0.6%	0.5%
East Hartford	7,475	26.1%	13.9%	12.5%	1.7%	3.5%	0.1%	3.3%	1.2%	9.7%	8.2%	12.3%	1.5%	2.7%	0.4%	2.7%
Westport	7,461	26.0%	22.4%	7.2%	7.3%	2.7%	0.2%	4.7%	1.9%	1.7%	10.8%	0.5%	5.7%	7.4%	0.2%	1.4%
Greenwich	7,546	25.5%	11.6%	11.1%	9.6%	3.7%	0.1%	10.5%	2.8%	0.8%	11.0%	0.5%	3.6%	7.1%	0.7%	1.3%
Monroe	4,241	24.2%	15.6%	8.7%	11.9%	3.8%	0.3%	11.7%	2.7%	2.5%	13.3%	0.5%	1.1%	2.4%	0.2%	1.0%
Plainville	3,450	23.9%	4.8%	7.9%	18.4%	5.0%	0.1%	7.7%	1.0%	4.9%	12.6%	0.9%	0.6%	10.1%	0.2%	1.8%
Berlin	5,441	23.8%	19.0%	5.7%	12.2%	2.8%	0.1%	9.8%	1.8%	6.0%	4.5%	1.0%	1.9%	10.7%	0.4%	0.2%
Southern CT State University	517	23.6%	12.2%	1.7%	14.1%	0.6%	0.0%	6.4%	4.8%	9.7%	4.6%	2.5%	1.2%	17.4%	1.2%	0.0%
Manchester	10,589	23.1%	12.3%	8.7%	12.2%	2.2%	0.2%	4.1%	1.1%	14.7%	8.1%	2.2%	0.5%	8.8%	0.4%	1.5%
Danbury	6,160	22.9%	34.9%	6.8%	5.6%	1.3%	0.1%	5.0%	3.4%	2.8%	5.3%	0.5%	0.7%	9.5%	0.7%	0.4%
Farmington	5,212	22.9%	16.1%	15.0%	8.5%	1.5%	0.1%	11.1%	1.1%	1.2%	6.2%	1.0%	8.3%	6.7%	0.2%	0.2%
Glastonbury	4,166	22.7%	14.8%	9.4%	18.2%	2.2%	0.2%	7.7%	2.3%	5.0%	7.6%	2.3%	0.4%	5.4%	0.4%	1.5%
Waterbury	3,052	22.4%	0.6%	16.6%	3.9%	5.2%	0.3%	9.8%	2.6%	1.0%	10.5%	7.1%	2.4%	14.1%	1.6%	2.1%
Darien	3,568	22.4%	11.2%	9.4%	12.6%	11.8%	0.1%	5.0%	2.3%	5.0%	6.7%	0.5%	6.1%	5.1%	0.1%	1.8%
Middletown	3,247	21.6%	2.8%	6.7%	19.9%	5.0%	0.5%	9.5%	4.4%	1.2%	13.2%	2.6%	0.3%	10.5%	0.4%	1.4%
Torrington	7,414	21.5%	1.9%	1.8%	27.7%	3.7%	0.5%	3.4%	2.3%	0.6%	23.4%	0.6%	1.3%	10.7%	0.3%	0.3%
Brookfield	2,187	21.5%	23.4%	1.6%	16.7%	1.1%	0.1%	10.2%	2.1%	3.4%	9.7%	0.0%	0.0%	9.9%	0.0%	0.3%
New Britain	7,328	21.4%	15.2%	5.3%	7.0%	2.5%	0.2%	6.8%	2.3%	4.0%	21.3%	3.1%	0.3%	8.3%	0.5%	1.9%
Groton Town	4,396	21.3%	6.5%	13.9%	13.9%	3.2%	0.1%	18.2%	1.5%	1.5%	5.1%	1.3%	1.4%	10.4%	0.3%	1.2%
Newington	5,541	21.2%	3.5%	17.1%	17.0%	2.6%	1.7%	10.3%	1.9%	0.7%	7.3%	2.0%	0.2%	10.6%	0.5%	3.6%
Wethersfield	2,899	21.0%	4.3%	11.6%	11.7%	8.2%	0.3%	12.5%	2.9%	1.5%	7.3%	5.3%	0.9%	9.8%	0.2%	2.6%
North Haven	2,633	21.0%	7.5%	21.2%	11.0%	3.3%	0.2%	6.3%	2.4%	2.8%	4.2%	7.9%	1.2%	8.7%	1.3%	1.0%
West Hartford	6,207	20.8%	30.4%	8.6%	4.5%	2.7%	0.2%	7.8%	3.0%	3.0%	4.3%	3.1%	1.0%	8.9%	0.5%	1.3%
Bloomfield	2,226	19.8%	5.8%	5.8%	9.8%	3.3%	0.1%	9.3%	1.1%	1.3%	16.1%	0.7%	4.4%	21.7%	0.1%	0.6%
Ansonia	3,569	19.7%	8.7%	3.4%	14.9%	2.2%	0.4%	5.4%	3.4%	2.1%	28.3%	0.9%	0.0%	9.2%	0.4%	0.8%
Vernon	3,378	18.7%	2.6%	3.6%	18.0%	3.9%	0.9%	29.7%	1.9%	1.1%	6.3%	0.5%	1.7%	10.7%	0.1%	0.3%
Plainfield	1,669	18.7%	3.5%	2.0%	17.7%	4.2%	0.3%	18.1%	3.9%	7.7%	16.8%	2.5%	0.0%	3.7%	0.5%	0.4%
South Windsor	3,850	18.4%	14.6%	8.4%	12.4%	7.2%	0.2%	4.5%	1.7%	11.9%	12.8%	0.9%	0.5%	6.0%	0.1%	0.2%
Cromwell	1,561	17.9%	13.2%	9.9%	17.0%	1.8%	0.2%	8.5%	3.4%	1.9%	9.5%	0.6%	0.4%	14.7%	0.3%	0.8%
Plymouth	1,650	17.9%	21.2%	8.1%	9.2%	4.3%	0.4%	7.9%	5.6%	2.8%	13.1%	3.6%	0.0%	3.0%	1.1%	1.9%

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Department Name	Total	Speed Related	Cell Phone	Registration	Defective Lights	Display of Plates	Equipment Violation	Moving Violation	Other	Seatbelt	Stop Sign	Administrative Offense	STC Violation	Traffic Control Signal	Unlicensed Operation	Window Tint
East Haven	2,503	16.9%	7.1%	5.3%	9.0%	10.1%	0.3%	11.6%	3.4%	1.3%	22.7%	1.6%	0.4%	6.8%	0.6%	2.8%
Norwalk	6,007	16.9%	16.2%	11.7%	7.2%	3.4%	0.3%	6.8%	4.3%	3.8%	11.1%	1.5%	4.3%	9.4%	1.2%	2.1%
Meriden	1,578	16.8%	14.6%	3.4%	7.4%	1.3%	0.3%	5.3%	15.0%	2.6%	18.6%	3.2%	1.0%	8.9%	1.0%	0.6%
Stratford	3,697	13.9%	6.9%	16.5%	10.5%	6.1%	0.2%	8.7%	4.2%	3.2%	12.0%	3.2%	1.4%	9.7%	0.6%	3.0%
Milford	4,462	13.8%	17.4%	2.7%	13.0%	6.7%	0.0%	3.5%	14.6%	3.7%	12.7%	1.7%	0.4%	9.3%	0.2%	0.2%
West Haven	8,790	12.0%	5.4%	20.6%	21.0%	6.0%	0.7%	5.4%	2.5%	1.1%	12.3%	1.1%	0.3%	9.2%	1.0%	1.5%
University of Connecticut	3,894	10.9%	9.9%	3.8%	26.2%	5.6%	0.6%	14.6%	3.8%	1.1%	17.5%	0.3%	1.3%	3.0%	0.1%	1.4%
New Haven	19,038	10.8%	4.5%	5.1%	8.4%	6.3%	0.0%	1.7%	20.2%	3.4%	6.8%	1.3%	0.9%	24.6%	0.4%	5.6%
Stamford	13,399	10.7%	21.8%	0.6%	13.5%	2.2%	0.1%	5.0%	5.5%	4.0%	9.2%	0.1%	0.3%	24.4%	0.2%	2.4%
Willimantic	2,331	10.2%	14.4%	8.0%	17.9%	2.2%	0.5%	7.1%	8.6%	3.6%	13.3%	2.4%	2.1%	8.1%	0.5%	1.2%
Wallingford	7,909	10.1%	13.9%	9.4%	11.1%	8.0%	0.8%	7.5%	5.4%	7.9%	8.8%	3.4%	0.5%	9.2%	0.6%	3.5%
Hamden	5,888	9.9%	27.4%	6.1%	6.3%	0.8%	0.2%	4.2%	18.2%	6.2%	4.9%	2.0%	4.3%	9.0%	0.5%	0.2%
Cheshire	2,313	9.3%	5.0%	0.7%	2.6%	0.9%	0.1%	2.1%	73.4%	1.6%	1.2%	0.6%	0.1%	1.8%	0.1%	0.5%
Hartford	8,243	9.2%	14.4%	2.0%	12.0%	6.3%	0.2%	6.8%	10.9%	4.1%	15.1%	1.6%	0.6%	11.7%	0.2%	4.7%
Middlebury	34	8.8%	0.0%	2.9%	8.8%	2.9%	0.0%	20.6%	38.2%	0.0%	2.9%	2.9%	5.9%	5.9%	0.0%	0.0%
Bridgeport	2,262	6.6%	23.3%	5.5%	6.1%	2.7%	0.4%	6.7%	2.9%	10.5%	12.1%	3.7%	0.5%	15.6%	1.9%	1.4%
Trumbull	2,749	5.4%	22.8%	23.9%	12.1%	8.3%	0.2%	3.6%	2.9%	2.2%	7.6%	1.7%	1.5%	6.1%	0.5%	1.3%
Eastern CT State University	207	3.9%	3.9%	0.5%	13.0%	0.0%	1.0%	1.4%	7.2%	3.4%	65.2%	0.0%	0.0%	0.0%	0.0%	0.5%
Orange	2,821	2.5%	0.9%	1.8%	1.0%	0.6%	0.0%	0.8%	87.9%	0.1%	0.6%	0.7%	0.7%	2.2%	0.0%	0.1%
Yale University	1,354	1.3%	1.0%	5.7%	9.5%	5.7%	0.0%	2.4%	35.6%	0.2%	1.2%	3.3%	0.0%	32.9%	0.7%	0.5%
State Capitol Police	174	0.6%	0.0%	0.0%	30.5%	1.1%	0.0%	16.1%	2.9%	0.0%	4.6%	0.6%	0.6%	43.1%	0.0%	0.0%
Western CT State University	7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	14.3%	57.1%	0.0%	0.0%	0.0%	0.0%	14.3%	0.0%	14.3%

Table B.3: Basis for Stop (Sorted by % Registration Violation)

Department Name	Total	Registration	Speed Related	Cell Phone	Defective Lights	Display of Plates	Equipment Violation	Moving Violation	Other	Seatbelt	Stop Sign	Administrative Offense	STC Violation	Traffic Control Signal	Unlicensed Operation	Window Tint
Trumbull	2,749	23.9%	5.4%	22.8%	12.1%	8.3%	0.2%	3.6%	2.9%	2.2%	7.6%	1.7%	1.5%	6.1%	0.5%	1.3%
CSP Troop L	8,981	22.0%	33.2%	1.9%	5.3%	4.5%	0.9%	7.5%	3.9%	1.7%	2.5%	3.4%	10.6%	0.6%	1.1%	1.0%
North Haven	2,633	21.2%	21.0%	7.5%	11.0%	3.3%	0.2%	6.3%	2.4%	2.8%	4.2%	7.9%	1.2%	8.7%	1.3%	1.0%
West Haven	8,790	20.6%	12.0%	5.4%	21.0%	6.0%	0.7%	5.4%	2.5%	1.1%	12.3%	1.1%	0.3%	9.2%	1.0%	1.5%
Redding	2,282	18.8%	51.3%	2.0%	8.2%	0.3%	0.0%	6.5%	2.8%	2.5%	5.7%	0.6%	0.4%	0.4%	0.4%	0.2%
CSP Troop B	6,437	18.6%	31.4%	1.4%	6.2%	1.5%	0.2%	6.0%	3.8%	2.4%	4.6%	1.4%	19.9%	1.3%	0.7%	0.6%
North Branford	843	18.3%	30.2%	3.9%	2.3%	0.6%	0.4%	12.8%	7.0%	0.6%	5.3%	1.8%	11.9%	4.4%	0.5%	0.1%
Branford	5,271	18.1%	32.3%	12.5%	3.5%	0.5%	0.2%	3.5%	4.5%	0.4%	7.5%	1.5%	0.6%	13.7%	0.4%	0.7%
Newington	5,541	17.1%	21.2%	3.5%	17.0%	2.6%	1.7%	10.3%	1.9%	0.7%	7.3%	2.0%	0.2%	10.6%	0.5%	3.6%
Waterbury	3,052	16.6%	22.4%	0.6%	3.9%	5.2%	0.3%	9.8%	2.6%	1.0%	10.5%	7.1%	2.4%	14.1%	1.6%	2.1%
Stratford	3,697	16.5%	13.9%	6.9%	10.5%	6.1%	0.2%	8.7%	4.2%	3.2%	12.0%	3.2%	1.4%	9.7%	0.6%	3.0%
CSP Troop G	13,997	15.7%	29.9%	4.5%	2.6%	1.3%	0.0%	20.1%	5.1%	2.1%	0.3%	2.1%	12.2%	1.8%	1.8%	0.6%
CSP Troop A	16,762	15.5%	32.1%	3.4%	3.1%	2.5%	0.1%	11.7%	6.1%	2.9%	2.1%	1.9%	14.5%	1.8%	1.8%	0.5%
Farmington	5,212	15.0%	22.9%	16.1%	8.5%	1.5%	0.1%	11.1%	1.1%	1.2%	6.2%	1.0%	8.3%	6.7%	0.2%	0.2%
Groton Town	4,396	13.9%	21.3%	6.5%	13.9%	3.2%	0.1%	18.2%	1.5%	1.5%	5.1%	1.3%	1.4%	10.4%	0.3%	1.2%
Easton	1,203	13.4%	53.5%	1.7%	3.2%	0.8%	0.2%	2.2%	4.0%	2.4%	13.9%	0.6%	2.0%	0.7%	1.1%	0.2%
CSP Troop H	17,680	13.1%	29.5%	3.6%	2.4%	1.1%	0.1%	12.3%	9.9%	1.4%	1.6%	2.0%	19.4%	1.7%	1.2%	0.6%
Watertown	1,665	13.0%	26.8%	15.5%	6.4%	5.2%	0.1%	6.2%	2.1%	5.5%	10.4%	1.1%	1.3%	4.7%	0.5%	1.1%
Derby	2,347	12.8%	29.3%	10.0%	5.4%	2.7%	0.2%	8.4%	2.5%	0.5%	8.7%	7.9%	1.9%	7.3%	0.5%	1.9%
CSP Troop K	15,428	12.7%	27.3%	2.8%	2.6%	3.0%	0.1%	4.8%	5.7%	2.2%	3.3%	1.4%	31.6%	1.1%	0.9%	0.3%
East Hartford	7,475	12.5%	26.1%	13.9%	1.7%	3.5%	0.1%	3.3%	1.2%	9.7%	8.2%	12.3%	1.5%	2.7%	0.4%	2.7%
Shelton	561	12.5%	27.3%	2.3%	10.0%	2.1%	0.5%	12.1%	4.5%	0.4%	11.1%	0.9%	2.5%	12.7%	0.2%	1.1%
CSP Troop F	17,331	12.1%	26.3%	4.1%	3.7%	0.8%	0.5%	8.3%	5.7%	3.4%	2.3%	0.8%	29.8%	1.1%	0.6%	0.5%
Norwalk	6,007	11.7%	16.9%	16.2%	7.2%	3.4%	0.3%	6.8%	4.3%	3.8%	11.1%	1.5%	4.3%	9.4%	1.2%	2.1%
Wethersfield	2,899	11.6%	21.0%	4.3%	11.7%	8.2%	0.3%	12.5%	2.9%	1.5%	7.3%	5.3%	0.9%	9.8%	0.2%	2.6%
CSP Troop I	12,551	11.3%	29.6%	4.4%	3.7%	1.9%	0.1%	14.9%	4.5%	2.5%	1.5%	1.8%	20.2%	1.6%	1.3%	0.8%
Greenwich	7,546	11.1%	25.5%	11.6%	9.6%	3.7%	0.1%	10.5%	2.8%	0.8%	11.0%	0.5%	3.6%	7.1%	0.7%	1.3%
CSP Troop D	11,154	11.0%	29.8%	1.3%	3.0%	1.9%	0.2%	6.9%	8.9%	0.7%	2.1%	2.4%	28.5%	1.7%	1.0%	0.4%
Madison	3,077	10.8%	36.5%	6.9%	10.9%	1.9%	0.4%	9.2%	2.1%	2.3%	9.2%	0.7%	6.1%	2.7%	0.3%	0.2%
CSP Troop E	15,525	10.2%	31.1%	3.2%	3.6%	1.2%	0.1%	9.8%	4.8%	2.0%	1.7%	1.6%	27.4%	2.1%	1.0%	0.3%
Cromwell	1,561	9.9%	17.9%	13.2%	17.0%	1.8%	0.2%	8.5%	3.4%	1.9%	9.5%	0.6%	0.4%	14.7%	0.3%	0.8%
Woodbridge	2,020	9.7%	29.1%	17.2%	7.0%	4.6%	0.1%	3.7%	4.3%	2.4%	5.0%	3.0%	6.0%	7.0%	0.8%	0.1%
Naugatuck	4,753	9.6%	28.4%	11.0%	12.8%	1.8%	0.1%	4.8%	4.5%	6.7%	8.6%	0.9%	0.5%	9.0%	0.3%	0.9%
Darien	3,568	9.4%	22.4%	11.2%	12.6%	11.8%	0.1%	5.0%	2.3%	5.0%	6.7%	0.5%	6.1%	5.1%	0.1%	1.8%
Glastonbury	4,166	9.4%	22.7%	14.8%	18.2%	2.2%	0.2%	7.7%	2.3%	5.0%	7.6%	2.3%	0.4%	5.4%	0.4%	1.5%
Wallingford	7,909	9.4%	10.1%	13.9%	11.1%	8.0%	0.8%	7.5%	5.4%	7.9%	8.8%	3.4%	0.5%	9.2%	0.6%	3.5%
Bristol	3,791	9.3%	35.3%	9.0%	5.4%	1.7%	0.2%	8.3%	2.9%	5.3%	8.0%	2.1%	0.2%	11.2%	0.8%	0.3%
CSP Troop C	20,499	9.3%	34.4%	2.4%	4.4%	1.4%	0.2%	6.1%	4.2%	2.6%	2.3%	0.8%	30.0%	1.0%	0.5%	0.6%
Monroe	4,241	8.7%	24.2%	15.6%	11.9%	3.8%	0.3%	11.7%	2.7%	2.5%	13.3%	0.5%	1.1%	2.4%	0.2%	1.0%
New Canaan	5,492	8.7%	35.7%	14.1%	16.4%	3.1%	0.2%	5.7%	1.6%	1.1%	6.6%	0.2%	0.2%	4.4%	0.3%	1.7%
Manchester	10,589	8.7%	23.1%	12.3%	12.2%	2.2%	0.2%	4.1%	1.1%	14.7%	8.1%	2.2%	0.5%	8.8%	0.4%	1.5%
West Hartford	6,207	8.6%	20.8%	30.4%	4.5%	2.7%	0.2%	7.8%	3.0%	3.0%	4.3%	3.1%	1.0%	8.9%	0.5%	1.3%
South Windsor	3,850	8.4%	18.4%	14.6%	12.4%	7.2%	0.2%	4.5%	1.7%	11.9%	12.8%	0.9%	0.5%	6.0%	0.1%	0.2%
Plymouth	1,650	8.1%	17.9%	21.2%	9.2%	4.3%	0.4%	7.9%	5.6%	2.8%	13.1%	3.6%	0.0%	3.0%	1.1%	1.9%
Willimantic	2,331	8.0%	10.2%	14.4%	17.9%	2.2%	0.5%	7.1%	8.6%	3.6%	13.3%	2.4%	2.1%	8.1%	0.5%	1.2%
Plainville	3,450	7.9%	23.9%	4.8%	18.4%	5.0%	0.1%	7.7%	1.0%	4.9%	12.6%	0.9%	0.6%	10.1%	0.2%	1.8%
Coventry	1,389	7.6%	38.4%	6.8%	15.2%	1.8%	0.5%	6.0%	3.5%	3.3%	3.7%	2.0%	6.9%	3.6%	0.5%	0.2%

Table B.3: Basis for Stop (Sorted by % Registration Violation)

Department Name	Total	Registration	Speed Related	Cell Phone	Defective Lights	Display of Plates	Equipment Violation	Moving Violation	Other	Seatbelt	Stop Sign	Administrative Offense	STC Violation	Traffic Control Signal	Unlicensed Operation	Window Tint
Department of Motor Vehicle	1,575	7.4%	35.4%	9.3%	2.2%	2.3%	2.0%	15.3%	5.9%	1.6%	1.7%	0.7%	4.9%	4.9%	1.4%	5.1%
Fairfield	8,320	7.2%	31.4%	15.4%	4.7%	2.0%	0.2%	5.8%	3.8%	9.3%	5.3%	2.8%	2.8%	7.6%	0.7%	0.9%
Wilton	5,219	7.2%	30.9%	8.0%	19.3%	1.8%	0.2%	10.8%	2.5%	0.8%	6.4%	0.2%	0.6%	8.9%	0.3%	2.2%
Westport	7,461	7.2%	26.0%	22.4%	7.3%	2.7%	0.2%	4.7%	1.9%	1.7%	10.8%	0.5%	5.7%	7.4%	0.2%	1.4%
East Hampton	769	7.0%	39.8%	6.8%	7.7%	1.4%	0.7%	10.7%	3.5%	2.0%	4.9%	0.7%	0.0%	14.3%	0.0%	0.7%
Ridgefield	6,733	6.9%	57.9%	11.9%	7.6%	0.1%	0.0%	1.5%	1.6%	1.8%	5.7%	0.1%	1.3%	2.7%	0.2%	0.6%
Danbury	6,160	6.8%	22.9%	34.9%	5.6%	1.3%	0.1%	5.0%	3.4%	2.8%	5.3%	0.5%	0.7%	9.5%	0.7%	0.4%
Middletown	3,247	6.7%	21.6%	2.8%	19.9%	5.0%	0.5%	9.5%	4.4%	1.2%	13.2%	2.6%	0.3%	10.5%	0.4%	1.4%
Newtown	3,547	6.3%	53.2%	5.3%	6.6%	1.8%	0.2%	11.0%	1.9%	0.9%	6.0%	0.5%	1.9%	3.9%	0.4%	0.1%
Hamden	5,888	6.1%	9.9%	27.4%	6.3%	0.8%	0.2%	4.2%	18.2%	6.2%	4.9%	2.0%	4.3%	9.0%	0.5%	0.2%
Bloomfield	2,226	5.8%	19.8%	5.8%	9.8%	3.3%	0.1%	9.3%	1.1%	1.3%	16.1%	0.7%	4.4%	21.7%	0.1%	0.6%
Yale University	1,354	5.7%	1.3%	1.0%	9.5%	5.7%	0.0%	2.4%	35.6%	0.2%	1.2%	3.3%	0.0%	32.9%	0.7%	0.5%
Berlin	5,441	5.7%	23.8%	19.0%	12.2%	2.8%	0.1%	9.8%	1.8%	6.0%	4.5%	1.0%	1.9%	10.7%	0.4%	0.2%
Bridgeport	2,262	5.5%	6.6%	23.3%	6.1%	2.7%	0.4%	6.7%	2.9%	10.5%	12.1%	3.7%	0.5%	15.6%	1.9%	1.4%
Avon	1,243	5.5%	42.5%	3.3%	9.5%	0.8%	0.0%	14.0%	5.5%	0.1%	11.5%	0.5%	0.1%	6.4%	0.3%	0.1%
Central CT State University	1,848	5.5%	34.7%	6.5%	10.4%	2.1%	0.1%	9.0%	3.9%	4.2%	6.4%	0.5%	4.2%	11.8%	0.5%	0.2%
Rocky Hill	4,055	5.4%	27.1%	15.1%	19.3%	2.0%	0.1%	5.6%	1.1%	0.8%	14.9%	0.5%	0.9%	6.8%	0.2%	0.0%
East Haven	2,503	5.3%	16.9%	7.1%	9.0%	10.1%	0.3%	11.6%	3.4%	1.3%	22.7%	1.6%	0.4%	6.8%	0.6%	2.8%
New Britain	7,328	5.3%	21.4%	15.2%	7.0%	2.5%	0.2%	6.8%	2.3%	4.0%	21.3%	3.1%	0.3%	8.3%	0.5%	1.9%
New Haven	19,038	5.1%	10.8%	4.5%	8.4%	6.3%	0.0%	1.7%	20.2%	3.4%	6.8%	1.3%	0.9%	24.6%	0.4%	5.6%
East Windsor	1,752	5.1%	35.3%	12.6%	18.4%	1.4%	0.3%	7.2%	3.2%	0.6%	7.5%	1.9%	0.9%	4.9%	0.5%	0.2%
Enfield	8,806	5.0%	54.5%	2.6%	7.4%	2.2%	0.4%	6.7%	1.6%	4.5%	2.9%	1.1%	0.5%	9.7%	0.3%	0.6%
New Milford	2,318	5.0%	51.5%	3.6%	12.4%	1.1%	0.9%	6.8%	3.5%	0.6%	4.3%	0.7%	0.3%	8.8%	0.3%	0.2%
East Lyme	379	4.7%	30.3%	2.4%	21.6%	1.3%	0.0%	10.3%	4.7%	3.2%	5.5%	3.2%	6.9%	5.3%	0.5%	0.0%
Stonington	4,976	4.6%	38.0%	6.4%	12.5%	0.2%	0.1%	10.2%	6.0%	1.5%	8.2%	1.1%	4.3%	6.3%	0.6%	0.1%
Old Saybrook	2,388	3.9%	43.2%	8.3%	14.2%	0.4%	0.1%	6.1%	2.9%	1.2%	10.2%	0.7%	1.1%	7.0%	0.3%	0.4%
University of Connecticut	3,894	3.8%	10.9%	9.9%	26.2%	5.6%	0.6%	14.6%	3.8%	1.1%	17.5%	0.3%	1.3%	3.0%	0.1%	1.4%
Vernon	3,378	3.6%	18.7%	2.6%	18.0%	3.9%	0.9%	29.7%	1.9%	1.1%	6.3%	0.5%	1.7%	10.7%	0.1%	0.3%
Southington	5,123	3.5%	50.4%	7.0%	15.9%	1.3%	0.1%	5.0%	1.2%	1.9%	4.3%	0.4%	1.6%	6.6%	0.3%	0.5%
Winsted	842	3.4%	26.6%	2.5%	15.6%	9.9%	0.8%	11.3%	4.6%	6.1%	6.5%	2.9%	2.7%	6.2%	0.8%	0.1%
Ansonia	3,569	3.4%	19.7%	8.7%	14.9%	2.2%	0.4%	5.4%	3.4%	2.1%	28.3%	0.9%	0.0%	9.2%	0.4%	0.8%
Meriden	1,578	3.4%	16.8%	14.6%	7.4%	1.3%	0.3%	5.3%	15.0%	2.6%	18.6%	3.2%	1.0%	8.9%	1.0%	0.6%
Granby	548	3.1%	35.0%	19.0%	12.0%	1.8%	0.2%	8.2%	1.8%	5.7%	6.6%	0.4%	0.2%	5.5%	0.4%	0.2%
Middlebury	34	2.9%	8.8%	0.0%	8.8%	2.9%	0.0%	20.6%	38.2%	0.0%	2.9%	2.9%	5.9%	5.9%	0.0%	0.0%
Portland	358	2.8%	48.9%	1.4%	8.1%	0.6%	0.0%	6.1%	2.0%	0.0%	12.8%	0.3%	0.0%	16.8%	0.3%	0.0%
Windsor	8,485	2.7%	38.1%	5.5%	18.4%	2.5%	0.0%	2.9%	0.9%	2.8%	8.9%	0.4%	0.4%	15.5%	0.2%	0.7%
Milford	4,462	2.7%	13.8%	17.4%	13.0%	6.7%	0.0%	3.5%	14.6%	3.7%	12.7%	1.7%	0.4%	9.3%	0.2%	0.2%
Windsor Locks	1,124	2.7%	52.6%	6.3%	7.4%	1.6%	0.3%	4.9%	2.8%	4.9%	5.2%	1.2%	0.2%	9.0%	0.3%	0.9%
Clinton	1,504	2.3%	31.8%	7.0%	12.8%	2.1%	0.9%	13.2%	2.5%	5.7%	10.1%	0.3%	2.4%	7.3%	0.5%	1.1%
Ledyard	2,191	2.1%	63.5%	0.8%	13.7%	2.0%	0.1%	7.1%	3.8%	0.2%	1.1%	1.3%	0.0%	1.2%	0.6%	2.3%
Bethel	3,107	2.1%	50.9%	11.5%	7.4%	0.8%	0.1%	2.0%	1.5%	3.6%	13.4%	0.3%	0.3%	4.1%	0.1%	1.9%
Hartford	8,243	2.0%	9.2%	14.4%	12.0%	6.3%	0.2%	6.8%	10.9%	4.1%	15.1%	1.6%	0.6%	11.7%	0.2%	4.7%
Plainfield	1,669	2.0%	18.7%	3.5%	17.7%	4.2%	0.3%	18.1%	3.9%	7.7%	16.8%	2.5%	0.0%	3.7%	0.5%	0.4%
Norwich	6,596	2.0%	28.8%	7.4%	18.1%	2.4%	0.2%	10.3%	4.9%	1.6%	7.3%	1.0%	0.7%	14.4%	0.5%	0.3%
CSP Headquarters	14,090	2.0%	58.8%	11.9%	0.3%	0.2%	0.0%	5.1%	1.4%	14.6%	0.2%	0.7%	3.8%	0.6%	0.3%	0.2%
Orange	2,821	1.8%	2.5%	0.9%	1.0%	0.6%	0.0%	0.8%	87.9%	0.1%	0.6%	0.7%	0.7%	2.2%	0.0%	0.1%
Torrington	7,414	1.8%	21.5%	1.9%	27.7%	3.7%	0.5%	3.4%	2.3%	0.6%	23.4%	0.6%	1.3%	10.7%	0.3%	0.3%

Table B.3: Basis for Stop (Sorted by % Registration Violation)

Department Name	Total	Registration	Speed Related	Cell Phone	Defective Lights	Display of Plates	Equipment Violation	Moving Violation	Other	Seatbelt	Stop Sign	Administrative Offense	STC Violation	Traffic Control Signal	Unlicensed Operation	Window Tint
Thomaston	1,278	1.8%	57.3%	1.0%	13.3%	1.6%	0.3%	6.1%	4.7%	1.8%	5.6%	1.6%	0.2%	4.2%	0.2%	0.4%
Southern CT State University	517	1.7%	23.6%	12.2%	14.1%	0.6%	0.0%	6.4%	4.8%	9.7%	4.6%	2.5%	1.2%	17.4%	1.2%	0.0%
Wolcott	120	1.7%	51.7%	2.5%	5.0%	0.8%	0.0%	5.8%	6.7%	1.7%	11.7%	3.3%	0.0%	4.2%	0.8%	4.2%
Seymour	3,883	1.6%	32.0%	8.4%	15.9%	2.3%	0.5%	6.8%	2.6%	3.8%	16.7%	0.3%	1.2%	7.0%	0.1%	0.8%
Brookfield	2,187	1.6%	21.5%	23.4%	16.7%	1.1%	0.1%	10.2%	2.1%	3.4%	9.7%	0.0%	0.0%	9.9%	0.0%	0.3%
Putnam	1,069	1.3%	37.0%	13.0%	16.2%	7.2%	0.3%	7.8%	2.6%	2.1%	2.7%	1.2%	0.0%	7.9%	0.5%	0.3%
Suffield	665	1.2%	53.2%	1.1%	15.9%	0.8%	0.0%	19.1%	1.4%	0.2%	2.9%	0.5%	0.2%	3.0%	0.8%	0.0%
Canton	931	1.1%	28.1%	18.8%	7.8%	0.5%	0.3%	8.8%	3.8%	1.3%	18.4%	0.6%	0.5%	8.7%	0.5%	0.6%
Simsbury	3,356	1.0%	57.4%	9.8%	9.6%	0.8%	0.1%	4.5%	1.6%	1.5%	6.2%	0.1%	0.1%	6.9%	0.1%	0.2%
Guilford	2,372	1.0%	54.1%	11.6%	9.3%	0.2%	0.0%	2.7%	1.5%	2.7%	9.0%	0.1%	0.1%	7.4%	0.3%	0.0%
Groton City	1,547	0.8%	28.7%	16.1%	11.8%	0.6%	0.1%	5.1%	2.5%	3.6%	17.0%	0.6%	0.5%	12.1%	0.6%	0.0%
Weston	611	0.8%	57.8%	1.5%	7.9%	0.5%	0.0%	4.9%	5.2%	0.2%	19.5%	0.2%	0.2%	1.3%	0.2%	0.0%
Cheshire	2,313	0.7%	9.3%	5.0%	2.6%	0.9%	0.1%	2.1%	73.4%	1.6%	1.2%	0.6%	0.1%	1.8%	0.1%	0.5%
Waterford	4,502	0.7%	44.2%	5.7%	14.1%	7.1%	0.1%	10.3%	2.6%	2.5%	1.1%	0.4%	0.3%	9.9%	0.1%	1.0%
New London	5,041	0.7%	36.2%	9.7%	6.9%	0.5%	0.1%	4.4%	3.7%	5.1%	12.6%	0.5%	1.9%	17.4%	0.2%	0.2%
Stamford	13,399	0.6%	10.7%	21.8%	13.5%	2.2%	0.1%	5.0%	5.5%	4.0%	9.2%	0.1%	0.3%	24.4%	0.2%	2.4%
Eastern CT State University	207	0.5%	3.9%	3.9%	13.0%	0.0%	1.0%	1.4%	7.2%	3.4%	65.2%	0.0%	0.0%	0.0%	0.0%	0.5%
Groton Long Point	66	0.0%	30.3%	9.1%	4.5%	0.0%	1.5%	0.0%	4.5%	12.1%	33.3%	1.5%	0.0%	0.0%	3.0%	0.0%
State Capitol Police	174	0.0%	0.6%	0.0%	30.5%	1.1%	0.0%	16.1%	2.9%	0.0%	4.6%	0.6%	0.6%	43.1%	0.0%	0.0%
Western CT State University	7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	14.3%	57.1%	0.0%	0.0%	0.0%	0.0%	14.3%	0.0%	14.3%

Table B.4: Basis for Stop (Sorted by % Cell Phone Violation)

Department Name	Total	Cell Phone	Speed Related	Registration	Defective Lights	Display of Plates	Equipment Violation	Moving Violation	Other	Seatbelt	Stop Sign	Administrative Offense	STC Violation	Traffic Control Signal	Unlicensed Operation	Window Tint
Danbury	6,160	34.9%	22.9%	6.8%	5.6%	1.3%	0.1%	5.0%	3.4%	2.8%	5.3%	0.5%	0.7%	9.5%	0.7%	0.4%
West Hartford	6,207	30.4%	20.8%	8.6%	4.5%	2.7%	0.2%	7.8%	3.0%	3.0%	4.3%	3.1%	1.0%	8.9%	0.5%	1.3%
Hamden	5,888	27.4%	9.9%	6.1%	6.3%	0.8%	0.2%	4.2%	18.2%	6.2%	4.9%	2.0%	4.3%	9.0%	0.5%	0.2%
Brookfield	2,187	23.4%	21.5%	1.6%	16.7%	1.1%	0.1%	10.2%	2.1%	3.4%	9.7%	0.0%	0.0%	9.9%	0.0%	0.3%
Bridgeport	2,262	23.3%	6.6%	5.5%	6.1%	2.7%	0.4%	6.7%	2.9%	10.5%	12.1%	3.7%	0.5%	15.6%	1.9%	1.4%
Trumbull	2,749	22.8%	5.4%	23.9%	12.1%	8.3%	0.2%	3.6%	2.9%	2.2%	7.6%	1.7%	1.5%	6.1%	0.5%	1.3%
Westport	7,461	22.4%	26.0%	7.2%	7.3%	2.7%	0.2%	4.7%	1.9%	1.7%	10.8%	0.5%	5.7%	7.4%	0.2%	1.4%
Stamford	13,399	21.8%	10.7%	0.6%	13.5%	2.2%	0.1%	5.0%	5.5%	4.0%	9.2%	0.1%	0.3%	24.4%	0.2%	2.4%
Plymouth	1,650	21.2%	17.9%	8.1%	9.2%	4.3%	0.4%	7.9%	5.6%	2.8%	13.1%	3.6%	0.0%	3.0%	1.1%	1.9%
Berlin	5,441	19.0%	23.8%	5.7%	12.2%	2.8%	0.1%	9.8%	1.8%	6.0%	4.5%	1.0%	1.9%	10.7%	0.4%	0.2%
Granby	548	19.0%	35.0%	3.1%	12.0%	1.8%	0.2%	8.2%	1.8%	5.7%	6.6%	0.4%	0.2%	5.5%	0.4%	0.2%
Canton	931	18.8%	28.1%	1.1%	7.8%	0.5%	0.3%	8.8%	3.8%	1.3%	18.4%	0.6%	0.5%	8.7%	0.5%	0.6%
Milford	4,462	17.4%	13.8%	2.7%	13.0%	6.7%	0.0%	3.5%	14.6%	3.7%	12.7%	1.7%	0.4%	9.3%	0.2%	0.2%
Woodbridge	2,020	17.2%	29.1%	9.7%	7.0%	4.6%	0.1%	3.7%	4.3%	2.4%	5.0%	3.0%	6.0%	7.0%	0.8%	0.1%
Norwalk	6,007	16.2%	16.9%	11.7%	7.2%	3.4%	0.3%	6.8%	4.3%	3.8%	11.1%	1.5%	4.3%	9.4%	1.2%	2.1%
Groton City	1,547	16.1%	28.7%	0.8%	11.8%	0.6%	0.1%	5.1%	2.5%	3.6%	17.0%	0.6%	0.5%	12.1%	0.6%	0.0%
Farmington	5,212	16.1%	22.9%	15.0%	8.5%	1.5%	0.1%	11.1%	1.1%	1.2%	6.2%	1.0%	8.3%	6.7%	0.2%	0.2%
Monroe	4,241	15.6%	24.2%	8.7%	11.9%	3.8%	0.3%	11.7%	2.7%	2.5%	13.3%	0.5%	1.1%	2.4%	0.2%	1.0%
Watertown	1,665	15.5%	26.8%	13.0%	6.4%	5.2%	0.1%	6.2%	2.1%	5.5%	10.4%	1.1%	1.3%	4.7%	0.5%	1.1%
Fairfield	8,320	15.4%	31.4%	7.2%	4.7%	2.0%	0.2%	5.8%	3.8%	9.3%	5.3%	2.8%	2.8%	7.6%	0.7%	0.9%
New Britain	7,328	15.2%	21.4%	5.3%	7.0%	2.5%	0.2%	6.8%	2.3%	4.0%	21.3%	3.1%	0.3%	8.3%	0.5%	1.9%
Rocky Hill	4,055	15.1%	27.1%	5.4%	19.3%	2.0%	0.1%	5.6%	1.1%	0.8%	14.9%	0.5%	0.9%	6.8%	0.2%	0.0%
Glastonbury	4,166	14.8%	22.7%	9.4%	18.2%	2.2%	0.2%	7.7%	2.3%	5.0%	7.6%	2.3%	0.4%	5.4%	0.4%	1.5%
South Windsor	3,850	14.6%	18.4%	8.4%	12.4%	7.2%	0.2%	4.5%	1.7%	11.9%	12.8%	0.9%	0.5%	6.0%	0.1%	0.2%
Meriden	1,578	14.6%	16.8%	3.4%	7.4%	1.3%	0.3%	5.3%	15.0%	2.6%	18.6%	3.2%	1.0%	8.9%	1.0%	0.6%
Hartford	8,243	14.4%	9.2%	2.0%	12.0%	6.3%	0.2%	6.8%	10.9%	4.1%	15.1%	1.6%	0.6%	11.7%	0.2%	4.7%
Willimantic	2,331	14.4%	10.2%	8.0%	17.9%	2.2%	0.5%	7.1%	8.6%	3.6%	13.3%	2.4%	2.1%	8.1%	0.5%	1.2%
New Canaan	5,492	14.1%	35.7%	8.7%	16.4%	3.1%	0.2%	5.7%	1.6%	1.1%	6.6%	0.2%	0.2%	4.4%	0.3%	1.7%
East Hartford	7,475	13.9%	26.1%	12.5%	1.7%	3.5%	0.1%	3.3%	1.2%	9.7%	8.2%	12.3%	1.5%	2.7%	0.4%	2.7%
Wallingford	7,909	13.9%	10.1%	9.4%	11.1%	8.0%	0.8%	7.5%	5.4%	7.9%	8.8%	3.4%	0.5%	9.2%	0.6%	3.5%
Cromwell	1,561	13.2%	17.9%	9.9%	17.0%	1.8%	0.2%	8.5%	3.4%	1.9%	9.5%	0.6%	0.4%	14.7%	0.3%	0.8%
Putnam	1,069	13.0%	37.0%	1.3%	16.2%	7.2%	0.3%	7.8%	2.6%	2.1%	2.7%	1.2%	0.0%	7.9%	0.5%	0.3%
East Windsor	1,752	12.6%	35.3%	5.1%	18.4%	1.4%	0.3%	7.2%	3.2%	0.6%	7.5%	1.9%	0.9%	4.9%	0.5%	0.2%
Branford	5,271	12.5%	32.3%	18.1%	3.5%	0.5%	0.2%	3.5%	4.5%	0.4%	7.5%	1.5%	0.6%	13.7%	0.4%	0.7%
Manchester	10,589	12.3%	23.1%	8.7%	12.2%	2.2%	0.2%	4.1%	1.1%	14.7%	8.1%	2.2%	0.5%	8.8%	0.4%	1.5%
Southern CT State University	517	12.2%	23.6%	1.7%	14.1%	0.6%	0.0%	6.4%	4.8%	9.7%	4.6%	2.5%	1.2%	17.4%	1.2%	0.0%
CSP Headquarters	14,090	11.9%	58.8%	2.0%	0.3%	0.2%	0.0%	5.1%	1.4%	14.6%	0.2%	0.7%	3.8%	0.6%	0.3%	0.2%
Ridgefield	6,733	11.9%	57.9%	6.9%	7.6%	0.1%	0.0%	1.5%	1.6%	1.8%	5.7%	0.1%	1.3%	2.7%	0.2%	0.6%
Greenwich	7,546	11.6%	25.5%	11.1%	9.6%	3.7%	0.1%	10.5%	2.8%	0.8%	11.0%	0.5%	3.6%	7.1%	0.7%	1.3%
Guilford	2,372	11.6%	54.1%	1.0%	9.3%	0.2%	0.0%	2.7%	1.5%	2.7%	9.0%	0.1%	0.1%	7.4%	0.3%	0.0%
Bethel	3,107	11.5%	50.9%	2.1%	7.4%	0.8%	0.1%	2.0%	1.5%	3.6%	13.4%	0.3%	0.3%	4.1%	0.1%	1.9%
Darien	3,568	11.2%	22.4%	9.4%	12.6%	11.8%	0.1%	5.0%	2.3%	5.0%	6.7%	0.5%	6.1%	5.1%	0.1%	1.8%
Naugatuck	4,753	11.0%	28.4%	9.6%	12.8%	1.8%	0.1%	4.8%	4.5%	6.7%	8.6%	0.9%	0.5%	9.0%	0.3%	0.9%
Derby	2,347	10.0%	29.3%	12.8%	5.4%	2.7%	0.2%	8.4%	2.5%	0.5%	8.7%	7.9%	1.9%	7.3%	0.5%	1.9%
University of Connecticut	3,894	9.9%	10.9%	3.8%	26.2%	5.6%	0.6%	14.6%	3.8%	1.1%	17.5%	0.3%	1.3%	3.0%	0.1%	1.4%
Simsbury	3,356	9.8%	57.4%	1.0%	9.6%	0.8%	0.1%	4.5%	1.6%	1.5%	6.2%	0.1%	0.1%	6.9%	0.1%	0.2%

Table B.4: Basis for Stop (Sorted by % Cell Phone Violation)

Department Name	Total	Cell Phone	Speed Related	Registration	Defective Lights	Display of Plates	Equipment Violation	Moving Violation	Other	Seatbelt	Stop Sign	Administrative Offense	STC Violation	Traffic Control Signal	Unlicensed Operation	Window Tint
New London	5,041	9.7%	36.2%	0.7%	6.9%	0.5%	0.1%	4.4%	3.7%	5.1%	12.6%	0.5%	1.9%	17.4%	0.2%	0.2%
Department of Motor Vehicle	1,575	9.3%	35.4%	7.4%	2.2%	2.3%	2.0%	15.3%	5.9%	1.6%	1.7%	0.7%	4.9%	4.9%	1.4%	5.1%
Groton Long Point	66	9.1%	30.3%	0.0%	4.5%	0.0%	1.5%	0.0%	4.5%	12.1%	33.3%	1.5%	0.0%	0.0%	3.0%	0.0%
Bristol	3,791	9.0%	35.3%	9.3%	5.4%	1.7%	0.2%	8.3%	2.9%	5.3%	8.0%	2.1%	0.2%	11.2%	0.8%	0.3%
Ansonia	3,569	8.7%	19.7%	3.4%	14.9%	2.2%	0.4%	5.4%	3.4%	2.1%	28.3%	0.9%	0.0%	9.2%	0.4%	0.8%
Seymour	3,883	8.4%	32.0%	1.6%	15.9%	2.3%	0.5%	6.8%	2.6%	3.8%	16.7%	0.3%	1.2%	7.0%	0.1%	0.8%
Old Saybrook	2,388	8.3%	43.2%	3.9%	14.2%	0.4%	0.1%	6.1%	2.9%	1.2%	10.2%	0.7%	1.1%	7.0%	0.3%	0.4%
Wilton	5,219	8.0%	30.9%	7.2%	19.3%	1.8%	0.2%	10.8%	2.5%	0.8%	6.4%	0.2%	0.6%	8.9%	0.3%	2.2%
North Haven	2,633	7.5%	21.0%	21.2%	11.0%	3.3%	0.2%	6.3%	2.4%	2.8%	4.2%	7.9%	1.2%	8.7%	1.3%	1.0%
Norwich	6,596	7.4%	28.8%	2.0%	18.1%	2.4%	0.2%	10.3%	4.9%	1.6%	7.3%	1.0%	0.7%	14.4%	0.5%	0.3%
East Haven	2,503	7.1%	16.9%	5.3%	9.0%	10.1%	0.3%	11.6%	3.4%	1.3%	22.7%	1.6%	0.4%	6.8%	0.6%	2.8%
Clinton	1,504	7.0%	31.8%	2.3%	12.8%	2.1%	0.9%	13.2%	2.5%	5.7%	10.1%	0.3%	2.4%	7.3%	0.5%	1.1%
Southington	5,123	7.0%	50.4%	3.5%	15.9%	1.3%	0.1%	5.0%	1.2%	1.9%	4.3%	0.4%	1.6%	6.6%	0.3%	0.5%
Stratford	3,697	6.9%	13.9%	16.5%	10.5%	6.1%	0.2%	8.7%	4.2%	3.2%	12.0%	3.2%	1.4%	9.7%	0.6%	3.0%
Madison	3,077	6.9%	36.5%	10.8%	10.9%	1.9%	0.4%	9.2%	2.1%	2.3%	9.2%	0.7%	6.1%	2.7%	0.3%	0.2%
Coventry	1,389	6.8%	38.4%	7.6%	15.2%	1.8%	0.5%	6.0%	3.5%	3.3%	3.7%	2.0%	6.9%	3.6%	0.5%	0.2%
East Hampton	769	6.8%	39.8%	7.0%	7.7%	1.4%	0.7%	10.7%	3.5%	2.0%	4.9%	0.7%	0.0%	14.3%	0.0%	0.7%
Central CT State University	1,848	6.5%	34.7%	5.5%	10.4%	2.1%	0.1%	9.0%	3.9%	4.2%	6.4%	0.5%	4.2%	11.8%	0.5%	0.2%
Groton Town	4,396	6.5%	21.3%	13.9%	13.9%	3.2%	0.1%	18.2%	1.5%	1.5%	5.1%	1.3%	1.4%	10.4%	0.3%	1.2%
Stonington	4,976	6.4%	38.0%	4.6%	12.5%	0.2%	0.1%	10.2%	6.0%	1.5%	8.2%	1.1%	4.3%	6.3%	0.6%	0.1%
Windsor Locks	1,124	6.3%	52.6%	2.7%	7.4%	1.6%	0.3%	4.9%	2.8%	4.9%	5.2%	1.2%	0.2%	9.0%	0.3%	0.9%
Bloomfield	2,226	5.8%	19.8%	5.8%	9.8%	3.3%	0.1%	9.3%	1.1%	1.3%	16.1%	0.7%	4.4%	21.7%	0.1%	0.6%
Waterford	4,502	5.7%	44.2%	0.7%	14.1%	7.1%	0.1%	10.3%	2.6%	2.5%	1.1%	0.4%	0.3%	9.9%	0.1%	1.0%
Windsor	8,485	5.5%	38.1%	2.7%	18.4%	2.5%	0.0%	2.9%	0.9%	2.8%	8.9%	0.4%	0.4%	15.5%	0.2%	0.7%
West Haven	8,790	5.4%	12.0%	20.6%	21.0%	6.0%	0.7%	5.4%	2.5%	1.1%	12.3%	1.1%	0.3%	9.2%	1.0%	1.5%
Newtown	3,547	5.3%	53.2%	6.3%	6.6%	1.8%	0.2%	11.0%	1.9%	0.9%	6.0%	0.5%	1.9%	3.9%	0.4%	0.1%
Cheshire	2,313	5.0%	9.3%	0.7%	2.6%	0.9%	0.1%	2.1%	73.4%	1.6%	1.2%	0.6%	0.1%	1.8%	0.1%	0.5%
Plainville	3,450	4.8%	23.9%	7.9%	18.4%	5.0%	0.1%	7.7%	1.0%	4.9%	12.6%	0.9%	0.6%	10.1%	0.2%	1.8%
New Haven	19,038	4.5%	10.8%	5.1%	8.4%	6.3%	0.0%	1.7%	20.2%	3.4%	6.8%	1.3%	0.9%	24.6%	0.4%	5.6%
CSP Troop G	13,997	4.5%	29.9%	15.7%	2.6%	1.3%	0.0%	20.1%	5.1%	2.1%	0.3%	2.1%	12.2%	1.8%	1.8%	0.6%
CSP Troop I	12,551	4.4%	29.6%	11.3%	3.7%	1.9%	0.1%	14.9%	4.5%	2.5%	1.5%	1.8%	20.2%	1.6%	1.3%	0.8%
Wethersfield	2,899	4.3%	21.0%	11.6%	11.7%	8.2%	0.3%	12.5%	2.9%	1.5%	7.3%	5.3%	0.9%	9.8%	0.2%	2.6%
CSP Troop F	17,331	4.1%	26.3%	12.1%	3.7%	0.8%	0.5%	8.3%	5.7%	3.4%	2.3%	0.8%	29.8%	1.1%	0.6%	0.5%
North Branford	843	3.9%	30.2%	18.3%	2.3%	0.6%	0.4%	12.8%	7.0%	0.6%	5.3%	1.8%	11.9%	4.4%	0.5%	0.1%
Eastern CT State University	207	3.9%	3.9%	0.5%	13.0%	0.0%	1.0%	1.4%	7.2%	3.4%	65.2%	0.0%	0.0%	0.0%	0.0%	0.5%
CSP Troop H	17,680	3.6%	29.5%	13.1%	2.4%	1.1%	0.1%	12.3%	9.9%	1.4%	1.6%	2.0%	19.4%	1.7%	1.2%	0.6%
New Milford	2,318	3.6%	51.5%	5.0%	12.4%	1.1%	0.9%	6.8%	3.5%	0.6%	4.3%	0.7%	0.3%	8.8%	0.3%	0.2%
Plainfield	1,669	3.5%	18.7%	2.0%	17.7%	4.2%	0.3%	18.1%	3.9%	7.7%	16.8%	2.5%	0.0%	3.7%	0.5%	0.4%
Newington	5,541	3.5%	21.2%	17.1%	17.0%	2.6%	1.7%	10.3%	1.9%	0.7%	7.3%	2.0%	0.2%	10.6%	0.5%	3.6%
CSP Troop A	16,762	3.4%	32.1%	15.5%	3.1%	2.5%	0.1%	11.7%	6.1%	2.9%	2.1%	1.9%	14.5%	1.8%	1.8%	0.5%
Avon	1,243	3.3%	42.5%	5.5%	9.5%	0.8%	0.0%	14.0%	5.5%	0.1%	11.5%	0.5%	0.1%	6.4%	0.3%	0.1%
CSP Troop E	15,525	3.2%	31.1%	10.2%	3.6%	1.2%	0.1%	9.8%	4.8%	2.0%	1.7%	1.6%	27.4%	2.1%	1.0%	0.3%
CSP Troop K	15,428	2.8%	27.3%	12.7%	2.6%	3.0%	0.1%	4.8%	5.7%	2.2%	3.3%	1.4%	31.6%	1.1%	0.9%	0.3%
Middletown	3,247	2.8%	21.6%	6.7%	19.9%	5.0%	0.5%	9.5%	4.4%	1.2%	13.2%	2.6%	0.3%	10.5%	0.4%	1.4%
Vernon	3,378	2.6%	18.7%	3.6%	18.0%	3.9%	0.9%	29.7%	1.9%	1.1%	6.3%	0.5%	1.7%	10.7%	0.1%	0.3%
Enfield	8,806	2.6%	54.5%	5.0%	7.4%	2.2%	0.4%	6.7%	1.6%	4.5%	2.9%	1.1%	0.5%	9.7%	0.3%	0.6%

Table B.4: Basis for Stop (Sorted by % Cell Phone Violation)

Department Name	Total	Cell Phone	Speed Related	Registration	Defective Lights	Display of Plates	Equipment Violation	Moving Violation	Other	Seatbelt	Stop Sign	Administrative Offense	STC Violation	Traffic Control Signal	Unlicensed Operation	Window Tint
Wolcott	120	2.5%	51.7%	1.7%	5.0%	0.8%	0.0%	5.8%	6.7%	1.7%	11.7%	3.3%	0.0%	4.2%	0.8%	4.2%
Winsted	842	2.5%	26.6%	3.4%	15.6%	9.9%	0.8%	11.3%	4.6%	6.1%	6.5%	2.9%	2.7%	6.2%	0.8%	0.1%
CSP Troop C	20,499	2.4%	34.4%	9.3%	4.4%	1.4%	0.2%	6.1%	4.2%	2.6%	2.3%	0.8%	30.0%	1.0%	0.5%	0.6%
East Lyme	379	2.4%	30.3%	4.7%	21.6%	1.3%	0.0%	10.3%	4.7%	3.2%	5.5%	3.2%	6.9%	5.3%	0.5%	0.0%
Shelton	561	2.3%	27.3%	12.5%	10.0%	2.1%	0.5%	12.1%	4.5%	0.4%	11.1%	0.9%	2.5%	12.7%	0.2%	1.1%
Redding	2,282	2.0%	51.3%	18.8%	8.2%	0.3%	0.0%	6.5%	2.8%	2.5%	5.7%	0.6%	0.4%	0.4%	0.4%	0.2%
Torrington	7,414	1.9%	21.5%	1.8%	27.7%	3.7%	0.5%	3.4%	2.3%	0.6%	23.4%	0.6%	1.3%	10.7%	0.3%	0.3%
CSP Troop L	8,981	1.9%	33.2%	22.0%	5.3%	4.5%	0.9%	7.5%	3.9%	1.7%	2.5%	3.4%	10.6%	0.6%	1.1%	1.0%
Easton	1,203	1.7%	53.5%	13.4%	3.2%	0.8%	0.2%	2.2%	4.0%	2.4%	13.9%	0.6%	2.0%	0.7%	1.1%	0.2%
Weston	611	1.5%	57.8%	0.8%	7.9%	0.5%	0.0%	4.9%	5.2%	0.2%	19.5%	0.2%	0.2%	1.3%	0.2%	0.0%
Portland	358	1.4%	48.9%	2.8%	8.1%	0.6%	0.0%	6.1%	2.0%	0.0%	12.8%	0.3%	0.0%	16.8%	0.3%	0.0%
CSP Troop B	6,437	1.4%	31.4%	18.6%	6.2%	1.5%	0.2%	6.0%	3.8%	2.4%	4.6%	1.4%	19.9%	1.3%	0.7%	0.6%
CSP Troop D	11,154	1.3%	29.8%	11.0%	3.0%	1.9%	0.2%	6.9%	8.9%	0.7%	2.1%	2.4%	28.5%	1.7%	1.0%	0.4%
Suffield	665	1.1%	53.2%	1.2%	15.9%	0.8%	0.0%	19.1%	1.4%	0.2%	2.9%	0.5%	0.2%	3.0%	0.8%	0.0%
Yale University	1,354	1.0%	1.3%	5.7%	9.5%	5.7%	0.0%	2.4%	35.6%	0.2%	1.2%	3.3%	0.0%	32.9%	0.7%	0.5%
Thomaston	1,278	1.0%	57.3%	1.8%	13.3%	1.6%	0.3%	6.1%	4.7%	1.8%	5.6%	1.6%	0.2%	4.2%	0.2%	0.4%
Orange	2,821	0.9%	2.5%	1.8%	1.0%	0.6%	0.0%	0.8%	87.9%	0.1%	0.6%	0.7%	0.7%	2.2%	0.0%	0.1%
Ledyard	2,191	0.8%	63.5%	2.1%	13.7%	2.0%	0.1%	7.1%	3.8%	0.2%	1.1%	1.3%	0.0%	1.2%	0.6%	2.3%
Waterbury	3,052	0.6%	22.4%	16.6%	3.9%	5.2%	0.3%	9.8%	2.6%	1.0%	10.5%	7.1%	2.4%	14.1%	1.6%	2.1%
Middlebury	34	0.0%	8.8%	2.9%	8.8%	2.9%	0.0%	20.6%	38.2%	0.0%	2.9%	2.9%	5.9%	5.9%	0.0%	0.0%
State Capitol Police	174	0.0%	0.6%	0.0%	30.5%	1.1%	0.0%	16.1%	2.9%	0.0%	4.6%	0.6%	0.6%	43.1%	0.0%	0.0%
Western CT State University	7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	14.3%	57.1%	0.0%	0.0%	0.0%	0.0%	14.3%	0.0%	14.3%

Table B.5: Outcome of Stop (Sorted by % Infraction Ticket)

Department Name	N	Infraction	UAR	Mis. Sum.	Written Warning	Verbal Warning	No Disposition
CSP Headquarters	14,090	89.2%	0.4%	3.6%	1.7%	4.4%	0.7%
CSP Troop F	17,331	72.0%	0.3%	2.7%	8.9%	14.7%	1.3%
CSP Troop C	20,499	71.4%	0.3%	3.0%	11.9%	12.5%	0.8%
CSP Troop H	17,680	71.1%	1.5%	5.4%	5.0%	15.2%	1.7%
CSP Troop E	15,525	69.2%	0.4%	4.5%	4.6%	20.3%	1.0%
CSP Troop G	13,997	67.0%	0.8%	6.3%	2.1%	22.2%	1.6%
CSP Troop I	12,551	64.9%	0.5%	6.0%	6.1%	20.9%	1.7%
Danbury	6,160	63.7%	1.9%	2.1%	0.2%	30.9%	1.1%
CSP Troop K	15,428	62.4%	0.3%	3.8%	7.4%	25.0%	1.1%
CSP Troop A	16,762	61.4%	0.4%	3.9%	5.4%	27.3%	1.6%
CSP Troop D	11,154	61.4%	0.4%	6.5%	8.3%	22.3%	1.1%
Bridgeport	2,262	59.9%	0.7%	5.6%	1.9%	31.4%	0.5%
New London	5,041	58.5%	2.0%	3.5%	4.8%	30.3%	0.9%
Department of Motor Vehicle	1,575	58.3%	0.3%	4.6%	9.8%	24.8%	2.2%
Trumbull	2,749	57.0%	0.8%	6.5%	4.6%	29.7%	1.4%
Hamden	5,888	55.3%	0.1%	2.6%	6.0%	34.9%	1.1%
Meriden	1,578	54.6%	1.2%	8.6%	3.6%	30.8%	1.3%
East Hartford	7,475	54.5%	1.4%	13.7%	5.8%	21.4%	3.3%
Norwalk	6,007	53.8%	0.8%	4.4%	0.6%	38.8%	1.5%
Branford	5,271	53.8%	0.2%	4.7%	0.0%	38.2%	3.0%
CSP Troop B	6,437	53.6%	0.4%	5.2%	23.2%	15.9%	1.6%
Manchester	10,589	53.0%	0.7%	4.6%	3.3%	37.0%	1.5%
Fairfield	8,320	49.9%	0.8%	5.3%	0.3%	41.5%	2.1%
Southern CT State University	517	49.5%	0.6%	10.1%	30.6%	9.3%	0.0%
West Hartford	6,207	48.5%	2.2%	5.3%	0.6%	41.7%	1.8%
CSP Troop L	8,981	47.4%	0.8%	6.9%	9.2%	32.7%	3.0%
New Britain	7,328	45.6%	1.9%	8.1%	0.7%	42.3%	1.4%
Hartford	8,243	44.5%	2.4%	10.9%	3.7%	37.4%	1.1%
Groton City	1,547	44.1%	1.0%	3.0%	11.0%	40.2%	0.6%
North Branford	843	42.6%	0.8%	3.8%	33.6%	16.0%	3.2%
Derby	2,347	42.3%	0.5%	13.9%	0.2%	41.2%	2.0%
Greenwich	7,546	41.8%	0.4%	2.0%	22.0%	32.3%	1.5%
Waterbury	3,052	39.6%	2.1%	17.7%	2.0%	36.1%	2.5%
New Haven	19,038	38.5%	0.7%	4.7%	8.1%	47.3%	0.7%
Glastonbury	4,166	36.9%	0.3%	4.4%	26.6%	30.6%	1.2%
Ridgefield	6,733	36.4%	0.1%	1.5%	44.9%	16.6%	0.5%
Stratford	3,697	35.8%	2.5%	7.9%	0.2%	51.3%	2.3%
Watertown	1,665	35.2%	0.7%	5.8%	41.0%	16.2%	1.2%
Bristol	3,791	35.1%	1.7%	6.2%	38.2%	11.7%	7.0%
Berlin	5,441	34.7%	0.6%	4.7%	30.3%	27.0%	2.8%
Farmington	5,212	34.6%	1.2%	7.1%	2.6%	53.2%	1.3%
Woodbridge	2,020	33.9%	0.0%	9.2%	15.6%	40.5%	0.7%
Stamford	13,399	33.8%	0.3%	2.0%	0.7%	61.1%	2.2%
Darien	3,568	33.7%	1.2%	3.6%	9.8%	50.3%	1.3%
Granby	548	32.8%	0.0%	4.6%	31.6%	30.3%	0.7%
Westport	7,461	31.9%	0.7%	3.1%	38.6%	24.5%	1.0%
Wallingford	7,909	31.5%	4.3%	8.2%	1.2%	53.0%	1.9%
Groton Long Point	66	30.3%	0.0%	0.0%	62.1%	4.5%	3.0%
North Haven	2,633	30.1%	0.5%	13.0%	1.3%	52.2%	2.9%
Canton	931	29.9%	0.3%	3.4%	11.2%	53.2%	2.0%
New Canaan	5,492	28.5%	0.2%	2.2%	2.6%	64.8%	1.7%
Naugatuck	4,753	27.9%	0.6%	0.8%	16.6%	52.8%	1.4%
Willimantic	2,331	27.9%	2.1%	6.4%	1.4%	59.9%	2.3%
South Windsor	3,850	27.2%	0.6%	3.6%	3.2%	63.6%	1.8%
Newtown	3,547	26.8%	0.3%	2.9%	9.2%	59.7%	1.2%
Orange	2,821	26.7%	0.1%	6.9%	3.0%	62.7%	0.6%
Newington	5,541	26.6%	0.6%	5.9%	57.1%	8.7%	1.1%
Monroe	4,241	26.6%	0.6%	3.1%	22.7%	46.0%	1.0%

Table B.5: Outcome of Stop (Sorted by % Infraction Ticket)

Department Name	N	Infraction	UAR	Mis. Sum.	Written Warning	Verbal Warning	No Disposition
Rocky Hill	4,055	25.6%	1.4%	2.3%	9.6%	60.7%	0.5%
Enfield	8,806	25.3%	0.5%	3.0%	63.0%	8.1%	0.2%
Plymouth	1,650	25.2%	1.2%	4.8%	4.7%	60.2%	3.9%
Brookfield	2,187	23.9%	0.4%	1.2%	19.5%	53.7%	1.4%
Plainville	3,450	23.2%	0.7%	2.8%	1.0%	71.7%	0.7%
New Milford	2,318	23.1%	0.6%	6.2%	36.3%	30.7%	3.1%
Cheshire	2,313	23.0%	1.3%	3.2%	68.8%	3.6%	0.1%
Ledyard	2,191	22.9%	0.4%	7.3%	25.7%	43.3%	0.5%
Shelton	561	22.3%	1.1%	4.8%	1.1%	69.0%	1.8%
Windsor Locks	1,124	22.2%	0.9%	4.4%	41.6%	30.5%	0.4%
Coventry	1,389	21.5%	0.1%	10.2%	20.7%	44.6%	3.0%
Cromwell	1,561	21.1%	0.4%	4.2%	8.4%	62.2%	3.7%
Windsor	8,485	20.8%	0.1%	3.6%	3.5%	71.4%	0.6%
Ansonia	3,569	20.5%	0.3%	3.8%	0.2%	74.0%	1.2%
East Windsor	1,752	20.3%	0.6%	4.2%	16.2%	57.8%	1.0%
West Haven	8,790	19.8%	0.8%	3.6%	1.6%	72.9%	1.3%
Bethel	3,107	18.6%	0.2%	2.3%	53.3%	25.5%	0.1%
Milford	4,462	18.4%	1.0%	3.3%	25.8%	50.7%	0.8%
Bloomfield	2,226	18.3%	2.2%	6.5%	46.7%	25.7%	0.6%
Stonington	4,976	18.0%	0.8%	2.8%	1.0%	75.4%	2.0%
East Lyme	379	17.7%	1.6%	5.8%	36.1%	35.4%	3.4%
Norwich	6,596	17.7%	1.3%	6.1%	54.4%	18.9%	1.6%
Yale University	1,354	17.7%	1.5%	12.5%	19.8%	47.5%	1.1%
East Hampton	769	17.2%	0.3%	5.1%	74.9%	2.5%	0.1%
Easton	1,203	16.8%	0.2%	3.9%	66.0%	11.2%	1.9%
Groton Town	4,396	16.0%	2.1%	4.9%	50.0%	26.7%	0.3%
University of Connecticut	3,894	16.0%	0.3%	2.2%	28.0%	53.0%	0.5%
Old Saybrook	2,388	16.0%	1.0%	3.4%	69.1%	10.2%	0.3%
Guilford	2,372	15.9%	0.2%	1.4%	77.5%	4.2%	0.8%
Thomaston	1,278	15.1%	1.1%	4.4%	25.4%	53.4%	0.6%
Middletown	3,247	15.1%	2.6%	7.0%	12.0%	60.6%	2.7%
Central CT State University	1,848	15.0%	0.1%	2.3%	2.8%	79.5%	0.3%
Madison	3,077	15.0%	0.2%	1.7%	65.2%	17.0%	0.9%
Southington	5,123	15.0%	0.1%	2.3%	70.3%	11.9%	0.4%
Simsbury	3,356	14.7%	0.1%	2.0%	24.3%	58.6%	0.3%
Wilton	5,219	14.5%	0.5%	3.2%	36.1%	44.7%	1.1%
Western CT State University	7	14.3%	0.0%	0.0%	14.3%	71.4%	0.0%
Wethersfield	2,899	14.2%	1.8%	12.3%	2.0%	67.9%	1.8%
Vernon	3,378	14.2%	2.5%	8.4%	58.2%	16.1%	0.7%
Clinton	1,504	14.2%	1.3%	5.2%	70.7%	8.6%	0.0%
Winsted	842	13.5%	1.2%	5.1%	25.7%	51.8%	2.7%
East Haven	2,503	13.1%	3.2%	8.2%	0.8%	72.8%	2.0%
Plainfield	1,669	12.6%	1.0%	4.9%	4.3%	76.3%	0.8%
Wolcott	120	11.7%	0.8%	5.8%	31.7%	46.7%	3.3%
Waterford	4,502	11.6%	0.7%	4.8%	38.3%	41.8%	2.9%
Suffield	665	11.3%	0.2%	8.3%	31.6%	48.7%	0.0%
Seymour	3,883	11.0%	0.5%	2.5%	1.6%	84.2%	0.2%
State Capitol Police	174	10.3%	0.0%	2.9%	2.9%	83.9%	0.0%
Avon	1,243	9.1%	1.0%	2.0%	38.9%	46.0%	2.9%
Eastern CT State University	207	8.7%	0.0%	0.5%	20.8%	70.0%	0.0%
Portland	358	8.7%	0.3%	2.5%	31.8%	54.5%	2.2%
Putnam	1,069	7.5%	2.8%	2.7%	40.0%	46.5%	0.5%
Redding	2,282	6.6%	0.0%	2.1%	76.6%	12.0%	2.8%
Torrington	7,414	6.6%	0.6%	2.9%	19.7%	69.6%	0.6%
Middlebury	34	5.9%	0.0%	5.9%	5.9%	76.5%	5.9%
Weston	611	3.3%	0.0%	0.8%	30.6%	63.7%	1.6%

Table B.6: Outcome of Stop (Sorted by % Warning)

Department Name	N	Warning	Infraction	UAR	Mis. Sum.	No Disposition
Weston	611	94.3%	3.3%	0.0%	0.8%	1.6%
Eastern CT State University	207	90.8%	8.7%	0.0%	0.5%	0.0%
Torrington	7,414	89.3%	6.6%	0.6%	2.9%	0.6%
Redding	2,282	88.6%	6.6%	0.0%	2.1%	2.8%
State Capitol Police	174	86.8%	10.3%	0.0%	2.9%	0.0%
Putnam	1,069	86.5%	7.5%	2.8%	2.7%	0.5%
Portland	358	86.3%	8.7%	0.3%	2.5%	2.2%
Seymour	3,883	85.8%	11.0%	0.5%	2.5%	0.2%
Western CT State University	7	85.7%	14.3%	0.0%	0.0%	0.0%
Avon	1,243	85.0%	9.1%	1.0%	2.0%	2.9%
Simsbury	3,356	82.8%	14.7%	0.1%	2.0%	0.3%
Middlebury	34	82.4%	5.9%	0.0%	5.9%	5.9%
Southington	5,123	82.3%	15.0%	0.1%	2.3%	0.4%
Central CT State University	1,848	82.3%	15.0%	0.1%	2.3%	0.3%
Madison	3,077	82.2%	15.0%	0.2%	1.7%	0.9%
Guilford	2,372	81.7%	15.9%	0.2%	1.4%	0.8%
University of Connecticut	3,894	81.0%	16.0%	0.3%	2.2%	0.5%
Wilton	5,219	80.8%	14.5%	0.5%	3.2%	1.1%
Plainfield	1,669	80.6%	12.6%	1.0%	4.9%	0.8%
Suffield	665	80.3%	11.3%	0.2%	8.3%	0.0%
Waterford	4,502	80.1%	11.6%	0.7%	4.8%	2.9%
Clinton	1,504	79.4%	14.2%	1.3%	5.2%	0.0%
Old Saybrook	2,388	79.3%	16.0%	1.0%	3.4%	0.3%
Thomaston	1,278	78.8%	15.1%	1.1%	4.4%	0.6%
Bethel	3,107	78.7%	18.6%	0.2%	2.3%	0.1%
Wolcott	120	78.3%	11.7%	0.8%	5.8%	3.3%
Winsted	842	77.4%	13.5%	1.2%	5.1%	2.7%
East Hampton	769	77.4%	17.2%	0.3%	5.1%	0.1%
Easton	1,203	77.2%	16.8%	0.2%	3.9%	1.9%
Groton Town	4,396	76.7%	16.0%	2.1%	4.9%	0.3%
Milford	4,462	76.5%	18.4%	1.0%	3.3%	0.8%
Stonington	4,976	76.4%	18.0%	0.8%	2.8%	2.0%
Windsor	8,485	74.9%	20.8%	0.1%	3.6%	0.6%
West Haven	8,790	74.5%	19.8%	0.8%	3.6%	1.3%
Vernon	3,378	74.3%	14.2%	2.5%	8.4%	0.7%
Ansonia	3,569	74.1%	20.5%	0.3%	3.8%	1.2%
East Windsor	1,752	74.0%	20.3%	0.6%	4.2%	1.0%
East Haven	2,503	73.6%	13.1%	3.2%	8.2%	2.0%
Norwich	6,596	73.3%	17.7%	1.3%	6.1%	1.6%
Brookfield	2,187	73.2%	23.9%	0.4%	1.2%	1.4%
Plainville	3,450	72.6%	23.2%	0.7%	2.8%	0.7%
Middletown	3,247	72.6%	15.1%	2.6%	7.0%	2.7%
Bloomfield	2,226	72.5%	18.3%	2.2%	6.5%	0.6%
Cheshire	2,313	72.4%	23.0%	1.3%	3.2%	0.1%
Windsor Locks	1,124	72.2%	22.2%	0.9%	4.4%	0.4%
East Lyme	379	71.5%	17.7%	1.6%	5.8%	3.4%
Enfield	8,806	71.0%	25.3%	0.5%	3.0%	0.2%
Cromwell	1,561	70.6%	21.1%	0.4%	4.2%	3.7%
Rocky Hill	4,055	70.3%	25.6%	1.4%	2.3%	0.5%
Shelton	561	70.1%	22.3%	1.1%	4.8%	1.8%
Wethersfield	2,899	69.9%	14.2%	1.8%	12.3%	1.8%
Naugatuck	4,753	69.4%	27.9%	0.6%	0.8%	1.4%
Ledyard	2,191	69.0%	22.9%	0.4%	7.3%	0.5%
Newtown	3,547	68.8%	26.8%	0.3%	2.9%	1.2%
Monroe	4,241	68.8%	26.6%	0.6%	3.1%	1.0%
New Canaan	5,492	67.4%	28.5%	0.2%	2.2%	1.7%
Yale University	1,354	67.3%	17.7%	1.5%	12.5%	1.1%
New Milford	2,318	67.0%	23.1%	0.6%	6.2%	3.1%

Table B.6: Outcome of Stop (Sorted by % Warning)

Department Name	N	Warning	Infraction	UAR	Mis. Sum.	No Disposition
South Windsor	3,850	66.7%	27.2%	0.6%	3.6%	1.8%
Groton Long Point	66	66.7%	30.3%	0.0%	0.0%	3.0%
Newington	5,541	65.8%	26.6%	0.6%	5.9%	1.1%
Orange	2,821	65.7%	26.7%	0.1%	6.9%	0.6%
Coventry	1,389	65.2%	21.5%	0.1%	10.2%	3.0%
Plymouth	1,650	64.8%	25.2%	1.2%	4.8%	3.9%
Canton	931	64.3%	29.9%	0.3%	3.4%	2.0%
Westport	7,461	63.1%	31.9%	0.7%	3.1%	1.0%
Granby	548	61.9%	32.8%	0.0%	4.6%	0.7%
Stamford	13,399	61.8%	33.8%	0.3%	2.0%	2.2%
Ridgefield	6,733	61.4%	36.4%	0.1%	1.5%	0.5%
Willimantic	2,331	61.3%	27.9%	2.1%	6.4%	2.3%
Darien	3,568	60.1%	33.7%	1.2%	3.6%	1.3%
Berlin	5,441	57.3%	34.7%	0.6%	4.7%	2.8%
Glastonbury	4,166	57.2%	36.9%	0.3%	4.4%	1.2%
Watertown	1,665	57.1%	35.2%	0.7%	5.8%	1.2%
Woodbridge	2,020	56.1%	33.9%	0.0%	9.2%	0.7%
Farmington	5,212	55.7%	34.6%	1.2%	7.1%	1.3%
New Haven	19,038	55.3%	38.5%	0.7%	4.7%	0.7%
Greenwich	7,546	54.3%	41.8%	0.4%	2.0%	1.5%
Wallingford	7,909	54.1%	31.5%	4.3%	8.2%	1.9%
North Haven	2,633	53.5%	30.1%	0.5%	13.0%	2.9%
Stratford	3,697	51.5%	35.8%	2.5%	7.9%	2.3%
Groton City	1,547	51.2%	44.1%	1.0%	3.0%	0.6%
Bristol	3,791	49.9%	35.1%	1.7%	6.2%	7.0%
North Branford	843	49.6%	42.6%	0.8%	3.8%	3.2%
New Britain	7,328	42.9%	45.6%	1.9%	8.1%	1.4%
West Hartford	6,207	42.3%	48.5%	2.2%	5.3%	1.8%
CSP Troop L	8,981	42.0%	47.4%	0.8%	6.9%	3.0%
Fairfield	8,320	41.9%	49.9%	0.8%	5.3%	2.1%
Derby	2,347	41.4%	42.3%	0.5%	13.9%	2.0%
Hartford	8,243	41.1%	44.5%	2.4%	10.9%	1.1%
Hamden	5,888	40.9%	55.3%	0.1%	2.6%	1.1%
Manchester	10,589	40.2%	53.0%	0.7%	4.6%	1.5%
Southern CT State University	517	39.8%	49.5%	0.6%	10.1%	0.0%
Norwalk	6,007	39.4%	53.8%	0.8%	4.4%	1.5%
CSP Troop B	6,437	39.1%	53.6%	0.4%	5.2%	1.6%
Branford	5,271	38.3%	53.8%	0.2%	4.7%	3.0%
Waterbury	3,052	38.1%	39.6%	2.1%	17.7%	2.5%
New London	5,041	35.1%	58.5%	2.0%	3.5%	0.9%
Department of Motor Vehicle	1,575	34.5%	58.3%	0.3%	4.6%	2.2%
Meriden	1,578	34.4%	54.6%	1.2%	8.6%	1.3%
Trumbull	2,749	34.3%	57.0%	0.8%	6.5%	1.4%
Bridgeport	2,262	33.3%	59.9%	0.7%	5.6%	0.5%
CSP Troop A	16,762	32.7%	61.4%	0.4%	3.9%	1.6%
CSP Troop K	15,428	32.4%	62.4%	0.3%	3.8%	1.1%
Danbury	6,160	31.1%	63.7%	1.9%	2.1%	1.1%
CSP Troop D	11,154	30.6%	61.4%	0.4%	6.5%	1.1%
East Hartford	7,475	27.2%	54.5%	1.4%	13.7%	3.3%
CSP Troop I	12,551	27.0%	64.9%	0.5%	6.0%	1.7%
CSP Troop E	15,525	24.9%	69.2%	0.4%	4.5%	1.0%
CSP Troop C	20,499	24.4%	71.4%	0.3%	3.0%	0.8%
CSP Troop G	13,997	24.3%	67.0%	0.8%	6.3%	1.6%
CSP Troop F	17,331	23.7%	72.0%	0.3%	2.7%	1.3%
CSP Troop H	17,680	20.2%	71.1%	1.5%	5.4%	1.7%
CSP Headquarters	14,090	6.1%	89.2%	0.4%	3.6%	0.7%

Table B.7: Outcome of Stop (Sorted by % Uniform Arrest Report)

Department Name	N	UAR	Infraction	Mis. Sum.	Written Warning	Verbal Warning	No Disposition
Wallingford	7,909	4.3%	31.5%	8.2%	1.2%	53.0%	1.9%
East Haven	2,503	3.2%	13.1%	8.2%	0.8%	72.8%	2.0%
Putnam	1,069	2.8%	7.5%	2.7%	40.0%	46.5%	0.5%
Middletown	3,247	2.6%	15.1%	7.0%	12.0%	60.6%	2.7%
Stratford	3,697	2.5%	35.8%	7.9%	0.2%	51.3%	2.3%
Vernon	3,378	2.5%	14.2%	8.4%	58.2%	16.1%	0.7%
Hartford	8,243	2.4%	44.5%	10.9%	3.7%	37.4%	1.1%
West Hartford	6,207	2.2%	48.5%	5.3%	0.6%	41.7%	1.8%
Bloomfield	2,226	2.2%	18.3%	6.5%	46.7%	25.7%	0.6%
Willimantic	2,331	2.1%	27.9%	6.4%	1.4%	59.9%	2.3%
Waterbury	3,052	2.1%	39.6%	17.7%	2.0%	36.1%	2.5%
Groton Town	4,396	2.1%	16.0%	4.9%	50.0%	26.7%	0.3%
New London	5,041	2.0%	58.5%	3.5%	4.8%	30.3%	0.9%
Danbury	6,160	1.9%	63.7%	2.1%	0.2%	30.9%	1.1%
New Britain	7,328	1.9%	45.6%	8.1%	0.7%	42.3%	1.4%
Wethersfield	2,899	1.8%	14.2%	12.3%	2.0%	67.9%	1.8%
Bristol	3,791	1.7%	35.1%	6.2%	38.2%	11.7%	7.0%
East Lyme	379	1.6%	17.7%	5.8%	36.1%	35.4%	3.4%
CSP Troop H	17,680	1.5%	71.1%	5.4%	5.0%	15.2%	1.7%
Yale University	1,354	1.5%	17.7%	12.5%	19.8%	47.5%	1.1%
Rocky Hill	4,055	1.4%	25.6%	2.3%	9.6%	60.7%	0.5%
East Hartford	7,475	1.4%	54.5%	13.7%	5.8%	21.4%	3.3%
Norwich	6,596	1.3%	17.7%	6.1%	54.4%	18.9%	1.6%
Cheshire	2,313	1.3%	23.0%	3.2%	68.8%	3.6%	0.1%
Clinton	1,504	1.3%	14.2%	5.2%	70.7%	8.6%	0.0%
Darien	3,568	1.2%	33.7%	3.6%	9.8%	50.3%	1.3%
Farmington	5,212	1.2%	34.6%	7.1%	2.6%	53.2%	1.3%
Meriden	1,578	1.2%	54.6%	8.6%	3.6%	30.8%	1.3%
Winsted	842	1.2%	13.5%	5.1%	25.7%	51.8%	2.7%
Plymouth	1,650	1.2%	25.2%	4.8%	4.7%	60.2%	3.9%
Thomaston	1,278	1.1%	15.1%	4.4%	25.4%	53.4%	0.6%
Shelton	561	1.1%	22.3%	4.8%	1.1%	69.0%	1.8%
Old Saybrook	2,388	1.0%	16.0%	3.4%	69.1%	10.2%	0.3%
Avon	1,243	1.0%	9.1%	2.0%	38.9%	46.0%	2.9%
Groton City	1,547	1.0%	44.1%	3.0%	11.0%	40.2%	0.6%
Plainfield	1,669	1.0%	12.6%	4.9%	4.3%	76.3%	0.8%
Milford	4,462	1.0%	18.4%	3.3%	25.8%	50.7%	0.8%
Windsor Locks	1,124	0.9%	22.2%	4.4%	41.6%	30.5%	0.4%
Wolcott	120	0.8%	11.7%	5.8%	31.7%	46.7%	3.3%
North Branford	843	0.8%	42.6%	3.8%	33.6%	16.0%	3.2%
Stonington	4,976	0.8%	18.0%	2.8%	1.0%	75.4%	2.0%
Norwalk	6,007	0.8%	53.8%	4.4%	0.6%	38.8%	1.5%
West Haven	8,790	0.8%	19.8%	3.6%	1.6%	72.9%	1.3%
Trumbull	2,749	0.8%	57.0%	6.5%	4.6%	29.7%	1.4%
Fairfield	8,320	0.8%	49.9%	5.3%	0.3%	41.5%	2.1%
CSP Troop L	8,981	0.8%	47.4%	6.9%	9.2%	32.7%	3.0%
CSP Troop G	13,997	0.8%	67.0%	6.3%	2.1%	22.2%	1.6%
Plainville	3,450	0.7%	23.2%	2.8%	1.0%	71.7%	0.7%
Westport	7,461	0.7%	31.9%	3.1%	38.6%	24.5%	1.0%
Watertown	1,665	0.7%	35.2%	5.8%	41.0%	16.2%	1.2%
Bridgeport	2,262	0.7%	59.9%	5.6%	1.9%	31.4%	0.5%
New Haven	19,038	0.7%	38.5%	4.7%	8.1%	47.3%	0.7%
Manchester	10,589	0.7%	53.0%	4.6%	3.3%	37.0%	1.5%
Waterford	4,502	0.7%	11.6%	4.8%	38.3%	41.8%	2.9%
New Milford	2,318	0.6%	23.1%	6.2%	36.3%	30.7%	3.1%
South Windsor	3,850	0.6%	27.2%	3.6%	3.2%	63.6%	1.8%
Newington	5,541	0.6%	26.6%	5.9%	57.1%	8.7%	1.1%
Southern CT State University	517	0.6%	49.5%	10.1%	30.6%	9.3%	0.0%

Table B.7: Outcome of Stop (Sorted by % Uniform Arrest Report)

Department Name	N	UAR	Infraction	Mis. Sum.	Written Warning	Verbal Warning	No Disposition
East Windsor	1,752	0.6%	20.3%	4.2%	16.2%	57.8%	1.0%
Naugatuck	4,753	0.6%	27.9%	0.8%	16.6%	52.8%	1.4%
Torrington	7,414	0.6%	6.6%	2.9%	19.7%	69.6%	0.6%
Monroe	4,241	0.6%	26.6%	3.1%	22.7%	46.0%	1.0%
Berlin	5,441	0.6%	34.7%	4.7%	30.3%	27.0%	2.8%
CSP Troop I	12,551	0.5%	64.9%	6.0%	6.1%	20.9%	1.7%
North Haven	2,633	0.5%	30.1%	13.0%	1.3%	52.2%	2.9%
Seymour	3,883	0.5%	11.0%	2.5%	1.6%	84.2%	0.2%
Derby	2,347	0.5%	42.3%	13.9%	0.2%	41.2%	2.0%
Enfield	8,806	0.5%	25.3%	3.0%	63.0%	8.1%	0.2%
Wilton	5,219	0.5%	14.5%	3.2%	36.1%	44.7%	1.1%
CSP Troop B	6,437	0.4%	53.6%	5.2%	23.2%	15.9%	1.6%
CSP Headquarters	14,090	0.4%	89.2%	3.6%	1.7%	4.4%	0.7%
Ledyard	2,191	0.4%	22.9%	7.3%	25.7%	43.3%	0.5%
CSP Troop E	15,525	0.4%	69.2%	4.5%	4.6%	20.3%	1.0%
CSP Troop D	11,154	0.4%	61.4%	6.5%	8.3%	22.3%	1.1%
Cromwell	1,561	0.4%	21.1%	4.2%	8.4%	62.2%	3.7%
Greenwich	7,546	0.4%	41.8%	2.0%	22.0%	32.3%	1.5%
Brookfield	2,187	0.4%	23.9%	1.2%	19.5%	53.7%	1.4%
CSP Troop A	16,762	0.4%	61.4%	3.9%	5.4%	27.3%	1.6%
Ansonia	3,569	0.3%	20.5%	3.8%	0.2%	74.0%	1.2%
Glastonbury	4,166	0.3%	36.9%	4.4%	26.6%	30.6%	1.2%
CSP Troop F	17,331	0.3%	72.0%	2.7%	8.9%	14.7%	1.3%
University of Connecticut	3,894	0.3%	16.0%	2.2%	28.0%	53.0%	0.5%
Canton	931	0.3%	29.9%	3.4%	11.2%	53.2%	2.0%
Department of Motor Vehicle	1,575	0.3%	58.3%	4.6%	9.8%	24.8%	2.2%
CSP Troop C	20,499	0.3%	71.4%	3.0%	11.9%	12.5%	0.8%
Newtown	3,547	0.3%	26.8%	2.9%	9.2%	59.7%	1.2%
Portland	358	0.3%	8.7%	2.5%	31.8%	54.5%	2.2%
CSP Troop K	15,428	0.3%	62.4%	3.8%	7.4%	25.0%	1.1%
Stamford	13,399	0.3%	33.8%	2.0%	0.7%	61.1%	2.2%
East Hampton	769	0.3%	17.2%	5.1%	74.9%	2.5%	0.1%
New Canaan	5,492	0.2%	28.5%	2.2%	2.6%	64.8%	1.7%
Bethel	3,107	0.2%	18.6%	2.3%	53.3%	25.5%	0.1%
Branford	5,271	0.2%	53.8%	4.7%	0.0%	38.2%	3.0%
Madison	3,077	0.2%	15.0%	1.7%	65.2%	17.0%	0.9%
Guilford	2,372	0.2%	15.9%	1.4%	77.5%	4.2%	0.8%
Easton	1,203	0.2%	16.8%	3.9%	66.0%	11.2%	1.9%
Suffield	665	0.2%	11.3%	8.3%	31.6%	48.7%	0.0%
Simsbury	3,356	0.1%	14.7%	2.0%	24.3%	58.6%	0.3%
Coventry	1,389	0.1%	21.5%	10.2%	20.7%	44.6%	3.0%
Windsor	8,485	0.1%	20.8%	3.6%	3.5%	71.4%	0.6%
Ridgefield	6,733	0.1%	36.4%	1.5%	44.9%	16.6%	0.5%
Central CT State University	1,848	0.1%	15.0%	2.3%	2.8%	79.5%	0.3%
Hamden	5,888	0.1%	55.3%	2.6%	6.0%	34.9%	1.1%
Orange	2,821	0.1%	26.7%	6.9%	3.0%	62.7%	0.6%
Southington	5,123	0.1%	15.0%	2.3%	70.3%	11.9%	0.4%
Woodbridge	2,020	0.0%	33.9%	9.2%	15.6%	40.5%	0.7%
State Capitol Police	174	0.0%	10.3%	2.9%	2.9%	83.9%	0.0%
Eastern CT State University	207	0.0%	8.7%	0.5%	20.8%	70.0%	0.0%
Granby	548	0.0%	32.8%	4.6%	31.6%	30.3%	0.7%
Groton Long Point	66	0.0%	30.3%	0.0%	62.1%	4.5%	3.0%
Middlebury	34	0.0%	5.9%	5.9%	5.9%	76.5%	5.9%
Redding	2,282	0.0%	6.6%	2.1%	76.6%	12.0%	2.8%
Western CT State University	7	0.0%	14.3%	0.0%	14.3%	71.4%	0.0%
Weston	611	0.0%	3.3%	0.8%	30.6%	63.7%	1.6%

Table B.8: Number of Searches (Sorted by % Search)

Department Name	Stops	Searches N	Searches %
Waterbury	3,052	544	17.8%
Stratford	3,697	588	15.9%
Yale University	1,354	162	12.0%
Vernon	3,378	393	11.6%
Bridgeport	2,262	245	10.8%
Middletown	3,247	333	10.3%
Derby	2,347	234	10.0%
New Haven	19,038	1,669	8.8%
Wallingford	7,909	662	8.4%
Trumbull	2,749	221	8.0%
Norwich	6,596	518	7.9%
Willimantic	2,331	181	7.8%
Wolcott	120	9	7.5%
East Lyme	379	27	7.1%
Wethersfield	2,899	201	6.9%
Clinton	1,504	104	6.9%
East Haven	2,503	170	6.8%
East Hartford	7,475	455	6.1%
Norwalk	6,007	365	6.1%
North Haven	2,633	154	5.8%
Milford	4,462	257	5.8%
Plainfield	1,669	94	5.6%
University of Connecticut	3,894	206	5.3%
New Britain	7,328	385	5.3%
Southern CT State University	517	27	5.2%
Glastonbury	4,166	216	5.2%
West Hartford	6,207	301	4.8%
Plainville	3,450	155	4.5%
Old Saybrook	2,388	106	4.4%
Watertown	1,665	73	4.4%
Newington	5,541	236	4.3%
Enfield	8,806	374	4.2%
Danbury	6,160	254	4.1%
Putnam	1,069	44	4.1%
Darien	3,568	138	3.9%
West Haven	8,790	333	3.8%
Suffield	665	23	3.5%
Groton City	1,547	52	3.4%
Plymouth	1,650	55	3.3%
Naugatuck	4,753	157	3.3%
Ledyard	2,191	68	3.1%
Bloomfield	2,226	69	3.1%
Thomaston	1,278	39	3.1%
Monroe	4,241	126	3.0%
Middlebury	34	1	2.9%
Seymour	3,883	114	2.9%
Bristol	3,791	110	2.9%
South Windsor	3,850	110	2.9%
Meriden	1,578	45	2.9%
Winsted	842	24	2.9%
CSP Troop G	13,997	395	2.8%
Rocky Hill	4,055	114	2.8%
Waterford	4,502	120	2.7%
Wilton	5,219	139	2.7%
Manchester	10,589	271	2.6%
Torrington	7,414	184	2.5%
Westport	7,461	183	2.5%
Groton Town	4,396	106	2.4%

Table B.8: Number of Searches (Sorted by % Search)

Department Name	Stops	Searches N	Searches %
Coventry	1,389	33	2.4%
Windsor Locks	1,124	26	2.3%
Fairfield	8,320	192	2.3%
State Capitol Police	174	4	2.3%
CSP Troop C	20,499	460	2.2%
Portland	358	8	2.2%
Farmington	5,212	112	2.1%
Brookfield	2,187	45	2.1%
CSP Troop L	8,981	184	2.0%
Berlin	5,441	110	2.0%
Greenwich	7,546	151	2.0%
CSP Troop A	16,762	335	2.0%
CSP Troop D	11,154	205	1.8%
Woodbridge	2,020	37	1.8%
Windsor	8,485	155	1.8%
Ansonia	3,569	65	1.8%
New Milford	2,318	42	1.8%
Hartford	8,243	147	1.8%
Stamford	13,399	238	1.8%
Cheshire	2,313	41	1.8%
New London	5,041	89	1.8%
Newtown	3,547	62	1.7%
CSP Troop E	15,525	267	1.7%
CSP Troop H	17,680	297	1.7%
Granby	548	9	1.6%
Shelton	561	9	1.6%
CSP Troop B	6,437	96	1.5%
CSP Troop I	12,551	185	1.5%
CSP Troop K	15,428	218	1.4%
CSP Troop F	17,331	226	1.3%
Canton	931	12	1.3%
Cromwell	1,561	19	1.2%
Avon	1,243	15	1.2%
East Windsor	1,752	21	1.2%
East Hampton	769	9	1.2%
New Canaan	5,492	64	1.2%
Branford	5,271	59	1.1%
Redding	2,282	25	1.1%
Southington	5,123	54	1.1%
Ridgefield	6,733	60	0.9%
Simsbury	3,356	27	0.8%
Madison	3,077	23	0.7%
Bethel	3,107	23	0.7%
Hamden	5,888	40	0.7%
Guilford	2,372	15	0.6%
Easton	1,203	6	0.5%
Weston	611	3	0.5%
Central CT State University	1,848	9	0.5%
North Branford	843	4	0.5%
Department of Motor Vehicle	1,575	5	0.3%
CSP Headquarters	14,090	40	0.3%
Stonington	4,976	12	0.2%
Orange	2,821	4	0.1%
Eastern CT State University	207	0	0.0%
Groton Long Point	66	0	0.0%
Western CT State University	7	0	0.0%

APPENDIX C

Table C.1: Logistic Regression of Minority Status on Daylight with Officer Fixed Effects, All Traffic Stops 2017

LHS: Minority Status		Non-Caucasian	Black	Hispanic	Black or Hispanic
Daylight	Coefficient	0.001	0.001	0.001	-0.001
	Standard Error	(0.017)	(0.023)	(0.028)	(0.024)
Sample Size		116596	111697	107687	131677
Pseudo R^2		0.067	0.079	0.056	0.068

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for time of the day, day of the week, analysis year, and department fixed-effects.
Note 3: Sample includes all traffic stops made during the inter-twilight window in 2017.

Table C.2: Logistic Regression of Minority Status on Daylight with Officer Fixed Effects, All Municipal Traffic Stops 2017

LHS: Minority Status		Non-Caucasian	Black	Hispanic	Black or Hispanic
Daylight	Coefficient	-0.024	-0.014	-0.029	-0.026
	Standard Error	(0.014)	(0.017)	(0.019)	(0.017)
Sample Size		81105	78190	74682	93527
Pseudo R^2		0.070	0.079	0.050	0.065

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for time of the day, day of the week, analysis year, and department fixed-effects.
Note 3: Sample includes all traffic stops made during the inter-twilight window in 2017.

Table C.3: Logistic Regression of Minority Status on Daylight with Officer Fixed Effects, All State Police Traffic Stops 2017

LHS: Minority Status		Non-Caucasian	Black	Hispanic	Black or Hispanic
Daylight	Coefficient	0.097***	0.096**	0.134***	0.119***
	Standard Error	(0.035)	(0.041)	(0.041)	(0.034)
Sample Size		33324	31478	31222	35825
Pseudo R^2		0.057	0.068	0.071	0.070

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for time of the day, day of the week, analysis year, and department fixed-effects.
Note 3: Sample includes all traffic stops made during the inter-twilight window in 2017.

Table C.4: Logistic Regression of Minority Status on Daylight with Officer Fixed Effects, All Moving Violations 2017

LHS: Minority Status		Non-Caucasian	Black	Hispanic	Black or Hispanic
Daylight	Coefficient	0.027	0.023	-0.048	-0.008
	Standard Error	(0.027)	(0.035)	(0.052)	(0.043)
Sample Size		65530	61840	60107	71844
Pseudo R^2		0.061	0.071	0.050	0.061

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for time of the day, day of the week, analysis year, and department fixed-effects.
Note 3: Sample includes all moving violations made during the inter-twilight window in 2017.

Table C.5: Logistic Regression of Minority Status on Daylight with Officer Fixed Effects, All Municipal Moving Violations 2017

LHS: Minority Status		Non-Caucasian	Black	Hispanic	Black or Hispanic
Daylight	Coefficient	-0.018	-0.001	-0.104***	-0.050
	Standard Error	(0.029)	(0.037)	(0.039)	(0.035)
Sample Size		42837	40809	39548	47986
Pseudo R^2		0.065	0.076	0.048	0.064

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for time of the day, day of the week, analysis year, and department fixed-effects.
Note 3: Sample includes all moving violations made during the inter-twilight window in 2017.

Table C.6: Logistic Regression of Minority Status on Daylight with Officer Fixed Effects, All State Police Moving Violations 2017

LHS: Minority Status		Non-Caucasian	Black	Hispanic	Black or Hispanic
Daylight	Coefficient	0.146***	0.115**	0.108*	0.127***
	Standard Error	(0.043)	(0.048)	(0.061)	(0.037)
Sample Size		21664	20068	19665	22722
Pseudo R^2		0.054	0.061	0.059	0.059

Note 1: The coefficients are presented as log odds-ratios along with standard errors clustered at the department level. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: All specifications include controls for time of the day, day of the week, analysis year, and department fixed-effects.
Note 3: Sample includes all moving violations made during the inter-twilight window in 2017.

Table C.7: Logistic Regression of Minority Status on Daylight by Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Ansonia	Coefficient	0.377	0.476+	0.187	0.381+
	Observations	774	769	776	902
	P-Value	0.136	0.065	0.449	0.050
	Pseudo R2	0.032	0.032	0.054	0.028
	Q-Value	0.574	0.361	0.768	0.305
	Standard Error	(0.252)	(0.259)	(0.246)	(0.194)
Berlin	Coefficient	-0.231	-0.226	-0.026	-0.144
	Observations	1119	1081	1157	1287
	P-Value	0.379	0.423	0.915	0.469
	Pseudo R2	0.025	0.020	0.025	0.016
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.263)	(0.284)	(0.239)	(0.200)
Bethel	Coefficient	N/A	N/A	-0.843+++	-0.541++
	Observations	N/A	N/A	562	621
	P-Value	N/A	N/A	0.009	0.037
	Pseudo R2	N/A	N/A	0.050	0.034
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	(0.328)	(0.261)
Bloomfield	Coefficient	-0.094	-0.068	N/A	-0.061
	Observations	572	564	N/A	603
	P-Value	0.714	0.794	N/A	0.813
	Pseudo R2	0.054	0.054	N/A	0.054
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.261)	(0.263)	N/A	(0.256)
Branford	Coefficient	-0.324	-0.310	-0.485	-0.400
	Observations	926	913	899	986
	P-Value	0.351	0.416	0.136	0.118
	Pseudo R2	0.071	0.063	0.037	0.043
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.349)	(0.381)	(0.324)	(0.256)
Bridgeport	Coefficient	N/A	N/A	N/A	-0.546
	Observations	N/A	N/A	N/A	541
	P-Value	N/A	N/A	N/A	0.104
	Pseudo R2	N/A	N/A	N/A	0.032
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	(0.337)
Bristol	Coefficient	0.275	0.321	-0.168	0.004
	Observations	1180	1173	1233	1354
	P-Value	0.259	0.201	0.449	0.984
	Pseudo R2	0.035	0.032	0.024	0.014
	Q-Value	0.680	0.640	N/A	0.987
	Standard Error	(0.244)	(0.252)	(0.224)	(0.180)
Brookfield	Coefficient	N/A	N/A	-0.136	0.070
	Observations	N/A	N/A	561	583
	P-Value	N/A	N/A	0.730	0.842
	Pseudo R2	N/A	N/A	0.043	0.035
	Q-Value	N/A	N/A	N/A	0.935
	Standard Error	N/A	N/A	(0.395)	(0.349)
Central CT State University	Coefficient	0.127	0.135	0.658+	0.296
	Observations	675	650	619	778
	P-Value	0.677	0.675	0.081	0.244
	Pseudo R2	0.027	0.028	0.039	0.020
	Q-Value	0.847	0.847	0.377	0.680
	Standard Error	(0.305)	(0.321)	(0.377)	(0.254)

*Results were not available across all specifications for departments not listed in this table.

Table C.7: Logistic Regression of Minority Status on Daylight by Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
CSP Headquarters	Coefficient	-0.143	0.057	-0.041	0.004
	Observations	1940	1838	1829	2181
	P-Value	0.388	0.762	0.824	0.976
	Pseudo R2	0.018	0.019	0.016	0.016
	Q-Value	N/A	0.875	N/A	0.987
	Standard Error	(0.165)	(0.193)	(0.185)	(0.148)
CSP Troop A	Coefficient	0.264++	0.277++	0.400***	0.305***
	Observations	3056	2925	3098	3551
	P-Value	0.025	0.035	0.001	0.002
	Pseudo R2	0.014	0.014	0.012	0.010
	Q-Value	0.233	0.268	0.001	0.035
	Standard Error	(0.118)	(0.131)	(0.120)	(0.098)
CSP Troop B	Coefficient	-0.215	0.230	0.203	0.240
	Observations	1197	1171	1084	1248
	P-Value	0.495	0.536	0.580	0.379
	Pseudo R2	0.050	0.061	0.035	0.028
	Q-Value	N/A	0.802	0.815	0.717
	Standard Error	(0.316)	(0.372)	(0.370)	(0.273)
CSP Troop C	Coefficient	0.340***	0.312++	0.370***	0.349***
	Observations	5454	5049	5026	5476
	P-Value	0	0.014	0.003	0
	Pseudo R2	0.009	0.013	0.021	0.016
	Q-Value	0.001	0.152	0.045	0.001
	Standard Error	(0.096)	(0.127)	(0.123)	(0.093)
CSP Troop D	Coefficient	0.303+	0.563+++	0.152	0.363++
	Observations	2704	2593	2609	2744
	P-Value	0.067	0.008	0.444	0.017
	Pseudo R2	0.024	0.028	0.032	0.024
	Q-Value	0.361	0.125	0.768	0.179
	Standard Error	(0.165)	(0.215)	(0.200)	(0.153)
CSP Troop E	Coefficient	-0.103	-0.138	0.019	-0.059
	Observations	4826	4535	4407	4957
	P-Value	0.273	0.209	0.871	0.509
	Pseudo R2	0.016	0.017	0.017	0.016
	Q-Value	N/A	N/A	0.944	N/A
	Standard Error	(0.093)	(0.111)	(0.123)	(0.089)
CSP Troop F	Coefficient	-0.172	-0.079	-0.107	-0.052
	Observations	4000	3890	3876	4175
	P-Value	0.192	0.597	0.514	0.658
	Pseudo R2	0.019	0.021	0.014	0.017
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.131)	(0.151)	(0.164)	(0.118)
CSP Troop G	Coefficient	-0.078	-0.130	0.162	0.002
	Observations	1697	1578	1582	2047
	P-Value	0.563	0.368	0.275	0.987
	Pseudo R2	0.012	0.014	0.020	0.012
	Q-Value	N/A	N/A	0.680	0.987
	Standard Error	(0.135)	(0.144)	(0.149)	(0.119)
CSP Troop H	Coefficient	0.244++	0.208	-0.202	0.017
	Observations	2306	2152	2047	2617
	P-Value	0.046	0.115	0.150	0.873
	Pseudo R2	0.013	0.014	0.012	0.008
	Q-Value	0.305	0.507	N/A	0.944
	Standard Error	(0.122)	(0.131)	(0.142)	(0.108)

*Results were not available across all specifications for departments not listed in this table.

Table C.7: Logistic Regression of Minority Status on Daylight by Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
CSP Troop I	Coefficient	0.028	0.046	-0.064	0.008
	Observations	2127	2023	1938	2361
	P-Value	0.834	0.762	0.693	0.944
	Pseudo R2	0.014	0.016	0.020	0.014
	Q-Value	0.935	0.875	N/A	0.987
	Standard Error	(0.138)	(0.151)	(0.164)	(0.119)
CSP Troop K	Coefficient	0.059	-0.085	0.612***	0.324++
	Observations	2820	2711	2793	3032
	P-Value	0.712	0.665	0	0.014
	Pseudo R2	0.012	0.013	0.023	0.009
	Q-Value	0.855	N/A	0.001	0.152
	Standard Error	(0.162)	(0.195)	(0.166)	(0.131)
CSP Troop L	Coefficient	0.248	0.112	0.358	0.298
	Observations	1693	1664	1708	1800
	P-Value	0.342	0.700	0.171	0.148
	Pseudo R2	0.045	0.046	0.027	0.025
	Q-Value	0.717	0.855	0.583	0.574
	Standard Error	(0.261)	(0.293)	(0.261)	(0.206)
Cheshire	Coefficient	0.386	0.414	-0.519	0.014
	Observations	649	619	607	672
	P-Value	0.284	0.287	0.143	0.957
	Pseudo R2	0.039	0.027	0.065	0.021
	Q-Value	0.680	0.680	N/A	0.987
	Standard Error	(0.361)	(0.389)	(0.354)	(0.280)
Clinton	Coefficient	N/A	N/A	-0.326	-0.305
	Observations	N/A	N/A	519	558
	P-Value	N/A	N/A	0.400	0.384
	Pseudo R2	N/A	N/A	0.075	0.071
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	(0.388)	(0.349)
Danbury	Coefficient	N/A	N/A	-0.277	-0.296
	Observations	N/A	N/A	691	751
	P-Value	N/A	N/A	0.175	0.125
	Pseudo R2	N/A	N/A	0.041	0.043
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	(0.203)	(0.193)
Darien	Coefficient	0.263	0.195	0.524+	0.421+
	Observations	567	547	559	680
	P-Value	0.375	0.529	0.072	0.079
	Pseudo R2	0.059	0.063	0.059	0.050
	Q-Value	0.717	0.802	0.375	0.377
	Standard Error	(0.296)	(0.312)	(0.291)	(0.239)
East Hartford	Coefficient	0.181	0.153	0.158	0.163
	Observations	804	782	643	1083
	P-Value	0.361	0.448	0.476	0.372
	Pseudo R2	0.024	0.026	0.048	0.029
	Q-Value	0.717	0.768	0.795	0.717
	Standard Error	(0.199)	(0.202)	(0.224)	(0.182)
East Haven	Coefficient	0.149	0.280	-0.185	-0.039
	Observations	548	539	580	662
	P-Value	0.649	0.425	0.476	0.856
	Pseudo R2	0.072	0.074	0.028	0.026
	Q-Value	0.834	0.764	N/A	N/A
	Standard Error	(0.328)	(0.354)	(0.259)	(0.217)

*Results were not available across all specifications for departments not listed in this table.

Table C.7: Logistic Regression of Minority Status on Daylight by Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Enfield	Coefficient	-0.046	0.016	0.207	0.064
	Observations	3416	3337	3257	3573
	P-Value	0.721	0.912	0.187	0.560
	Pseudo R2	0.013	0.014	0.017	0.010
	Q-Value	N/A	0.968	0.607	0.802
	Standard Error	(0.129)	(0.143)	(0.157)	(0.111)
Fairfield	Coefficient	0.456***	0.483***	0.261++	0.379***
	Observations	2724	2628	2592	3030
	P-Value	0	0	0.039	0
	Pseudo R2	0.014	0.018	0.028	0.019
	Q-Value	0.001	0.001	0.282	0.001
	Standard Error	(0.115)	(0.126)	(0.128)	(0.097)
Farmington	Coefficient	0.238	0.103	-0.317	-0.134
	Observations	1112	996	1029	1148
	P-Value	0.324	0.740	0.248	0.538
	Pseudo R2	0.037	0.035	0.043	0.028
	Q-Value	0.708	0.865	N/A	N/A
	Standard Error	(0.240)	(0.312)	(0.275)	(0.217)
Glastonbury	Coefficient	-0.435+	-0.470	-0.093	-0.301
	Observations	1107	1043	1039	1150
	P-Value	0.068	0.108	0.727	0.141
	Pseudo R2	0.048	0.059	0.034	0.026
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.238)	(0.293)	(0.270)	(0.204)
Greenwich	Coefficient	-0.114	-0.072	-0.175	-0.159
	Observations	1754	1579	1782	1982
	P-Value	0.458	0.711	0.229	0.204
	Pseudo R2	0.021	0.024	0.013	0.013
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.152)	(0.196)	(0.146)	(0.127)
Groton Town	Coefficient	-0.087	-0.256	-0.400+	-0.282
	Observations	1033	978	954	1101
	P-Value	0.646	0.234	0.097	0.104
	Pseudo R2	0.025	0.020	0.050	0.025
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.193)	(0.216)	(0.241)	(0.173)
Guilford	Coefficient	0.310	N/A	N/A	N/A
	Observations	504	N/A	N/A	N/A
	P-Value	0.537	N/A	N/A	N/A
	Pseudo R2	0.050	N/A	N/A	N/A
	Q-Value	0.802	N/A	N/A	N/A
	Standard Error	(0.504)	N/A	N/A	N/A
Hamden	Coefficient	-0.056	-0.046	-0.284	-0.090
	Observations	1632	1612	1186	1753
	P-Value	0.727	0.774	0.268	0.554
	Pseudo R2	0.012	0.012	0.032	0.009
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.159)	(0.162)	(0.256)	(0.151)
Hartford	Coefficient	-0.165	-0.163	0.052	-0.093
	Observations	2077	2035	1404	2883
	P-Value	0.254	0.264	0.739	0.486
	Pseudo R2	0.071	0.071	0.064	0.059
	Q-Value	N/A	N/A	0.865	N/A
	Standard Error	(0.144)	(0.145)	(0.158)	(0.134)

*Results were not available across all specifications for departments not listed in this table.

Table C.7: Logistic Regression of Minority Status on Daylight by Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Ledyard	Coefficient	-0.219	-0.216	-0.551	-0.294
	Observations	621	605	542	661
	P-Value	0.407	0.439	0.114	0.218
	Pseudo R2	0.030	0.029	0.082	0.041
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.266)	(0.280)	(0.349)	(0.239)
Madison	Coefficient	0.395	N/A	N/A	N/A
	Observations	504	N/A	N/A	N/A
	P-Value	0.448	N/A	N/A	N/A
	Pseudo R2	0.067	N/A	N/A	N/A
	Q-Value	0.768	N/A	N/A	N/A
	Standard Error	(0.522)	N/A	N/A	N/A
Manchester	Coefficient	-0.181	-0.211+	-0.103	-0.171+
	Observations	2514	2422	2101	2836
	P-Value	0.112	0.078	0.495	0.098
	Pseudo R2	0.009	0.010	0.017	0.008
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.115)	(0.119)	(0.150)	(0.104)
Middletown	Coefficient	0.128	0.131	-0.039	0.087
	Observations	750	740	550	818
	P-Value	0.495	0.493	0.890	0.612
	Pseudo R2	0.037	0.039	0.063	0.035
	Q-Value	0.797	0.797	N/A	0.833
	Standard Error	(0.188)	(0.193)	(0.282)	(0.173)
Milford	Coefficient	-0.082	-0.130	0.008	-0.016
	Observations	625	611	592	696
	P-Value	0.758	0.648	0.980	0.941
	Pseudo R2	0.052	0.057	0.057	0.035
	Q-Value	N/A	N/A	0.987	N/A
	Standard Error	(0.268)	(0.287)	(0.301)	(0.216)
Monroe	Coefficient	0.052	0.202	-0.017	0.100
	Observations	1100	1077	1035	1173
	P-Value	0.841	0.469	0.949	0.632
	Pseudo R2	0.037	0.037	0.026	0.023
	Q-Value	0.935	0.790	N/A	0.834
	Standard Error	(0.259)	(0.279)	(0.280)	(0.209)
Naugatuck	Coefficient	0.303	0.368	0.400	0.349+
	Observations	1226	1212	1235	1376
	P-Value	0.207	0.143	0.108	0.059
	Pseudo R2	0.028	0.034	0.027	0.019
	Q-Value	0.644	0.574	0.492	0.347
	Standard Error	(0.240)	(0.252)	(0.250)	(0.185)
New Britain	Coefficient	-0.386++	-0.418++	-0.238+	-0.310++
	Observations	1224	1203	1722	2072
	P-Value	0.039	0.029	0.093	0.017
	Pseudo R2	0.028	0.029	0.014	0.016
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.187)	(0.193)	(0.142)	(0.130)
New Canaan	Coefficient	-0.089	-0.056	0.226	0.107
	Observations	1183	1144	1140	1277
	P-Value	0.759	0.865	0.419	0.639
	Pseudo R2	0.026	0.035	0.028	0.028
	Q-Value	N/A	N/A	0.764	0.834
	Standard Error	(0.291)	(0.328)	(0.282)	(0.229)

*Results were not available across all specifications for departments not listed in this table.

Table C.7: Logistic Regression of Minority Status on Daylight by Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
New Haven	Coefficient	-0.094	-0.096	-0.135+	-0.104+
	Observations	7241	7120	4930	9257
	P-Value	0.142	0.136	0.078	0.087
	Pseudo R2	0.013	0.013	0.008	0.009
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.064)	(0.064)	(0.075)	(0.061)
New London	Coefficient	-0.449+	-0.593++	-0.769+++	-0.640+++
	Observations	991	965	994	1187
	P-Value	0.061	0.017	0.001	0.001
	Pseudo R2	0.029	0.032	0.043	0.032
	Q-Value	N/A	N/A	N/A	0.001
	Standard Error	(0.239)	(0.250)	(0.237)	(0.188)
Newington	Coefficient	-0.337+	-0.268	-0.287+	-0.270+
	Observations	1282	1226	1325	1526
	P-Value	0.056	0.166	0.082	0.052
	Pseudo R2	0.032	0.035	0.024	0.021
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.175)	(0.194)	(0.165)	(0.138)
Newtown	Coefficient	-0.185	-0.020	0.054	0.019
	Observations	720	664	726	797
	P-Value	0.625	0.961	0.898	0.949
	Pseudo R2	0.087	0.079	0.054	0.043
	Q-Value	N/A	N/A	0.959	0.987
	Standard Error	(0.377)	(0.437)	(0.418)	(0.314)
North Haven	Coefficient	-0.634++	-0.617++	0.122	-0.273
	Observations	633	617	571	715
	P-Value	0.020	0.035	0.741	0.256
	Pseudo R2	0.029	0.024	0.046	0.018
	Q-Value	N/A	N/A	0.865	N/A
	Standard Error	(0.275)	(0.293)	(0.368)	(0.240)
Norwalk	Coefficient	-0.331++	-0.340++	-0.052	-0.203
	Observations	1224	1183	1200	1560
	P-Value	0.027	0.028	0.735	0.104
	Pseudo R2	0.029	0.032	0.024	0.025
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.150)	(0.156)	(0.155)	(0.126)
Norwich	Coefficient	-0.078	-0.133	0.030	-0.063
	Observations	1317	1261	1194	1490
	P-Value	0.619	0.423	0.869	0.642
	Pseudo R2	0.028	0.026	0.023	0.020
	Q-Value	N/A	N/A	0.944	N/A
	Standard Error	(0.158)	(0.166)	(0.186)	(0.136)
Old Saybrook	Coefficient	-0.400	-0.236	-0.202	-0.246
	Observations	664	589	740	762
	P-Value	0.321	0.626	0.619	0.449
	Pseudo R2	0.057	0.056	0.050	0.039
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.402)	(0.485)	(0.407)	(0.326)
Plainville	Coefficient	0.127	0.187	0.037	0.079
	Observations	774	763	808	903
	P-Value	0.666	0.546	0.876	0.689
	Pseudo R2	0.050	0.082	0.056	0.048
	Q-Value	0.847	0.802	0.944	0.853
	Standard Error	(0.293)	(0.310)	(0.237)	(0.200)

*Results were not available across all specifications for departments not listed in this table.

Table C.7: Logistic Regression of Minority Status on Daylight by Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Ridgefield	Coefficient	0.340	0.256	0.240	0.231
	Observations	1158	1090	1159	1239
	P-Value	0.287	0.513	0.386	0.335
	Pseudo R2	0.037	0.046	0.030	0.020
	Q-Value	0.680	0.802	0.721	0.717
	Standard Error	(0.319)	(0.393)	(0.279)	(0.240)
Rocky Hill	Coefficient	0.096	0.303	0.386	0.340
	Observations	981	949	885	1010
	P-Value	0.703	0.287	0.254	0.138
	Pseudo R2	0.041	0.043	0.054	0.037
	Q-Value	0.855	0.680	0.680	0.574
	Standard Error	(0.252)	(0.284)	(0.338)	(0.231)
Seymour	Coefficient	0.130	0.263	-0.589++	-0.146
	Observations	1093	1083	1059	1173
	P-Value	0.623	0.354	0.045	0.495
	Pseudo R2	0.046	0.052	0.025	0.026
	Q-Value	0.834	0.717	N/A	N/A
	Standard Error	(0.266)	(0.284)	(0.294)	(0.215)
Simsbury	Coefficient	-0.247	0.560	0.115	0.412
	Observations	777	647	703	778
	P-Value	0.521	0.303	0.800	0.263
	Pseudo R2	0.039	0.043	0.067	0.037
	Q-Value	N/A	0.684	0.912	0.680
	Standard Error	(0.386)	(0.544)	(0.456)	(0.368)
South Windsor	Coefficient	-0.068	0.146	0.400	0.245
	Observations	1119	1054	994	1139
	P-Value	0.773	0.614	0.291	0.314
	Pseudo R2	0.046	0.054	0.048	0.037
	Q-Value	N/A	0.833	0.680	0.699
	Standard Error	(0.240)	(0.291)	(0.379)	(0.243)
Southington	Coefficient	0.481	0.597	0.170	0.338
	Observations	957	921	996	1066
	P-Value	0.175	0.159	0.644	0.231
	Pseudo R2	0.048	0.063	0.024	0.025
	Q-Value	0.586	0.577	0.834	0.680
	Standard Error	(0.356)	(0.425)	(0.368)	(0.284)
Stamford	Coefficient	-0.321+++	-0.280++	0.112	-0.052
	Observations	2876	2757	2886	3553
	P-Value	0.004	0.018	0.298	0.546
	Pseudo R2	0.026	0.028	0.010	0.014
	Q-Value	N/A	N/A	0.684	N/A
	Standard Error	(0.111)	(0.119)	(0.108)	(0.089)
Stonington	Coefficient	-0.093	-0.707	0.907	-0.212
	Observations	1027	804	580	968
	P-Value	0.783	0.112	0.165	0.564
	Pseudo R2	0.052	0.052	0.064	0.056
	Q-Value	N/A	N/A	0.577	N/A
	Standard Error	(0.338)	(0.446)	(0.653)	(0.368)
Stratford	Coefficient	0.300	0.252	N/A	0.116
	Observations	634	613	N/A	781
	P-Value	0.164	0.248	N/A	0.561
	Pseudo R2	0.039	0.043	N/A	0.032
	Q-Value	0.577	0.680	N/A	0.802
	Standard Error	(0.216)	(0.218)	N/A	(0.201)

*Results were not available across all specifications for departments not listed in this table.

Table C.7: Logistic Regression of Minority Status on Daylight by Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Torrington	Coefficient	-0.303	-0.384	-0.354	-0.333
	Observations	571	534	525	612
	P-Value	0.490	0.501	0.345	0.293
	Pseudo R2	0.061	0.081	0.065	0.052
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.442)	(0.572)	(0.377)	(0.317)
Trumbull	Coefficient	-0.006	-0.138	N/A	0.168
	Observations	564	545	N/A	637
	P-Value	0.982	0.617	N/A	0.488
	Pseudo R2	0.057	0.061	N/A	0.039
	Q-Value	N/A	N/A	N/A	0.797
	Standard Error	(0.270)	(0.277)	N/A	(0.244)
University of Connecticut	Coefficient	-0.305	-0.214	-1.603+++	-0.504+
	Observations	831	761	513	801
	P-Value	0.275	0.541	0.006	0.097
	Pseudo R2	0.020	0.034	0.115	0.043
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.280)	(0.349)	(0.587)	(0.303)
Vernon	Coefficient	0.402	N/A	N/A	0.152
	Observations	526	N/A	N/A	589
	P-Value	0.263	N/A	N/A	0.602
	Pseudo R2	0.057	N/A	N/A	0.048
	Q-Value	0.680	N/A	N/A	0.833
	Standard Error	(0.358)	N/A	N/A	(0.293)
Wallingford	Coefficient	-0.128	-0.070	-0.014	-0.050
	Observations	1877	1843	1971	2187
	P-Value	0.456	0.707	0.930	0.694
	Pseudo R2	0.019	0.023	0.016	0.014
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.173)	(0.185)	(0.157)	(0.128)
Waterbury	Coefficient	N/A	N/A	N/A	0.247
	Observations	N/A	N/A	N/A	669
	P-Value	N/A	N/A	N/A	0.256
	Pseudo R2	N/A	N/A	N/A	0.029
	Q-Value	N/A	N/A	N/A	0.680
	Standard Error	N/A	N/A	N/A	(0.217)
Waterford	Coefficient	0.289	0.203	-0.209	-0.018
	Observations	1291	1255	1251	1425
	P-Value	0.151	0.347	0.317	0.907
	Pseudo R2	0.028	0.025	0.030	0.023
	Q-Value	0.574	0.717	N/A	N/A
	Standard Error	(0.202)	(0.216)	(0.209)	(0.162)
West Hartford	Coefficient	-0.192	-0.236	-0.416+++	-0.349+++
	Observations	1620	1475	1489	1816
	P-Value	0.187	0.151	0.008	0.007
	Pseudo R2	0.014	0.012	0.025	0.014
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.145)	(0.165)	(0.160)	(0.128)
West Haven	Coefficient	0.041	0.071	-0.081	0.004
	Observations	1883	1852	1621	2338
	P-Value	0.714	0.545	0.537	0.959
	Pseudo R2	0.014	0.014	0.014	0.012
	Q-Value	0.855	0.802	N/A	0.987
	Standard Error	(0.115)	(0.116)	(0.131)	(0.100)

*Results were not available across all specifications for departments not listed in this table.

Table C.7: Logistic Regression of Minority Status on Daylight by Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Westport	Coefficient	0.310+	0.423++	0.182	0.305++
	Observations	1710	1662	1646	1835
	P-Value	0.075	0.028	0.365	0.039
	Pseudo R2	0.028	0.030	0.030	0.020
	Q-Value	0.377	0.247	0.717	0.282
	Standard Error	(0.174)	(0.193)	(0.202)	(0.148)
Wethersfield	Coefficient	0.310	N/A	0.129	0.159
	Observations	509	N/A	589	711
	P-Value	0.240	N/A	0.560	0.411
	Pseudo R2	0.030	N/A	0.028	0.018
	Q-Value	0.680	N/A	0.802	0.758
	Standard Error	(0.264)	N/A	(0.224)	(0.194)
Wilton	Coefficient	0.133	0.240	0.515++	0.370++
	Observations	1119	1047	1094	1211
	P-Value	0.517	0.347	0.034	0.048
	Pseudo R2	0.014	0.028	0.028	0.017
	Q-Value	0.802	0.717	0.268	0.305
	Standard Error	(0.204)	(0.256)	(0.244)	(0.187)
Windsor	Coefficient	-0.266++	-0.261++	-0.349+	-0.272++
	Observations	1870	1794	1112	2014
	P-Value	0.030	0.037	0.065	0.023
	Pseudo R2	0.023	0.025	0.024	0.021
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.123)	(0.126)	(0.189)	(0.119)
Woodbridge	Coefficient	-0.041	0.126	0.261	0.127
	Observations	715	683	546	731
	P-Value	0.861	0.629	0.527	0.583
	Pseudo R2	0.035	0.029	0.105	0.019
	Q-Value	N/A	0.834	0.802	0.815
	Standard Error	(0.238)	(0.261)	(0.412)	(0.231)
Yale University	Coefficient	N/A	N/A	N/A	0.628++
	Observations	N/A	N/A	N/A	501
	P-Value	N/A	N/A	N/A	0.013
	Pseudo R2	N/A	N/A	N/A	0.050
	Q-Value	N/A	N/A	N/A	0.152
	Standard Error	N/A	N/A	N/A	(0.252)

*Results were not available across all specifications for departments not listed in this table.

Table C.8: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Ansonia	Coefficient	0.402***	0.493***	0.282	0.441***
	Observations	767	762	769	895
	P-Value	0.004	0.001	0.177	0.001
	Pseudo R2	0.050	0.050	0.068	0.035
	Q-Value	0.039	0.001	0.425	0.001
	Standard Error	(0.143)	(0.075)	(0.209)	(0.071)
Berlin	Coefficient	-0.326	-0.356+	-0.002	-0.164
	Observations	1104	1055	1153	1283
	P-Value	0.137	0.090	0.994	0.368
	Pseudo R2	0.035	0.032	0.034	0.024
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.218)	(0.209)	(0.312)	(0.181)
Bethel	Coefficient	N/A	N/A	-0.781+++	-0.499+++
	Observations	N/A	N/A	558	621
	P-Value	N/A	N/A	0	0
	Pseudo R2	N/A	N/A	0.063	0.039
	Q-Value	N/A	N/A	0.001	0.001
	Standard Error	N/A	N/A	(0.130)	(0.129)
Bloomfield	Coefficient	-0.109	-0.082	N/A	-0.041
	Observations	568	560	N/A	603
	P-Value	0.301	0.409	N/A	0.602
	Pseudo R2	0.061	0.061	N/A	0.068
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.107)	(0.098)	N/A	(0.079)
Branford	Coefficient	-0.230	-0.209	-0.574+	-0.423
	Observations	887	859	862	977
	P-Value	0.340	0.388	0.075	0.101
	Pseudo R2	0.087	0.075	0.064	0.057
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.241)	(0.243)	(0.321)	(0.257)
Bridgeport	Coefficient	N/A	N/A	N/A	-0.465+++
	Observations	N/A	N/A	N/A	541
	P-Value	N/A	N/A	N/A	0
	Pseudo R2	N/A	N/A	N/A	0.046
	Q-Value	N/A	N/A	N/A	0.001
	Standard Error	N/A	N/A	N/A	(0.067)
Bristol	Coefficient	0.298++	0.349***	-0.182++	0.003
	Observations	1175	1168	1227	1349
	P-Value	0.023	0.006	0.024	0.947
	Pseudo R2	0.052	0.050	0.034	0.028
	Q-Value	0.109	0.039	N/A	0.953
	Standard Error	(0.131)	(0.127)	(0.081)	(0.048)
Brookfield	Coefficient	N/A	N/A	-0.067	0.129
	Observations	N/A	N/A	555	577
	P-Value	N/A	N/A	0.681	0.501
	Pseudo R2	N/A	N/A	0.054	0.054
	Q-Value	N/A	N/A	N/A	0.709
	Standard Error	N/A	N/A	(0.164)	(0.193)
Central CT State University	Coefficient	0.103	0.130	0.643	0.286
	Observations	675	650	618	778
	P-Value	0.816	0.777	0.118	0.442
	Pseudo R2	0.050	0.050	0.048	0.034
	Q-Value	0.893	0.873	0.328	0.666
	Standard Error	(0.444)	(0.462)	(0.412)	(0.372)

*Results were not available across all specifications for departments not listed in this table.

Table C.8: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
CSP Headquarters	Coefficient	-0.083	0.120	0.052	0.093
	Observations	1940	1835	1823	2178
	P-Value	0.303	0.238	0.667	0.210
	Pseudo R2	0.039	0.050	0.041	0.035
	Q-Value	N/A	0.490	0.786	0.455
	Standard Error	(0.082)	(0.103)	(0.120)	(0.074)
CSP Troop A	Coefficient	0.225++	0.238+	0.363***	0.252***
	Observations	3032	2882	3038	3511
	P-Value	0.039	0.052	0.006	0.007
	Pseudo R2	0.079	0.092	0.064	0.070
	Q-Value	0.162	0.201	0.041	0.043
	Standard Error	(0.109)	(0.123)	(0.133)	(0.093)
CSP Troop B	Coefficient	-0.108	0.358	0.324	0.356+
	Observations	1117	1060	992	1173
	P-Value	0.741	0.407	0.291	0.068
	Pseudo R2	0.079	0.090	0.054	0.046
	Q-Value	N/A	0.656	0.551	0.234
	Standard Error	(0.330)	(0.432)	(0.307)	(0.195)
CSP Troop C	Coefficient	0.384***	0.370***	0.395***	0.381***
	Observations	5418	4882	4922	5392
	P-Value	0.002	0.008	0.002	0.001
	Pseudo R2	0.057	0.057	0.057	0.052
	Q-Value	0.017	0.050	0.024	0.013
	Standard Error	(0.123)	(0.142)	(0.129)	(0.116)
CSP Troop D	Coefficient	0.298+	0.648***	0.082	0.361***
	Observations	2656	2518	2538	2696
	P-Value	0.052	0.001	0.615	0.003
	Pseudo R2	0.046	0.063	0.061	0.048
	Q-Value	0.201	0.001	0.767	0.028
	Standard Error	(0.155)	(0.188)	(0.165)	(0.120)
CSP Troop E	Coefficient	-0.076	-0.130	0.068	-0.032
	Observations	4815	4509	4347	4952
	P-Value	0.344	0.143	0.551	0.677
	Pseudo R2	0.035	0.039	0.039	0.035
	Q-Value	N/A	N/A	0.744	N/A
	Standard Error	(0.082)	(0.089)	(0.115)	(0.079)
CSP Troop F	Coefficient	-0.167	-0.096	-0.120	-0.056
	Observations	3846	3711	3783	4105
	P-Value	0.273	0.546	0.358	0.490
	Pseudo R2	0.064	0.065	0.054	0.056
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.152)	(0.158)	(0.131)	(0.081)
CSP Troop G	Coefficient	-0.125	-0.182	0.075	-0.065
	Observations	1694	1568	1556	2038
	P-Value	0.481	0.284	0.296	0.455
	Pseudo R2	0.032	0.039	0.061	0.041
	Q-Value	N/A	N/A	0.551	N/A
	Standard Error	(0.178)	(0.171)	(0.071)	(0.087)
CSP Troop H	Coefficient	0.244++	0.212+	-0.194+	0.023
	Observations	2295	2126	1995	2590
	P-Value	0.043	0.096	0.081	0.805
	Pseudo R2	0.032	0.037	0.035	0.026
	Q-Value	0.172	0.286	N/A	0.888
	Standard Error	(0.119)	(0.128)	(0.111)	(0.094)

*Results were not available across all specifications for departments not listed in this table.

Table C.8: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
CSP Troop I	Coefficient	-0.019	-0.039	-0.104	-0.046
	Observations	2096	1990	1907	2348
	P-Value	0.873	0.765	0.564	0.755
	Pseudo R2	0.030	0.034	0.057	0.032
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.127)	(0.130)	(0.182)	(0.146)
CSP Troop K	Coefficient	0.143	0.027	0.500***	0.314**
	Observations	2778	2648	2670	2994
	P-Value	0.268	0.885	0.007	0.017
	Pseudo R2	0.057	0.064	0.108	0.070
	Q-Value	0.528	0.916	0.041	0.090
	Standard Error	(0.128)	(0.187)	(0.184)	(0.134)
CSP Troop L	Coefficient	0.039	0.008	0.187	0.130
	Observations	1609	1575	1685	1777
	P-Value	0.893	0.976	0.554	0.686
	Pseudo R2	0.094	0.097	0.090	0.081
	Q-Value	0.916	0.976	0.744	0.795
	Standard Error	(0.294)	(0.310)	(0.317)	(0.326)
Cheshire	Coefficient	0.365***	0.395***	-0.625+++	-0.046
	Observations	635	606	603	668
	P-Value	0.001	0.001	0	0.337
	Pseudo R2	0.043	0.032	0.086	0.030
	Q-Value	0.001	0.001	0.001	N/A
	Standard Error	(0.079)	(0.081)	(0.129)	(0.048)
Clinton	Coefficient	N/A	N/A	N/A	-0.277++
	Observations	N/A	N/A	N/A	530
	P-Value	N/A	N/A	N/A	0.035
	Pseudo R2	N/A	N/A	N/A	0.097
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	(0.130)
Danbury	Coefficient	N/A	N/A	0.052	0.037
	Observations	N/A	N/A	690	751
	P-Value	N/A	N/A	0.861	0.894
	Pseudo R2	N/A	N/A	0.093	0.093
	Q-Value	N/A	N/A	0.916	0.916
	Standard Error	N/A	N/A	(0.301)	(0.289)
Darien	Coefficient	0.165	0.093	0.386***	0.307**
	Observations	562	542	557	675
	P-Value	0.351	0.638	0.004	0.018
	Pseudo R2	0.093	0.098	0.087	0.081
	Q-Value	0.607	0.769	0.029	0.090
	Standard Error	(0.178)	(0.197)	(0.133)	(0.130)
East Hartford	Coefficient	0.195	0.153	0.173	0.166
	Observations	800	778	641	1078
	P-Value	0.455	0.606	0.597	0.584
	Pseudo R2	0.041	0.043	0.071	0.048
	Q-Value	0.671	0.764	0.764	0.764
	Standard Error	(0.261)	(0.300)	(0.330)	(0.305)
East Haven	Coefficient	0.187	0.331	-0.180	-0.010
	Observations	544	535	576	658
	P-Value	0.425	0.127	0.280	0.944
	Pseudo R2	0.079	0.086	0.043	0.037
	Q-Value	0.666	0.328	N/A	N/A
	Standard Error	(0.234)	(0.216)	(0.167)	(0.158)

*Results were not available across all specifications for departments not listed in this table.

Table C.8: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Enfield	Coefficient	0.039	0.108	0.223++	0.125
	Observations	3411	3293	3231	3568
	P-Value	0.731	0.500	0.037	0.331
	Pseudo R2	0.035	0.037	0.039	0.030
	Q-Value	0.839	0.709	0.160	0.595
	Standard Error	(0.115)	(0.162)	(0.107)	(0.128)
Fairfield	Coefficient	0.442***	0.485***	0.282+	0.388***
	Observations	2724	2628	2592	3030
	P-Value	0.001	0.004	0.076	0.001
	Pseudo R2	0.054	0.067	0.086	0.070
	Q-Value	0.001	0.039	0.250	0.001
	Standard Error	(0.134)	(0.172)	(0.159)	(0.114)
Farmington	Coefficient	0.189	0.072	-0.282	-0.116
	Observations	1081	948	1024	1148
	P-Value	0.206	0.779	0.232	0.632
	Pseudo R2	0.065	0.064	0.065	0.045
	Q-Value	0.451	0.873	N/A	N/A
	Standard Error	(0.150)	(0.261)	(0.237)	(0.244)
Glastonbury	Coefficient	-0.375+++	-0.411+++	0.025	-0.215++
	Observations	1092	999	990	1129
	P-Value	0.003	0.002	0.841	0.039
	Pseudo R2	0.071	0.092	0.076	0.059
	Q-Value	N/A	N/A	0.906	N/A
	Standard Error	(0.128)	(0.133)	(0.123)	(0.104)
Greenwich	Coefficient	-0.082	-0.052	-0.148++	-0.130+++
	Observations	1744	1541	1774	1974
	P-Value	0.141	0.593	0.018	0.004
	Pseudo R2	0.046	0.061	0.039	0.039
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.056)	(0.100)	(0.063)	(0.046)
Groton Town	Coefficient	-0.082	-0.218+++	-0.421+	-0.266+++
	Observations	1031	968	938	1099
	P-Value	0.425	0.001	0.064	0.002
	Pseudo R2	0.037	0.032	0.057	0.035
	Q-Value	N/A	0.001	N/A	N/A
	Standard Error	(0.103)	(0.063)	(0.228)	(0.087)
Guilford	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Hamden	Coefficient	-0.085	-0.071	-0.280	-0.098
	Observations	1627	1608	1173	1749
	P-Value	0.165	0.199	0.397	0.294
	Pseudo R2	0.037	0.035	0.109	0.041
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.061)	(0.056)	(0.331)	(0.093)
Hartford	Coefficient	-0.361+++	-0.354+++	-0.028	-0.247+++
	Observations	2068	2026	1399	2870
	P-Value	0	0	0.802	0.007
	Pseudo R2	0.138	0.141	0.109	0.112
	Q-Value	0.001	0.001	N/A	N/A
	Standard Error	(0.093)	(0.093)	(0.118)	(0.092)

*Results were not available across all specifications for departments not listed in this table.

Table C.8: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Ledyard	Coefficient	-0.252+++	-0.250++	-0.523	-0.289++
	Observations	621	605	542	661
	P-Value	0.004	0.021	0.216	0.018
	Pseudo R2	0.059	0.057	0.104	0.065
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.086)	(0.108)	(0.425)	(0.123)
Madison	Coefficient	0.360	N/A	N/A	N/A
	Observations	502	N/A	N/A	N/A
	P-Value	0.128	N/A	N/A	N/A
	Pseudo R2	0.097	N/A	N/A	N/A
	Q-Value	0.328	N/A	N/A	N/A
	Standard Error	(0.237)	N/A	N/A	N/A
Manchester	Coefficient	-0.136	-0.165	-0.075	-0.135+
	Observations	2503	2412	2076	2832
	P-Value	0.397	0.208	0.662	0.098
	Pseudo R2	0.019	0.019	0.026	0.017
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.160)	(0.130)	(0.174)	(0.082)
Middletown	Coefficient	0.150+	0.158+	-0.052	0.103+
	Observations	747	737	541	815
	P-Value	0.097	0.072	0.204	0.097
	Pseudo R2	0.048	0.050	0.074	0.046
	Q-Value	0.286	0.243	N/A	0.286
	Standard Error	(0.090)	(0.087)	(0.041)	(0.061)
Milford	Coefficient	-0.034	-0.115	-0.012	-0.045
	Observations	621	607	580	693
	P-Value	0.707	0.263	0.888	0.583
	Pseudo R2	0.074	0.079	0.063	0.043
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.090)	(0.103)	(0.086)	(0.082)
Monroe	Coefficient	0.039	0.171	-0.056	0.059
	Observations	1069	1042	990	1138
	P-Value	0.897	0.672	0.870	0.629
	Pseudo R2	0.046	0.048	0.064	0.043
	Q-Value	0.916	0.786	N/A	0.767
	Standard Error	(0.301)	(0.407)	(0.342)	(0.123)
Naugatuck	Coefficient	0.298	0.349+	0.433++	0.349***
	Observations	1206	1192	1220	1361
	P-Value	0.186	0.094	0.039	0.008
	Pseudo R2	0.048	0.052	0.064	0.039
	Q-Value	0.430	0.286	0.162	0.050
	Standard Error	(0.225)	(0.209)	(0.209)	(0.133)
New Britain	Coefficient	-0.305+++	-0.347+++	-0.148+++	-0.224+++
	Observations	1215	1194	1720	2065
	P-Value	0	0	0.006	0
	Pseudo R2	0.029	0.032	0.020	0.020
	Q-Value	0.001	0.001	N/A	0.001
	Standard Error	(0.059)	(0.071)	(0.054)	(0.050)
New Canaan	Coefficient	-0.224	-0.238	0.197	0.016
	Observations	1140	1089	1133	1273
	P-Value	0.469	0.409	0.319	0.930
	Pseudo R2	0.043	0.052	0.039	0.037
	Q-Value	N/A	N/A	0.582	0.944
	Standard Error	(0.310)	(0.289)	(0.199)	(0.185)

*Results were not available across all specifications for departments not listed in this table.

Table C.8: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
New Haven	Coefficient	-0.010	-0.006	-0.078	-0.017
	Observations	7234	7113	4917	9248
	P-Value	0.887	0.944	0.439	0.857
	Pseudo R2	0.050	0.054	0.039	0.043
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.078)	(0.086)	(0.101)	(0.093)
New London	Coefficient	-0.312++	-0.437+++	-0.483+++	-0.435+++
	Observations	989	963	982	1182
	P-Value	0.023	0.001	0	0
	Pseudo R2	0.037	0.041	0.068	0.046
	Q-Value	N/A	N/A	0.001	0.001
	Standard Error	(0.137)	(0.134)	(0.112)	(0.116)
Newington	Coefficient	-0.433+++	-0.331	-0.372+++	-0.344+++
	Observations	1271	1215	1303	1516
	P-Value	0.008	0.105	0.006	0.006
	Pseudo R2	0.050	0.057	0.052	0.041
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.165)	(0.204)	(0.135)	(0.125)
Newtown	Coefficient	-0.050	0.050	0.079	0.046
	Observations	684	620	720	791
	P-Value	0.735	0.760	0.875	0.884
	Pseudo R2	0.103	0.101	0.063	0.054
	Q-Value	N/A	0.865	0.916	0.916
	Standard Error	(0.150)	(0.166)	(0.504)	(0.323)
North Haven	Coefficient	-0.486++	-0.453+++	0.180	-0.142+++
	Observations	632	616	569	714
	P-Value	0.027	0.006	0.437	0
	Pseudo R2	0.050	0.046	0.075	0.041
	Q-Value	N/A	N/A	0.666	0.001
	Standard Error	(0.221)	(0.164)	(0.232)	(0.021)
Norwalk	Coefficient	-0.241	-0.218+	0.039	-0.097
	Observations	1223	1182	1200	1560
	P-Value	0.174	0.097	0.785	0.456
	Pseudo R2	0.061	0.070	0.054	0.056
	Q-Value	N/A	N/A	0.873	N/A
	Standard Error	(0.179)	(0.131)	(0.142)	(0.130)
Norwich	Coefficient	-0.046	-0.086	0.032	-0.039
	Observations	1317	1261	1183	1490
	P-Value	0.570	0.449	0.667	0.644
	Pseudo R2	0.035	0.035	0.028	0.025
	Q-Value	N/A	N/A	0.786	N/A
	Standard Error	(0.082)	(0.114)	(0.074)	(0.086)
Old Saybrook	Coefficient	-0.397	-0.209	-0.224	-0.226
	Observations	648	519	626	693
	P-Value	0.469	0.606	0.518	0.216
	Pseudo R2	0.076	0.064	0.070	0.059
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.549)	(0.407)	(0.345)	(0.182)
Plainville	Coefficient	0.104	0.215	0.061	0.114
	Observations	742	731	797	896
	P-Value	0.629	0.194	0.838	0.527
	Pseudo R2	0.064	0.097	0.070	0.059
	Q-Value	0.767	0.430	0.906	0.731
	Standard Error	(0.216)	(0.165)	(0.307)	(0.180)

*Results were not available across all specifications for departments not listed in this table.

Table C.8: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Ridgefield	Coefficient	0.239	0.216	0.136	0.145
	Observations	1154	1057	1157	1237
	P-Value	0.405	0.510	0.625	0.356
	Pseudo R2	0.050	0.059	0.054	0.037
	Q-Value	0.656	0.714	0.767	0.607
	Standard Error	(0.287)	(0.328)	(0.277)	(0.158)
Rocky Hill	Coefficient	0.163	0.384**	0.419	0.402***
	Observations	959	911	847	971
	P-Value	0.365	0.010	0.128	0.004
	Pseudo R2	0.059	0.071	0.079	0.059
	Q-Value	0.615	0.059	0.328	0.029
	Standard Error	(0.180)	(0.150)	(0.277)	(0.137)
Seymour	Coefficient	0.181	0.330	-0.700+++	-0.163
	Observations	1080	1070	1059	1173
	P-Value	0.453	0.150	0.003	0.207
	Pseudo R2	0.052	0.059	0.050	0.037
	Q-Value	0.671	0.379	N/A	N/A
	Standard Error	(0.243)	(0.230)	(0.234)	(0.129)
Simsbury	Coefficient	-0.156	0.527	-0.041	0.340
	Observations	766	619	676	750
	P-Value	0.563	0.354	0.888	0.172
	Pseudo R2	0.046	0.067	0.101	0.064
	Q-Value	N/A	0.607	N/A	0.425
	Standard Error	(0.270)	(0.569)	(0.298)	(0.248)
South Windsor	Coefficient	-0.021	0.164	0.477***	0.300**
	Observations	1107	1042	967	1127
	P-Value	0.828	0.275	0.001	0.017
	Pseudo R2	0.057	0.071	0.070	0.048
	Q-Value	N/A	0.533	0.001	0.090
	Standard Error	(0.101)	(0.150)	(0.096)	(0.126)
Southington	Coefficient	0.379	0.541	0.092	0.293
	Observations	874	801	915	1020
	P-Value	0.439	0.291	0.603	0.186
	Pseudo R2	0.071	0.087	0.043	0.050
	Q-Value	0.666	0.551	0.764	0.430
	Standard Error	(0.488)	(0.512)	(0.177)	(0.222)
Stamford	Coefficient	-0.319+++	-0.272++	0.098	-0.064
	Observations	2871	2752	2881	3548
	P-Value	0.001	0.014	0.257	0.356
	Pseudo R2	0.057	0.061	0.039	0.041
	Q-Value	0.001	N/A	0.517	N/A
	Standard Error	(0.096)	(0.111)	(0.087)	(0.070)
Stonington	Coefficient	-0.064	-0.782	N/A	-0.331
	Observations	1014	794	N/A	960
	P-Value	0.875	0.324	N/A	0.513
	Pseudo R2	0.075	0.082	N/A	0.086
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.412)	(0.796)	N/A	(0.507)
Stratford	Coefficient	0.354+	0.300	N/A	0.187
	Observations	634	613	N/A	781
	P-Value	0.061	0.122	N/A	0.223
	Pseudo R2	0.076	0.086	N/A	0.065
	Q-Value	0.222	0.328	N/A	0.467
	Standard Error	(0.189)	(0.194)	N/A	(0.155)

*Results were not available across all specifications for departments not listed in this table.

Table C.8: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Torrington	Coefficient	-0.012	N/A	N/A	-0.259
	Observations	522	N/A	N/A	588
	P-Value	0.973	N/A	N/A	0.388
	Pseudo R2	0.116	N/A	N/A	0.075
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.358)	N/A	N/A	(0.300)
Trumbull	Coefficient	0.097	-0.043	N/A	0.209
	Observations	561	542	N/A	634
	P-Value	0.400	0.708	N/A	0.256
	Pseudo R2	0.086	0.093	N/A	0.054
	Q-Value	0.656	N/A	N/A	0.517
	Standard Error	(0.115)	(0.119)	N/A	(0.184)
University of Connecticut	Coefficient	-0.363	-0.231	-1.827+++	-0.547+++
	Observations	828	752	500	792
	P-Value	0.188	0.546	0.001	0
	Pseudo R2	0.027	0.035	0.140	0.046
	Q-Value	N/A	N/A	N/A	0.001
	Standard Error	(0.275)	(0.384)	(0.166)	(0.138)
Vernon	Coefficient	0.404***	N/A	N/A	0.145++
	Observations	523	N/A	N/A	584
	P-Value	0.001	N/A	N/A	0.032
	Pseudo R2	0.081	N/A	N/A	0.057
	Q-Value	0.001	N/A	N/A	0.145
	Standard Error	(0.094)	N/A	N/A	(0.068)
Wallingford	Coefficient	-0.143+	-0.074	0.059	-0.014
	Observations	1854	1791	1908	2141
	P-Value	0.071	0.428	0.597	0.810
	Pseudo R2	0.034	0.037	0.039	0.032
	Q-Value	N/A	N/A	0.764	N/A
	Standard Error	(0.079)	(0.093)	(0.112)	(0.059)
Waterbury	Coefficient	N/A	N/A	N/A	0.287***
	Observations	N/A	N/A	N/A	669
	P-Value	N/A	N/A	N/A	0.001
	Pseudo R2	N/A	N/A	N/A	0.043
	Q-Value	N/A	N/A	N/A	0.001
	Standard Error	N/A	N/A	N/A	(0.048)
Waterford	Coefficient	0.250	0.150	-0.211	-0.050
	Observations	1271	1221	1236	1411
	P-Value	0.222	0.535	0.216	0.786
	Pseudo R2	0.052	0.054	0.050	0.041
	Q-Value	0.467	0.735	N/A	N/A
	Standard Error	(0.203)	(0.244)	(0.171)	(0.187)
West Hartford	Coefficient	-0.128	-0.150	-0.349+++	-0.279+++
	Observations	1614	1464	1489	1816
	P-Value	0.120	0.135	0	0
	Pseudo R2	0.037	0.039	0.064	0.046
	Q-Value	N/A	N/A	0.001	0.001
	Standard Error	(0.082)	(0.101)	(0.082)	(0.075)
West Haven	Coefficient	0.071	0.098	-0.029	0.039
	Observations	1877	1841	1604	2327
	P-Value	0.469	0.303	0.680	0.644
	Pseudo R2	0.028	0.028	0.028	0.027
	Q-Value	0.675	0.556	N/A	0.772
	Standard Error	(0.100)	(0.096)	(0.071)	(0.083)

*Results were not available across all specifications for departments not listed in this table.

Table C.8: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Westport	Coefficient	0.207	0.301+	0.158	0.221
	Observations	1676	1584	1594	1803
	P-Value	0.189	0.064	0.462	0.193
	Pseudo R2	0.067	0.083	0.076	0.070
	Q-Value	0.430	0.223	0.674	0.430
	Standard Error	(0.158)	(0.163)	(0.216)	(0.170)
Wethersfield	Coefficient	0.272	N/A	0.141	0.145
	Observations	504	N/A	589	711
	P-Value	0.107	N/A	0.414	0.393
	Pseudo R2	0.037	N/A	0.046	0.032
	Q-Value	0.305	N/A	0.657	0.656
	Standard Error	(0.168)	N/A	(0.172)	(0.171)
Wilton	Coefficient	0.128	0.275	0.584+	0.425+
	Observations	1105	1033	1090	1209
	P-Value	0.441	0.126	0.059	0.093
	Pseudo R2	0.030	0.056	0.039	0.029
	Q-Value	0.666	0.328	0.216	0.286
	Standard Error	(0.167)	(0.180)	(0.310)	(0.254)
Windsor	Coefficient	-0.314+++	-0.296+++	-0.358+	-0.314+++
	Observations	1867	1791	1112	2011
	P-Value	0.002	0.004	0.086	0.003
	Pseudo R2	0.043	0.046	0.057	0.043
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.100)	(0.103)	(0.208)	(0.104)
Woodbridge	Coefficient	-0.037	0.118	0.263	0.119
	Observations	713	681	544	729
	P-Value	0.837	0.558	0.340	0.595
	Pseudo R2	0.037	0.034	0.108	0.023
	Q-Value	N/A	0.744	0.601	0.764
	Standard Error	(0.181)	(0.201)	(0.275)	(0.224)
Yale University	Coefficient	N/A	N/A	N/A	0.606***
	Observations	N/A	N/A	N/A	501
	P-Value	N/A	N/A	N/A	0.001
	Pseudo R2	N/A	N/A	N/A	0.050
	Q-Value	N/A	N/A	N/A	0.013
	Standard Error	N/A	N/A	N/A	(0.020)

*Results were not available across all specifications for departments not listed in this table.

Table C.9: Logistic Regression of Minority Status on Daylight by Department, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Ansonia	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Berlin	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Bethel	Coefficient	N/A	N/A	N/A	-0.824+++
	Observations	N/A	N/A	N/A	515
	P-Value	N/A	N/A	N/A	0.007
	Pseudo R2	N/A	N/A	N/A	0.063
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	(0.305)
Bloomfield	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Branford	Coefficient	N/A	N/A	N/A	-0.435
	Observations	N/A	N/A	N/A	573
	P-Value	N/A	N/A	N/A	0.187
	Pseudo R2	N/A	N/A	N/A	0.059
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	(0.330)
Bridgeport	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Bristol	Coefficient	0.340	0.432	-0.474	-0.074
	Observations	715	710	738	807
	P-Value	0.314	0.221	0.135	0.771
	Pseudo R2	0.070	0.071	0.052	0.035
	Q-Value	0.643	0.596	N/A	N/A
	Standard Error	(0.337)	(0.352)	(0.317)	(0.254)
Brookfield	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Central CT State University	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A

*Results were not available across all specifications for departments not listed in this table.

Table C.9: Logistic Regression of Minority Status on Daylight by Department, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
CSP Headquarters	Coefficient	-0.111	0.097	0.026	0.079
	Observations	1265	1186	1168	1404
	P-Value	0.551	0.646	0.902	0.637
	Pseudo R2	0.030	0.028	0.025	0.024
	Q-Value	N/A	0.809	0.922	0.809
	Standard Error	(0.186)	(0.214)	(0.214)	(0.166)
CSP Troop A	Coefficient	0.197	0.167	0.247	0.167
	Observations	1805	1712	1773	1993
	P-Value	0.223	0.368	0.159	0.234
	Pseudo R2	0.028	0.037	0.023	0.026
	Q-Value	0.596	0.662	0.596	0.607
	Standard Error	(0.163)	(0.187)	(0.177)	(0.141)
CSP Troop B	Coefficient	-0.241	0.282	0.246	0.317
	Observations	768	749	655	800
	P-Value	0.603	0.600	0.652	0.423
	Pseudo R2	0.054	0.064	0.039	0.037
	Q-Value	N/A	0.787	0.809	0.720
	Standard Error	(0.465)	(0.540)	(0.546)	(0.397)
CSP Troop C	Coefficient	0.460***	0.411+++	0.416***	0.432***
	Observations	3872	3532	3531	3853
	P-Value	0	0.006	0.003	0
	Pseudo R2	0.016	0.017	0.027	0.018
	Q-Value	0.001	0.108	0.075	0.001
	Standard Error	(0.109)	(0.150)	(0.142)	(0.109)
CSP Troop D	Coefficient	0.527+++	0.776***	-0.035	0.360+
	Observations	1872	1786	1795	1893
	P-Value	0.008	0.003	0.884	0.052
	Pseudo R2	0.029	0.037	0.064	0.034
	Q-Value	0.114	0.075	N/A	0.419
	Standard Error	(0.197)	(0.264)	(0.240)	(0.186)
CSP Troop E	Coefficient	-0.096	-0.172	0.167	-0.013
	Observations	3516	3275	3180	3576
	P-Value	0.379	0.187	0.247	0.901
	Pseudo R2	0.021	0.026	0.029	0.026
	Q-Value	N/A	N/A	0.614	N/A
	Standard Error	(0.108)	(0.131)	(0.144)	(0.105)
CSP Troop F	Coefficient	0.032	0.166	-0.229	0.028
	Observations	2442	2354	2343	2545
	P-Value	0.833	0.358	0.229	0.843
	Pseudo R2	0.019	0.027	0.028	0.027
	Q-Value	0.893	0.662	N/A	0.893
	Standard Error	(0.153)	(0.181)	(0.189)	(0.140)
CSP Troop G	Coefficient	-0.056	-0.187	0.196	0.002
	Observations	1005	928	901	1138
	P-Value	0.754	0.333	0.347	0.989
	Pseudo R2	0.017	0.023	0.023	0.017
	Q-Value	N/A	N/A	0.662	0.996
	Standard Error	(0.178)	(0.194)	(0.209)	(0.160)
CSP Troop H	Coefficient	0.201	0.130	-0.314	-0.043
	Observations	1399	1289	1191	1530
	P-Value	0.210	0.456	0.109	0.768
	Pseudo R2	0.013	0.018	0.027	0.014
	Q-Value	0.596	0.722	N/A	N/A
	Standard Error	(0.160)	(0.174)	(0.196)	(0.146)

*Results were not available across all specifications for departments not listed in this table.

Table C.9: Logistic Regression of Minority Status on Daylight by Department, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
CSP Troop I	Coefficient	-0.237	-0.331+	-0.472++	-0.402++
	Observations	1339	1270	1199	1448
	P-Value	0.190	0.096	0.035	0.012
	Pseudo R2	0.028	0.034	0.028	0.021
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.180)	(0.199)	(0.224)	(0.158)
CSP Troop K	Coefficient	0.246	0.175	0.476++	0.310+
	Observations	1882	1792	1786	1967
	P-Value	0.202	0.458	0.032	0.068
	Pseudo R2	0.016	0.020	0.029	0.013
	Q-Value	0.596	0.722	0.277	0.437
	Standard Error	(0.193)	(0.238)	(0.222)	(0.170)
CSP Troop L	Coefficient	0.324	0.109	0.430	0.351
	Observations	884	863	827	973
	P-Value	0.328	0.774	0.252	0.216
	Pseudo R2	0.059	0.059	0.043	0.052
	Q-Value	0.654	0.884	0.614	0.596
	Standard Error	(0.331)	(0.386)	(0.375)	(0.284)
Cheshire	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Clinton	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Danbury	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Darien	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
East Hartford	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
East Haven	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A

*Results were not available across all specifications for departments not listed in this table.

Table C.9: Logistic Regression of Minority Status on Daylight by Department, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Enfield	Coefficient	0.037	0.068	0.140	0.037
	Observations	2545	2483	2424	2636
	P-Value	0.806	0.685	0.460	0.778
	Pseudo R2	0.014	0.019	0.029	0.014
	Q-Value	0.890	0.814	0.722	0.884
	Standard Error	(0.150)	(0.167)	(0.189)	(0.133)
Fairfield	Coefficient	0.370++	0.395++	-0.028	0.196
	Observations	1740	1676	1658	1856
	P-Value	0.014	0.020	0.870	0.130
	Pseudo R2	0.017	0.023	0.037	0.017
	Q-Value	0.171	0.202	N/A	0.596
	Standard Error	(0.150)	(0.171)	(0.178)	(0.130)
Farmington	Coefficient	0.465	N/A	N/A	-0.043
	Observations	549	N/A	N/A	558
	P-Value	0.178	N/A	N/A	0.888
	Pseudo R2	0.054	N/A	N/A	0.043
	Q-Value	0.596	N/A	N/A	N/A
	Standard Error	(0.345)	N/A	N/A	(0.310)
Glastonbury	Coefficient	-0.277	N/A	N/A	-0.298
	Observations	501	N/A	N/A	502
	P-Value	0.444	N/A	N/A	0.372
	Pseudo R2	0.071	N/A	N/A	0.041
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.361)	N/A	N/A	(0.333)
Greenwich	Coefficient	0.083	0.238	-0.163	-0.071
	Observations	1006	891	1010	1100
	P-Value	0.671	0.384	0.418	0.679
	Pseudo R2	0.025	0.029	0.028	0.021
	Q-Value	0.810	0.677	N/A	N/A
	Standard Error	(0.197)	(0.275)	(0.201)	(0.174)
Groton Town	Coefficient	0.001	-0.225	N/A	-0.263
	Observations	563	510	N/A	586
	P-Value	0.996	0.449	N/A	0.277
	Pseudo R2	0.035	0.026	N/A	0.035
	Q-Value	0.996	N/A	N/A	N/A
	Standard Error	(0.263)	(0.298)	N/A	(0.243)
Guilford	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Hamden	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Hartford	Coefficient	-0.358	-0.365	-0.177	-0.263
	Observations	847	824	533	1143
	P-Value	0.114	0.109	0.472	0.208
	Pseudo R2	0.041	0.041	0.032	0.029
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.226)	(0.228)	(0.246)	(0.209)

*Results were not available across all specifications for departments not listed in this table.

Table C.9: Logistic Regression of Minority Status on Daylight by Department, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Ledyard	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Madison	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Manchester	Coefficient	0.187	0.207	-0.025	0.104
	Observations	1143	1098	1008	1296
	P-Value	0.296	0.280	0.912	0.500
	Pseudo R2	0.020	0.028	0.026	0.021
	Q-Value	0.619	0.615	N/A	0.754
	Standard Error	(0.180)	(0.192)	(0.224)	(0.156)
Middletown	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Milford	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Monroe	Coefficient	N/A	N/A	N/A	0.180
	Observations	N/A	N/A	N/A	546
	P-Value	N/A	N/A	N/A	0.579
	Pseudo R2	N/A	N/A	N/A	0.061
	Q-Value	N/A	N/A	N/A	0.774
	Standard Error	N/A	N/A	N/A	(0.324)
Naugatuck	Coefficient	0.052	0.109	0.216	0.120
	Observations	574	548	572	628
	P-Value	0.885	0.778	0.578	0.671
	Pseudo R2	0.093	0.090	0.052	0.041
	Q-Value	0.916	0.884	0.774	0.810
	Standard Error	(0.370)	(0.389)	(0.388)	(0.284)
New Britain	Coefficient	-0.277	-0.307	-0.056	-0.150
	Observations	744	733	996	1200
	P-Value	0.234	0.202	0.767	0.374
	Pseudo R2	0.026	0.026	0.025	0.023
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.233)	(0.240)	(0.188)	(0.168)
New Canaan	Coefficient	0.252	0.597	-0.071	0.187
	Observations	672	577	647	696
	P-Value	0.578	0.214	0.882	0.615
	Pseudo R2	0.045	0.050	0.046	0.041
	Q-Value	0.774	0.596	N/A	0.796
	Standard Error	(0.455)	(0.479)	(0.479)	(0.375)

*Results were not available across all specifications for departments not listed in this table.

Table C.9: Logistic Regression of Minority Status on Daylight by Department, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
New Haven	Coefficient	-0.128	-0.123	-0.131	-0.115
	Observations	3284	3211	2361	4006
	P-Value	0.162	0.182	0.250	0.177
	Pseudo R2	0.008	0.008	0.008	0.007
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.090)	(0.092)	(0.115)	(0.086)
New London	Coefficient	-0.709++	-0.921+++	-1.243+++	-1.021+++
	Observations	722	703	721	849
	P-Value	0.014	0.002	0	0
	Pseudo R2	0.037	0.045	0.061	0.046
	Q-Value	N/A	N/A	0.001	0.001
	Standard Error	(0.289)	(0.303)	(0.289)	(0.231)
Newington	Coefficient	-0.347	-0.068	-0.512+	-0.282
	Observations	601	566	602	668
	P-Value	0.194	0.832	0.064	0.210
	Pseudo R2	0.048	0.068	0.061	0.039
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.266)	(0.324)	(0.277)	(0.225)
Newtown	Coefficient	-0.241	N/A	-0.293	-0.136
	Observations	510	N/A	504	583
	P-Value	0.587	N/A	0.522	0.708
	Pseudo R2	0.097	N/A	0.107	0.057
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.446)	N/A	(0.458)	(0.365)
North Haven	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Norwalk	Coefficient	-0.316	-0.277	0.043	-0.116
	Observations	568	546	560	701
	P-Value	0.172	0.256	0.852	0.536
	Pseudo R2	0.043	0.037	0.050	0.034
	Q-Value	N/A	N/A	0.893	N/A
	Standard Error	(0.231)	(0.244)	(0.231)	(0.189)
Norwich	Coefficient	-0.195	-0.307	0.177	-0.120
	Observations	807	763	712	894
	P-Value	0.333	0.158	0.479	0.497
	Pseudo R2	0.045	0.043	0.046	0.035
	Q-Value	N/A	N/A	0.739	N/A
	Standard Error	(0.202)	(0.217)	(0.248)	(0.177)
Old Saybrook	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Plainville	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A

*Results were not available across all specifications for departments not listed in this table.

Table C.9: Logistic Regression of Minority Status on Daylight by Department, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Ridgefield	Coefficient	0.740+	0.610	0.451	0.518+
	Observations	693	615	646	724
	P-Value	0.061	0.206	0.187	0.085
	Pseudo R2	0.070	0.070	0.072	0.061
	Q-Value	0.437	0.596	0.596	0.479
	Standard Error	(0.393)	(0.481)	(0.340)	(0.300)
Rocky Hill	Coefficient	0.239	0.625	0.284	0.486
	Observations	595	547	538	607
	P-Value	0.504	0.153	0.523	0.143
	Pseudo R2	0.065	0.072	0.061	0.057
	Q-Value	0.754	0.596	0.755	0.596
	Standard Error	(0.361)	(0.437)	(0.446)	(0.331)
Seymour	Coefficient	0.363	0.606+	-0.326	0.167
	Observations	688	679	693	779
	P-Value	0.257	0.086	0.379	0.523
	Pseudo R2	0.061	0.078	0.048	0.039
	Q-Value	0.614	0.479	N/A	0.755
	Standard Error	(0.321)	(0.354)	(0.370)	(0.263)
Simsbury	Coefficient	N/A	N/A	N/A	0.469
	Observations	N/A	N/A	N/A	506
	P-Value	N/A	N/A	N/A	0.287
	Pseudo R2	N/A	N/A	N/A	0.067
	Q-Value	N/A	N/A	N/A	0.615
	Standard Error	N/A	N/A	N/A	(0.441)
South Windsor	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Southington	Coefficient	N/A	N/A	0.254	0.551
	Observations	N/A	N/A	613	649
	P-Value	N/A	N/A	0.580	0.150
	Pseudo R2	N/A	N/A	0.064	0.071
	Q-Value	N/A	N/A	0.774	0.596
	Standard Error	N/A	N/A	(0.462)	(0.384)
Stamford	Coefficient	-0.363++	-0.280+	0.143	-0.041
	Observations	1439	1372	1428	1737
	P-Value	0.019	0.096	0.345	0.736
	Pseudo R2	0.026	0.028	0.013	0.014
	Q-Value	N/A	N/A	0.662	N/A
	Standard Error	(0.156)	(0.167)	(0.152)	(0.123)
Stonington	Coefficient	-0.064	N/A	N/A	0.105
	Observations	633	N/A	N/A	520
	P-Value	0.867	N/A	N/A	0.814
	Pseudo R2	0.056	N/A	N/A	0.037
	Q-Value	N/A	N/A	N/A	0.890
	Standard Error	(0.388)	N/A	N/A	(0.451)
Stratford	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A

*Results were not available across all specifications for departments not listed in this table.

Table C.9: Logistic Regression of Minority Status on Daylight by Department, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Torrington	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Trumbull	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
University of Connecticut	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Vernon	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Wallingford	Coefficient	-0.052	-0.172	-0.354	-0.291
	Observations	642	629	658	715
	P-Value	0.878	0.652	0.287	0.266
	Pseudo R2	0.050	0.061	0.061	0.043
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.342)	(0.381)	(0.333)	(0.261)
Waterbury	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Waterford	Coefficient	0.275	0.162	-0.367	-0.112
	Observations	904	865	870	964
	P-Value	0.277	0.568	0.199	0.600
	Pseudo R2	0.037	0.039	0.050	0.032
	Q-Value	0.615	0.774	N/A	N/A
	Standard Error	(0.254)	(0.282)	(0.286)	(0.215)
West Hartford	Coefficient	-0.340	-0.773++	-0.308	-0.522++
	Observations	676	612	619	723
	P-Value	0.158	0.014	0.270	0.017
	Pseudo R2	0.035	0.046	0.046	0.030
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.240)	(0.314)	(0.280)	(0.222)
West Haven	Coefficient	0.149	0.160	-0.098	0.045
	Observations	700	683	632	853
	P-Value	0.446	0.425	0.647	0.783
	Pseudo R2	0.030	0.030	0.029	0.023
	Q-Value	0.722	0.720	N/A	0.884
	Standard Error	(0.195)	(0.202)	(0.216)	(0.165)

*Results were not available across all specifications for departments not listed in this table.

Table C.9: Logistic Regression of Minority Status on Daylight by Department, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Westport	Coefficient	0.305	0.625++	0.061	0.358+
	Observations	972	906	906	1023
	P-Value	0.179	0.016	0.819	0.070
	Pseudo R2	0.048	0.054	0.054	0.043
	Q-Value	0.596	0.171	0.890	0.437
	Standard Error	(0.226)	(0.259)	(0.270)	(0.197)
Wethersfield	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Wilton	Coefficient	0.238	0.374	0.448	0.398
	Observations	713	623	699	754
	P-Value	0.367	0.268	0.150	0.112
	Pseudo R2	0.020	0.061	0.070	0.059
	Q-Value	0.662	0.615	0.596	0.587
	Standard Error	(0.263)	(0.337)	(0.310)	(0.252)
Windsor	Coefficient	-0.104	-0.094	-0.287	-0.115
	Observations	1208	1157	717	1294
	P-Value	0.483	0.536	0.225	0.430
	Pseudo R2	0.035	0.035	0.029	0.028
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.150)	(0.153)	(0.238)	(0.145)
Woodbridge	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Yale University	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A

*Results were not available across all specifications for departments not listed in this table.

Table C.10: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Ansonia	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Berlin	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Bethel	Coefficient	N/A	N/A	N/A	-0.763+++
	Observations	N/A	N/A	N/A	515
	P-Value	N/A	N/A	N/A	0
	Pseudo R2	N/A	N/A	N/A	0.076
	Q-Value	N/A	N/A	N/A	0.001
	Standard Error	N/A	N/A	N/A	(0.094)
Bloomfield	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Branford	Coefficient	N/A	N/A	N/A	-0.317
	Observations	N/A	N/A	N/A	556
	P-Value	N/A	N/A	N/A	0.333
	Pseudo R2	N/A	N/A	N/A	0.087
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	(0.328)
Bridgeport	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Bristol	Coefficient	0.328	0.458+	-0.519+++	-0.107
	Observations	667	662	733	801
	P-Value	0.234	0.068	0	0.232
	Pseudo R2	0.078	0.079	0.074	0.059
	Q-Value	0.560	0.314	0.001	N/A
	Standard Error	(0.277)	(0.252)	(0.108)	(0.090)
Brookfield	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Central CT State University	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A

*Results were not available across all specifications for departments not listed in this table.

Table C.10: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
CSP Headquarters	Coefficient	-0.059	0.157	0.104	0.151
	Observations	1264	1185	1150	1403
	P-Value	0.493	0.178	0.541	0.150
	Pseudo R2	0.045	0.054	0.043	0.035
	Q-Value	N/A	0.546	0.740	0.497
	Standard Error	(0.085)	(0.115)	(0.172)	(0.105)
CSP Troop A	Coefficient	0.136	0.089	0.212	0.093
	Observations	1790	1688	1696	1969
	P-Value	0.481	0.662	0.363	0.444
	Pseudo R2	0.076	0.093	0.054	0.059
	Q-Value	0.697	0.781	0.642	0.695
	Standard Error	(0.194)	(0.203)	(0.233)	(0.122)
CSP Troop B	Coefficient	-0.202	0.307	0.342	0.386
	Observations	731	667	584	749
	P-Value	0.665	0.629	0.472	0.310
	Pseudo R2	0.096	0.103	0.068	0.063
	Q-Value	N/A	0.781	0.697	0.642
	Standard Error	(0.469)	(0.638)	(0.476)	(0.379)
CSP Troop C	Coefficient	0.453***	0.377***	0.428***	0.421***
	Observations	3839	3393	3420	3782
	P-Value	0.001	0.008	0.003	0.002
	Pseudo R2	0.065	0.064	0.068	0.057
	Q-Value	0.001	0.065	0.035	0.021
	Standard Error	(0.135)	(0.143)	(0.145)	(0.133)
CSP Troop D	Coefficient	0.500***	0.819***	-0.160	0.303
	Observations	1839	1729	1735	1856
	P-Value	0.002	0.001	0.528	0.116
	Pseudo R2	0.061	0.081	0.093	0.064
	Q-Value	0.021	0.001	N/A	0.423
	Standard Error	(0.158)	(0.185)	(0.256)	(0.193)
CSP Troop E	Coefficient	-0.061	-0.136	0.216	0.028
	Observations	3510	3259	3134	3570
	P-Value	0.519	0.214	0.118	0.782
	Pseudo R2	0.048	0.056	0.059	0.050
	Q-Value	N/A	N/A	0.423	0.841
	Standard Error	(0.096)	(0.108)	(0.138)	(0.104)
CSP Troop F	Coefficient	0.086	0.195	-0.237	0.059
	Observations	2285	2174	2284	2506
	P-Value	0.699	0.456	0.298	0.620
	Pseudo R2	0.079	0.082	0.093	0.085
	Q-Value	0.791	0.697	N/A	0.781
	Standard Error	(0.224)	(0.263)	(0.228)	(0.120)
CSP Troop G	Coefficient	-0.070	-0.190	0.168	-0.018
	Observations	987	909	880	1128
	P-Value	0.721	0.293	0.207	0.848
	Pseudo R2	0.039	0.050	0.064	0.043
	Q-Value	N/A	N/A	0.560	N/A
	Standard Error	(0.194)	(0.181)	(0.134)	(0.100)
CSP Troop H	Coefficient	0.188	0.123	-0.402++	-0.071
	Observations	1379	1258	1121	1501
	P-Value	0.263	0.518	0.035	0.629
	Pseudo R2	0.029	0.039	0.059	0.035
	Q-Value	0.589	0.726	N/A	N/A
	Standard Error	(0.168)	(0.189)	(0.192)	(0.148)

*Results were not available across all specifications for departments not listed in this table.

Table C.10: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
CSP Troop I	Coefficient	-0.291+	-0.382++	-0.598++	-0.460++
	Observations	1303	1231	1172	1438
	P-Value	0.093	0.028	0.017	0.017
	Pseudo R2	0.041	0.045	0.075	0.043
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.173)	(0.174)	(0.250)	(0.193)
CSP Troop K	Coefficient	0.379***	0.344***	0.456***	0.400***
	Observations	1757	1594	1627	1859
	P-Value	0.001	0.003	0.004	0
	Pseudo R2	0.052	0.061	0.057	0.045
	Q-Value	0.001	0.032	0.039	0.001
	Standard Error	(0.115)	(0.114)	(0.160)	(0.098)
CSP Troop L	Coefficient	0.064	0.081	0.075	0.145
	Observations	846	820	705	939
	P-Value	0.869	0.852	0.801	0.660
	Pseudo R2	0.107	0.111	0.098	0.108
	Q-Value	0.889	0.889	0.851	0.781
	Standard Error	(0.398)	(0.439)	(0.298)	(0.331)
Cheshire	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Clinton	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Danbury	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Darien	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
East Hartford	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
East Haven	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A

*Results were not available across all specifications for departments not listed in this table.

Table C.10: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Enfield	Coefficient	0.125	0.171	0.114	0.086
	Observations	2524	2396	2393	2625
	P-Value	0.370	0.358	0.268	0.559
	Pseudo R2	0.037	0.041	0.050	0.032
	Q-Value	0.642	0.642	0.589	0.749
	Standard Error	(0.140)	(0.186)	(0.103)	(0.145)
Fairfield	Coefficient	0.352***	0.405++	0.004	0.214+
	Observations	1720	1656	1633	1851
	P-Value	0.004	0.020	0.977	0.059
	Pseudo R2	0.027	0.035	0.078	0.035
	Q-Value	0.039	0.129	0.977	0.291
	Standard Error	(0.123)	(0.175)	(0.196)	(0.114)
Farmington	Coefficient	0.531+	N/A	N/A	-0.032
	Observations	517	N/A	N/A	545
	P-Value	0.081	N/A	N/A	0.894
	Pseudo R2	0.082	N/A	N/A	0.081
	Q-Value	0.347	N/A	N/A	N/A
	Standard Error	(0.303)	N/A	N/A	(0.243)
Glastonbury	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Greenwich	Coefficient	0.123	0.310+	-0.155+++	-0.048
	Observations	982	819	1002	1092
	P-Value	0.173	0.054	0.008	0.425
	Pseudo R2	0.041	0.078	0.054	0.050
	Q-Value	0.546	0.289	N/A	N/A
	Standard Error	(0.090)	(0.160)	(0.059)	(0.061)
Groton Town	Coefficient	-0.115	N/A	N/A	-0.411+++
	Observations	548	N/A	N/A	571
	P-Value	0.446	N/A	N/A	0.002
	Pseudo R2	0.064	N/A	N/A	0.076
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.150)	N/A	N/A	(0.135)
Guilford	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Hamden	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Hartford	Coefficient	-0.481++	-0.497++	-0.127	-0.326
	Observations	798	776	507	1072
	P-Value	0.032	0.027	0.574	0.141
	Pseudo R2	0.096	0.097	0.075	0.074
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.225)	(0.224)	(0.226)	(0.222)

*Results were not available across all specifications for departments not listed in this table.

Table C.10: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Ledyard	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Madison	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Manchester	Coefficient	0.287	0.319	0.100	0.216
	Observations	1139	1095	993	1292
	P-Value	0.240	0.189	0.639	0.204
	Pseudo R2	0.048	0.054	0.035	0.039
	Q-Value	0.560	0.560	0.781	0.560
	Standard Error	(0.244)	(0.243)	(0.214)	(0.170)
Middletown	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Milford	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Monroe	Coefficient	N/A	N/A	N/A	-0.083
	Observations	N/A	N/A	N/A	520
	P-Value	N/A	N/A	N/A	0.617
	Pseudo R2	N/A	N/A	N/A	0.092
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	(0.167)
Naugatuck	Coefficient	0.291	0.300	0.319	0.221
	Observations	539	514	543	612
	P-Value	0.481	0.565	0.372	0.391
	Pseudo R2	0.116	0.111	0.092	0.071
	Q-Value	0.697	0.749	0.642	0.656
	Standard Error	(0.414)	(0.523)	(0.358)	(0.256)
New Britain	Coefficient	-0.221	-0.252	0.027	-0.071
	Observations	742	731	993	1195
	P-Value	0.151	0.188	0.685	0.356
	Pseudo R2	0.029	0.030	0.030	0.027
	Q-Value	N/A	N/A	0.791	N/A
	Standard Error	(0.153)	(0.193)	(0.064)	(0.078)
New Canaan	Coefficient	0.192	0.460	-0.157	0.112
	Observations	641	532	623	681
	P-Value	0.758	0.404	0.739	0.731
	Pseudo R2	0.061	0.078	0.057	0.048
	Q-Value	0.824	0.656	N/A	0.810
	Standard Error	(0.625)	(0.551)	(0.470)	(0.331)

*Results were not available across all specifications for departments not listed in this table.

Table C.10: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
New Haven	Coefficient	-0.048	-0.037	-0.050	-0.021
	Observations	3259	3187	2341	3971
	P-Value	0.621	0.723	0.714	0.852
	Pseudo R2	0.023	0.024	0.027	0.019
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.097)	(0.104)	(0.136)	(0.119)
New London	Coefficient	-0.533+++	-0.736+++	-0.855+++	-0.771+++
	Observations	719	700	713	846
	P-Value	0.001	0	0	0
	Pseudo R2	0.046	0.054	0.096	0.064
	Q-Value	N/A	0.001	0.001	0.001
	Standard Error	(0.164)	(0.157)	(0.103)	(0.133)
Newington	Coefficient	-0.552+++	-0.128	-0.499++	-0.256
	Observations	581	544	587	663
	P-Value	0	0.584	0.045	0.231
	Pseudo R2	0.070	0.082	0.093	0.059
	Q-Value	0.001	N/A	N/A	N/A
	Standard Error	(0.136)	(0.237)	(0.248)	(0.215)
Newtown	Coefficient	N/A	N/A	N/A	-0.114
	Observations	N/A	N/A	N/A	564
	P-Value	N/A	N/A	N/A	0.712
	Pseudo R2	N/A	N/A	N/A	0.064
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	(0.307)
North Haven	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Norwalk	Coefficient	-0.136	-0.020	0.261	0.116
	Observations	562	541	557	695
	P-Value	0.690	0.948	0.365	0.693
	Pseudo R2	0.071	0.079	0.090	0.070
	Q-Value	N/A	N/A	0.642	0.791
	Standard Error	(0.340)	(0.317)	(0.287)	(0.296)
Norwich	Coefficient	-0.137	-0.236	0.216	-0.057
	Observations	807	762	708	893
	P-Value	0.256	0.165	0.137	0.720
	Pseudo R2	0.056	0.057	0.054	0.043
	Q-Value	N/A	N/A	0.474	N/A
	Standard Error	(0.122)	(0.170)	(0.145)	(0.158)
Old Saybrook	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Plainville	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A

*Results were not available across all specifications for departments not listed in this table.

Table C.10: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Ridgefield	Coefficient	0.630++	0.558	0.321	0.442+
	Observations	687	587	646	724
	P-Value	0.043	0.223	0.338	0.061
	Pseudo R2	0.090	0.100	0.101	0.082
	Q-Value	0.254	0.560	0.642	0.291
	Standard Error	(0.314)	(0.458)	(0.337)	(0.236)
Rocky Hill	Coefficient	0.270	N/A	N/A	0.500**
	Observations	562	N/A	N/A	570
	P-Value	0.225	N/A	N/A	0.010
	Pseudo R2	0.096	N/A	N/A	0.092
	Q-Value	0.560	N/A	N/A	0.078
	Standard Error	(0.223)	N/A	N/A	(0.196)
Seymour	Coefficient	0.375	0.648+	-0.412	0.152
	Observations	683	674	672	779
	P-Value	0.324	0.087	0.173	0.432
	Pseudo R2	0.071	0.090	0.074	0.059
	Q-Value	0.642	0.356	N/A	0.689
	Standard Error	(0.379)	(0.379)	(0.303)	(0.195)
Simsbury	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
South Windsor	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Southington	Coefficient	N/A	N/A	0.377	0.628++
	Observations	N/A	N/A	542	611
	P-Value	N/A	N/A	0.237	0.020
	Pseudo R2	N/A	N/A	0.087	0.090
	Q-Value	N/A	N/A	0.560	0.129
	Standard Error	N/A	N/A	(0.319)	(0.272)
Stamford	Coefficient	-0.388+++	-0.284+	0.092	-0.079
	Observations	1432	1365	1424	1732
	P-Value	0.008	0.070	0.523	0.577
	Pseudo R2	0.061	0.070	0.043	0.039
	Q-Value	N/A	N/A	0.726	N/A
	Standard Error	(0.146)	(0.156)	(0.144)	(0.141)
Stonington	Coefficient	-0.074	N/A	N/A	-0.114
	Observations	623	N/A	N/A	517
	P-Value	0.907	N/A	N/A	0.879
	Pseudo R2	0.096	N/A	N/A	0.119
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.634)	N/A	N/A	(0.754)
Stratford	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A

*Results were not available across all specifications for departments not listed in this table.

Table C.10: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Torrington	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Trumbull	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
University of Connecticut	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Vernon	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Wallingford	Coefficient	0.035	-0.059	-0.294	-0.210
	Observations	614	595	586	684
	P-Value	0.859	0.810	0.129	0.166
	Pseudo R2	0.082	0.097	0.087	0.068
	Q-Value	0.889	N/A	N/A	N/A
	Standard Error	(0.197)	(0.250)	(0.194)	(0.151)
Waterbury	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Waterford	Coefficient	0.284	0.177	-0.301	-0.085
	Observations	859	796	851	950
	P-Value	0.352	0.620	0.123	0.709
	Pseudo R2	0.057	0.057	0.061	0.041
	Q-Value	0.642	0.781	N/A	N/A
	Standard Error	(0.307)	(0.358)	(0.195)	(0.229)
West Hartford	Coefficient	-0.382	-0.809+++	-0.335++	-0.554+++
	Observations	672	607	617	721
	P-Value	0.127	0.009	0.025	0
	Pseudo R2	0.050	0.063	0.064	0.043
	Q-Value	N/A	N/A	N/A	0.001
	Standard Error	(0.250)	(0.312)	(0.150)	(0.156)
West Haven	Coefficient	0.105	0.104	-0.143	-0.017
	Observations	670	650	615	843
	P-Value	0.657	0.587	0.238	0.873
	Pseudo R2	0.059	0.059	0.046	0.056
	Q-Value	0.781	0.765	N/A	N/A
	Standard Error	(0.238)	(0.194)	(0.122)	(0.104)

*Results were not available across all specifications for departments not listed in this table.

Table C.10: Logistic Regression of Minority Status on Daylight by Department with Officer Fixed-Effects, All Moving Violations 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Westport	Coefficient	0.233	0.583+	0.064	0.300
	Observations	907	835	846	971
	P-Value	0.326	0.090	0.882	0.402
	Pseudo R2	0.074	0.103	0.086	0.075
	Q-Value	0.642	0.356	0.892	0.656
	Standard Error	(0.238)	(0.345)	(0.428)	(0.360)
Wethersfield	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Wilton	Coefficient	0.090	0.195	0.472	0.368
	Observations	687	534	696	751
	P-Value	0.735	0.486	0.217	0.308
	Pseudo R2	0.041	0.067	0.082	0.071
	Q-Value	0.810	0.697	0.560	0.642
	Standard Error	(0.266)	(0.280)	(0.382)	(0.361)
Windsor	Coefficient	-0.079	-0.059	-0.219	-0.085
	Observations	1201	1150	707	1292
	P-Value	0.535	0.694	0.423	0.544
	Pseudo R2	0.056	0.057	0.071	0.054
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.128)	(0.150)	(0.275)	(0.140)
Woodbridge	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Yale University	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A

*Results were not available across all specifications for departments not listed in this table.

Table C.11: List of Departments Where No Results were Available across all Specifications

Avon	Easton	Plainfield	Watertown
Canton	Granby	Portland	Weston
Coventry	Groton City	Putnam	Willimantic
Dept. of Motor Vehicle	Groton Long Point	Redding	Windsor Locks
Derby	Meriden	Southern CT State Univ.	Winsted
Eastern CT State Univ.	Middlebury	Shelton	Wolcott
East Hampton	New Milford	State Capitol Police	
East Lyme	North Branford	Suffield	
East Windsor	Orange	Thomaston	

APPENDIX D

Table D.1: Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Ansonia	Coefficient	0.001	0.001	0.001	0.001
	Observations	70698	70698	70698	70698
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Avon	Coefficient	0.001	0.001	0.001	0.001
	Observations	48568	48568	48568	48568
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Berlin	Coefficient	0.001	0.001	0.001	0.001
	Observations	63515	63515	63515	63515
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Bethel	Coefficient	0.001	0.001	0.001	0.001
	Observations	72123	72123	72123	72123
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Bloomfield	Coefficient	0.001	0.001	0.001	0.001
	Observations	58085	58085	58085	58085
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Branford	Coefficient	0.001	0.001	0.001	0.001
	Observations	29589	29589	29589	29589
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Bridgeport	Coefficient	0.001	0.001	0.001	0.001
	Observations	78426	78426	78426	78426
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Bristol	Coefficient	0.001	0.001	0.001	0.001
	Observations	65874	65874	65874	65874
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Brookfield	Coefficient	0.001	0.001	0.001	0.001
	Observations	76196	76196	76196	76196
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.1: Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Central CT State University	Coefficient	0.001	0.001	0.001	0.001
	Observations	1848	1848	1848	1848
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
CSP Headquarters	Coefficient	0.001	0.001	0.001	0.001
	Observations	14090	14090	14090	14090
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
CSP Troop A	Coefficient	0.001	0.001	0.001	0.001
	Observations	16762	16762	16762	16762
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
CSP Troop B	Coefficient	0.001	0.001	0.001	0.001
	Observations	6437	6437	6437	6437
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
CSP Troop C	Coefficient	0.001	0.001	0.001	0.001
	Observations	20499	20499	20499	20499
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
CSP Troop D	Coefficient	0.001	0.001	0.001	0.001
	Observations	11154	11154	11154	11154
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
CSP Troop E	Coefficient	0.001	0.001	0.001	0.001
	Observations	15525	15525	15525	15525
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
CSP Troop F	Coefficient	0.001	0.001	0.001	0.001
	Observations	17331	17331	17331	17331
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
CSP Troop G	Coefficient	0.001	0.001	0.001	0.001
	Observations	13997	13997	13997	13997
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.1: Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
CSP Troop H	Coefficient	0.001	0.001	0.001	0.001
	Observations	17680	17680	17680	17680
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
CSP Troop I	Coefficient	0.001	0.001	0.001	0.001
	Observations	12551	12551	12551	12551
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
CSP Troop K	Coefficient	0.001	0.001	0.001	0.001
	Observations	15428	15428	15428	15428
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
CSP Troop L	Coefficient	0.001	0.001	0.001	0.001
	Observations	8981	8981	8981	8981
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Canton	Coefficient	0.001	0.001	0.001	0.001
	Observations	75507	75507	75507	75507
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Cheshire	Coefficient	0.001	0.001	0.001	0.001
	Observations	100192	100192	100192	100192
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Clinton	Coefficient	0.001	0.001	0.001	0.001
	Observations	11465	11465	11465	11465
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Coventry	Coefficient	0.001	0.001	0.001	0.001
	Observations	76240	76240	76240	76240
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Cromwell	Coefficient	0.001	0.001	0.001	0.001
	Observations	48456	48456	48456	48456
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.1: Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Department of Motor Vehicle	Coefficient	0.001	0.001	0.001	0.001
	Observations	1575	1575	1575	1575
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Danbury	Coefficient	0.001	0.001	0.001	0.001
	Observations	46400	46400	46400	46400
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Darien	Coefficient	0.001	0.001	0.001	0.001
	Observations	102366	102366	102366	102366
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Derby	Coefficient	-0.004	0.061	1.184***	-0.123+++
	Observations	89080	89080	89080	89080
	P-Value	0.949	0.287	0.001	0.008
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	1	0.046	N/A
	Standard Error	(0.056)	(0.057)	(0.054)	(0.048)
East Hampton	Coefficient	0.001	0.001	0.001	0.001
	Observations	769	769	769	769
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
East Hartford	Coefficient	0.001	0.001	0.001	0.001
	Observations	7475	7475	7475	7475
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
East Haven	Coefficient	0.001	0.001	0.001	0.001
	Observations	2503	2503	2503	2503
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
East Windsor	Coefficient	0.001	0.001	0.001	0.001
	Observations	1752	1752	1752	1752
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Easton	Coefficient	0.001	0.001	0.001	0.001
	Observations	68664	68664	68664	68664
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.1: Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Enfield	Coefficient	0.001	0.001	0.001	0.001
	Observations	66012	66012	66012	66012
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Fairfield	Coefficient	0.001	0.001	0.001	0.001
	Observations	76092	76092	76092	76092
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Farmington	Coefficient	0.001	0.001	0.001	0.001
	Observations	29357	29357	29357	29357
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Glastonbury	Coefficient	0.001	0.001	0.001	0.001
	Observations	81682	81682	81682	81682
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Granby	Coefficient	0.001	0.001	0.001	0.001
	Observations	27752	27752	27752	27752
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Greenwich	Coefficient	0.001	0.001	0.001	0.001
	Observations	31753	31753	31753	31753
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Groton City	Coefficient	0.001	0.001	0.001	0.001
	Observations	1547	1547	1547	1547
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Groton Town	Coefficient	0.001	0.001	0.001	0.001
	Observations	4396	4396	4396	4396
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Guilford	Coefficient	0.001	0.001	0.001	0.001
	Observations	32013	32013	32013	32013
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.1: Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Hamden	Coefficient	0.001	0.001	0.001	0.001
	Observations	12409	12409	12409	12409
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Hartford	Coefficient	0.001	0.001	0.001	0.001
	Observations	213685	213685	213685	213685
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Ledyard	Coefficient	0.001	0.001	0.001	0.001
	Observations	37908	37908	37908	37908
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Madison	Coefficient	0.001	0.001	0.001	0.001
	Observations	35242	35242	35242	35242
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Manchester	Coefficient	0.001	0.001	0.001	0.001
	Observations	65804	65804	65804	65804
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Meriden	Coefficient	-0.532+++	-0.522+++	0.892***	0.317***
	Observations	98683	98683	98683	98683
	P-Value	0.001	0	0.001	0.001
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	0.001	0.046	0.001
	Standard Error	(0.064)	(0.065)	(0.054)	(0.052)
Middlebury	Coefficient	0.001	0.001	0.001	0.001
	Observations	47596	47596	47596	47596
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Middletown	Coefficient	0.488***	0.523***	-0.360+++	0.232***
	Observations	63744	63744	63744	63744
	P-Value	0.001	0.001	0	0.001
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	0.046	0.046	0.001	0.001
	Standard Error	(0.043)	(0.043)	(0.061)	(0.039)
Milford	Coefficient	0.001	0.001	0.001	0.001
	Observations	67595	67595	67595	67595
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.1: Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Monroe	Coefficient	0.001	0.001	0.001	0.001
	Observations	46281	46281	46281	46281
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Naugatuck	Coefficient	0.001	0.001	0.001	0.001
	Observations	59115	59115	59115	59115
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
New Britain	Coefficient	0.001	0.001	0.001	0.001
	Observations	7328	7328	7328	7328
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
New Canaan	Coefficient	0.001	0.001	0.001	0.001
	Observations	5492	5492	5492	5492
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
New Haven	Coefficient	0.001	0.001	0.001	0.001
	Observations	19038	19038	19038	19038
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
New London	Coefficient	0.001	0.001	0.001	0.001
	Observations	5041	5041	5041	5041
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
New Milford	Coefficient	0.001	0.001	0.001	0.001
	Observations	2318	2318	2318	2318
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Newington	Coefficient	0.001	0.001	0.001	0.001
	Observations	69898	69898	69898	69898
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Newtown	Coefficient	0.001	0.001	0.001	0.001
	Observations	16838	16838	16838	16838
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.1: Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
North Branford	Coefficient	0.001	0.001	0.001	0.001
	Observations	843	843	843	843
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
North Haven	Coefficient	0.001	0.001	0.001	0.001
	Observations	2633	2633	2633	2633
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Norwalk	Coefficient	0.001	0.001	0.001	0.001
	Observations	23172	23172	23172	23172
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Norwich	Coefficient	0.001	0.001	0.001	0.001
	Observations	59891	59891	59891	59891
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Old Saybrook	Coefficient	0.001	0.001	0.001	0.001
	Observations	2388	2388	2388	2388
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Orange	Coefficient	0.001	0.001	0.001	0.001
	Observations	47801	47801	47801	47801
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Plainfield	Coefficient	0.001	0.001	0.001	0.001
	Observations	1710	1710	1710	1710
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Plainville	Coefficient	0.001	0.001	0.001	0.001
	Observations	81568	81568	81568	81568
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Plymouth	Coefficient	0.001	0.001	0.001	0.001
	Observations	62780	62780	62780	62780
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.1: Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Portland	Coefficient	0.001	0.001	0.001	0.001
	Observations	41462	41462	41462	41462
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Putnam	Coefficient	0.001	0.001	0.001	0.001
	Observations	50641	50641	50641	50641
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Redding	Coefficient	0.001	0.001	0.001	0.001
	Observations	49703	49703	49703	49703
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Ridgefield	Coefficient	0.001	0.001	0.001	0.001
	Observations	60735	60735	60735	60735
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Rocky Hill	Coefficient	0.001	0.001	0.001	0.001
	Observations	4055	4055	4055	4055
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Southern CT State University	Coefficient	0.001	0.001	0.001	0.001
	Observations	517	517	517	517
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Seymour	Coefficient	-0.345+++	-0.261+++	N/A	-0.337+++
	Observations	271491	271491	271491	271491
	P-Value	0	0	0.001	0
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	0.001	0.001	N/A	0.001
	Standard Error	(0.056)	(0.059)	(0.059)	(0.045)
Shelton	Coefficient	0.001	0.001	0.001	0.001
	Observations	95882	95882	95882	95882
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Simsbury	Coefficient	-0.916+++	N/A	4.059+++	-1.363+++
	Observations	81982	81982	81982	81982
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.061)	(0.070)	(0.086)	(0.059)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.1: Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
South Windsor	Coefficient	0.001	0.001	0.001	0.001
	Observations	3850	3850	3850	3850
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Southington	Coefficient	0.001	0.001	0.001	0.001
	Observations	56294	56294	56294	56294
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Stamford	Coefficient	0.001	0.001	0.001	0.001
	Observations	74025	74025	74025	74025
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Stonington	Coefficient	0.001	0.001	0.001	0.001
	Observations	4976	4976	4976	4976
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Stratford	Coefficient	0.001	0.001	0.001	0.001
	Observations	76205	76205	76205	76205
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Suffield	Coefficient	0.001	0.001	0.001	0.001
	Observations	52292	52292	52292	52292
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Thomaston	Coefficient	0.001	0.001	0.001	0.001
	Observations	7183	7183	7183	7183
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Torrington	Coefficient	0.001	0.001	0.001	0.001
	Observations	23121	23121	23121	23121
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Trumbull	Coefficient	0.001	0.001	0.001	0.001
	Observations	74385	74385	74385	74385
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.1: Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
University of Connecticut	Coefficient	0.001	0.001	0.001	0.001
	Observations	3894	3894	3894	3894
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Vernon	Coefficient	0.001	0.001	0.001	0.001
	Observations	83855	83855	83855	83855
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Wallingford	Coefficient	-0.616	-0.760	2.266+++	0.199
	Observations	38711	38711	38711	38711
	P-Value	0.273	0.177	0.006	0.712
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	0.232	1
	Standard Error	(0.563)	(0.564)	(0.818)	(0.538)
Waterbury	Coefficient	0.001	0.001	0.001	0.001
	Observations	49965	49965	49965	49965
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Waterford	Coefficient	0.001	0.001	0.001	0.001
	Observations	8372	8372	8372	8372
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Watertown	Coefficient	N/A	6.209+++	0.421***	4.302+++
	Observations	82660	82660	82660	82660
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	0.001	N/A
	Standard Error	(0.081)	(0.083)	(0.092)	(0.065)
West Hartford	Coefficient	0.001	0.001	0.001	0.001
	Observations	6207	6207	6207	6207
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
West Haven	Coefficient	0.001	0.001	0.001	0.001
	Observations	8790	8790	8790	8790
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Weston	Coefficient	0.001	0.001	0.001	0.001
	Observations	17054	17054	17054	17054
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.1: Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Westport	Coefficient	0.001	0.001	0.001	0.001
	Observations	51443	51443	51443	51443
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Wethersfield	Coefficient	7.094+++	N/A	1.123***	0.165***
	Observations	79077	79077	79077	79077
	P-Value	0.001	0.001	0.001	0
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	0.046	0.001
	Standard Error	(0.046)	(0.048)	(0.046)	(0.039)
Willimantic	Coefficient	0.001	0.001	0.001	0.001
	Observations	2331	2331	2331	2331
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Wilton	Coefficient	0.001	0.001	0.001	0.001
	Observations	60975	60975	60975	60975
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Windsor	Coefficient	0.001	0.001	0.001	0.001
	Observations	80762	80762	80762	80762
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Windsor Locks	Coefficient	0.001	0.001	0.001	0.001
	Observations	1124	1124	1124	1124
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Winsted	Coefficient	0.001	0.001	0.001	0.001
	Observations	842	842	842	842
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Wolcott	Coefficient	0.001	0.001	0.001	0.001
	Observations	37538	37538	37538	37538
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Woodbridge	Coefficient	0.001	0.001	0.001	0.001
	Observations	69579	69579	69579	69579
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.1: Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Yale University	Coefficient	0.001	0.001	0.001	0.001
	Observations	1354	1354	1354	1354
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.2: Doubly-Robust Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Ansonia	Coefficient	0.001	0.001	0.001	0.001
	Observations	70698	70698	70698	70698
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Avon	Coefficient	0.001	0.001	0.001	0.001
	Observations	48568	48568	48568	48568
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Berlin	Coefficient	0.001	0.001	0.001	0.001
	Observations	63515	63515	63515	63515
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Bethel	Coefficient	0.001	0.001	0.001	0.001
	Observations	72123	72123	72123	72123
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Bloomfield	Coefficient	0.001	0.001	0.001	0.001
	Observations	58085	58085	58085	58085
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Branford	Coefficient	0.001	0.001	0.001	0.001
	Observations	29589	29589	29589	29589
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Bridgeport	Coefficient	0.001	0.001	0.001	0.001
	Observations	78426	78426	78426	78426
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Bristol	Coefficient	0.001	0.001	0.001	0.001
	Observations	65874	65874	65874	65874
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Brookfield	Coefficient	0.001	0.001	0.001	0.001
	Observations	76196	76196	76196	76196
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.2: Doubly-Robust Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Central CT State University	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
CSP Headquarters	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
CSP Troop A	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
CSP Troop B	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
CSP Troop C	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
CSP Troop D	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
CSP Troop E	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
CSP Troop F	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
CSP Troop G	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.2: Doubly-Robust Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
CSP Troop H	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
CSP Troop I	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
CSP Troop K	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
CSP Troop L	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Canton	Coefficient	0.001	0.001	0.001	0.001
	Observations	75507	75507	75507	75507
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Cheshire	Coefficient	0.001	0.001	0.001	0.001
	Observations	100192	100192	100192	100192
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Clinton	Coefficient	0.001	0.001	0.001	0.001
	Observations	11465	11465	11465	11465
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Coventry	Coefficient	0.001	0.001	0.001	0.001
	Observations	76240	76240	76240	76240
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Cromwell	Coefficient	0.001	0.001	0.001	0.001
	Observations	48456	48456	48456	48456
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.2: Doubly-Robust Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Department of Motor Vehicle	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Danbury	Coefficient	0.001	0.001	0.001	0.001
	Observations	46400	46400	46400	46400
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Darien	Coefficient	0.001	0.001	0.001	0.001
	Observations	102366	102366	102366	102366
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Derby	Coefficient	1.350***	0.504+++	-0.356++	0.034
	Observations	89080	89080	89080	89080
	P-Value	0.001	0.008	0.025	0.825
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	0.001	0.230	N/A	1
	Standard Error	(0.202)	(0.188)	(0.158)	(0.151)
East Hampton	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
East Hartford	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
East Haven	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
East Windsor	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Easton	Coefficient	0.001	0.001	0.001	0.001
	Observations	68664	68664	68664	68664
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.2: Doubly-Robust Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Enfield	Coefficient	0.001	0.001	0.001	0.001
	Observations	66012	66012	66012	66012
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Fairfield	Coefficient	0.001	0.001	0.001	0.001
	Observations	76092	76092	76092	76092
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Farmington	Coefficient	0.001	0.001	0.001	0.001
	Observations	29357	29357	29357	29357
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Glastonbury	Coefficient	0.001	0.001	0.001	0.001
	Observations	81682	81682	81682	81682
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Granby	Coefficient	0.001	0.001	0.001	0.001
	Observations	27752	27752	27752	27752
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Greenwich	Coefficient	0.001	0.001	0.001	0.001
	Observations	31753	31753	31753	31753
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Groton City	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Groton Town	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Guilford	Coefficient	0.001	0.001	0.001	0.001
	Observations	32013	32013	32013	32013
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.2: Doubly-Robust Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Hamden	Coefficient	0.001	0.001	0.001	0.001
	Observations	12409	12409	12409	12409
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Hartford	Coefficient	0.001	0.001	0.001	0.001
	Observations	213685	213685	213685	213685
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Ledyard	Coefficient	0.001	0.001	0.001	0.001
	Observations	37908	37908	37908	37908
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Madison	Coefficient	0.001	0.001	0.001	0.001
	Observations	35242	35242	35242	35242
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Manchester	Coefficient	0.001	0.001	0.001	0.001
	Observations	65804	65804	65804	65804
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Meriden	Coefficient	-0.094	-0.624+++	1.238***	0.526***
	Observations	98683	98683	98683	98683
	P-Value	0.689	0.002	0.001	0.001
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	0.001	0.001
	Standard Error	(0.238)	(0.196)	(0.178)	(0.158)
Middlebury	Coefficient	0.001	0.001	0.001	0.001
	Observations	47596	47596	47596	47596
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Middletown	Coefficient	3.838	3.690	-2.502	0.644
	Observations	63744	63744	63744	63744
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Milford	Coefficient	0.001	0.001	0.001	0.001
	Observations	67595	67595	67595	67595
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.2: Doubly-Robust Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Monroe	Coefficient	0.001	0.001	0.001	0.001
	Observations	46281	46281	46281	46281
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Naugatuck	Coefficient	0.001	0.001	0.001	0.001
	Observations	59115	59115	59115	59115
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
New Britain	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
New Canaan	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
New Haven	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
New London	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
New Milford	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Newington	Coefficient	0.001	0.001	0.001	0.001
	Observations	69898	69898	69898	69898
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Newtown	Coefficient	0.001	0.001	0.001	0.001
	Observations	16838	16838	16838	16838
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.2: Doubly-Robust Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
North Branford	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
North Haven	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Norwalk	Coefficient	0.001	0.001	0.001	0.001
	Observations	23172	23172	23172	23172
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Norwich	Coefficient	0.001	0.001	0.001	0.001
	Observations	59891	59891	59891	59891
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Old Saybrook	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Orange	Coefficient	0.001	0.001	0.001	0.001
	Observations	47801	47801	47801	47801
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Plainfield	Coefficient	0.001	0.001	0.001	0.001
	Observations	1710	1710	1710	1710
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Plainville	Coefficient	0.001	0.001	0.001	0.001
	Observations	81568	81568	81568	81568
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Plymouth	Coefficient	0.001	0.001	0.001	0.001
	Observations	62780	62780	62780	62780
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.2: Doubly-Robust Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Portland	Coefficient	0.001	0.001	0.001	0.001
	Observations	41462	41462	41462	41462
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Putnam	Coefficient	0.001	0.001	0.001	0.001
	Observations	50641	50641	50641	50641
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Redding	Coefficient	0.001	0.001	0.001	0.001
	Observations	49703	49703	49703	49703
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Ridgefield	Coefficient	0.001	0.001	0.001	0.001
	Observations	60735	60735	60735	60735
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Rocky Hill	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Southern CT State University	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Seymour	Coefficient	-0.201+++	-0.021	-0.168+++	-0.201+++
	Observations	271491	271491	271491	271491
	P-Value	0.001	0.731	0.008	0
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	0.001	N/A	N/A	0.001
	Standard Error	(0.059)	(0.064)	(0.064)	(0.046)
Shelton	Coefficient	0.001	0.001	0.001	0.001
	Observations	95882	95882	95882	95882
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Simsbury	Coefficient	-0.050	-0.523	-0.689	-0.597++
	Observations	81982	81982	81982	81982
	P-Value	0.808	N/A	N/A	0.024
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	(0.207)	(0.001)	(0.001)	(0.264)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.2: Doubly-Robust Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
South Windsor	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Southington	Coefficient	0.001	0.001	0.001	0.001
	Observations	56294	56294	56294	56294
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Stamford	Coefficient	0.001	0.001	0.001	0.001
	Observations	74025	74025	74025	74025
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Stonington	Coefficient	0.001	0.001	0.001	0.001
	Observations	4976	4976	4976	4976
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Stratford	Coefficient	0.001	0.001	0.001	0.001
	Observations	76205	76205	76205	76205
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Suffield	Coefficient	0.001	0.001	0.001	0.001
	Observations	52292	52292	52292	52292
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Thomaston	Coefficient	0.001	0.001	0.001	0.001
	Observations	7183	7183	7183	7183
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Torrington	Coefficient	0.001	0.001	0.001	0.001
	Observations	23121	23121	23121	23121
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Trumbull	Coefficient	0.001	0.001	0.001	0.001
	Observations	74385	74385	74385	74385
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.2: Doubly-Robust Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
University of Connecticut	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Vernon	Coefficient	0.001	0.001	0.001	0.001
	Observations	83855	83855	83855	83855
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Wallingford	Coefficient	1.674	1.728	2.154***	1.110***
	Observations	38711	38711	38711	38711
	P-Value	N/A	N/A	0.001	0.001
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	0.001	0.001
	Standard Error	(0.001)	(0.001)	(0.347)	(0.337)
Waterbury	Coefficient	0.001	0.001	0.001	0.001
	Observations	49965	49965	49965	49965
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Waterford	Coefficient	0.001	0.001	0.001	0.001
	Observations	8372	8372	8372	8372
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Watertown	Coefficient	0.109	1.802***	-0.586	0.474
	Observations	82660	82660	82660	82660
	P-Value	0.981	0.001	N/A	0.735
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	0.041	N/A	1
	Standard Error	(4.754)	(0.559)	(0.001)	(1.404)
West Hartford	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
West Haven	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Weston	Coefficient	0.001	0.001	0.001	0.001
	Observations	17054	17054	17054	17054
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.2: Doubly-Robust Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Westport	Coefficient	0.001	0.001	0.001	0.001
	Observations	51443	51443	51443	51443
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Wethersfield	Coefficient	2.355***	2.229***	6.282+++	3.528+++
	Observations	79077	79077	79077	79077
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	0.037	0.037	N/A	N/A
	Standard Error	(0.076)	(0.081)	(0.068)	(0.061)
Willimantic	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Wilton	Coefficient	0.001	0.001	0.001	0.001
	Observations	60975	60975	60975	60975
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Windsor	Coefficient	0.001	0.001	0.001	0.001
	Observations	80762	80762	80762	80762
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Windsor Locks	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Winsted	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A
Wolcott	Coefficient	0.001	0.001	0.001	0.001
	Observations	37538	37538	37538	37538
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)
Woodbridge	Coefficient	0.001	0.001	0.001	0.001
	Observations	69579	69579	69579	69579
	P-Value	1	1	1	1
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	1	1	1	1
	Standard Error	(0.001)	(0.001)	(0.001)	(0.001)

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

Table D.2: Doubly-Robust Inverse Propensity Score Weighted Logistic Regression of Minority Status on Department, All Traffic Stops 2017

Department	Variable	Non-Caucasian	Black	Hispanic	Black or Hispanic
Yale University	Coefficient	N/A	N/A	N/A	N/A
	Observations	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A
	Standard Error	N/A	N/A	N/A	N/A

*Data was not available for ECSU, East Lyme, Groton Long Point, State Capitol PD, and WCSU

APPENDIX E

Table E.1: Statewide Average Comparisons for Minority Motorists, All Departments 2017

Department Name	Minority Stops	Difference Between Town and State Average	Minority Residents Age 16+	Difference Between Town and State Average	Difference Between Net Differences
Ansonia	31.8%	1.2%	25.6%	0.4%	0.8%
Avon	20.6%	-10.0%	9.8%	-15.4%	5.4%
Berlin	29.8%	-0.8%	5.8%	-19.5%	18.6%
Bethel	21.8%	-8.8%	13.5%	-11.7%	3.0%
Bloomfield	63.7%	33.1%	61.5%	36.3%	-3.2%
Branford	15.0%	-15.6%	8.5%	-16.7%	1.1%
Bridgeport	71.4%	40.8%	73.3%	48.0%	-7.2%
Bristol	25.7%	-4.9%	12.7%	-12.5%	7.6%
Brookfield	18.3%	-12.3%	8.1%	-17.1%	4.8%
Canton	9.7%	-20.9%	3.3%	-22.0%	1.0%
Cheshire	21.9%	-8.7%	8.6%	-16.6%	7.9%
Clinton	14.5%	-16.1%	6.1%	-19.1%	3.0%
Coventry	15.5%	-15.1%	3.8%	-21.4%	6.3%
Cromwell	20.1%	-10.5%	10.6%	-14.7%	4.2%
Danbury	37.7%	7.1%	38.6%	13.4%	-6.3%
Darien	36.0%	5.4%	7.2%	-18.1%	23.5%
Derby	38.5%	7.9%	20.6%	-4.7%	12.6%
East Hampton	6.5%	-24.1%	4.6%	-20.6%	-3.5%
East Hartford	68.1%	37.5%	51.6%	26.4%	11.1%
East Haven	29.3%	-1.3%	14.0%	-11.3%	10.0%
East Lyme	15.3%	-15.3%	16.5%	-8.7%	-6.6%
East Windsor	25.3%	-5.3%	14.6%	-10.7%	5.4%
Easton	16.0%	-14.6%	5.6%	-19.7%	5.1%
Enfield	21.9%	-8.7%	8.7%	-16.6%	7.9%
Fairfield	31.5%	0.9%	10.0%	-15.2%	16.1%
Farmington	26.5%	-4.1%	12.6%	-12.6%	8.5%
Glastonbury	25.3%	-5.3%	11.8%	-13.4%	8.1%
Granby	10.4%	-20.2%	3.2%	-22.0%	1.8%
Greenwich	34.4%	3.8%	18.0%	-7.3%	11.1%
Groton City*	32.3%	1.7%	26.9%	1.7%	0.0%
Groton Long Point*	12.1%	-18.5%	0.0%	-25.2%	6.8%
Groton Town	29.5%	-1.1%	20.4%	-4.8%	3.7%
Guilford	10.1%	-20.5%	5.7%	-19.6%	-0.9%
Hamden	41.5%	10.9%	30.9%	5.7%	5.3%
Hartford	75.3%	44.7%	80.8%	55.5%	-10.8%
Ledyard	28.5%	-2.1%	13.4%	-11.8%	9.8%
Madison	9.4%	-21.2%	4.3%	-21.0%	-0.3%
Manchester	42.0%	11.4%	27.9%	2.7%	8.6%
Meriden	56.0%	25.4%	34.9%	9.6%	15.8%
Middlebury	8.8%	-21.8%	5.6%	-19.7%	-2.1%
Middletown	37.4%	6.8%	23.5%	-1.7%	8.5%
Milford	26.0%	-4.6%	11.6%	-13.6%	9.0%
Monroe	17.3%	-13.3%	7.6%	-17.7%	4.4%
Naugatuck	27.7%	-2.9%	15.2%	-10.1%	7.2%
New Britain	59.3%	28.7%	45.0%	19.8%	8.9%
New Canaan	22.9%	-7.7%	7.2%	-18.1%	10.4%
New Haven	69.9%	39.3%	62.8%	37.6%	1.7%
New London	35.8%	5.2%	43.6%	18.3%	-13.2%
New Milford	19.1%	-11.5%	9.7%	-15.5%	4.0%

*Census populations within the political sub-division are used as the basis for the benchmark

Table E.1: Statewide Average Comparisons for Minority Motorists, All Departments 2017

Department Name	Minority Stops	Difference Between Town and State Average	Minority Residents Age 16+	Difference Between Town and State Average	Difference Between Net Differences
Newington	40.1%	9.5%	14.5%	-10.7%	20.2%
Newtown	16.5%	-14.1%	5.8%	-19.5%	5.3%
North Branford	7.9%	-22.7%	5.0%	-20.2%	-2.4%
North Haven	30.8%	0.2%	10.5%	-14.7%	14.9%
Norwalk	45.7%	15.1%	40.8%	15.6%	-0.5%
Norwich	41.3%	10.7%	29.1%	3.9%	6.8%
Old Saybrook	11.1%	-19.5%	5.2%	-20.1%	0.5%
Orange	10.5%	-20.1%	10.7%	-14.5%	-5.6%
Plainfield	8.1%	-22.5%	5.3%	-19.9%	-2.5%
Plainville	21.3%	-9.3%	10.0%	-15.2%	5.9%
Plymouth	12.8%	-17.8%	2.5%	-22.8%	5.0%
Portland	11.5%	-19.1%	4.6%	-20.6%	1.5%
Putnam	8.1%	-22.5%	3.4%	-21.9%	-0.6%
Redding	21.8%	-8.8%	4.4%	-20.9%	12.0%
Ridgefield	20.3%	-10.3%	7.3%	-17.9%	7.6%
Rocky Hill	21.4%	-9.2%	17.2%	-8.0%	-1.1%
Seymour	17.9%	-12.7%	9.8%	-15.5%	2.8%
Shelton	17.3%	-13.3%	10.8%	-14.4%	1.1%
Simsbury	13.8%	-16.8%	7.6%	-17.6%	0.7%
South Windsor	26.6%	-4.0%	14.6%	-10.6%	6.7%
Southington	12.9%	-17.7%	6.2%	-19.1%	1.4%
Stamford	44.1%	13.5%	43.9%	18.6%	-5.2%
Stonington	8.3%	-22.3%	4.4%	-20.9%	-1.4%
Stratford	57.5%	26.9%	27.2%	2.0%	24.9%
Suffield	14.9%	-15.7%	4.9%	-20.3%	4.6%
Thomaston	7.4%	-23.2%	2.1%	-23.1%	-0.1%
Torrington	15.6%	-15.0%	11.0%	-14.2%	-0.7%
Trumbull	37.7%	7.1%	11.9%	-13.3%	20.4%
Vernon	29.4%	-1.2%	14.1%	-11.2%	10.0%
Wallingford	27.8%	-2.8%	11.1%	-14.1%	11.3%
Waterbury	60.5%	29.9%	48.1%	22.9%	7.0%
Waterford	27.9%	-2.7%	9.8%	-15.4%	12.7%
Watertown	17.4%	-13.2%	5.8%	-19.4%	6.2%
West Hartford	39.9%	9.3%	21.8%	-3.4%	12.8%
West Haven	51.8%	21.2%	37.6%	12.4%	8.8%
Weston	12.9%	-17.7%	7.3%	-18.0%	0.3%
Westport	22.6%	-8.0%	8.3%	-16.9%	8.9%
Wethersfield	52.8%	22.2%	12.5%	-12.8%	34.9%
Willimantic	42.7%	12.1%	34.6%	9.3%	2.8%
Wilton	29.3%	-1.3%	8.1%	-17.1%	15.9%
Windsor	59.2%	28.6%	43.9%	18.7%	9.9%
Windsor Locks	30.7%	0.1%	12.7%	-12.5%	12.6%
Winsted	8.3%	-22.3%	6.1%	-19.1%	-3.2%
Wolcott	30.8%	0.2%	5.4%	-19.8%	20.0%
Woodbridge	35.9%	5.3%	12.8%	-12.4%	17.7%

*Census populations within the political sub-division are used as the basis for the benchmark

Table E.2: Statewide Average Comparisons for Black Motorists, All Departments 2017

Department Name	Black Stops	Difference Between Town and State Average	Black Residents Age 16+	Difference Between Town and State Average	Difference Between Net Differences
Ansonia	17.3%	1.0%	9.7%	0.6%	0.4%
Avon	11.0%	-5.3%	1.4%	-7.7%	2.4%
Berlin	11.2%	-5.1%	0.7%	-8.5%	3.3%
Bethel	6.1%	-10.2%	1.7%	-7.4%	-2.8%
Bloomfield	54.0%	37.7%	54.8%	45.6%	-7.9%
Branford	6.1%	-10.2%	1.8%	-7.4%	-2.8%
Bridgeport	39.3%	23.0%	31.8%	22.7%	0.3%
Bristol	10.8%	-5.5%	3.2%	-5.9%	0.4%
Brookfield	4.8%	-11.5%	1.1%	-8.1%	-3.4%
Canton	4.1%	-12.2%	0.0%	-9.1%	-3.1%
Cheshire	11.4%	-4.9%	1.3%	-7.8%	2.9%
Clinton	3.4%	-12.9%	0.0%	-9.1%	-3.8%
Coventry	5.5%	-10.8%	0.8%	-8.3%	-2.5%
Cromwell	12.3%	-4.0%	3.7%	-5.4%	1.4%
Danbury	7.9%	-8.4%	6.4%	-2.7%	-5.7%
Darien	14.5%	-1.8%	0.0%	-9.1%	7.3%
Derby	20.4%	4.1%	6.0%	-3.1%	7.2%
East Hampton	3.3%	-13.0%	1.1%	-8.0%	-5.0%
East Hartford	38.2%	21.9%	22.5%	13.4%	8.5%
East Haven	11.1%	-5.2%	2.5%	-6.6%	1.4%
East Lyme	5.5%	-10.8%	5.9%	-3.2%	-7.5%
East Windsor	14.0%	-2.3%	6.0%	-3.2%	0.8%
Easton	5.3%	-11.0%	0.0%	-9.1%	-1.9%
Enfield	11.0%	-5.3%	2.6%	-6.5%	1.2%
Fairfield	15.0%	-1.3%	1.7%	-7.4%	6.1%
Farmington	9.9%	-6.4%	2.2%	-6.9%	0.5%
Glastonbury	11.3%	-5.0%	1.8%	-7.3%	2.3%
Granby	5.3%	-11.0%	0.9%	-8.2%	-2.8%
Greenwich	9.2%	-7.1%	2.0%	-7.1%	0.0%
Groton City*	14.7%	-1.6%	7.7%	-1.4%	-0.1%
Groton Long Point*	3.0%	-13.3%	0.0%	-9.1%	-4.1%
Groton Town	14.9%	-1.4%	6.1%	-3.0%	1.7%
Guilford	2.9%	-13.4%	0.7%	-8.4%	-5.0%
Hamden	31.5%	15.2%	18.3%	9.2%	6.0%
Hartford	46.3%	30.0%	35.8%	26.7%	3.3%
Ledyard	16.3%	0.0%	3.1%	-6.0%	6.0%
Madison	3.2%	-13.1%	0.5%	-8.6%	-4.5%
Manchester	24.6%	8.3%	10.2%	1.0%	7.3%
Meriden	18.0%	1.7%	7.8%	-1.3%	3.0%
Middlebury	2.9%	-13.4%	0.0%	-9.1%	-4.2%
Middletown	25.3%	9.0%	11.7%	2.6%	6.5%
Milford	13.2%	-3.1%	2.2%	-6.9%	3.7%
Monroe	7.8%	-8.5%	1.3%	-7.8%	-0.7%
Naugatuck	11.7%	-4.6%	4.1%	-5.0%	0.4%
New Britain	18.1%	1.8%	10.7%	1.6%	0.2%
New Canaan	8.5%	-7.8%	1.1%	-8.1%	0.3%
New Haven	45.9%	29.6%	32.2%	23.0%	6.6%
New London	16.6%	0.3%	15.2%	6.1%	-5.8%
New Milford	5.5%	-10.8%	1.7%	-7.4%	-3.3%

*Census populations within the political sub-division are used as the basis for the benchmark

Table E.2: Statewide Average Comparisons for Black Motorists, All Departments 2017

Department Name	Black Stops	Difference Between Town and State Average	Black Residents Age 16+	Difference Between Town and State Average	Difference Between Net Differences
Newington	15.9%	-0.4%	3.0%	-6.1%	5.7%
Newtown	6.9%	-9.4%	0.7%	-8.4%	-1.0%
North Branford	4.0%	-12.3%	1.3%	-7.8%	-4.5%
North Haven	17.0%	0.7%	2.9%	-6.2%	6.9%
Norwalk	21.3%	5.0%	13.1%	4.0%	1.0%
Norwich	21.2%	4.9%	9.0%	-0.2%	5.0%
Old Saybrook	3.2%	-13.1%	0.0%	-9.1%	-4.0%
Orange	5.8%	-10.5%	1.3%	-7.8%	-2.7%
Plainfield	3.2%	-13.1%	1.0%	-8.2%	-4.9%
Plainville	7.3%	-9.0%	2.7%	-6.4%	-2.6%
Plymouth	5.3%	-11.0%	0.0%	-9.1%	-1.9%
Portland	5.6%	-10.7%	1.9%	-7.2%	-3.5%
Putnam	4.5%	-11.8%	1.2%	-7.9%	-3.9%
Redding	5.9%	-10.4%	0.0%	-9.1%	-1.3%
Ridgefield	5.6%	-10.7%	0.8%	-8.4%	-2.3%
Rocky Hill	10.8%	-5.5%	3.8%	-5.4%	-0.2%
Seymour	8.8%	-7.5%	2.2%	-6.9%	-0.6%
Shelton	10.3%	-6.0%	2.1%	-7.1%	1.1%
Simsbury	6.3%	-10.0%	1.5%	-7.7%	-2.3%
South Windsor	13.2%	-3.1%	3.7%	-5.4%	2.3%
Southington	5.5%	-10.8%	1.3%	-7.8%	-3.0%
Stamford	19.3%	3.0%	12.9%	3.7%	-0.8%
Stonington	3.9%	-12.4%	0.8%	-8.3%	-4.1%
Stratford	35.4%	19.1%	12.8%	3.6%	15.4%
Suffield	6.8%	-9.5%	1.4%	-7.7%	-1.8%
Thomaston	3.8%	-12.5%	0.0%	-9.1%	-3.4%
Torrington	5.5%	-10.8%	2.1%	-7.0%	-3.8%
Trumbull	21.2%	4.9%	2.9%	-6.2%	11.2%
Vernon	17.8%	1.5%	4.7%	-4.4%	5.9%
Wallingford	10.8%	-5.5%	1.3%	-7.8%	2.3%
Waterbury	30.2%	13.9%	17.4%	8.3%	5.6%
Waterford	12.7%	-3.6%	2.3%	-6.8%	3.2%
Watertown	8.6%	-7.7%	1.2%	-7.9%	0.2%
West Hartford	16.4%	0.1%	5.7%	-3.5%	3.5%
West Haven	29.0%	12.7%	17.7%	8.6%	4.1%
Weston	3.9%	-12.4%	1.3%	-7.9%	-4.5%
Westport	10.8%	-5.5%	1.2%	-7.9%	2.4%
Wethersfield	18.0%	1.7%	2.7%	-6.4%	8.1%
Willimantic	7.1%	-9.2%	4.1%	-5.0%	-4.2%
Wilton	10.0%	-6.3%	1.0%	-8.1%	1.9%
Windsor	42.8%	26.5%	32.2%	23.1%	3.5%
Windsor Locks	20.6%	4.3%	4.3%	-4.8%	9.1%
Winsted	5.2%	-11.1%	1.0%	-8.1%	-3.0%
Wolcott	10.8%	-5.5%	1.5%	-7.6%	2.1%
Woodbridge	23.6%	7.3%	1.9%	-7.2%	14.4%

*Census populations within the political sub-division are used as the basis for the benchmark

Table E.3: Statewide Average Comparisons for Hispanic Motorists, All Departments 2017

Department Name	Hispanic Stops	Difference Between Town and State Average	Hispanic Residents Age 16+	Difference Between Town and State Average	Difference Between Net Differences
Ansonia	13.5%	-0.69%	14.0%	2.1%	-2.81%
Avon	5.8%	-8.41%	2.8%	-9.2%	0.75%
Berlin	16.3%	2.07%	2.7%	-9.2%	11.30%
Bethel	13.9%	-0.33%	6.7%	-5.3%	4.93%
Bloomfield	8.6%	-5.62%	4.8%	-7.1%	1.51%
Branford	7.6%	-6.65%	3.4%	-8.5%	1.81%
Bridgeport	30.5%	16.35%	36.2%	24.3%	-7.94%
Bristol	13.8%	-0.43%	7.6%	-4.3%	3.83%
Brookfield	11.0%	-3.23%	3.8%	-8.1%	4.89%
Canton	3.7%	-10.55%	1.9%	-10.0%	-0.58%
Cheshire	9.1%	-5.08%	2.3%	-9.6%	4.48%
Clinton	9.6%	-4.56%	4.4%	-7.5%	2.94%
Coventry	7.1%	-7.07%	2.2%	-9.7%	2.63%
Cromwell	6.0%	-8.24%	3.9%	-8.0%	-0.23%
Danbury	27.4%	13.24%	23.3%	11.3%	1.89%
Darien	19.3%	5.08%	3.5%	-8.4%	13.50%
Derby	16.6%	2.42%	12.4%	0.5%	1.96%
East Hampton	2.1%	-12.12%	2.0%	-9.9%	-2.23%
East Hartford	27.7%	13.48%	22.9%	11.0%	2.48%
East Haven	16.1%	1.94%	8.4%	-3.5%	5.42%
East Lyme	6.6%	-7.60%	5.1%	-6.8%	-0.79%
East Windsor	10.0%	-4.15%	4.3%	-7.6%	3.41%
Easton	9.4%	-4.81%	2.6%	-9.4%	4.55%
Enfield	8.9%	-5.29%	4.0%	-7.9%	2.63%
Fairfield	14.0%	-0.17%	4.5%	-7.4%	7.22%
Farmington	10.6%	-3.65%	3.2%	-8.7%	5.06%
Glastonbury	9.6%	-4.60%	3.6%	-8.3%	3.71%
Granby	3.6%	-10.55%	1.4%	-10.5%	-0.03%
Greenwich	19.0%	4.84%	9.2%	-2.8%	7.60%
Groton City*	14.1%	-0.11%	11.8%	-0.1%	0.00%
Groton Long Point*	9.1%	-5.11%	0.0%	-11.9%	6.80%
Groton Town	11.1%	-3.10%	7.4%	-4.5%	1.41%
Guilford	4.2%	-9.98%	2.9%	-9.0%	-0.98%
Hamden	8.8%	-5.42%	7.6%	-4.3%	-1.09%
Hartford	27.8%	13.63%	41.0%	29.1%	-15.48%
Ledyard	9.6%	-4.57%	4.6%	-7.3%	2.77%
Madison	4.4%	-9.78%	1.7%	-10.2%	0.40%
Manchester	14.7%	0.50%	9.9%	-2.0%	2.52%
Meriden	36.8%	22.62%	24.9%	13.0%	9.67%
Middlebury	2.9%	-11.26%	2.2%	-9.7%	-1.57%
Middletown	9.9%	-4.28%	6.8%	-5.1%	0.86%
Milford	10.4%	-3.85%	4.4%	-7.5%	3.62%
Monroe	7.7%	-6.51%	4.3%	-7.6%	1.09%
Naugatuck	14.7%	0.46%	7.8%	-4.1%	4.61%
New Britain	40.1%	25.85%	31.8%	19.8%	6.01%
New Canaan	11.3%	-2.89%	2.7%	-9.2%	6.33%
New Haven	22.7%	8.48%	24.8%	12.9%	-4.40%
New London	17.6%	3.44%	25.1%	13.2%	-9.73%
New Milford	11.9%	-2.25%	5.5%	-6.5%	4.20%

*Census populations within the political sub-division are used as the basis for the benchmark

Table E.3: Statewide Average Comparisons for Hispanic Motorists, All Departments 2017

Department Name	Hispanic Stops	Difference Between Town and State Average	Hispanic Residents Age 16+	Difference Between Town and State Average	Difference Between Net Differences
Newington	20.6%	6.43%	6.4%	-5.5%	11.95%
Newtown	7.3%	-6.90%	2.9%	-9.0%	2.15%
North Branford	2.8%	-11.35%	2.3%	-9.6%	-1.75%
North Haven	11.5%	-2.73%	3.3%	-8.6%	5.92%
Norwalk	22.2%	8.04%	22.7%	10.8%	-2.72%
Norwich	16.0%	1.84%	10.6%	-1.3%	3.16%
Old Saybrook	5.8%	-8.42%	2.9%	-9.0%	0.56%
Orange	3.8%	-10.44%	2.5%	-9.4%	-1.07%
Plainfield	4.7%	-9.53%	3.3%	-8.6%	-0.95%
Plainville	12.7%	-1.53%	5.2%	-6.7%	5.19%
Plymouth	6.5%	-7.65%	2.5%	-9.4%	1.78%
Portland	3.1%	-11.13%	2.8%	-9.2%	-1.97%
Putnam	2.4%	-11.77%	2.2%	-9.7%	-2.06%
Redding	13.2%	-1.01%	2.4%	-9.5%	8.53%
Ridgefield	11.3%	-2.91%	3.5%	-8.4%	5.54%
Rocky Hill	7.3%	-6.90%	4.7%	-7.3%	0.36%
Seymour	8.0%	-6.16%	5.5%	-6.4%	0.22%
Shelton	6.2%	-7.96%	5.2%	-6.7%	-1.22%
Simsbury	4.1%	-10.06%	2.6%	-9.3%	-0.76%
South Windsor	8.6%	-5.55%	3.6%	-8.3%	2.74%
Southington	6.3%	-7.88%	2.8%	-9.1%	1.23%
Stamford	21.7%	7.48%	22.9%	11.0%	-3.48%
Stonington	2.3%	-11.93%	1.9%	-10.0%	-1.93%
Stratford	20.3%	6.09%	11.9%	0.0%	6.08%
Suffield	6.6%	-7.58%	2.2%	-9.7%	2.13%
Thomaston	2.4%	-11.77%	2.1%	-9.8%	-1.95%
Torrington	8.6%	-5.62%	6.9%	-5.0%	-0.63%
Trumbull	14.0%	-0.23%	5.1%	-6.9%	6.62%
Vernon	9.5%	-4.70%	5.2%	-6.7%	2.00%
Wallingford	15.5%	1.30%	6.7%	-5.2%	6.50%
Waterbury	29.6%	15.42%	27.5%	15.6%	-0.21%
Waterford	12.9%	-1.34%	4.1%	-7.8%	6.50%
Watertown	7.7%	-6.45%	3.0%	-8.9%	2.47%
West Hartford	16.7%	2.52%	8.8%	-3.1%	5.65%
West Haven	21.5%	7.26%	16.0%	4.1%	3.20%
Weston	6.9%	-7.33%	3.1%	-8.9%	1.52%
Westport	9.6%	-4.59%	3.2%	-8.7%	4.13%
Wethersfield	32.7%	18.47%	7.1%	-4.8%	23.27%
Willimantic	34.5%	20.29%	28.9%	17.0%	3.32%
Wilton	14.3%	0.06%	2.7%	-9.2%	9.23%
Windsor	12.4%	-1.81%	7.3%	-4.6%	2.76%
Windsor Locks	8.2%	-6.01%	3.5%	-8.5%	2.44%
Winsted	2.1%	-12.06%	4.3%	-7.6%	-4.43%
Wolcott	16.7%	2.47%	2.8%	-9.1%	11.55%
Woodbridge	8.4%	-5.83%	2.7%	-9.2%	3.39%

*Census populations within the political sub-division are used as the basis for the benchmark

Table E.4: Ratio of Minority EDP to Minority Stops, All Departments 2017

Department Name	Number of Stops	% Minority Stops	% Minority EDP	Absolute Difference	Ratio
Ansonia	1,178	29.1%	25.1%	4.0%	1.16
Avon	324	19.1%	13.3%	5.9%	1.44
Berlin	2,026	24.8%	12.9%	11.9%	1.92
Bethel	1,323	21.5%	16.5%	4.9%	1.30
Bloomfield	741	57.6%	42.7%	14.9%	1.35
Branford	1,781	13.6%	13.1%	0.5%	1.04
Bridgeport	728	71.0%	61.8%	9.2%	1.15
Bristol	1,239	21.7%	14.2%	7.5%	1.53
Brookfield	737	14.1%	10.3%	3.8%	1.37
Canton	393	7.6%	6.9%	0.7%	1.11
Cheshire	928	18.6%	14.5%	4.2%	1.29
Clinton	606	12.2%	8.4%	3.8%	1.46
Coventry	297	9.1%	5.0%	4.1%	1.80
Cromwell	453	12.6%	15.7%	-3.1%	0.80
Danbury	2,462	34.9%	32.0%	3.0%	1.09
Darien	1,323	36.8%	15.9%	20.9%	2.31
Derby	612	35.0%	21.1%	13.8%	1.65
East Hampton	331	5.1%	5.8%	-0.7%	0.88
East Hartford	3,156	67.7%	40.0%	27.6%	1.69
East Haven	708	25.8%	16.6%	9.3%	1.56
East Lyme	70	11.4%	10.7%	0.7%	1.07
East Windsor	521	18.6%	19.2%	-0.5%	0.97
Easton	456	18.4%	7.5%	10.9%	2.45
Enfield	2,163	19.4%	12.6%	6.7%	1.53
Fairfield	3,954	29.2%	17.5%	11.7%	1.67
Farmington	1,773	24.3%	18.8%	5.4%	1.29
Glastonbury	1,464	18.5%	16.0%	2.5%	1.16
Granby	253	6.3%	6.3%	0.0%	1.00
Greenwich	2,134	32.3%	24.6%	7.6%	1.31
Groton City	611	24.7%	18.4%	6.3%	1.34
Groton Long Point	22	4.5%	18.4%	-13.9%	0.25
Groton Town	990	25.8%	18.4%	7.4%	1.40
Guilford	984	7.8%	8.3%	-0.5%	0.94
Hamden	2,910	39.1%	29.5%	9.6%	1.33
Hartford	3,091	66.2%	50.1%	16.2%	1.32
Ledyard	612	24.3%	15.8%	8.5%	1.54
Madison	1,011	10.1%	6.5%	3.6%	1.56
Manchester	4,817	38.1%	26.7%	11.4%	1.43
Meriden	634	56.2%	31.4%	24.7%	1.79
Middlebury	11	27.3%	11.4%	15.9%	2.40
Middletown	733	30.2%	21.9%	8.3%	1.38
Milford	1,002	20.7%	18.0%	2.7%	1.15
Monroe	1,363	14.5%	11.6%	3.0%	1.26
Naugatuck	1,453	22.7%	16.9%	5.8%	1.34
New Britain	2,766	55.1%	38.9%	16.2%	1.42
New Canaan	1,892	21.4%	13.8%	7.6%	1.55
New Haven	8,353	65.8%	46.3%	19.5%	1.42

Table E.4: Ratio of Minority EDP to Minority Stops, All Departments 2017

Department Name	Number of Stops	% Minority Stops	% Minority EDP	Absolute Difference	Ratio
New London	2,119	33.2%	33.7%	-0.6%	0.98
New Milford	802	16.6%	11.3%	5.3%	1.47
Newington	1,471	33.3%	19.0%	14.3%	1.75
Newtown	1,235	15.9%	9.5%	6.4%	1.68
North Branford	318	6.6%	8.8%	-2.2%	0.75
North Haven	888	30.9%	17.5%	13.3%	1.76
Norwalk	2,388	40.3%	36.9%	3.4%	1.09
Norwich	1,314	34.8%	24.7%	10.1%	1.41
Old Saybrook	646	11.1%	8.5%	2.6%	1.31
Orange	90	30.0%	19.5%	10.5%	1.54
Plainfield	377	8.2%	6.7%	1.5%	1.22
Plainville	1,221	16.7%	14.3%	2.5%	1.17
Plymouth	327	11.0%	4.6%	6.4%	2.39
Portland	90	11.1%	7.0%	4.1%	1.59
Putnam	226	3.1%	6.1%	-3.0%	0.50
Redding	959	20.0%	7.6%	12.4%	2.65
Ridgefield	2,862	20.0%	13.1%	6.9%	1.53
Rocky Hill	1,137	19.2%	19.6%	-0.4%	0.98
Seymour	1,297	15.6%	12.4%	3.2%	1.25
Shelton	85	14.1%	17.2%	-3.1%	0.82
Simsbury	1,321	11.5%	11.3%	0.2%	1.01
South Windsor	1,611	21.2%	17.9%	3.3%	1.18
Southington	1,457	9.7%	10.2%	-0.6%	0.95
Stamford	5,558	39.5%	38.8%	0.7%	1.02
Stonington	1,102	5.7%	7.4%	-1.6%	0.78
Stratford	1,036	51.2%	27.9%	23.3%	1.84
Suffield	139	11.5%	8.6%	2.9%	1.33
Thomaston	295	3.1%	6.4%	-3.3%	0.48
Torrington	891	14.6%	12.2%	2.4%	1.20
Trumbull	833	31.2%	18.2%	13.0%	1.71
Vernon	517	20.7%	15.4%	5.3%	1.34
Wallingford	2,645	25.4%	15.6%	9.7%	1.62
Waterbury	894	62.5%	40.1%	22.4%	1.56
Waterford	1,282	23.3%	13.9%	9.4%	1.68
Watertown	793	15.0%	10.6%	4.4%	1.42
West Hartford	2,263	38.5%	24.1%	14.4%	1.60
West Haven	2,210	47.3%	35.6%	11.7%	1.33
Weston	286	10.8%	9.5%	1.3%	1.14
Westport	3,079	23.5%	18.1%	5.5%	1.30
Wethersfield	730	45.3%	16.6%	28.7%	2.73
Willimantic	432	42.6%	29.3%	13.3%	1.45
Wilton	1,403	25.6%	17.4%	8.2%	1.47
Winchester	237	6.3%	7.0%	-0.7%	0.90
Windsor	3,610	52.4%	33.2%	19.2%	1.58
Windsor Locks	324	25.0%	18.8%	6.2%	1.33
Wolcott	46	34.8%	8.2%	26.6%	4.25
Woodbridge	783	28.7%	17.3%	11.4%	1.66

Table E.5: Ratio of Black EDP to Black Stops, All Departments 2017

Department Name	Number of Stops	% Black Stops	% Black EDP	Absolute Difference	Ratio
Ansonia	1,178	14.1%	9.5%	4.6%	1.49
Avon	324	8.6%	3.5%	5.2%	2.49
Berlin	2,026	9.3%	3.5%	5.8%	2.67
Bethel	1,323	6.4%	2.9%	3.5%	2.19
Bloomfield	741	48.7%	31.1%	17.6%	1.56
Branford	1,781	5.2%	4.1%	1.2%	1.28
Bridgeport	728	38.3%	26.5%	11.9%	1.45
Bristol	1,239	8.2%	3.9%	4.3%	2.09
Brookfield	737	3.4%	2.0%	1.4%	1.68
Canton	393	3.6%	1.5%	2.1%	2.38
Cheshire	928	9.8%	3.9%	5.9%	2.49
Clinton	606	1.8%	1.2%	0.6%	1.53
Coventry	297	2.7%	1.2%	1.5%	2.25
Cromwell	453	7.9%	5.6%	2.3%	1.41
Danbury	2,462	7.4%	6.1%	1.2%	1.20
Darien	1,323	15.3%	3.6%	11.7%	4.28
Derby	612	16.8%	6.7%	10.1%	2.51
East Hampton	331	2.4%	1.5%	0.9%	1.57
East Hartford	3,156	38.2%	17.0%	21.3%	2.26
East Haven	708	8.5%	4.2%	4.3%	2.02
East Lyme	70	4.3%	1.8%	2.5%	2.39
East Windsor	521	8.8%	7.9%	0.9%	1.11
Easton	456	5.5%	0.9%	4.6%	6.24
Enfield	2,163	9.3%	4.1%	5.2%	2.25
Fairfield	3,954	13.1%	5.3%	7.9%	2.49
Farmington	1,773	8.4%	5.9%	2.6%	1.44
Glastonbury	1,464	7.3%	4.3%	3.0%	1.68
Granby	253	3.6%	2.2%	1.3%	1.59
Greenwich	2,134	7.9%	5.6%	2.3%	1.41
Groton City	611	9.7%	5.5%	4.2%	1.77
Groton Long Point	22	0.0%	5.5%	-5.5%	0.00
Groton Town	990	11.6%	5.5%	6.1%	2.12
Guilford	984	2.4%	1.9%	0.5%	1.27
Hamden	2,910	28.3%	16.1%	12.2%	1.76
Hartford	3,091	39.5%	21.6%	17.9%	1.83
Ledyard	612	14.7%	4.3%	10.4%	3.45
Madison	1,011	3.5%	1.4%	2.1%	2.49
Manchester	4,817	22.3%	9.9%	12.4%	2.25
Meriden	634	14.5%	7.7%	6.8%	1.87
Middlebury	11	9.1%	2.6%	6.5%	3.46
Middletown	733	20.2%	9.7%	10.5%	2.08
Milford	1,002	9.1%	5.6%	3.5%	1.62
Monroe	1,363	6.2%	3.0%	3.2%	2.05
Naugatuck	1,453	9.1%	4.9%	4.2%	1.85
New Britain	2,766	16.0%	10.0%	6.0%	1.61
New Canaan	1,892	6.9%	3.5%	3.4%	1.98
New Haven	8,353	41.5%	22.6%	18.9%	1.83

Table E.5: Ratio of Black EDP to Black Stops, All Departments 2017

Department Name	Number of Stops	% Black Stops	% Black EDP	Absolute Difference	Ratio
New London	2,119	15.1%	11.4%	3.7%	1.32
New Milford	802	4.0%	2.3%	1.7%	1.74
Newington	1,471	12.8%	5.5%	7.3%	2.32
Newtown	1,235	5.5%	2.0%	3.5%	2.78
North Branford	318	3.5%	2.9%	0.6%	1.21
North Haven	888	15.9%	6.3%	9.6%	2.52
Norwalk	2,388	18.0%	12.0%	6.0%	1.50
Norwich	1,314	17.2%	7.5%	9.7%	2.29
Old Saybrook	646	3.1%	1.6%	1.5%	1.97
Orange	90	15.6%	6.3%	9.3%	2.49
Plainfield	377	2.4%	1.5%	0.9%	1.58
Plainville	1,221	4.9%	4.3%	0.6%	1.15
Plymouth	327	4.3%	0.8%	3.5%	5.42
Portland	90	7.8%	2.7%	5.1%	2.91
Putnam	226	1.8%	1.8%	-0.1%	0.97
Redding	959	4.8%	1.1%	3.7%	4.23
Ridgefield	2,862	4.6%	2.7%	2.0%	1.74
Rocky Hill	1,137	9.1%	5.8%	3.3%	1.56
Seymour	1,297	7.4%	3.4%	4.0%	2.15
Shelton	85	9.4%	5.3%	4.2%	1.79
Simsbury	1,321	5.4%	3.4%	2.0%	1.58
South Windsor	1,611	9.2%	5.8%	3.4%	1.59
Southington	1,457	4.3%	2.8%	1.5%	1.54
Stamford	5,558	16.6%	11.7%	4.8%	1.41
Stonington	1,102	3.0%	1.8%	1.2%	1.65
Stratford	1,036	31.3%	12.1%	19.2%	2.58
Suffield	139	4.3%	2.9%	1.4%	1.49
Thomaston	295	1.7%	1.6%	0.1%	1.07
Torrington	891	3.7%	2.9%	0.8%	1.27
Trumbull	833	13.9%	5.9%	8.1%	2.37
Vernon	517	10.8%	5.3%	5.5%	2.04
Wallingford	2,645	9.0%	3.8%	5.3%	2.39
Waterbury	894	29.2%	14.3%	14.9%	2.04
Waterford	1,282	10.8%	3.9%	6.9%	2.76
Watertown	793	7.1%	3.0%	4.0%	2.33
West Hartford	2,263	16.1%	7.6%	8.4%	2.10
West Haven	2,210	25.8%	16.4%	9.4%	1.58
Weston	286	2.8%	2.1%	0.7%	1.35
Westport	3,079	11.0%	5.3%	5.7%	2.08
Wethersfield	730	14.7%	4.9%	9.8%	2.99
Willimantic	432	5.1%	4.2%	0.9%	1.21
Wilton	1,403	7.1%	4.7%	2.5%	1.53
Winchester	237	4.2%	1.4%	2.8%	2.96
Windsor	3,610	35.3%	20.1%	15.2%	1.76
Windsor Locks	324	15.7%	7.1%	8.6%	2.20
Wolcott	46	10.9%	2.5%	8.3%	4.29
Woodbridge	783	18.3%	4.8%	13.5%	3.83

Table E.6: Ratio of Hispanic EDP to Hispanic Stops, All Departments 2017

Department Name	Number of Stops	% Hispanic Stops	% Hispanic EDP	Absolute Difference	Ratio
Ansonia	1,178	14.1%	13.5%	0.6%	1.04
Avon	324	4.3%	4.9%	-0.6%	0.88
Berlin	2,026	13.9%	6.6%	7.3%	2.11
Bethel	1,323	13.3%	8.5%	4.8%	1.56
Bloomfield	741	8.2%	8.5%	-0.3%	0.97
Branford	1,781	7.4%	5.6%	1.7%	1.30
Bridgeport	728	31.2%	30.4%	0.8%	1.03
Bristol	1,239	12.5%	8.1%	4.4%	1.55
Brookfield	737	8.5%	5.0%	3.6%	1.72
Canton	393	2.8%	3.6%	-0.8%	0.78
Cheshire	928	7.5%	6.2%	1.3%	1.21
Clinton	606	9.1%	5.2%	3.9%	1.76
Coventry	297	4.4%	2.8%	1.6%	1.59
Cromwell	453	4.0%	6.8%	-2.8%	0.59
Danbury	2,462	25.5%	18.6%	6.9%	1.37
Darien	1,323	19.0%	8.0%	11.1%	2.38
Derby	612	16.7%	11.8%	4.8%	1.41
East Hampton	331	1.5%	2.6%	-1.1%	0.58
East Hartford	3,156	27.4%	17.8%	9.6%	1.54
East Haven	708	16.1%	9.1%	7.0%	1.77
East Lyme	70	7.1%	3.9%	3.2%	1.82
East Windsor	521	8.8%	7.2%	1.6%	1.22
Easton	456	11.0%	3.5%	7.5%	3.14
Enfield	2,163	8.2%	6.0%	2.2%	1.36
Fairfield	3,954	13.6%	8.2%	5.4%	1.65
Farmington	1,773	8.9%	8.0%	0.9%	1.11
Glastonbury	1,464	7.2%	6.1%	1.2%	1.19
Granby	253	2.0%	2.8%	-0.8%	0.72
Greenwich	2,134	18.0%	12.4%	5.6%	1.45
Groton City	611	10.1%	7.3%	2.9%	1.40
Groton Long Point	22	4.5%	7.3%	-2.7%	0.63
Groton Town	990	11.3%	7.3%	4.1%	1.56
Guilford	984	3.3%	4.0%	-0.8%	0.80
Hamden	2,910	9.3%	8.6%	0.7%	1.08
Hartford	3,091	25.6%	24.4%	1.2%	1.05
Ledyard	612	7.7%	6.3%	1.3%	1.21
Madison	1,011	4.6%	2.8%	1.8%	1.64
Manchester	4,817	13.0%	10.2%	2.8%	1.27
Meriden	634	40.5%	21.1%	19.4%	1.92
Middlebury	11	9.1%	5.6%	3.5%	1.64
Middletown	733	8.0%	7.8%	0.3%	1.04
Milford	1,002	9.0%	7.7%	1.3%	1.17
Monroe	1,363	7.1%	6.1%	1.0%	1.17
Naugatuck	1,453	12.6%	8.8%	3.8%	1.44
New Britain	2,766	38.1%	26.0%	12.1%	1.46
New Canaan	1,892	11.7%	6.4%	5.3%	1.83
New Haven	8,353	23.0%	18.6%	4.4%	1.23

Table E.6: Ratio of Hispanic EDP to Hispanic Stops, All Departments 2017

Department Name	Number of Stops	% Hispanic Stops	% Hispanic EDP	Absolute Difference	Ratio
New London	2,119	16.8%	18.6%	-1.8%	0.90
New Milford	802	11.2%	6.2%	5.0%	1.80
Newington	1,471	17.7%	8.9%	8.8%	1.99
Newtown	1,235	7.8%	4.8%	3.0%	1.61
North Branford	318	2.2%	4.0%	-1.8%	0.55
North Haven	888	12.0%	7.1%	4.9%	1.69
Norwalk	2,388	20.1%	19.9%	0.3%	1.01
Norwich	1,314	14.8%	9.5%	5.4%	1.57
Old Saybrook	646	6.2%	4.4%	1.8%	1.40
Orange	90	12.2%	7.7%	4.5%	1.59
Plainfield	377	5.6%	3.8%	1.7%	1.45
Plainville	1,221	10.4%	7.4%	3.0%	1.40
Plymouth	327	5.8%	3.4%	2.4%	1.69
Portland	90	2.2%	3.7%	-1.5%	0.60
Putnam	226	0.9%	3.4%	-2.6%	0.26
Redding	959	12.6%	4.0%	8.6%	3.16
Ridgefield	2,862	12.1%	6.7%	5.4%	1.81
Rocky Hill	1,137	6.5%	7.4%	-0.9%	0.88
Seymour	1,297	6.9%	6.7%	0.2%	1.03
Shelton	85	3.5%	8.3%	-4.7%	0.43
Simsbury	1,321	3.1%	4.4%	-1.3%	0.70
South Windsor	1,611	7.3%	6.1%	1.3%	1.21
Southington	1,457	4.3%	5.1%	-0.8%	0.85
Stamford	5,558	20.0%	20.0%	0.1%	1.00
Stonington	1,102	1.4%	3.3%	-2.0%	0.41
Stratford	1,036	18.1%	12.7%	5.5%	1.43
Suffield	139	5.8%	4.0%	1.7%	1.44
Thomaston	295	1.4%	4.2%	-2.8%	0.32
Torrington	891	9.4%	7.2%	2.3%	1.32
Trumbull	833	14.6%	8.3%	6.3%	1.76
Vernon	517	7.7%	6.0%	1.7%	1.29
Wallingford	2,645	14.8%	8.6%	6.2%	1.71
Waterbury	894	32.9%	22.7%	10.2%	1.45
Waterford	1,282	10.1%	6.2%	3.9%	1.63
Watertown	793	6.9%	5.6%	1.3%	1.23
West Hartford	2,263	16.6%	10.3%	6.3%	1.62
West Haven	2,210	20.2%	15.2%	5.0%	1.33
Weston	286	6.6%	4.2%	2.4%	1.56
Westport	3,079	10.6%	8.4%	2.3%	1.27
Wethersfield	730	29.7%	8.7%	21.1%	3.43
Willimantic	432	36.1%	23.1%	13.0%	1.56
Wilton	1,403	13.4%	8.1%	5.3%	1.65
Winchester	237	1.7%	4.6%	-2.9%	0.37
Windsor	3,610	13.2%	9.1%	4.1%	1.45
Windsor Locks	324	8.0%	7.3%	0.7%	1.10
Wolcott	46	15.2%	4.3%	10.9%	3.51
Woodbridge	783	6.0%	5.5%	0.5%	1.08

Table E.7: Ratio of Minority Residents to Minority Resident Stops, All Departments

Department Name	Number of Residents	Minority Residents	Resident Stops	Minority Resident Stops	Difference	Ratio
Ansonia	14,979	25.6%	1,458	33.3%	7.6%	1.30
Avon	13,855	9.8%	353	9.6%	-0.2%	0.98
Berlin	16,083	5.8%	1,327	7.9%	2.1%	1.37
Bethel	14,675	13.5%	1,083	16.0%	2.5%	1.18
Bloomfield	16,982	61.5%	701	81.0%	19.5%	1.32
Branford	23,532	8.5%	2,055	10.6%	2.1%	1.25
Bridgeport	109,401	73.3%	1,920	74.3%	1.0%	1.01
Bristol	48,439	12.7%	1,648	26.3%	13.6%	2.07
Brookfield	12,847	8.1%	734	11.3%	3.2%	1.39
Canton	7,992	3.3%	204	5.9%	2.6%	1.81
Cheshire	21,049	8.6%	1,188	17.6%	9.0%	2.04
Clinton	10,540	6.1%	1,420	13.8%	7.7%	2.26
Coventry	9,779	3.8%	539	6.9%	3.1%	1.81
Cromwell	11,357	10.6%	554	9.9%	-0.6%	0.94
Danbury	64,361	38.6%	1,386	51.9%	13.2%	1.34
Darien	14,004	7.2%	776	7.9%	0.7%	1.10
Derby	10,391	20.6%	416	46.4%	25.8%	2.26
East Hampton	10,255	4.6%	446	5.4%	0.8%	1.17
East Hartford	40,229	51.6%	3,485	73.1%	21.5%	1.42
East Haven	24,114	14.0%	1,083	17.5%	3.6%	1.25
East Lyme	15,943	16.5%	137	8.8%	-7.7%	0.53
East Windsor	9,164	14.6%	401	22.2%	7.6%	1.52
Easton	5,553	5.6%	269	5.2%	-0.4%	0.94
Enfield	33,218	8.7%	3,645	15.8%	7.1%	1.83
Fairfield	45,567	10.0%	1,325	10.6%	0.6%	1.06
Farmington	20,318	12.6%	806	20.1%	7.5%	1.60
Glastonbury	26,217	11.8%	1,656	16.6%	4.8%	1.41
Granby	8,716	3.2%	192	3.6%	0.5%	1.14
Greenwich	46,370	18.0%	2,170	22.7%	4.8%	1.27
Groton City*	7,960	26.9%	437	43.7%	16.8%	1.62
Groton Long Point*	2,030	0.0%	15	6.7%	6.7%	N/A
Groton Town	31,520	20.4%	1,461	27.4%	7.0%	1.34
Guilford	17,672	5.7%	1,196	6.8%	1.1%	1.19
Hamden	50,012	30.9%	1,814	46.1%	15.2%	1.49
Hartford	93,669	80.8%	7,190	76.9%	-3.8%	0.95
Ledyard	11,527	13.4%	556	20.5%	7.1%	1.53
Madison	14,073	4.3%	1,251	4.7%	0.5%	1.11
Manchester	46,667	27.9%	4,551	41.9%	14.0%	1.50
Meriden	47,445	34.9%	1,086	61.5%	26.7%	1.76
Middlebury	5,843	5.6%	4	0.0%	-5.6%	0.00
Middletown	38,747	23.5%	3,027	37.8%	14.3%	1.61
Milford	43,135	11.6%	2,389	12.8%	1.1%	1.10
Monroe	14,918	7.6%	1,218	7.5%	-0.1%	0.99
Naugatuck	25,099	15.2%	2,248	23.2%	8.0%	1.53
New Britain	57,164	45.0%	4,731	66.3%	21.3%	1.47
New Canaan	14,138	7.2%	1,685	9.1%	2.0%	1.28
New Haven	100,702	62.8%	11,897	82.8%	19.9%	1.32

*Census populations within the political sub-division are used as the basis for the benchmark.

Table E.7: Ratio of Minority Residents to Minority Resident Stops, All Departments

Department Name	Number of Residents	Minority Residents	Resident Stops	Minority Resident Stops	Difference	Ratio
New London	21,835	43.6%	1,811	58.0%	14.5%	1.33
New Milford	21,891	9.7%	1,210	18.2%	8.5%	1.88
Newington	24,978	14.5%	1,336	22.0%	7.5%	1.52
Newtown	20,171	5.8%	989	5.3%	-0.5%	0.91
North Branford	11,549	5.0%	252	1.6%	-3.4%	0.32
North Haven	19,608	10.5%	483	10.4%	-0.2%	0.98
Norwalk	68,034	40.8%	2,373	54.2%	13.4%	1.33
Norwich	31,638	29.1%	3,384	49.3%	20.2%	1.70
Old Saybrook	8,330	5.2%	696	10.6%	5.5%	2.06
Orange	11,017	10.7%	32	12.5%	1.8%	1.16
Plainfield	11,918	5.3%	789	7.4%	2.0%	1.38
Plainville	14,605	10.0%	1,195	14.3%	4.3%	1.43
Plymouth	9,660	2.5%	543	5.9%	3.4%	2.38
Portland	7,480	4.6%	146	9.6%	5.0%	2.07
Putnam	7,507	3.4%	905	7.0%	3.6%	2.07
Redding	6,955	4.4%	535	6.9%	2.5%	1.58
Ridgefield	18,111	7.3%	2,170	7.5%	0.2%	1.03
Rocky Hill	16,224	17.2%	1,259	16.6%	-0.6%	0.97
Seymour	13,260	9.8%	1,312	13.4%	3.6%	1.37
Shelton	32,010	10.8%	272	9.6%	-1.3%	0.88
Simsbury	17,773	7.6%	1,396	8.2%	0.6%	1.08
South Windsor	20,162	14.6%	1,376	18.4%	3.8%	1.26
Southington	34,301	6.2%	2,374	5.2%	-1.0%	0.85
Stamford	98,070	43.9%	6,865	48.1%	4.2%	1.10
Stonington	15,078	4.4%	1,620	5.5%	1.1%	1.26
Stratford	40,980	27.2%	1,272	54.2%	27.0%	1.99
Suffield	10,782	4.9%	169	3.0%	-2.0%	0.60
Thomaston	6,224	2.1%	438	3.0%	0.9%	1.42
Torrington	29,251	11.0%	4,530	17.6%	6.6%	1.60
Trumbull	27,678	11.9%	477	17.6%	5.7%	1.48
Vernon	23,800	14.1%	1,262	28.2%	14.2%	2.01
Wallingford	36,530	11.1%	2,968	15.4%	4.2%	1.38
Waterbury	83,964	48.1%	1,888	70.7%	22.6%	1.47
Waterford	15,760	9.8%	920	13.6%	3.7%	1.38
Watertown	18,154	5.8%	556	6.1%	0.3%	1.05
West Hartford	49,650	21.8%	1,054	30.2%	8.4%	1.38
West Haven	44,518	37.6%	4,225	47.4%	9.8%	1.26
Weston	7,255	7.3%	298	9.1%	1.8%	1.25
Westport	19,410	8.3%	1,968	6.0%	-2.3%	0.72
Wethersfield	21,607	12.5%	652	25.3%	12.8%	2.03
Willimantic	20,176	34.6%	1,172	59.0%	24.5%	1.71
Wilton	12,973	8.1%	1,004	13.1%	5.1%	1.62
Windsor	23,222	43.9%	2,677	65.1%	21.2%	1.48
Windsor Locks	10,117	12.7%	288	20.8%	8.1%	1.64
Winsted	9,133	6.1%	374	7.0%	0.8%	1.14
Wolcott	13,175	5.4%	54	9.3%	3.8%	1.71
Woodbridge	7,119	12.8%	267	17.6%	4.8%	1.37

*Census populations within the political sub-division are used as the basis for the benchmark.

Table E.8: Ratio of Black Residents to Black Resident Stops, All Departments

Department Name	Number of Residents	Black Residents	Resident Stops	Black Resident Stops	Difference	Ratio
Ansonia	14,979	9.74%	1,458	18.7%	8.9%	1.92
Avon	13,855	1.41%	353	3.7%	2.3%	2.60
Berlin	16,083	0.65%	1,327	2.1%	1.5%	3.23
Bethel	14,675	1.74%	1,083	2.6%	0.8%	1.49
Bloomfield	16,982	54.76%	701	76.9%	22.1%	1.40
Branford	23,532	1.76%	2,055	4.1%	2.4%	2.35
Bridgeport	109,401	31.82%	1,920	40.3%	8.4%	1.27
Bristol	48,439	3.24%	1,648	11.3%	8.0%	3.49
Brookfield	12,847	1.05%	734	3.1%	2.1%	2.98
Canton	7,992	0.00%	204	2.0%	2.0%	N/A
Cheshire	21,049	1.27%	1,188	8.8%	7.5%	6.87
Clinton	10,540	0.00%	1,420	3.3%	3.3%	N/A
Coventry	9,779	0.79%	539	2.4%	1.6%	3.06
Cromwell	11,357	3.69%	554	6.9%	3.2%	1.86
Danbury	64,361	6.42%	1,386	10.3%	3.9%	1.61
Darien	14,004	0.00%	776	2.1%	2.1%	N/A
Derby	10,391	6.03%	416	23.3%	17.3%	3.86
East Hampton	10,255	1.10%	446	2.5%	1.4%	2.24
East Hartford	40,229	22.52%	3,485	40.5%	17.9%	1.80
East Haven	24,114	2.47%	1,083	4.7%	2.2%	1.91
East Lyme	15,943	5.90%	137	2.9%	-3.0%	0.49
East Windsor	9,164	5.96%	401	12.7%	6.8%	2.13
Easton	5,553	0.00%	269	0.7%	0.7%	N/A
Enfield	33,218	2.63%	3,645	6.9%	4.3%	2.62
Fairfield	45,567	1.73%	1,325	3.3%	1.6%	1.92
Farmington	20,318	2.20%	806	4.5%	2.3%	2.03
Glastonbury	26,217	1.80%	1,656	5.6%	3.8%	3.08
Granby	8,716	0.92%	192	1.6%	0.6%	1.70
Greenwich	46,370	2.03%	2,170	3.7%	1.7%	1.84
Groton City*	7,960	7.70%	437	19.0%	11.3%	2.47
Groton Long Point*	2,030	0.00%	15	6.7%	6.7%	N/A
Groton Town	31,520	6.07%	1,461	13.9%	7.8%	2.29
Guilford	17,672	0.70%	1,196	1.7%	1.0%	2.38
Hamden	50,012	18.28%	1,814	35.4%	17.2%	1.94
Hartford	93,669	35.80%	7,190	46.6%	10.8%	1.30
Ledyard	11,527	3.10%	556	12.6%	9.5%	4.06
Madison	14,073	0.49%	1,251	1.4%	0.9%	2.77
Manchester	46,667	10.15%	4,551	23.9%	13.7%	2.35
Meriden	47,445	7.80%	1,086	18.0%	10.3%	2.31
Middlebury	5,843	0.00%	4	0.0%	0.0%	N/A
Middletown	38,747	11.68%	3,027	25.9%	14.2%	2.22
Milford	43,135	2.23%	2,389	4.9%	2.7%	2.19
Monroe	14,918	1.32%	1,218	3.2%	1.9%	2.42
Naugatuck	25,099	4.11%	2,248	8.9%	4.8%	2.16
New Britain	57,164	10.67%	4,731	17.1%	6.4%	1.60
New Canaan	14,138	1.06%	1,685	2.2%	1.1%	2.07
New Haven	100,702	32.16%	11,897	54.6%	22.5%	1.70

*Census populations within the political sub-division are used as the basis for the benchmark.

Table E.8: Ratio of Black Residents to Black Resident Stops, All Departments

Department Name	Number of Residents	Black Residents	Resident Stops	Black Resident Stops	Difference	Ratio
New London	21,835	15.18%	1,811	27.1%	11.9%	1.78
New Milford	21,891	1.69%	1,210	4.8%	3.1%	2.84
Newington	24,978	2.99%	1,336	7.3%	4.3%	2.42
Newtown	20,171	0.68%	989	1.3%	0.6%	1.93
North Branford	11,549	1.33%	252	0.4%	-0.9%	0.30
North Haven	19,608	2.91%	483	5.6%	2.7%	1.92
Norwalk	68,034	13.13%	2,373	26.2%	13.1%	2.00
Norwich	31,638	8.96%	3,384	26.3%	17.3%	2.93
Old Saybrook	8,330	0.00%	696	1.7%	1.7%	N/A
Orange	11,017	1.31%	32	6.3%	4.9%	4.78
Plainfield	11,918	0.96%	789	2.9%	2.0%	3.02
Plainville	14,605	2.73%	1,195	4.9%	2.1%	1.78
Plymouth	9,660	0.00%	543	2.0%	2.0%	N/A
Portland	7,480	1.87%	146	3.4%	1.6%	1.83
Putnam	7,507	1.17%	905	4.2%	3.0%	3.58
Redding	6,955	0.00%	535	1.5%	1.5%	N/A
Ridgefield	18,111	0.77%	2,170	1.2%	0.4%	1.50
Rocky Hill	16,224	3.77%	1,259	7.3%	3.5%	1.94
Seymour	13,260	2.25%	1,312	5.6%	3.4%	2.51
Shelton	32,010	2.07%	272	7.7%	5.7%	3.73
Simsbury	17,773	1.46%	1,396	2.6%	1.1%	1.76
South Windsor	20,162	3.68%	1,376	6.8%	3.2%	1.86
Southington	34,301	1.34%	2,374	2.2%	0.9%	1.67
Stamford	98,070	12.86%	6,865	21.1%	8.2%	1.64
Stonington	15,078	0.82%	1,620	2.6%	1.8%	3.18
Stratford	40,980	12.76%	1,272	35.8%	23.0%	2.80
Suffield	10,782	1.40%	169	0.6%	-0.8%	0.42
Thomaston	6,224	0.00%	438	1.8%	1.8%	N/A
Torrington	29,251	2.12%	4,530	5.9%	3.8%	2.80
Trumbull	27,678	2.90%	477	8.6%	5.7%	2.97
Vernon	23,800	4.70%	1,262	16.4%	11.7%	3.49
Wallingford	36,530	1.34%	2,968	3.4%	2.1%	2.55
Waterbury	83,964	17.37%	1,888	36.7%	19.3%	2.11
Waterford	15,760	2.29%	920	5.1%	2.8%	2.23
Watertown	18,154	1.24%	556	3.4%	2.2%	2.76
West Hartford	49,650	5.65%	1,054	9.9%	4.2%	1.75
West Haven	44,518	17.70%	4,225	27.4%	9.7%	1.55
Weston	7,255	1.25%	298	2.7%	1.4%	2.14
Westport	19,410	1.22%	1,968	1.6%	0.4%	1.30
Wethersfield	21,607	2.75%	652	5.2%	2.5%	1.89
Willimantic	20,176	4.08%	1,172	6.6%	2.5%	1.61
Wilton	12,973	1.01%	1,004	1.5%	0.5%	1.48
Windsor	23,222	32.20%	2,677	53.0%	20.8%	1.65
Windsor Locks	10,117	4.27%	288	12.8%	8.6%	3.01
Winsted	9,133	1.04%	374	4.0%	3.0%	3.86
Wolcott	13,175	1.53%	54	0.0%	-1.5%	0.00
Woodbridge	7,119	1.94%	267	6.0%	4.1%	3.09

*Census populations within the political sub-division are used as the basis for the benchmark.

Table E.9: Ratio of Hispanic Residents to Hispanic Resident Stops, All Departments

Department Name	Number of Residents	Hispanic Residents	Resident Stops	Hispanic Resident Stops	Difference	Ratio
Ansonia	14,979	14.03%	1,458	13.9%	-0.2%	0.99
Avon	13,855	2.76%	353	1.1%	-1.6%	0.41
Berlin	16,083	2.67%	1,327	4.1%	1.4%	1.52
Bethel	14,675	6.65%	1,083	10.9%	4.2%	1.64
Bloomfield	16,982	4.78%	701	3.6%	-1.2%	0.75
Branford	23,532	3.45%	2,055	4.8%	1.4%	1.40
Bridgeport	109,401	36.20%	1,920	32.8%	-3.4%	0.90
Bristol	48,439	7.65%	1,648	13.9%	6.2%	1.82
Brookfield	12,847	3.79%	734	6.9%	3.2%	1.83
Canton	7,992	1.94%	204	2.9%	1.0%	1.52
Cheshire	21,049	2.35%	1,188	6.7%	4.4%	2.87
Clinton	10,540	4.41%	1,420	9.1%	4.7%	2.06
Coventry	9,779	2.21%	539	3.5%	1.3%	1.60
Cromwell	11,357	3.90%	554	2.0%	-1.9%	0.51
Danbury	64,361	23.25%	1,386	39.5%	16.3%	1.70
Darien	14,004	3.49%	776	3.9%	0.4%	1.11
Derby	10,391	12.37%	416	20.4%	8.1%	1.65
East Hampton	10,255	2.02%	446	1.6%	-0.4%	0.78
East Hartford	40,229	22.91%	3,485	31.0%	8.0%	1.35
East Haven	24,114	8.43%	1,083	10.7%	2.3%	1.27
East Lyme	15,943	5.10%	137	2.9%	-2.2%	0.57
East Windsor	9,164	4.34%	401	8.7%	4.4%	2.01
Easton	5,553	2.56%	269	3.7%	1.2%	1.45
Enfield	33,218	4.00%	3,645	6.9%	2.9%	1.73
Fairfield	45,567	4.51%	1,325	5.2%	0.7%	1.15
Farmington	20,318	3.20%	806	6.5%	3.2%	2.01
Glastonbury	26,217	3.60%	1,656	4.6%	1.0%	1.29
Granby	8,716	1.39%	192	1.0%	-0.3%	0.75
Greenwich	46,370	9.15%	2,170	14.1%	5.0%	1.54
Groton City*	7,960	11.80%	437	21.5%	9.7%	1.82
Groton Long Point*	2,030	0.00%	15	0.0%	0.0%	N/A
Groton Town	31,520	7.40%	1,461	9.2%	1.8%	1.24
Guilford	17,672	2.90%	1,196	2.2%	-0.7%	0.75
Hamden	50,012	7.58%	1,814	8.9%	1.4%	1.18
Hartford	93,669	41.02%	7,190	29.4%	-11.6%	0.72
Ledyard	11,527	4.57%	556	5.6%	1.0%	1.22
Madison	14,073	1.73%	1,251	1.6%	-0.1%	0.93
Manchester	46,667	9.89%	4,551	15.0%	5.1%	1.52
Meriden	47,445	24.86%	1,086	42.5%	17.7%	1.71
Middlebury	5,843	2.22%	4	0.0%	-2.2%	0.00
Middletown	38,747	6.77%	3,027	9.9%	3.2%	1.47
Milford	43,135	4.45%	2,389	5.5%	1.0%	1.23
Monroe	14,918	4.30%	1,218	3.0%	-1.3%	0.71
Naugatuck	25,099	7.77%	2,248	13.0%	5.2%	1.67
New Britain	57,164	31.75%	4,731	48.5%	16.7%	1.53
New Canaan	14,138	2.69%	1,685	3.0%	0.3%	1.13
New Haven	100,702	24.79%	11,897	27.5%	2.7%	1.11

*Census populations within the political sub-division are used as the basis for the benchmark.

Table E.9: Ratio of Hispanic Residents to Hispanic Resident Stops, All Departments

Department Name	Number of Residents	Hispanic Residents	Resident Stops	Hispanic Resident Stops	Difference	Ratio
New London	21,835	25.08%	1,811	29.9%	4.8%	1.19
New Milford	21,891	5.46%	1,210	11.7%	6.2%	2.13
Newington	24,978	6.39%	1,336	10.3%	3.9%	1.62
Newtown	20,171	2.86%	989	1.9%	-0.9%	0.67
North Branford	11,549	2.31%	252	1.2%	-1.1%	0.51
North Haven	19,608	3.26%	483	2.5%	-0.8%	0.76
Norwalk	68,034	22.67%	2,373	26.8%	4.1%	1.18
Norwich	31,638	10.59%	3,384	18.6%	8.1%	1.76
Old Saybrook	8,330	2.93%	696	5.5%	2.5%	1.86
Orange	11,017	2.54%	32	3.1%	0.6%	1.23
Plainfield	11,918	3.33%	789	4.2%	0.9%	1.26
Plainville	14,605	5.18%	1,195	8.4%	3.2%	1.61
Plymouth	9,660	2.47%	543	2.6%	0.1%	1.04
Portland	7,480	2.75%	146	3.4%	0.7%	1.24
Putnam	7,507	2.20%	905	1.9%	-0.3%	0.85
Redding	6,955	2.37%	535	3.4%	1.0%	1.42
Ridgefield	18,111	3.46%	2,170	2.5%	-1.0%	0.72
Rocky Hill	16,224	4.65%	1,259	4.2%	-0.4%	0.90
Seymour	13,260	5.53%	1,312	6.8%	1.3%	1.23
Shelton	32,010	5.17%	272	1.8%	-3.3%	0.36
Simsbury	17,773	2.61%	1,396	2.1%	-0.5%	0.80
South Windsor	20,162	3.62%	1,376	4.1%	0.5%	1.15
Southington	34,301	2.80%	2,374	2.3%	-0.5%	0.81
Stamford	98,070	22.87%	6,865	24.2%	1.3%	1.06
Stonington	15,078	1.91%	1,620	0.9%	-1.0%	0.45
Stratford	40,980	11.92%	1,272	16.7%	4.7%	1.40
Suffield	10,782	2.20%	169	1.2%	-1.0%	0.54
Thomaston	6,224	2.09%	438	0.9%	-1.2%	0.44
Torrington	29,251	6.92%	4,530	10.0%	3.1%	1.45
Trumbull	27,678	5.06%	477	6.3%	1.2%	1.24
Vernon	23,800	5.21%	1,262	9.4%	4.1%	1.79
Wallingford	36,530	6.71%	2,968	10.0%	3.3%	1.49
Waterbury	83,964	27.54%	1,888	33.6%	6.0%	1.22
Waterford	15,760	4.07%	920	5.2%	1.1%	1.28
Watertown	18,154	2.99%	556	2.2%	-0.8%	0.72
West Hartford	49,650	8.78%	1,054	12.2%	3.5%	1.39
West Haven	44,518	15.96%	4,225	18.9%	2.9%	1.18
Weston	7,255	3.06%	298	3.4%	0.3%	1.10
Westport	19,410	3.19%	1,968	1.9%	-1.3%	0.59
Wethersfield	21,607	7.10%	652	16.7%	9.6%	2.35
Willimantic	20,176	28.88%	1,172	52.0%	23.1%	1.80
Wilton	12,973	2.74%	1,004	4.6%	1.8%	1.67
Windsor	23,222	7.33%	2,677	9.0%	1.6%	1.22
Windsor Locks	10,117	3.46%	288	4.5%	1.1%	1.30
Winsted	9,133	4.28%	374	2.4%	-1.9%	0.56
Wolcott	13,175	2.83%	54	9.3%	6.4%	3.27
Woodbridge	7,119	2.68%	267	3.7%	1.1%	1.40

*Census populations within the political sub-division are used as the basis for the benchmark.

Table E.10: Departments with Disparities Relative to Descriptive Benchmarks (Sorted by Total Score)

	State Average			EDP			Resident Population			
Department Name	M	B	H	M	B	H	M	B	H	Total
Meriden	15.8%			24.7%	6.8%	19.4%	26.7%	10.3%	17.7%	6.5
Stratford	24.9%	15.4%		23.3%	19.2%		27.0%	23.0%		6.0
Wethersfield	34.9%		23.3%	28.7%	9.8%	21.1%	12.8%		9.6%	6.0
Darien	23.5%		13.5%	20.9%	11.7%	11.1%				5.0
Derby	12.6%			13.8%	10.1%		25.8%	17.3%		5.0
East Hartford	11.1%			27.6%	21.3%		21.5%	17.9%		5.0
Waterbury				22.4%	14.9%	10.2%	22.6%	19.3%		5.0
Wolcott	20.0%		11.6%	26.6%	8.3%	10.9%			6.4%	5.0
Trumbull	20.4%	11.2%		13.0%	8.1%	6.3%		5.7%		4.5
Berlin	18.6%		11.3%	11.9%	5.8%	7.3%				4.0
Bloomfield				14.9%	17.6%		19.5%	22.1%		4.0
Manchester				11.4%	12.4%		14.0%	13.7%		4.0
New Britain				16.2%		12.1%	21.3%		16.7%	4.0
New Haven				19.5%	18.9%		19.9%	22.5%		4.0
Newington	20.2%		12.0%	14.3%	7.3%	8.8%				4.0
Norwich				10.1%	9.7%		20.2%	17.3%	8.1%	4.0
Willimantic				13.3%		13.0%	24.5%		23.1%	4.0
Windsor				19.2%	15.2%		21.2%	20.8%		4.0
Woodbridge	17.7%	14.4%		11.4%	13.5%					4.0
Vernon	10.0%				5.5%		14.2%	11.7%		3.5
Hamden					12.2%		15.2%	17.2%		3.0
Hartford				16.2%	17.9%			10.8%		3.0
Middletown					10.5%		14.3%	14.2%		3.0
Fairfield	16.1%			11.7%	7.9%					2.5
Groton City*							16.8%	11.3%	9.7%	2.5
North Haven	14.9%			13.3%	9.6%					2.5
West Hartford	12.8%			14.4%	8.4%					2.5
Redding	12.0%			12.4%		8.6%				2.5
Bristol							13.6%	8.0%	6.2%	2.0
Danbury							13.2%		16.3%	2.0
New London							14.5%	11.9%		2.0
Norwalk							13.4%	13.1%		2.0
Windsor Locks	12.6%				8.6%			8.6%		2.0
Cheshire					5.9%		9.0%	7.5%		1.5
East Haven	10.0%					7.0%				1.5
Easton				10.9%		7.5%				1.5
Ledyard					10.4%			9.5%		1.5
Middlebury*				15.9%	6.5%					1.5
New Canaan	10.4%					5.3%				1.5
New Milford						5.0%	8.5%		6.2%	1.5
Orange				10.5%	9.3%					1.5
Wallingford	11.3%				5.3%					1.5
Waterford	12.7%				6.9%					1.5
Bridgeport					11.9%					1.0
Enfield					5.2%		7.1%			1.0
Greenwich	11.1%									1.0
Groton Town					6.1%			7.8%		1.0
Portland					5.1%		5.0%			1.0
West Haven				11.7%						1.0
Wilton	15.9%									1.0
Ansonia								8.9%		0.5
Avon					5.2%					0.5
Clinton							7.7%			0.5
East Windsor								6.8%		0.5
Old Saybrook							5.5%			0.5
Ridgefield						5.4%				0.5
Shelton								5.7%		0.5
Westport					5.7%					0.5
Plymouth				6.4%						0.5

APPENDIX F

Table F.1: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop by Department, All Traffic Stops 2017

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Ansonia	Chi^2	N/A	N/A	N/A	N/A
	Observations	3105	3063	2898	3515
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.324	0.326	0.333	0.331
	Q-Value	N/A	N/A	N/A	N/A
Avon	Chi^2	N/A	N/A	N/A	N/A
	Observations	1175	1128	1059	1196
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.519	0.526	0.559	0.551
	Q-Value	N/A	N/A	N/A	N/A
Berlin	Chi^2	17.615+	24.714***	23.618***	19.957**
	Observations	4564	4436	4700	5307
	P-Value	0.061	0.006	0.008	0.029
	Pseudo R2	0.365	0.37	0.368	0.344
	Q-Value	0.162	0.019	0.028	0.081
Bethel	Chi^2	N/A	N/A	N/A	N/A
	Observations	2681	2625	2859	3050
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.351	0.354	0.34	0.337
	Q-Value	N/A	N/A	N/A	N/A
Bloomfield	Chi^2	15.444	N/A	N/A	N/A
	Observations	2057	2034	997	2200
	P-Value	0.163	N/A	N/A	N/A
	Pseudo R2	0.33	0.335	0.517	0.31
	Q-Value	0.423	1	1	1
Branford	Chi^2	N/A	N/A	N/A	N/A
	Observations	4868	4801	4870	5193
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.239	0.238	0.238	0.239
	Q-Value	N/A	N/A	N/A	N/A
Bridgeport	Chi^2	9.949	12.92	4.408	N/A
	Observations	1581	1546	1335	2223
	P-Value	0.268	0.115	0.819	N/A
	Pseudo R2	0.68	0.686	0.754	0.652
	Q-Value	0.681	0.344	1	1
Bristol	Chi^2	2,774.594***	N/A	577.804***	7.697
	Observations	3279	3237	3330	3741
	P-Value	0.001	N/A	0.001	0.657
	Pseudo R2	0.368	0.368	0.37	0.354
	Q-Value	0.003	1	0.004	1
Brookfield	Chi^2	N/A	N/A	N/A	N/A
	Observations	1947	1893	2022	2128
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.416	0.421	0.4	0.386
	Q-Value	N/A	N/A	N/A	N/A

Table F.1: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop by Department, All Traffic Stops 2017

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Capitol Police	Chi^2	N/A	N/A	N/A	N/A
	Observations	146	139	117	167
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	1	1	1	1
	Q-Value	N/A	N/A	N/A	N/A
Central CT State University	Chi^2	N/A	N/A	N/A	N/A
	Observations	1568	1517	1432	1797
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.518	0.513	0.485	0.485
	Q-Value	N/A	N/A	N/A	N/A
CSP Headquarters	Chi^2	N/A	N/A	N/A	29.361***
	Observations	12082	11456	11149	13454
	P-Value	N/A	N/A	N/A	0.002
	Pseudo R2	0.349	0.344	0.365	0.358
	Q-Value	N/A	N/A	N/A	0.002
CSP Troop A	Chi^2	1,699.104***	830.054***	793.068***	1,179.629***
	Observations	14098	13521	13969	16168
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.209	0.211	0.204	0.201
	Q-Value	0.003	0.003	0.004	0.003
CSP Troop B	Chi^2	N/A	N/A	N/A	N/A
	Observations	6093	5971	5987	6298
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.289	0.293	0.293	0.296
	Q-Value	N/A	N/A	N/A	N/A
CSP Troop C	Chi^2	833.474***	N/A	287.898***	266.756***
	Observations	18750	17328	17025	19048
	P-Value	0.001	N/A	0.001	0.001
	Pseudo R2	0.232	0.232	0.241	0.234
	Q-Value	0.003	1	0.004	0.003
CSP Troop D	Chi^2	852.833***	744.942***	1,124.583***	1,776.163***
	Observations	10438	10011	10110	10719
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.18	0.18	0.184	0.182
	Q-Value	0.003	0.003	0.004	0.003
CSP Troop E	Chi^2	655.073***	1,210.104***	3,183.506***	754.943***
	Observations	14171	13319	12820	14651
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.179	0.182	0.182	0.18
	Q-Value	0.003	0.003	0.004	0.003
CSP Troop F	Chi^2	1,122.364***	11.248	5,137.013***	3,845.933***
	Observations	15716	15047	15001	16620
	P-Value	0.001	0.259	0.001	0.001
	Pseudo R2	0.317	0.321	0.323	0.317
	Q-Value	0.003	0.739	0.004	0.003

Table F.1: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop by Department, All Traffic Stops 2017

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
CSP Troop G	Chi^2	337.295***	315.859***	33.604***	24.065**
	Observations	11099	10319	9625	13200
	P-Value	0.001	0.001	0.001	0.019
	Pseudo R2	0.188	0.188	0.2	0.187
	Q-Value	0.003	0.003	0.004	0.056
CSP Troop H	Chi^2	1,248.609***	1,189.729***	19.562++	N/A
	Observations	14740	13870	12586	16801
	P-Value	0.001	0.001	0.034	N/A
	Pseudo R2	0.231	0.233	0.241	0.224
	Q-Value	0.003	0.003	0.101	1
CSP Troop I	Chi^2	1,087.854***	1,237.550***	1,100.081***	1,465.916***
	Observations	10606	10069	9385	11989
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.182	0.187	0.197	0.182
	Q-Value	0.003	0.003	0.004	0.003
CSP Troop K	Chi^2	408.062***	650.309***	11.001	451.023***
	Observations	14003	13449	13425	14849
	P-Value	0.001	0.001	0.275	0.001
	Pseudo R2	0.303	0.305	0.31	0.303
	Q-Value	0.003	0.003	0.748	0.003
CSP Troop L	Chi^2	299.820***	N/A	245.468***	282.535***
	Observations	8241	8077	8198	8808
	P-Value	0.001	N/A	0.001	0.001
	Pseudo R2	0.221	0.224	0.223	0.218
	Q-Value	0.003	1	0.004	0.003
Canton	Chi^2	255.126***	988.195***	1,918.026***	397.235***
	Observations	897	877	870	908
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.573	0.58	0.587	0.587
	Q-Value	0.003	0.003	0.004	0.003
Cheshire	Chi^2	N/A	N/A	N/A	N/A
	Observations	2107	2074	2017	2280
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.47	0.467	0.5	0.458
	Q-Value	N/A	N/A	N/A	N/A
Clinton	Chi^2	N/A	856.469***	819.812***	462.223***
	Observations	1369	1347	1428	1479
	P-Value	N/A	0.001	0.001	0.001
	Pseudo R2	0.358	0.356	0.347	0.335
	Q-Value	N/A	0.001	0.001	0.001
Coventry	Chi^2	N/A	1,483.626***	N/A	186.326***
	Observations	1290	1250	1270	1345
	P-Value	N/A	0.001	N/A	0.001
	Pseudo R2	0.349	0.356	0.321	0.317
	Q-Value	N/A	0.001	N/A	0.001

Table F.1: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop by Department, All Traffic Stops 2017

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Cromwell	Chi^2	N/A	N/A	847.026***	1,184.446***
	Observations	1471	1442	1338	1530
	P-Value	N/A	N/A	0.001	0.001
	Pseudo R2	0.462	0.453	0.467	0.453
	Q-Value	N/A	N/A	0.001	0.001
Department of Motor Vehicle	Chi^2	1.45	1.386	N/A	5.238
	Observations	1378	1323	1247	1516
	P-Value	0.834	0.847	N/A	0.263
	Pseudo R2	0.326	0.326	0.349	0.317
	Q-Value	1	1	1	0.654
Danbury	Chi^2	920.606***	637.987***	21.393++	20.860+
	Observations	4475	4332	5519	6007
	P-Value	0.001	0.001	0.045	0.052
	Pseudo R2	0.368	0.374	0.333	0.328
	Q-Value	0.003	0.003	0.128	0.141
Darien	Chi^2	N/A	N/A	N/A	N/A
	Observations	2871	2790	2949	3466
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.384	0.388	0.4	0.365
	Q-Value	N/A	N/A	N/A	N/A
Derby	Chi^2	140.572***	136.464***	116.481***	171.647***
	Observations	1953	1917	1821	2298
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.277	0.275	0.282	0.263
	Q-Value	0.003	0.003	0.004	0.003
Eastern CT State University	Chi^2	N/A	N/A	N/A	N/A
	Observations	186	181	179	202
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	1	1	1	1
	Q-Value	N/A	N/A	N/A	N/A
East Hampton	Chi^2	N/A	N/A	N/A	N/A
	Observations	752	743	734	759
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.485	0.488	0.486	0.479
	Q-Value	N/A	N/A	N/A	N/A
East Hartford	Chi^2	N/A	N/A	N/A	12.154
	Observations	5457	5293	4453	7307
	P-Value	N/A	N/A	N/A	0.432
	Pseudo R2	0.395	0.395	0.398	0.363
	Q-Value	N/A	N/A	N/A	0.432
East Haven	Chi^2	N/A	N/A	N/A	N/A
	Observations	2106	2052	2168	2445
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.326	0.331	0.317	0.291
	Q-Value	N/A	N/A	N/A	N/A

Table F.1: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop by Department, All Traffic Stops 2017

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
East Lyme	Chi^2	408.009***	N/A	197.897***	556.616***
	Observations	353	340	343	364
	P-Value	0.001	N/A	0.001	0.001
	Pseudo R2	0.985	0.999	0.953	0.925
	Q-Value	0.003	1	0.004	0.003
East Windsor	Chi^2	1,380.093***	1,216.500***	457.910***	N/A
	Observations	1572	1549	1480	1724
	P-Value	0.001	0.001	0.001	N/A
	Pseudo R2	0.54	0.541	0.546	0.517
	Q-Value	0.003	0.003	0.004	1
Easton	Chi^2	2.236	N/A	N/A	N/A
	Observations	1092	1076	1123	1187
	P-Value	0.524	N/A	N/A	N/A
	Pseudo R2	0.414	0.416	0.423	0.439
	Q-Value	1	1	1	1
Enfield	Chi^2	N/A	N/A	19.197**	103.695***
	Observations	8044	7872	7647	8614
	P-Value	N/A	N/A	0.014	0.001
	Pseudo R2	0.328	0.328	0.34	0.328
	Q-Value	N/A	N/A	0.014	0.001
Fairfield	Chi^2	N/A	N/A	2,241.333***	N/A
	Observations	7182	6974	6859	8104
	P-Value	N/A	N/A	0.001	N/A
	Pseudo R2	0.305	0.305	0.305	0.301
	Q-Value	N/A	N/A	0.001	N/A
Farmington	Chi^2	N/A	N/A	N/A	N/A
	Observations	4672	4360	4379	4896
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.236	0.238	0.239	0.226
	Q-Value	N/A	N/A	N/A	N/A
Glastonbury	Chi^2	N/A	N/A	N/A	N/A
	Observations	3783	3597	3508	3977
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.463	0.463	0.472	0.462
	Q-Value	N/A	N/A	N/A	N/A
Granby	Chi^2	771.041***	907.010***	957.921***	842.554***
	Observations	527	519	510	539
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.497	0.505	0.488	0.476
	Q-Value	0.003	0.003	0.004	0.003
Greenwich	Chi^2	N/A	N/A	N/A	N/A
	Observations	6126	5665	6375	7070
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.308	0.316	0.296	0.291
	Q-Value	N/A	N/A	N/A	N/A

Table F.1: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop by Department, All Traffic Stops 2017

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Groton City	Chi^2	N/A	N/A	531.318***	N/A
	Observations	1339	1285	1266	1493
	P-Value	N/A	N/A	0.001	N/A
	Pseudo R2	0.351	0.363	0.368	0.337
	Q-Value	N/A	N/A	0.001	N/A
Groton Long Point	Chi^2	N/A	N/A	N/A	N/A
	Observations	60	60	64	66
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	1	1	1	1
	Q-Value	N/A	N/A	N/A	N/A
Groton Town	Chi^2	1,315.665***	910.671***	566.166***	220.212***
	Observations	3932	3780	3580	4234
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.241	0.248	0.261	0.23
	Q-Value	0.003	0.003	0.004	0.003
Guilford	Chi^2	N/A	N/A	N/A	N/A
	Observations	2273	2201	2228	2297
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.446	0.444	0.437	0.432
	Q-Value	N/A	N/A	N/A	N/A
Hamden	Chi^2	31.688***	27.815***	N/A	18.233**
	Observations	5370	5293	3947	5799
	P-Value	0.001	0.001	N/A	0.019
	Pseudo R2	0.601	0.602	0.611	0.545
	Q-Value	0.003	0.003	1	0.056
Hartford	Chi^2	21.045+	N/A	438.897***	23.090**
	Observations	5994	5897	4324	8129
	P-Value	0.05	N/A	0.001	0.027
	Pseudo R2	0.602	0.603	0.614	0.56
	Q-Value	0.136	1	0.004	0.076
Ledyard	Chi^2	N/A	N/A	N/A	N/A
	Observations	1990	1932	1774	2131
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.266	0.266	0.261	0.256
	Q-Value	N/A	N/A	N/A	N/A
Madison	Chi^2	9,942.966***	3,852.464***	1,537.336***	2,161.687***
	Observations	2941	2888	2917	3016
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.261	0.263	0.28	0.279
	Q-Value	0.003	0.003	0.004	0.003
Manchester	Chi^2	92.561***	18.284	304.295***	25.854***
	Observations	9075	8789	7696	10297
	P-Value	0.001	0.107	0.001	0.01
	Pseudo R2	0.395	0.379	0.405	0.377
	Q-Value	0.003	0.328	0.004	0.03

Table F.1: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop by Department, All Traffic Stops 2017

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Meriden	Chi^2	N/A	N/A	N/A	N/A
	Observations	1008	989	1269	1553
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.469	0.479	0.449	0.384
	Q-Value	N/A	N/A	N/A	N/A
Middlebury	Chi^2	N/A	N/A	N/A	N/A
	Observations	33	32	32	33
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	1	1	1	1
	Q-Value	N/A	N/A	N/A	N/A
Middletown	Chi^2	N/A	N/A	N/A	N/A
	Observations	2927	2857	2350	3172
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.246	0.25	0.261	0.234
	Q-Value	N/A	N/A	N/A	N/A
Milford	Chi^2	N/A	N/A	N/A	N/A
	Observations	4003	3892	3757	4342
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.414	0.414	0.407	0.409
	Q-Value	N/A	N/A	N/A	N/A
Monroe	Chi^2	N/A	N/A	N/A	N/A
	Observations	3909	3830	3824	4155
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.386	0.386	0.381	0.372
	Q-Value	N/A	N/A	N/A	N/A
Naugatuck	Chi^2	N/A	N/A	N/A	N/A
	Observations	4075	4009	4121	4677
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.296	0.296	0.291	0.287
	Q-Value	N/A	N/A	N/A	N/A
New Britain	Chi^2	19.738++	24.569***	21.531**	534.539***
	Observations	4472	4385	5914	7238
	P-Value	0.048	0.01	0.017	0.001
	Pseudo R2	0.421	0.442	0.407	0.372
	Q-Value	0.134	0.032	0.052	0.003
New Canaan	Chi^2	483.434***	537.471***	N/A	N/A
	Observations	4877	4704	4843	5312
	P-Value	0.001	0.001	N/A	N/A
	Pseudo R2	0.223	0.224	0.214	0.215
	Q-Value	0.003	0.003	1	1
New Haven	Chi^2	9.63	286.713***	24.711**	14.833
	Observations	14907	14652	10031	18761
	P-Value	0.564	0.001	0.016	0.25
	Pseudo R2	0.451	0.451	0.458	0.425
	Q-Value	1	0.003	0.05	0.635

Table F.1: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop by Department, All Traffic Stops 2017

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
New London	Chi^2	232.539***	309.697***	23.634**	16.597
	Observations	4208	4124	4121	4955
	P-Value	0.001	0.001	0.014	0.119
	Pseudo R2	0.289	0.291	0.298	0.273
	Q-Value	0.003	0.003	0.045	0.316
New Milford	Chi^2	N/A	N/A	N/A	N/A
	Observations	2036	1998	2141	2269
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.238	0.238	0.241	0.231
	Q-Value	N/A	N/A	N/A	N/A
Newington	Chi^2	N/A	N/A	N/A	N/A
	Observations	4410	4212	4453	5334
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.252	0.259	0.241	0.241
	Q-Value	N/A	N/A	N/A	N/A
Newtown	Chi^2	N/A	N/A	N/A	N/A
	Observations	3288	3205	3215	3458
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.31	0.312	0.307	0.307
	Q-Value	N/A	N/A	N/A	N/A
North Branford	Chi^2	1,632.006***	1,802.219***	448.098***	1,479.582***
	Observations	817	808	797	831
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.347	0.349	0.347	0.34
	Q-Value	0.003	0.003	0.004	0.003
North Haven	Chi^2	1,743.107***	N/A	670.976***	2,124.779***
	Observations	2335	2275	2116	2563
	P-Value	0.001	N/A	0.001	0.001
	Pseudo R2	0.277	0.279	0.301	0.28
	Q-Value	0.003	1	0.004	0.003
Norwalk	Chi^2	65.842***	62.159***	N/A	159.123***
	Observations	4668	4543	4584	5866
	P-Value	0.001	0.001	N/A	0.001
	Pseudo R2	0.328	0.33	0.316	0.31
	Q-Value	0.003	0.003	1	0.003
Norwich	Chi^2	N/A	N/A	N/A	N/A
	Observations	5580	5312	4924	6319
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.245	0.247	0.261	0.231
	Q-Value	N/A	N/A	N/A	N/A
Old Saybrook	Chi^2	N/A	N/A	N/A	N/A
	Observations	2251	2201	2260	2336
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.351	0.354	0.36	0.34
	Q-Value	N/A	N/A	N/A	N/A

Table F.1: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop by Department, All Traffic Stops 2017

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Orange	Chi^2	N/A	N/A	N/A	N/A
	Observations	2471	2444	2383	2540
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.916	0.92	0.916	0.907
	Q-Value	N/A	N/A	N/A	N/A
Plainfield	Chi^2	N/A	N/A	N/A	N/A
	Observations	1590	1586	1605	1659
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.354	0.354	0.333	0.337
	Q-Value	N/A	N/A	N/A	N/A
Plainville	Chi^2	N/A	N/A	N/A	N/A
	Observations	3004	2958	3139	3389
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.338	0.337	0.349	0.34
	Q-Value	N/A	N/A	N/A	N/A
Plymouth	Chi^2	N/A	N/A	N/A	N/A
	Observations	1541	1524	1543	1630
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.442	0.439	0.425	0.419
	Q-Value	N/A	N/A	N/A	N/A
Portland	Chi^2	70.794***	726.703***	N/A	N/A
	Observations	348	338	328	348
	P-Value	0.001	0.001	N/A	N/A
	Pseudo R2	0.805	0.996	0.759	0.74
	Q-Value	0.003	0.003	1	1
Putnam	Chi^2	N/A	N/A	N/A	N/A
	Observations	1040	1027	1004	1051
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.561	0.56	0.578	0.564
	Q-Value	N/A	N/A	N/A	N/A
Redding	Chi^2	N/A	N/A	N/A	N/A
	Observations	1973	1908	2071	2206
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.291	0.291	0.298	0.275
	Q-Value	N/A	N/A	N/A	N/A
Ridgefield	Chi^2	18.016***	335.648***	1.797	584.844***
	Observations	5958	5732	6112	6492
	P-Value	0.006	0.001	0.773	0.001
	Pseudo R2	0.275	0.272	0.279	0.273
	Q-Value	0.017	0.003	1	0.003
Rocky Hill	Chi^2	400.536***	297.726***	10.947	870.463***
	Observations	3760	3624	3476	3913
	P-Value	0.001	0.001	0.204	0.001
	Pseudo R2	0.321	0.321	0.333	0.317
	Q-Value	0.003	0.003	0.568	0.003

Table F.1: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop by Department, All Traffic Stops 2017

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Southern CT State University	Chi^2	29.523***	740.838***	N/A	12,924.452***
	Observations	448	441	255	509
	P-Value	0.001	0.001	N/A	0.001
	Pseudo R2	0.551	0.568	0.764	0.589
	Q-Value	0.003	0.003	1	0.003
Seymour	Chi^2	N/A	N/A	N/A	N/A
	Observations	3567	3525	3491	3832
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.286	0.287	0.296	0.28
	Q-Value	N/A	N/A	N/A	N/A
Shelton	Chi^2	N/A	N/A	N/A	N/A
	Observations	525	521	496	554
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.58	0.578	0.574	0.577
	Q-Value	N/A	N/A	N/A	N/A
Simsbury	Chi^2	N/A	N/A	N/A	N/A
	Observations	3221	3109	3031	3243
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.337	0.342	0.333	0.328
	Q-Value	N/A	N/A	N/A	N/A
South Windsor	Chi^2	N/A	N/A	N/A	N/A
	Observations	3521	3335	3156	3663
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.412	0.428	0.423	0.414
	Q-Value	N/A	N/A	N/A	N/A
Southington	Chi^2	N/A	N/A	N/A	N/A
	Observations	4800	4742	4780	5061
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.36	0.36	0.354	0.349
	Q-Value	N/A	N/A	N/A	N/A
Stamford	Chi^2	712.616***	N/A	N/A	71.328***
	Observations	10543	10123	10387	12965
	P-Value	0.001	N/A	N/A	0.001
	Pseudo R2	0.46	0.458	0.43	0.425
	Q-Value	0.003	1	1	0.003
Stonington	Chi^2	2,475.531***	6,684.526***	4,082.468***	4,133.728***
	Observations	4864	4755	4663	4857
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.31	0.314	0.31	0.312
	Q-Value	0.003	0.003	0.004	0.003
Stratford	Chi^2	N/A	N/A	N/A	N/A
	Observations	3000	2928	2315	3621
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.34	0.344	0.358	0.337
	Q-Value	N/A	N/A	N/A	N/A

Table F.1: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop by Department, All Traffic Stops 2017

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Suffield	Chi^2	461.660***	404.778***	233.462***	227.511***
	Observations	621	611	609	654
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.663	0.663	0.654	0.642
	Q-Value	0.003	0.003	0.004	0.003
Thomaston	Chi^2	N/A	N/A	N/A	N/A
	Observations	1247	1232	1215	1263
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.4	0.4	0.407	0.398
	Q-Value	N/A	N/A	N/A	N/A
Torrington	Chi^2	N/A	N/A	N/A	N/A
	Observations	6668	6552	6712	7112
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.224	0.226	0.23	0.224
	Q-Value	N/A	N/A	N/A	N/A
Trumbull	Chi^2	N/A	N/A	N/A	N/A
	Observations	2365	2296	2092	2676
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.404	0.409	0.398	0.388
	Q-Value	N/A	N/A	N/A	N/A
University of Connecticut	Chi^2	N/A	N/A	N/A	N/A
	Observations	3640	3323	3156	3574
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.231	0.25	0.236	0.23
	Q-Value	N/A	N/A	N/A	N/A
Vernon	Chi^2	N/A	N/A	N/A	N/A
	Observations	3057	2986	2703	3304
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.259	0.266	0.291	0.259
	Q-Value	N/A	N/A	N/A	N/A
Western CT State University	Chi^2	N/A	N/A	N/A	N/A
	Observations	5	5	6	7
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	1	1	1	1
	Q-Value	N/A	N/A	N/A	N/A
Wallingford	Chi^2	504.684***	N/A	40.793***	N/A
	Observations	6684	6563	6924	7777
	P-Value	0.001	N/A	0.001	N/A
	Pseudo R2	0.298	0.303	0.293	0.277
	Q-Value	0.003	1	0.004	1
Waterbury	Chi^2	N/A	N/A	N/A	26.837***
	Observations	2185	2163	2105	3025
	P-Value	N/A	N/A	N/A	0.008
	Pseudo R2	0.425	0.425	0.428	0.372
	Q-Value	N/A	N/A	N/A	0.008

Table F.1: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop by Department, All Traffic Stops 2017

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Waterford	Chi^2	N/A	N/A	N/A	N/A
	Observations	3948	3841	3819	4391
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.259	0.261	0.263	0.234
	Q-Value	N/A	N/A	N/A	N/A
Watertown	Chi^2	N/A	N/A	N/A	88.991***
	Observations	1544	1529	1503	1647
	P-Value	N/A	N/A	N/A	0.001
	Pseudo R2	0.416	0.412	0.416	0.405
	Q-Value	N/A	N/A	N/A	0.001
West Hartford	Chi^2	1,104.332***	975.797***	1,930.178***	3,142.916***
	Observations	5185	4764	4750	5766
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.279	0.282	0.296	0.277
	Q-Value	0.003	0.003	0.004	0.003
West Haven	Chi^2	423.938***	105.415***	283.785***	495.888***
	Observations	6907	6794	6116	8662
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.264	0.263	0.266	0.241
	Q-Value	0.003	0.003	0.004	0.003
Weston	Chi^2	N/A	N/A	N/A	N/A
	Observations	557	544	562	586
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.783	0.79	0.755	0.765
	Q-Value	N/A	N/A	N/A	N/A
Westport	Chi^2	200.955***	303.157***	302.269***	200.869***
	Observations	6741	6582	6482	7289
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.268	0.268	0.264	0.259
	Q-Value	0.003	0.003	0.004	0.003
Wethersfield	Chi^2	N/A	N/A	N/A	N/A
	Observations	1677	1620	1958	2398
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	0.24	0.238	0.252	0.224
	Q-Value	N/A	N/A	N/A	N/A
Willimantic	Chi^2	N/A	12.668	209.365***	57.570***
	Observations	1529	1503	2132	2297
	P-Value	N/A	0.123	0.001	0.001
	Pseudo R2	0.405	0.407	0.365	0.351
	Q-Value	N/A	0.123	0.001	0.001
Wilton	Chi^2	N/A	656.392***	N/A	N/A
	Observations	4481	4208	4411	4935
	P-Value	N/A	0.001	N/A	N/A
	Pseudo R2	0.275	0.286	0.296	0.277
	Q-Value	N/A	0.001	N/A	N/A

Table F.1: Multinomial Logistic Regression of Outcome on Minority Status and Reason for Stop by Department, All Traffic Stops 2017

Department	Variable	Non-White	Black	Hispanic	Black or Hispanic
Windsor	Chi^2	308.812***	15.805+	N/A	N/A
	Observations	7512	7176	4505	8138
	P-Value	0.001	0.071	N/A	N/A
	Pseudo R2	0.294	0.273	0.344	0.247
	Q-Value	0.003	0.224	1	1
Windsor Locks	Chi^2	2,497.678***	1,965.234***	N/A	2,750.147***
	Observations	1030	1008	867	1098
	P-Value	0.001	0.001	N/A	0.001
	Pseudo R2	0.526	0.536	0.561	0.531
	Q-Value	0.003	0.003	1	0.003
Winsted	Chi^2	N/A	N/A	461.205***	N/A
	Observations	825	817	787	831
	P-Value	N/A	N/A	0.001	N/A
	Pseudo R2	0.545	0.541	0.61	0.537
	Q-Value	N/A	N/A	0.001	N/A
Wolcott	Chi^2	N/A	N/A	N/A	N/A
	Observations	102	98	103	116
	P-Value	N/A	N/A	N/A	N/A
	Pseudo R2	1	1	1	1
	Q-Value	N/A	N/A	N/A	N/A
Woodbridge	Chi^2	2,613.989***	2,405.135***	740.164***	3,871.762***
	Observations	1859	1778	1460	1936
	P-Value	0.001	0.001	0.001	0.001
	Pseudo R2	0.202	0.207	0.216	0.209
	Q-Value	0.003	0.003	0.004	0.003
Yale University	Chi^2	138.647***	N/A	14.795++	12.467
	Observations	1168	1119	746	1299
	P-Value	0.001	N/A	0.039	0.131
	Pseudo R2	0.384	0.395	0.531	0.372
	Q-Value	0.003	1	0.114	0.34

APPENDIX G

Table G.1: Chi-Square Test of Hit-Rate by Department, All Discretionary Searches

Department	Variable	Caucasian	Non-Caucasian	Black	Hispanic	Black or Hispanic
Bridgeport	Chi2	N/A	N/A	N/A	N/A	2.105
	Searches	N/A	N/A	N/A	N/A	35
	Hit Rate	N/A	N/A	N/A	N/A	2.857%
	Q-Value	N/A	N/A	N/A	N/A	0.469
	Contraband	N/A	N/A	N/A	N/A	1
	P-Value	N/A	N/A	N/A	N/A	0.146
CSP Troop A	Chi2	N/A	N/A	N/A	4.374	5.660
	Searches	45	N/A	N/A	35	58
	Hit Rate	31.111%	N/A	N/A	11.428%%++	12.069%%++
	Q-Value	N/A	N/A	N/A	0.222	0.141
	Contraband	14	N/A	N/A	4	7
	P-Value	N/A	N/A	N/A	0.035	0.017
CSP Troop C	Chi2	N/A	1.894	2.953	1.284	2.290
	Searches	214	61	57	49	100
	Hit Rate	28.504%	37.705%	40.351%%+	36.735%	37%
	Q-Value	N/A	0.469	0.446	0.514	0.469
	Contraband	61	23	23	18	37
	P-Value	N/A	0.168	0.086	0.256	0.129
CSP Troop D	Chi2	N/A	N/A	N/A	N/A	N/A
	Searches	106	N/A	N/A	N/A	N/A
	Hit Rate	34.905%	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A	N/A
	Contraband	37	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A	N/A
CSP Troop E	Chi2	N/A	0.004	0.004	N/A	0.004
	Searches	95	35	35	N/A	56
	Hit Rate	26.315%	25.714%	25.714%	N/A	26.785%
	Q-Value	N/A	0.994	0.994	N/A	0.994
	Contraband	25	9	9	N/A	15
	P-Value	N/A	0.944	0.944	N/A	0.949
CSP Troop F	Chi2	N/A	N/A	N/A	N/A	0.247
	Searches	61	N/A	N/A	N/A	39
	Hit Rate	36.066%	N/A	N/A	N/A	41.026%
	Q-Value	N/A	N/A	N/A	N/A	0.805
	Contraband	22	N/A	N/A	N/A	16
	P-Value	N/A	N/A	N/A	N/A	0.617
CSP Troop G	Chi2	N/A	0.542	0.542	0.101	0.449
	Searches	35	71	71	50	118
	Hit Rate	22.857%	16.900%	16.900%	20%	17.797%
	Q-Value	N/A	0.686	0.686	0.890	0.732
	Contraband	8	12	12	10	21
	P-Value	N/A	0.460	0.460	0.750	0.501
CSP Troop H	Chi2	N/A	0.796	0.717	1.759	1.960
	Searches	30	46	45	36	80
	Hit Rate	23.333%	15.217%	15.555%	11.111%	12.500%
	Q-Value	N/A	0.591	0.616	0.469	0.469
	Contraband	7	7	7	4	10
	P-Value	N/A	0.372	0.397	0.185	0.162
CSP Troop I	Chi2	N/A	N/A	N/A	N/A	5.142
	Searches	30	N/A	N/A	N/A	52
	Hit Rate	40%	N/A	N/A	N/A	17.308%%++
	Q-Value	N/A	N/A	N/A	N/A	0.155
	Contraband	12	N/A	N/A	N/A	9
	P-Value	N/A	N/A	N/A	N/A	0.023

*Results were not available across all specifications for departments not listed in this table.

Table G.1: Chi-Square Test of Hit-Rate by Department, All Discretionary Searches

Department	Variable	Caucasian	Non-Caucasian	Black	Hispanic	Black or Hispanic
CSP Troop K	Chi2	N/A	N/A	N/A	N/A	1.029
	Searches	66	N/A	N/A	N/A	34
	Hit Rate	39.394%	N/A	N/A	N/A	50%
	Q-Value	N/A	N/A	N/A	N/A	0.549
	Contraband	26	N/A	N/A	N/A	17
	P-Value	N/A	N/A	N/A	N/A	0.310
CSP Troop L	Chi2	N/A	N/A	N/A	N/A	N/A
	Searches	67	N/A	N/A	N/A	N/A
	Hit Rate	35.820%	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A	N/A
	Contraband	24	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A	N/A
East Hartford	Chi2	N/A	0.256	0.352	2.473	1.006
	Searches	58	79	78	44	119
	Hit Rate	44.827%	40.506%	39.743%	29.545%	36.974%
	Q-Value	N/A	0.805	0.774	0.469	0.549
	Contraband	26	32	31	13	44
	P-Value	N/A	0.612	0.551	0.115	0.316
Enfield	Chi2	N/A	N/A	N/A	N/A	N/A
	Searches	54	N/A	N/A	N/A	N/A
	Hit Rate	16.666%	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A	N/A
	Contraband	9	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A	N/A
Fairfield	Chi2	N/A	N/A	N/A	N/A	0.229
	Searches	36	N/A	N/A	N/A	36
	Hit Rate	44.444%	N/A	N/A	N/A	38.888%
	Q-Value	N/A	N/A	N/A	N/A	0.810
	Contraband	16	N/A	N/A	N/A	14
	P-Value	N/A	N/A	N/A	N/A	0.633
Glastonbury	Chi2	N/A	N/A	N/A	N/A	N/A
	Searches	32	N/A	N/A	N/A	N/A
	Hit Rate	21.875%	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A	N/A
	Contraband	7	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A	N/A
Greenwich	Chi2	N/A	N/A	N/A	N/A	6.671
	Searches	N/A	N/A	N/A	N/A	37
	Hit Rate	N/A	N/A	N/A	N/A	21.621%%+++
	Q-Value	N/A	N/A	N/A	N/A	0.141
	Contraband	N/A	N/A	N/A	N/A	8
	P-Value	N/A	N/A	N/A	N/A	0.009
Hartford	Chi2	N/A	6.047	6.047	N/A	8.581
	Searches	N/A	44	44	N/A	70
	Hit Rate	N/A	11.364%%++	11.364%%++	N/A	10%%+++
	Q-Value	N/A	0.141	0.141	N/A	0.123
	Contraband	N/A	5	5	N/A	7
	P-Value	N/A	0.014	0.014	N/A	0.003
Ledyard	Chi2	N/A	N/A	N/A	N/A	N/A
	Searches	30	N/A	N/A	N/A	N/A
	Hit Rate	30%	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A	N/A
	Contraband	9	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A	N/A

*Results were not available across all specifications for departments not listed in this table.

Table G.1: Chi-Square Test of Hit-Rate by Department, All Discretionary Searches

Department	Variable	Caucasian	Non-Caucasian	Black	Hispanic	Black or Hispanic
Manchester	Chi2	N/A	1.353	1.353	N/A	1.292
	Searches	30	40	40	N/A	64
	Hit Rate	20%	32.500%	32.500%	N/A	31.250%
	Q-Value	N/A	0.514	0.514	N/A	0.514
	Contraband	6	13	13	N/A	20
	P-Value	N/A	0.244	0.244	N/A	0.256
Middletown	Chi2	N/A	2.237	2.538	N/A	1.807
	Searches	58	41	40	N/A	53
	Hit Rate	29.309%	43.902%	45%	N/A	41.508%
	Q-Value	N/A	0.469	0.469	N/A	0.469
	Contraband	17	18	18	N/A	22
	P-Value	N/A	0.135	0.111	N/A	0.179
Milford	Chi2	N/A	N/A	N/A	N/A	13.215
	Searches	62	N/A	N/A	N/A	40
	Hit Rate	9.677%	N/A	N/A	N/A	40%***
	Q-Value	N/A	N/A	N/A	N/A	0.001
	Contraband	6	N/A	N/A	N/A	16
	P-Value	N/A	N/A	N/A	N/A	0.001
Naugatuck	Chi2	N/A	N/A	N/A	N/A	N/A
	Searches	33	N/A	N/A	N/A	N/A
	Hit Rate	42.423%	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A	N/A
	Contraband	14	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A	N/A
New Britain	Chi2	N/A	N/A	N/A	6.419	7.314
	Searches	37	N/A	N/A	73	98
	Hit Rate	48.648%	N/A	N/A	24.658%%++	24.489%%+++
	Q-Value	N/A	N/A	N/A	0.141	0.141
	Contraband	18	N/A	N/A	18	24
	P-Value	N/A	N/A	N/A	0.010	0.007
New Haven	Chi2	N/A	1.095	1.088	0.374	0.856
	Searches	135	575	574	283	845
	Hit Rate	5.184%	3.303%	3.309%	3.887%	3.549%
	Q-Value	N/A	0.541	0.541	0.773	0.588
	Contraband	7	19	19	11	30
	P-Value	N/A	0.294	0.296	0.541	0.354
Norwalk	Chi2	N/A	0.277	0.158	1.985	0.888
	Searches	43	56	54	43	96
	Hit Rate	37.208%	32.143%	33.333%	23.256%	29.166%
	Q-Value	N/A	0.805	0.870	0.469	0.587
	Contraband	16	18	18	10	28
	P-Value	N/A	0.598	0.690	0.158	0.345
Norwich	Chi2	N/A	0.802	1.457	1.723	2.815
	Searches	90	54	52	31	82
	Hit Rate	38.888%	31.481%	28.846%	25.805%	26.829%%+
	Q-Value	N/A	0.591	0.514	0.469	0.453
	Contraband	35	17	15	8	22
	P-Value	N/A	0.370	0.226	0.188	0.093
Plainfield	Chi2	N/A	N/A	N/A	N/A	N/A
	Searches	74	N/A	N/A	N/A	N/A
	Hit Rate	N/A	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A	N/A
	Contraband	N/A	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A	N/A

*Results were not available across all specifications for departments not listed in this table.

Table G.1: Chi-Square Test of Hit-Rate by Department, All Discretionary Searches

Department	Variable	Caucasian	Non-Caucasian	Black	Hispanic	Black or Hispanic
Plainville	Chi2	N/A	N/A	N/A	N/A	N/A
	Searches	37	N/A	N/A	N/A	N/A
	Hit Rate	18.919%	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A	N/A
	Contraband	7	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A	N/A
Stamford	Chi2	N/A	N/A	N/A	N/A	0.257
	Searches	N/A	N/A	N/A	N/A	41
	Hit Rate	N/A	N/A	N/A	N/A	17.072%
	Q-Value	N/A	N/A	N/A	N/A	0.805
	Contraband	N/A	N/A	N/A	N/A	7
	P-Value	N/A	N/A	N/A	N/A	0.611
Stratford	Chi2	N/A	0.001	0.001	0.068	0.001
	Searches	43	106	106	39	142
	Hit Rate	9.302%	9.434%	9.434%	7.691%	9.154%
	Q-Value	N/A	0.994	0.994	0.921	0.994
	Contraband	4	10	10	3	13
	P-Value	N/A	0.980	0.980	0.794	0.976
Torrington	Chi2	N/A	N/A	N/A	N/A	N/A
	Searches	39	N/A	N/A	N/A	N/A
	Hit Rate	15.385%	N/A	N/A	N/A	N/A
	Q-Value	N/A	N/A	N/A	N/A	N/A
	Contraband	6	N/A	N/A	N/A	N/A
	P-Value	N/A	N/A	N/A	N/A	N/A
Trumbull	Chi2	N/A	N/A	N/A	N/A	3.578
	Searches	34	N/A	N/A	N/A	34
	Hit Rate	17.646%	N/A	N/A	N/A	38.235%%+
	Q-Value	N/A	N/A	N/A	N/A	0.328
	Contraband	6	N/A	N/A	N/A	13
	P-Value	N/A	N/A	N/A	N/A	0.059
University of Connecticut	Chi2	N/A	N/A	N/A	N/A	0.096
	Searches	N/A	N/A	N/A	N/A	32
	Hit Rate	N/A	N/A	N/A	N/A	62.500%
	Q-Value	N/A	N/A	N/A	N/A	0.890
	Contraband	N/A	N/A	N/A	N/A	20
	P-Value	N/A	N/A	N/A	N/A	0.757
Vernon	Chi2	N/A	2.283	2.019	0.001	1.233
	Searches	137	77	76	32	108
	Hit Rate	56.203%	45.455%	46.053%	56.250%	49.074%
	Q-Value	N/A	0.469	0.469	0.995	0.514
	Contraband	77	35	35	18	53
	P-Value	N/A	0.130	0.155	0.995	0.266
Wallingford	Chi2	N/A	N/A	N/A	N/A	5.372
	Searches	63	N/A	N/A	N/A	47
	Hit Rate	31.746%	N/A	N/A	N/A	12.765%%++
	Q-Value	N/A	N/A	N/A	N/A	0.149
	Contraband	20	N/A	N/A	N/A	6
	P-Value	N/A	N/A	N/A	N/A	0.019
Waterbury	Chi2	N/A	1.644	1.644	N/A	1.804
	Searches	30	38	38	N/A	62
	Hit Rate	10%	2.631%	2.631%	N/A	3.226%
	Q-Value	N/A	0.469	0.469	N/A	0.469
	Contraband	3	1	1	N/A	2
	P-Value	N/A	0.200	0.200	N/A	0.179

*Results were not available across all specifications for departments not listed in this table.

Table G.1: Chi-Square Test of Hit-Rate by Department, All Discretionary Searches

Department	Variable	Caucasian	Non-Caucasian	Black	Hispanic	Black or Hispanic
West Hartford	Chi2	N/A	N/A	N/A	N/A	5.818
	Searches	N/A	N/A	N/A	N/A	33
	Hit Rate	N/A	N/A	N/A	N/A	33.333%%++
	Q-Value	N/A	N/A	N/A	N/A	0.141
	Contraband	N/A	N/A	N/A	N/A	11
	P-Value	N/A	N/A	N/A	N/A	0.016
West Haven	Chi2	N/A	N/A	N/A	N/A	0.119
	Searches	N/A	N/A	N/A	N/A	41
	Hit Rate	N/A	N/A	N/A	N/A	9.755%
	Q-Value	N/A	N/A	N/A	N/A	0.888
	Contraband	N/A	N/A	N/A	N/A	4
	P-Value	N/A	N/A	N/A	N/A	0.731
Westport	Chi2	N/A	N/A	N/A	N/A	1.225
	Searches	38	N/A	N/A	N/A	43
	Hit Rate	26.315%	N/A	N/A	N/A	16.278%
	Q-Value	N/A	N/A	N/A	N/A	0.514
	Contraband	10	N/A	N/A	N/A	7
	P-Value	N/A	N/A	N/A	N/A	0.268
Wethersfield	Chi2	N/A	N/A	N/A	0.046	0.008
	Searches	N/A	N/A	N/A	31	42
	Hit Rate	N/A	N/A	N/A	32.257%	28.570%
	Q-Value	N/A	N/A	N/A	0.945	0.994
	Contraband	N/A	N/A	N/A	10	12
	P-Value	N/A	N/A	N/A	0.828	0.925
Willimantic	Chi2	N/A	N/A	N/A	0.140	0.010
	Searches	67	N/A	N/A	64	82
	Hit Rate	16.417%	N/A	N/A	14.062%	17.072%
	Q-Value	N/A	N/A	N/A	0.875	0.994
	Contraband	11	N/A	N/A	9	14
	P-Value	N/A	N/A	N/A	0.708	0.915

*Results were not available across all specifications for departments not listed in this table.

Table G.2: List of Departments with No Results Available across all Specifications

Ansonia	Darien	Monroe	Shelton
Avon	Derby	New Canaan	Simsbury
Berlin	DMV	New London	South Windsor
Bethel	East Hampton	New Milford	Southington
Bloomfield	East Haven	Newington	Stonington
Branford	East Lyme	Newtown	Suffield
Bristol	East Windsor	North Branford	Thomaston
Brookfield	Easton	North Haven	Waterford
Canton	Farmington	Old Saybrook	Watertown
Capitol Police	Granby	Orange	Weston
CCSU	Groton City	Plymouth	Wilton
Cheshire	Groton Town	Portland	Windsor
Clinton	Groton Long Point	Putnam	Windsor Locks
Coventry	Guilford	Redding	Winsted
Cromwell	Hamden	Ridgefield	Wolcott
CSP Headquarters	Madison	Rocky Hill	Woodbridge
CSP Troop B	Meriden	SCSU	Yale
Danbury	Middlebury	Seymour	

APPENDIX H

H.1: OFFICER LEVEL ANALYSIS DETAILED METHODOLOGICAL OVERVIEW

In observational studies, as opposed to randomized control trials, it is difficult to estimate the causal effect of treatment. The difficulty emerges because assignment to treatment occurs on a non-random basis and is often confounded with other variables. Regression analysis can accurately estimate the effect of treatment if all possible factors driving treatment are available to the analyst and the model is specified correctly. In reality, however, there are both observed as well as unobserved variables that confound the effect of treatment. These confounding variables create bias that muddles the true impact of treatment on the outcome variable. As a result, it becomes impossible to disentangle the effect of treatment from compositional differences in the observed and unobserved variables. The problem arises because these variables affect both selection into treatment and outcome.

In the context of this analysis of racial and ethnic disparities, treatment is defined as a traffic stop made by an individual officer from each of two municipal police departments. These policing agencies were selected for inclusion in this analysis based on the findings from Part I of this report. The outcome variable represents the probability that a motorist is a member of a racial or ethnic minority conditional on his or her being stopped by the treatment officer.[21] In an effort to produce a significantly more robust analysis of racial and ethnic disparities for individual officers, the analysis proceeds with an analytical framework that estimates treatment using inverse propensity score weights. The propensity score, an estimate of the probability of treatment conditional on observed variables, is used as a weight in the construction of the control group for each individual officer. Weighting the observations by the inverse of the propensity score ensures that the distribution of pre-stop observable characteristics for the control group is consistent with the treatment officer. As long as the observed variables are predictive of unobserved confounders, inverse propensity score weighting will allow for an unbiased estimate of the treatment effect.

Using inverse propensity score weighting, an internal benchmark is created for each individual officer that is composed of other stops from that officer's department that are similar in terms of pre-stop observables. The internal benchmark is used to evaluate whether each individual officer stopped a disproportionate number of minority motorists relative to their individual benchmark. This methodology follows a rich and extensive literature spanning the fields of statistics, economics, and public policy. The application of this methodology to policing data has recently entered the criminal justice literature through notable applications by McCaffrey et al. (2004), Ridgeway (2006) and Ridgeway and MacDonald (2009).

Rosenbaum and Rubin (1983) characterize the propensity score as the probability of assignment to treatment conditional on pretreatment variables. The key insight is that conditional on this scalar function, assignment to treatment will be independent of the outcome variable. Simply put, given some *observed* pretreatment variables, it is possible to identify the conditional probability of treatment. Correctly adjusting for this conditional probability allows for the bias associated with *observed* covariates to be statistically controlled. If these observed covariates are correlated with

[21] In the proceeding methodological discussion, the details of the estimation procedure are presented as if a single treatment effect were estimated using a single outcome variable. However, the estimates were constructed for 658 distinct officers across three departments using four different outcome variables.

unobserved variables, these confounding factors will also be controlled for statistically. This methodology allows for a causal interpretation of the difference between outcomes associated with treatment and control.

Hirano and Imbens (2001) note that a useful adjustment is to weight observations according to their propensity scores. This adjustment effectively creates a balanced sample among treatment and control observations. Conveniently, when the estimate of interest is the treatment effect on the treated, only potential control observations need to be weighted. In this context, the weight that balances the sample and removes bias associated with pretreatment confounding factors is exactly the inverse of the propensity score. Ridgeway and MacDonald (2009) apply this technique in the context of policing data by matching the joint distribution of a particular officer's stop features to those by other officers.

Ridgeway and MacDonald (2009) estimate the propensity scores using a boosted logistic regression technique. Boosted regression [see McCaffrey et al. 2004] has two benefits over standard logistic regression when it comes to the computation of propensity scores. The first is that it is not limited to a set parametric or semi-parametric specification of covariates. The method searches over a wide range of interactions and higher-order polynomials. The second benefit, closely related to the first, is that boosted regression incorporates a penalty function on the size of the coefficients. The two characteristics together allow for much greater predictive power through a dynamic functional form, while contemporaneously constraining and removing unimportant coefficients.

Following Ridgeway and McDonald (2009), the propensity score is estimated using a boosted logistic regression such that the log-likelihood function:

$$\ell(\alpha) = \sum_{i=1}^{n} t_i \alpha' h(x_i) - log\left(1 + exp\big(\alpha' h(x_i)\big)\right) - \lambda \sum_{j=1}^{J} |\alpha_j|$$

The sample of stops for each internal benchmark is restricted to those made by other officers within the same department as the officer of interest. The variable t_i is a dichotomous binary indicator of treatment that, in this case, represents stops made by the officer of interest. The function $h(x)$ is the collection of piecewise constant functions of x_j variables and their two-way interactions. The variables used in the estimate of the propensity to treat include all pre-stop observable characteristics in the traffic stop data. The of variables x_j includes six categorical variables representing the reason for the stop, four for the season of the year, seven for the day of the week, time of the day, an indicator of a Connecticut license plate, an indicator that the stop was made of a local resident time of day, and the location of the stop (in terms of latitude and longitude).

The shrinkage parameter λ reduces the effect of each successive regression tree so that the impact of an incorrectly specified branch is minimized. In estimating the propensity score, the shrinkage parameter is set such that $\lambda = .05$ which is consistent with existing applications. As noted by Friedman (2001), selecting a random sample of the residuals at each iteration of the regression tree is thought to reduce variation in the outcome variable without affecting bias. Following the related literature, the training sample was set to 50 percent of the residual at each iteration.

The propensity score p_i is estimated using the boosted logistic regression outlined in Equation 1. A weighting variable w_i is constructed such that the stops made by the officer of interest are set to unity and those made by all other officers in the department are set to $w_i = p_i/(1 - p_i)$. Applying a propensity score weight to stops made by other officers in the same department creates an internal benchmark with a comparable distribution of pre-stop observable characteristics. The propensity score and resulting weight for those stops with characteristics that are drastically different than stops made by the officer of interest will approach zero. As a result, the internal benchmark will consist of the stops that are similar, in terms of pre-stop observable characteristics, to the stops made by the officer of interest. The construction of an internal benchmark using propensity scores allows the comparison to reflect the average treatment effect on the treated and abstract from potential bias in so far as the observable covariates control for selection into treatment.

Hirano and Imbens (2001) extend the weighting framework to what Robins and Ritov (1997) refer to as doubly robust estimation. That is, including additional covariates to a semi-parametric least-squares regression model to capture a more precise estimate of the treatment effect. It is shown in both of these discussions that such an estimator is consistent if either of the models is specified correctly. Ridgeway and MacDonald (2009) further extend the doubly robust propensity score framework to policing data. Specifically, the authors look at whether the officer of interest deviates from the internal benchmark along the outcome dimension.

Treatment effects are estimated following Ridgeway and McDonald (2009) who structure the doubly robust estimation using a logistic regression approach such that the log-likelihood function:

$$\ell(\beta) = \sum_{i=1}^{n} w_i \left(y_i(\beta_0 + \beta_1 t_i + \gamma' x_i) - log\big(1 + exp(\beta_0 + \beta_1 t_i + \gamma' x_i)\big) \right)$$

If a particular officer is designated as a treatment to a group of stops, it follows that the outcome of interest would be driver race. Simply, does the intervention by a particular officer result in a relatively higher stop rate of minority drivers, controlling for all observable factors? Mixing propensity score weighting with regression analysis allows for a more precise answer to this question. In the circumstance where the benchmark and individual officer do not perfectly match along all dimensions of stop features, there is potential for bias in any comparison, especially if those features by which they differentiate relate to a driver's race. Doubly robust estimation helps to remove this potential bias by controlling for these features, resulting in a much more accurate officer effect.