2023 TRAFFIC STOP DATA ANALYSIS



SUFFOLK COUNTY POLICE DEPARTMENT

February 2025



Executive Summary

This report analyzes nearly 160,000 traffic stops conducted in Suffolk County, New York, in 2023, with the goal of assessing whether racial or ethnic disparities exist in stop and search practices. The study applies two key statistical tests: the Veil-of-Darkness test to evaluate racial bias in stop decisions and the Hit Rate test to examine search outcomes across different racial and ethnic groups. The data were obtained through the Suffolk County Police Department. The data were cleaned and standardized to ensure consistency across the reporting period of calendar year 2023.

The Veil-of-Darkness test compares traffic stops made during daylight and nighttime hours, under the assumption that officers are less able to discern a driver's race at night. Logistic regression models were used to assess whether minority drivers were stopped more frequently in daylight than at night, controlling for various factors such as officer command type. The results showed no statistically significant relationship between daylight stops and the likelihood of stopping minority drivers, as compared to White drivers. The odds ratios for minority drivers remained close to 1.0, indicating that racial bias did not appear to be a significant factor in initial stop decisions.

The second component of the analysis focused on traffic stops with searches using the Hit Rate test, which assesses whether searches yielded a positive result, which is defined as a search yielding illegal drugs, illegal weapons, or other contraband or evidence. Although the data revealed variation in hit rates across racial and ethnic groups, with White drivers having the highest positive result rate, statistical tests found no significant difference in hit rates between White drivers and Black or Hispanic drivers across geographic areas. While White drivers were more likely to have positive result searches, the difference was not statistically significant, suggesting that variations in search outcomes may be influenced by other factors rather than bias in policing practices.

Overall, the study found no evidence of racial bias in traffic stop decisions based on the Veil-of-Darkness test and no statistically significant differences in search hit rates between minority and White drivers. However, the findings highlight the importance of ongoing monitoring and refinement of data collection practices to ensure transparency and fairness in law enforcement activities. Future research should explore additional variables that may contribute to disparities in post-stop outcomes and continue evaluating traffic stop data over time to detect any emerging patterns or policy impacts.

Table of Contents

Executive Summary	2
Introduction	7
Background	7
Methodology	10
Results	12
Overall Traffic Stops	12
Driver Demographics	
Police Department Characteristics	15
Assessing Bias in Traffic Stop Decisions	17
Assessing Bias in Traffic Stop Search Decisions	24
Conclusions	30
References	32
Appendix	33
Precinct # 1	35
Assessing Bias in Traffic Stop Decisions	
Assessing Bias in Traffic Stop Search Decisions	36
Precinct # 2	37
Assessing Bias in Traffic Stop Decisions	
Assessing Bias in Traffic Stop Search Decisions	
Precinct # 3	
Assessing Bias in Traffic Stop Decisions	
Assessing Bias in Traffic Stop Search Decisions	
Precinct # 4	
Assessing Bias in Traffic Stop Decisions	
Assessing Bias in Traffic Stop Search Decisions	
Precinct # 5	
Assessing Bias in Traffic Stop Decisions	
Assessing Bias in Traffic Stop Search Decisions	
Precinct # 6	
Assessing Bias in Traffic Stop Decisions	
Assessing Bias in Traffic Stop Search Decisions	
Precinct # 7	
Assessing Bias in Traffic Stop Decisions	
Assessing Bias in Traffic Stop Search Decisions	
Precinct # 9	
Assessing Bias in Traffic Stop Decisions	
Assessing Bias in Traffic Stop Search Decisions	50

Table Listings

Table 1. Traffic Stops by Time of Day	13
Table 2. Traffic Stops by Weekday	13
Table 3. Driver Characteristics Overview	14
Table 4. 2023 Race and Hispanic Origin Estimates for Suffolk County	15
Table 5. Traffic Stops by Pooled Officer Command Type	15
Table 6. Traffic Stops by Driver Disposition	
Table 7. Adjusted Logistic Regression Model Results (Minority Driver)	21
Table 8. Adjusted Logistic Regression Model Results (Black Driver)	
Table 9. Adjusted Logistic Regression Model Results (Hispanic Driver)	22
Table 10. Adjusted Logistic Regression Model Results (Asian Driver)	
Table 11. Adjusted Logistic Regression Model Results (Other Driver)	
Table 12. Traffic Stop Searches and Result Outcome Findings	24
Table 13. Traffic Stop with Searches and Search Outcome Results by Race/Ethnicity	
Table 14. Traffic Stops by Officer Command (Pooled and Non-Pooled)	
Table 15. Precinct # 1 Adjusted Logistic Regression Model Results (Black Driver)	
Table 16. Precinct # 1 Adjusted Logistic Regression Model Results (Hispanic Driver)	
Table 17. Precinct # 1 Adjusted Logistic Regression Model Results (Asian Driver)	
Table 18. Precinct # 1 Adjusted Logistic Regression Model Results (Other Driver)	36
Table 19. Precinct #2 Adjusted Logistic Regression Model Results (Black Driver)	
Table 20. Precinct #2 Adjusted Logistic Regression Model Results (Hispanic Driver)	
Table 21. Precinct #2 Adjusted Logistic Regression Model Results (Asian Driver)	
Table 22. Precinct #2 Adjusted Logistic Regression Model Results (Other Driver)	
Table 23. Precinct #3 Adjusted Logistic Regression Model Results (Black Driver)	
Table 24. Precinct #3 Adjusted Logistic Regression Model Results (Hispanic Driver)	
Table 25. Precinct #3 Adjusted Logistic Regression Model Results (Asian Driver)	
Table 26. Precinct #3 Adjusted Logistic Regression Model Results (Other Driver)	
Table 27. Precinct #4 Adjusted Logistic Regression Model Results (Black Driver)	
Table 28. Precinct #4 Adjusted Logistic Regression Model Results (Hispanic Driver)	
Table 29. Precinct #4 Adjusted Logistic Regression Model Results (Asian Driver)	
Table 30. Precinct #4 Adjusted Logistic Regression Model Results (Other Driver)	
Table 31. Precinct #5 Adjusted Logistic Regression Model Results (Black Driver)	43
Table 32. Precinct #5 Adjusted Logistic Regression Model Results (Hispanic Driver)	43
Table 33. Precinct #5 Adjusted Logistic Regression Model Results (Asian Driver)	43
Table 34. Precinct #5 Adjusted Logistic Regression Model Results (Other Driver)	44
Table 35. Precinct #6 Adjusted Logistic Regression Model Results (Black Driver)	45
Table 36. Precinct #6 Adjusted Logistic Regression Model Results (Hispanic Driver)	45
Table 37. Precinct #6 Adjusted Logistic Regression Model Results (Asian Driver)	45
Table 38. Precinct #6 Adjusted Logistic Regression Model Results (Other Driver)	
Table 39. Precinct #7 Adjusted Logistic Regression Model Results (Black Driver)	
Table 40. Precinct #7 Adjusted Logistic Regression Model Results (Hispanic Driver)	
Table 41. Precinct #7 Adjusted Logistic Regression Model Results (Asian Driver)	47

Table 42. Precinct #7 Adjusted Logistic Regression Model Results (Other Driver)	48
Table 43. Precinct #9 Adjusted Logistic Regression Model Results (Black Driver)	49
Table 44. Precinct #9 Adjusted Logistic Regression Model Results (Hispanic Driver)	49
Table 45. Precinct #9 Adjusted Logistic Regression Model Results (Asian Driver)	49
Table 46. Precinct #9 Adjusted Logistic Regression Model Results (Other Driver)	50

Figure Listings

Figure 1. Distribution of Traffic Stops Over Time	12
Figure 2. Black Driver Traffic Stops Before and After Dusk	17
Figure 3. Hispanic Driver Traffic Stops Before and After Dusk	18
Figure 4. Asian Driver Traffic Stops Before and After Dusk	19
Figure 5. Other Driver Traffic Stops Before and After Dusk	20
Figure 1. Traffic Stops with Searches by Pooled Officer Command Category	24
Figure 7. Black Driver and White Driver Hit Rates by Hamlet	26
Figure 8. Hispanic Driver and White Drive Hit Rates by Hamlet	27
Figure 9. Asian Driver and White Driver Hit Rates by Hamlet	28
Figure 10. Other Driver and White Driver Hit Rates by Hamlet	29

Introduction

This report presents the findings from nearly 160,000 traffic stops conducted in Suffolk County, New York, during the 2023 calendar year. Stonewall Analytics, an independent evaluator selected through a competitive process, was tasked with reviewing and analyzing traffic stop and pedestrian stop data. An annual third-party analysis of traffic stop data provides the Suffolk County Police Department (SCPD) with a critical tool for assessing overall organizational performance, optimizing resource deployment, and identifying atypical traffic stop patterns among similarly situated officers. This includes, but is not limited to, stops based on reasonable suspicion of criminal activity. Due to small sample size, the analysis of pedestrian stops was not performed.

In 2014, SCPD entered into an agreement with the U.S. Department of Justice, mandating the collection and analysis of traffic stop data. Given that traffic stops are one of the most frequent interactions between police officers and community members, it is essential to conduct thorough data analysis. This analysis helps uncover trends in traffic stops and their outcomes while identifying any potential disparities that may indicate biased or unfair policing practices, particularly those affecting minority populations within Suffolk County.

The results of this report are divided into two main sections. First, the evaluators introduce a series of descriptive and summary statistics for the readers to digest who is being stopped, the nature of the traffic stop, and at what rate of occurrence. Then, the evaluators test whether minority populations have increased odds for traffic stops as compared to White drivers. This also includes examining search outcomes among minority drivers as compared to White drivers.

Background

A recent analysis of nearly 100 million traffic stops across the United States revealed significant racial disparities in stop and search practices (Pierson et al., 2020). Using the Veil-of-Darkness test, Pierson et al. (2020) examined whether Black and Hispanic drivers were more likely to be stopped during daylight, when a driver's race is more visible, compared to after sunset. The results showed that Black drivers made up a smaller proportion of stops after sunset than during daylight hours, suggesting that race may influence stop decisions when it can be discerned. This pattern held true across both state patrol and municipal police departments, indicating systemic racial bias in stop decisions.

An outcome test further highlighted nation-wide disparities in search decisions following traffic stops (Pierson et al., 2020). Black and Hispanic drivers were searched at significantly higher rates than White drivers, yet searches of White drivers were more likely to yield positive results. This pattern could suggest that a lower evidentiary standard was applied when deciding to search minority drivers, compared to White drivers, although several confounders limit this

assertion. An improved test, however, referred to as the threshold test, which accounts for both search rates and hit rates, did find that Black and Hispanic drivers were searched with less evidence than White drivers, pointing to potential discriminatory practices in post-stop outcomes.

In 2020, the Finn Institute (Worden et al., 2020) conducted a comprehensive analysis of traffic stop data from the Suffolk County Police Department, covering traffic stops made between March 2018 and March 2019. This analysis included an examination of post-stop outcomes and the application of the Veil-of-Darkness test. The analysis of post-stop outcomes revealed notable patterns and disparities. Searches of vehicles or drivers were relatively uncommon, occurring in only about 3% of all traffic stops. However, the likelihood of a search varied significantly by the race and ethnicity of the driver. The Finn Institute report found that Black and Hispanic drivers were searched at higher rates compared to White drivers, with 6% of Black drivers. Most vehicle searches were justified by probable cause for illicit drugs, which accounted for over two-thirds of searches conducted by precinct patrol and crime units. Other reasons for searches, such as evidence of a crime in plain view or founded suspicion with driver consent, were less frequent.

In the Finn Institute report, the Veil-of-Darkness test was applied to assess whether racial bias influenced the decision to stop drivers. This test operates under the assumption that during hours of darkness, police officers are less able to discern a driver's race, creating a more race-neutral benchmark for comparison. The analysis evaluated the likelihood of Black and Hispanic drivers being stopped in daylight versus darkness, while controlling for variables such as time of day, day of the week, and precinct. Across multiple regression models, the results showed no statistically significant differences in stop rates for Black or Hispanic drivers during daylight compared to darkness. Relative risk ratios for both groups remained near 1.0, with confidence intervals including this value, indicating no evidence of systematic bias in the initial decision to stop drivers. While Black and Hispanic drivers were overrepresented in traffic stops relative to their proportion of the county's population, the Veil-of-Darkness analysis suggested these disparities were likely due to factors other than racial bias in stop decisions.

These national findings and the reporting of the Finn Institute highlight the importance of distinguishing between disparities and bias and underscore the complexities involved in analyzing traffic stop data. While post-stop disparities, particularly in search rates, raise important concerns, the Veil-of-Darkness results suggest that racial bias may not be a primary factor influencing initial stop decisions. Further research is necessary to better understand the root causes of disparities in post-stop outcomes.

Annual traffic stop data analyses and descriptive statistics are now available through the Suffolk County Police Department Transparency Hub, with public access provided for download and independent analysis. Over the years, significant effort has been dedicated to refining traffic stop data analysis to identify and address unfair policing practices. For the purposes of this report, such practices are defined as increased odds of being involved in a traffic stop or experiencing a higher frequency of post-stop searches for positive results among minority populations compared to White populations.

The Suffolk County Police Department's data collection systems and methodologies have evolved considerably over time. Outdated legacy systems and paper forms have been replaced with more robust digital platforms, and data fields have been revised to enhance accuracy and clarity. In the fourth quarter of calendar year 2023, the SCPD further updated its data collection processes to improve external transparency and minimize internal challenges, reflecting ongoing efforts to promote accountability and equity in policing.

Methodology

The evaluators received a restricted data file containing traffic stop records for calendar year 2023 through secure means. While most of the data fields are available to the public via the Suffolk County Police Department's Transparency Hub, certain sensitive variables, such as license plate numbers and identifiable information about officers, were excluded from the publicly available dataset. In the fourth quarter of calendar year 2023, enhancements were made to the variables and granularity of the data. To ensure consistency across the calendar year, data cleaning and alignment were required to standardize the fourth quarter with earlier quarters.

To evaluate whether police officers exhibit undue bias by stopping minority drivers at higher rates than White drivers, the analysis employed a refined version of the Veil-of-Darkness test. This test compares traffic stops made during daylight hours to those made at night, operating under the assumption that officers are less likely to discern a driver's race at night. The absence of a statistical association between daylight traffic stops and the proportion of minority drivers would suggest race-neutral policing practices. Conversely, a statistically significant association could indicate potential bias, though further investigation would be necessary to confirm this. It is important to note that the presence or absence of such an association alone does not definitively prove or disprove bias.

For this analysis, race and ethnicity data were based on officer-reported categories, which include White non-Hispanic, Hispanic, Black/African American, Asian/Pacific Islander, and Other. While race and ethnicity are complex topics, the analysis relied on these officer-reported classifications, which may not always align with individuals' self-reported identities. Population counts and proportions from the 2020 American Community Survey were also reviewed, though these figures do not necessarily represent the demographic distribution of drivers involved in traffic stops, as stops should be based solely on legal justifications rather than demographic factors.

The dataset included latitude and longitude coordinates along with timestamped data for each traffic stop. Traffic stops were classified as occurring during daytime (from sunrise to sunset) or nighttime. Nighttime was further refined to the inter-twilight period (approximately 5:00 pm to 9:00 pm), as prior research suggests that traffic during this window is more comparable to daytime traffic than late-night or early-morning traffic. This refinement ensures a more accurate comparison of stops conducted during periods of limited visibility to that during the day.

Logistic regression models were used to evaluate the Veil-of-Darkness test. The dependent variable was whether the driver was a minority (1 = yes, 0 = no), and the independent variables included a dichotomous indicator for daytime (1 = day, 0 = night) and the pooled officer command category (referred to as the adjusted model). The pooled officer command category was included to adjust for operational differences between police officer commands.

The unadjusted model included only the daytime indicator. The logistic regression formula for the adjusted model is as follows:

$$log\left(\frac{P(Black = 1)}{P(Black = 0)}\right) = \beta_0 + \beta_1(daytime) + \beta_2(officer \ command \ category)$$

All statistical models were evaluated at a significance level of α = 0.05. Separate models were run for each minority classification.

The second component of the analysis focused on post-stop search outcomes (i.e., traffic stops with a search) using the Hit Rate test. This test evaluates whether searches conducted during traffic stops yielded tangible results, such as illegal weapons, illegal drugs, or other contraband or evidence. Searches are typically conducted for reasons such as probable cause, visible drug paraphernalia, or an outstanding arrest warrant. Of note, most traffic stops do not involve a search of the vehicle, driver, or occupants. While it is difficult to assess bias solely based on the decision to conduct a search due to the influence of numerous unobservable factors, the Hit Rate test evaluates potential disparities in search outcomes. Differences in hit rates between minority and White drivers could indicate potential bias, though such disparities may also be influenced by infra-marginality—a phenomenon where drivers' differing levels of risk-taking behavior and officers' decision to search thresholds can create apparent disparities. This analysis examined hit rates across various hamlets, comparing outcomes for minority and White drivers. A paired, two-sided t-test was conducted to evaluate differences in hit rates across search statistically significant ($\alpha = 0.05$).

The appendix contains separate analyses consisting of the Veil of Darkness test and the Hit Rate test by precinct. Data analysis was conducted using R (R Core Team, 2023), utilizing the following packages: dplyr for data manipulation (Wickham et al., 2023), ggplot2 for data visualization (Wickham, 2016), hms for handling time data (Müller, 2023), stringr for string processing (Wickham, 2019), tidyverse for cohesive data workflows (Wickham et al., 2019), tigris for geographic and spatial data (Walker, 2023), sf for spatial analysis (Pebesma, 2018), and ggrepel for enhanced visualization labeling (Slowikowski, 2023).

Results

The results of the analysis on traffic stop data are presented in three key sections. First, descriptive and summary statistics offer an overview of the data, highlighting key trends and distributions. Following this is the Veil-of-Darkness test, which examines whether racial disparities in traffic stops occur more frequently during daylight versus darkness, controlling for visibility. Lastly, the Hit Rate test assesses whether there are differences in the likelihood of a positive result during a traffic stop with a search across racial or demographic groups. These analyses collectively aim to evaluate potential disparities and biases in outcomes where a traffic stop with a search was conducted.

Overall Traffic Stops

Figure 1 depicts the daily counts of traffic stops from January 2023 to December 2023. The yaxis represents the number of traffic stops per day, while the x-axis shows the timeline across months. The data displays a consistent fluctuation in the daily counts, with peaks reaching close to 800 stops on some days and dips below 100 stops on others. Although there is variability from day to day, the overall trend remains relatively stable throughout the year, with no dramatic increases or decreases over time. The slight decline in traffic stops towards the end of December 2023 and January 2024 may suggest seasonal or holiday patterns.

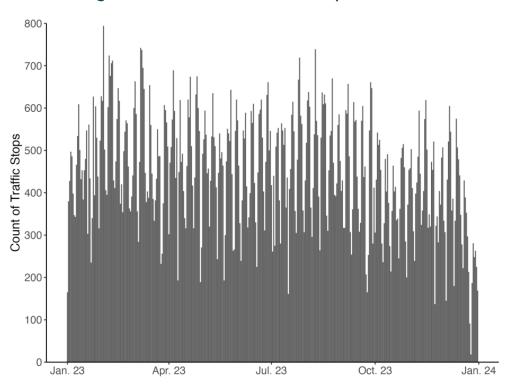


Figure 1. Distribution of Traffic Stops Over Time

The distribution of traffic stops by time of day provides important context for analyzing racial and ethnic disparities and patterns in policing practices. As shown in Table 1, most stops occurred during the daytime, accounting for 71.2% of all stops (116,957 stops), while nighttime stops comprised 28.8% (47,223 stops). This division reflects typical traffic patterns, with more vehicles on the road during daylight hours. Nighttime was specifically defined to correspond with the period from dusk to dawn, with dusk marking the point when the sun is 6 degrees below the horizon, and it is generally considered "dark."

Time of Day Grouping	Percentage	Count
Daytime	71.2%	116,957
Nighttime	28.8%	47,223

Table 1. Traffic Stops by Time of Day

Weekday Percentage Count Monday 13.0% 21,355 Tuesday 16.8% 27,664 Wednesday 17.9% 29,345 Thursday 17.2% 28,282 Friday 14.7% 24,108 Saturday 11.3% 18,521 Sunday 9.1% 14,905			
Tuesday16.8%27,664Wednesday17.9%29,345Thursday17.2%28,282Friday14.7%24,108Saturday11.3%18,521	Weekday	Percentage	Count
Wednesday17.9%29,345Thursday17.2%28,282Friday14.7%24,108Saturday11.3%18,521	Monday	13.0%	21,355
Thursday17.2%28,282Friday14.7%24,108Saturday11.3%18,521	Tuesday	16.8%	27,664
Friday14.7%24,108Saturday11.3%18,521	Wednesday	17.9%	29,345
Saturday11.3%18,521	Thursday	17.2%	28,282
,	Friday	14.7%	24,108
Sunday 9.1% 14,905	Saturday	11.3%	18,521
	Sunday	9.1%	14,905

Table 2. Traffic Stops by Weekday

The distribution of traffic stops by day of the week reveals notable patterns in enforcement activity. The highest proportion of stops occurred on Wednesdays (17.9%; 29,345 stops) and Thursdays (17.2%; 28,282 stops), indicating that midweek days see the most active enforcement. Tuesdays also contributed significantly to the total, accounting for 16.8% of stops (27,664 stops). Fridays saw a moderate level of activity, with 14.7% of stops (24,108 stops), while the weekend showed the lowest levels of traffic enforcement. Saturdays accounted for 11.3% of stops (18,521 stops), and Sundays had the smallest share, comprising only 9.1% of stops (14,905 stops). These trends suggest that weekday traffic enforcement is substantially more active than weekend enforcement, possibly reflecting differences in traffic patterns, staffing levels, or enforcement priorities. The relatively higher number of stops on weekdays might correspond to increased commuting traffic and targeted enforcement efforts during peak travel periods. In contrast, the reduced activity on weekends could be attributed to lighter traffic volumes or shifts in enforcement focus to other priorities.

Driver Demographics

Table 3 below describes the demographic breakdown of the overall calendar year 2023 traffic stops population based on officer-reported age, officer-reported gender and officer-reported race/ethnicity. Overall, the distribution shows a younger to middle-aged population, with a heavier male representation and a predominantly White non-Hispanic and Hispanic racial composition. The largest group by age is 26-35 years with 50,087 individuals representing 30.5% of the total population. The least represented age grouping is the less than 16 group with only 87 individuals and 0.1% of the traffic stop population (as expected). The population is a majority male, making up seven-tenths of all traffic stops. By race/ethnicity, a majority of drivers stopped are White non-Hispanic with 74,589 individuals representing 45.4% of the population. Asian or Pacific Islander represent the traffic stop population the least at 2.6% with 4,256 individuals.

Category	Percentage	Count
Age Group (Years)		
Less than 16	0.1%	87
16 to 25	20.5%	33,600
26 to 35	30.5%	50,087
36 to 45	22.0%	36,155
46 to 55	15.2%	24,895
56 to 65	8.8%	14,434
66 and Over	3.0%	4,922
Gender		
Male	70.1%	115,168
Female	29.9%	49,012
Race/Ethnicity		
White non-Hispanic	45.4%	74,589
Hispanic	27.9%	45,797
Black/African American	19.0%	31,190
Other	5.1%	8,348
Asian/Pacific Islander	2.6%	4,256

Table 3. Driver Characteristics Overview

Table 4 presents race and Hispanic origin data for Suffolk County, as reported by the US Census Bureau (2024). A comparison between these estimates and officer-reported race and ethnicity data for drivers involved in traffic stops reveals notable differences. The Census Bureau estimates indicate a higher proportion of White residents and a lower proportion of Black/African American residents compared to the officer-reported data. However, methodological differences in categorizing race and ethnicity complicate direct comparisons. As the US Census Bureau (2024) notes, "Hispanics may be of any race, so also are included in applicable race categories," which may contribute to these discrepancies.

Race/Ethnicity	Percentage	Count
White alone, not Hispanic or Latino	62.7%	955,027
Hispanic	23.1%	351,852
Black/African American	9.6%	146,224
Asian/Pacific Islander	4.9%	74,635
Other	3.0%	45,695

Table 4. 2023 Race and Hispanic Origin Estimates for Suffolk County

Note: Percentage values will not sum to 100 as Hispanics can be any race. Other category was calculated by taking the difference 100% and the sum of White alone, Black/African American, and Asian/Pacific Islander.

Police Department Characteristics

Table 5 summarizes traffic stops by pooled officer command type, highlighting the distribution of stops across different operational units. The pooled categories include Patrol, Highway, Precinct Crime sections, and Other. Precinct Crime sections assist and support Patrol Division commands in actively suppressing violent crimes, assaults, illegal weapons possession, gang activities and other crimes, which adversely affect quality of life within communities. Precinct Crime Sections also conduct special patrols and stakeouts, execute warrants (other than felony warrants), and conduct targeted enforcement of local ordinances and traffic laws. Most of the traffic stops (51.9%) were conducted by patrol officers, accounting for 85,149 stops. Highway officers were responsible for 29.1% of stops (47,619), reflecting their focus on traffic enforcement in high-speed and highway areas. Precinct Crime Section units conducted 17.4% of stops (28,525), often targeting specific criminal activities or areas of concern. Stops categorized as "Other" comprised only 1.6% (2,616), indicating relatively infrequent activity outside the primary command types. These figures illustrate how traffic enforcement is distributed among various police units and their respective roles in traffic safety and crime prevention. Please refer to the appendix for a crosswalk between pooled officer command types and officer commands.

Pooled Category	Percentage	Count
Patrol	51.9%	85,149
Highway	29.1%	47,619
Precinct Crime Section	17.4%	28,525
Other	1.6%	2,616

Table 5. Traffic Stops by Pooled Officer Command Type

Table 6 provides a breakdown of traffic stops by driver disposition, summarizing the outcomes observed during the analyzed period. Most traffic stops resulted in a verbal warning, accounting for 50.6% of all cases (83,010 stops). Summons were issued in 47.0% of cases (77,227 stops), making this the second most common outcome. Other dispositions, such as arrests and lights-on vouchers, occurred much less frequently. Arrests were made in only 0.7% of stops (1,086 cases), and lights-on vouchers, a specific intervention for broken vehicle lights, were provided in 0.6% of stops (909 cases). Less common outcomes include no police action taken (0.3%), field appearance tickets (0.1%), and instances where drivers were aided, meaning first aid or other assistance was provided for a medical emergency. These results highlight the range of potential outcomes following traffic stops and the relative prevalence of different enforcement actions.

Category	Percentage	Count
Verbal Warning Issued	50.6%	83,010
Summons	47.0%	77,227
Other	0.8%	1,253
Arrest	0.7%	1,086
Lights-On Voucher	0.6%	909
No Police Action Taken	0.3%	527
Field Appearance Ticket	0.1%	165
Aided	0.0%	3

Table 6. Traffic Stops by Driver Disposition

The next two sub-sections address results from the analysis of potential bias in traffic stop decisions and potential bias in search decisions.

Assessing Bias in Traffic Stop Decisions

Figure 2 depicts the proportion of Black drivers stopped before and after dusk as a function of time relative to dusk. The x-axis represents time in minutes relative to dusk (with 0 marking dusk), while the y-axis shows the mean percentage of Black drivers stopped. Stops before dusk are indicated by blue markers and those after dusk by red markers. The horizontal dashed lines represent the average percentage of Black drivers stopped during these time periods. The sizes of the data points reflect the number of Black traffic stops in each time window. The graph demonstrates that the percentage of Black drivers stopped is slightly higher after dusk compared to before dusk. This trend highlights the importance of the Veil-of-Darkness test, which posits that if racial bias affects stop decisions, the proportion of Black drivers stopped should decrease after dusk, when it becomes more difficult to discern a driver's race. In this view in Figure 2, visually this is not the case.

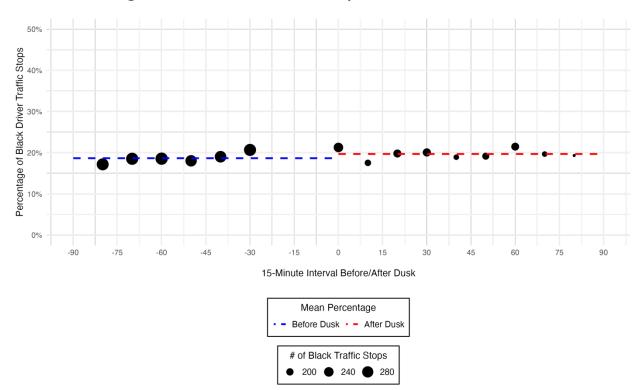


Figure 2. Black Driver Traffic Stops Before and After Dusk

Note: Values in between 0 and -30 are excluded from the figure as this time represents a transitional period that is neither fully light nor fully dark.

Figure 3 shows minimal change in the percentage of Hispanic drivers stopped before and after dusk, with the mean percentages remaining relatively constant across the time periods. The lack of a noticeable difference between stops before and after dusk suggests that unlike in some cases for other demographic groups, the ability to discern a driver's race in daylight may not significantly influence stop decisions for Hispanic drivers.

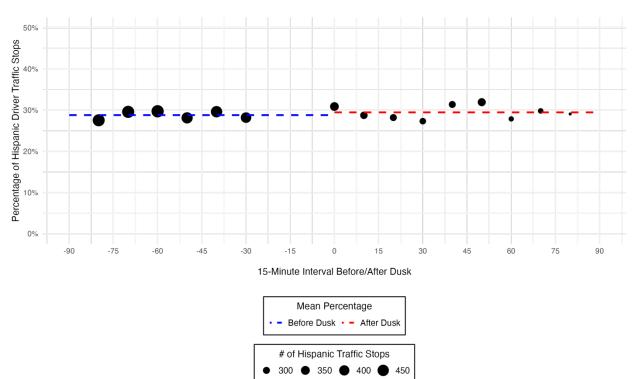
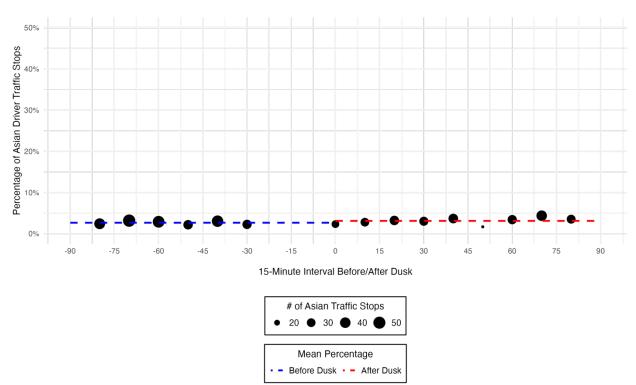


Figure 3. Hispanic Driver Traffic Stops Before and After Dusk

Note: Values in between 0 and -30 are excluded from the figure as this time represents a transitional period that is neither fully light nor fully dark.

Figure 4 shows that the percentage of Asian drivers stopped remains relatively consistent before and after dusk, with only slight variations in the mean percentages. This stability suggests that the time of day, and the corresponding ability to discern a driver's race, has little impact on stop decisions involving Asian drivers. The relatively small size of the data points indicates fewer total stops involving Asian drivers compared to other racial or ethnic groups, which could also affect the statistical significance of any observed trends.





Note: Values in between 0 and -30 are excluded from the figure as this time represents a transitional period that is neither fully light nor fully dark.

Figure 5 reveals little variation in the percentage of "Other" drivers stopped before and after dusk, with the mean percentages remaining relatively stable. This stability suggests that the ability to discern a driver's race or ethnicity during daylight hours does not appear to influence stop decisions for this group. The relatively small sizes of the data points indicate a lower volume of stops for drivers in the "Other" category, which could limit the ability to detect significant patterns or differences.

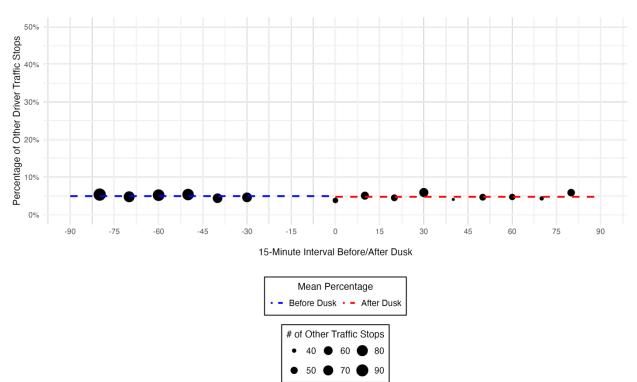


Figure 5. Other Driver Traffic Stops Before and After Dusk

Note: Values in between 0 and -30 are excluded from the figure as this time represents a transitional period that is neither fully light nor fully dark.

The logistic regression models estimate the odds of a traffic stop for different racial and ethnic groups compared to White drivers. The models adjust for the time of day, the officer command type, with precinct patrol section as the reference category and nighttime stops as the comparison group. The models have estimates presented as odds ratios (ORs). ORs are a measure of association between an independent variable and an outcome, representing the odds of the outcome occurring in one group relative to a reference group. An OR greater than 1 indicates that the odds of the outcome are higher in the comparison group than in the reference group, while an OR less than 1 indicates that the odds are lower. For example, an OR of 1.50 suggests that the odds of the outcome are 50 percent higher in the comparison group, whereas an OR of 0.75 suggests that the odds are 25 percent lower. The statistical significance of an odds ratio is typically assessed using a p-value, which tests the null hypothesis that the OR is equal to 1 (no association). A p-value < 0.05 indicates that there is strong evidence against the null hypothesis, suggesting that the observed association is unlikely to be due to random chance. However, statistical significance does not imply practical significance, and the confidence interval (CI) should also be considered. If the 95 percent CI does not include 1, it supports a statistically significant association, whereas a CI that crosses 1 suggests that the effect may not be meaningful or consistent across samples.

For all minority drivers, the odds of a daytime stop are 25.6 percent lower than for nighttime stops, with an odds ratio of 0.744. The odds of a precinct crime stop are 15.9 percent higher than in patrol stops, with an odds ratio of 1.159. The odds of a highway stop are 12.7 percent lower than in patrol sections, with an odds ratio of 0.873. The odds of a stop occurring in other locations are 14.4 percent higher than in patrol sections, with an odds ratio sections, with an odds ratio sections.

Term	OR Estimate	Standard Error	p- value	95% OR CI
Intercept ¹	1.502	0.010	<0.001	[1.472, 1.533]
Daytime	0.744	0.011	<0.001	[0.728, 0.760]
Precinct Crime	1.159	0.014	<0.001	[1.128, 1.191]
Highway	0.873	0.012	<0.001	[0.853, 0.892]
Other	1.144	0.040	<0.001	[1.057, 1.238]

Table 7. Adjusted Logistic Regression Model Results (Minority Driver)

For Black drivers, the odds of a daytime stop are 32 percent lower than for nighttime stops, with an odds ratio of 0.676. The odds of a precinct crime stop are 31 percent higher than in patrol stops, with an odds ratio of 1.309. The odds of a highway stop are 23 percent lower than in patrol sections, with an odds ratio of 0.764. The odds of a stop occurring in other locations are 9 percent higher than in patrol sections, with an odds ratio sections, with an odds ratio.

Term	OR Estimate	Standard Error	p- value	95% OR CI
Intercept	0.563	0.014	<0.001	[0.549 <i>,</i> 0.579]
Daytime	0.676	0.015	<0.001	[0.657, 0.696]
Precinct Crime	1.309	0.018	<0.001	[1.263, 1.356]
Highway	0.764	0.016	<0.001	[0.740, 0.789]
Other	1.088	0.055	0.122	[0.977, 1.210]

Table 8. Adjusted Logistic Regression Model Results (Black Driver)

For Hispanic drivers, the odds of a daytime stop are 21 percent lower than for nighttime stops, with an odds ratio of 0.791. The odds of a precinct crime stop are 12 percent higher than in patrol stops, with an odds ratio of 1.122. The odds of a highway stop are 20 percent lower than in patrol sections, with an odds ratio of 0.804. The odds of a stop occurring in other locations are 13 percent higher than in patrol sections, with an odds ratio sections, with an odds ratio sections, with an odds ratio sections.

¹ In logistic regression models, the Intercept (i.e., y-intercept), represents the odds of the outcome occurring when all predictor variables are zero. It normally does not have an interpretive aspect to model findings.

Term	OR Estimate	Standard Error	p- value	95% OR CI
Intercept	0.757	0.012	<0.001	[0.739, 0.776]
Daytime	0.791	0.013	<0.001	[0.771, 0.812]
Precinct Crime	1.122	0.016	<0.001	[1.087, 1.159]
Highway	0.804	0.014	<0.001	[0.783, 0.827]
Other	1.130	0.047	0.010	[1.029, 1.240]

Table 9. Adjusted Logistic Regression Model Results (Hispanic Driver)

For Asian drivers, the odds of a daytime stop are 30.6 percent lower than for nighttime stops, with an odds ratio of 0.694. The odds of a precinct crime stop are 33.2 percent lower than in patrol stops, with an odds ratio of 0.668. The odds of a highway stop are 15.5 percent lower than in patrol sections, with an odds ratio of 0.845. The odds of a stop occurring in other locations are 4.7 percent higher than in patrol sections, with an odds ratio (p = 0.712)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.082	0.030	<0.001	[0.077, 0.087]
Daytime	0.694	0.034	<0.001	[0.650, 0.742]
Precinct Crime	0.668	0.050	<0.001	[0.605, 0.736]
Highway	0.845	0.036	<0.001	[0.787, 0.906]
Other	1.047	0.124	0.712	[0.815, 1.323]

Table 10. Adjusted Logistic Regression Model Results (Asian Driver)

For Other drivers, the odds of a daytime stop are 22.3 percent lower than for nighttime stops, with an odds ratio of 0.777. The odds of a precinct crime stop are 4.6 percent higher than in patrol stops, with an odds ratio of 1.046, though this result is not statistically significant (p = 0.217). The odds of a highway stop are 87.2 percent higher than in patrol sections, with an odds ratio of 1.872. The odds of a stop occurring in other locations are 58.4 percent higher than in patrol sections, with an odds ratio of 1.584

Term	OR Estimate	Standard Error	p- value	95% OR CI
Intercept	0.104	0.025	<0.001	[0.099, 0.109]
Daytime	0.777	0.026	<0.001	[0.739, 0.818]
Precinct Crime	1.046	0.037	0.217	[0.973, 1.124]
Highway	1.872	0.025	<0.001	[1.781, 1.967]
Other	1.584	0.089	<0.001	[1.326, 1.880]

Table 11. Adjusted Logistic Regression Model Results (Other Driver)

Assessing Bias in Traffic Stop Search Decisions

Figure 6 displays the distribution of traffic stops with a search by officer command category. The precinct crime section and patrol categories account for most of the traffic stops with a search, with the precinct crime section conducting the highest number, followed closely by patrol. In contrast, highway and other commands are responsible for significantly fewer stops.

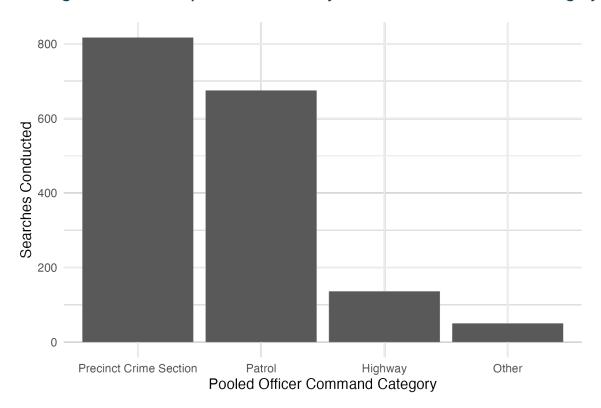


Figure 6. Traffic Stops with Searches by Pooled Officer Command Category

As not all vehicles or drivers are searched following a traffic stop, Table 12 presents the count of traffic stops with searches and the outcome of the search.

Table 12. Traffic Stop	Searches and Result	Outcome Findings
------------------------	---------------------	-------------------------

Search Conducted	Positive Search Result	Negative Search Result
Yes	393	1,285
No	0	162,502

These results indicate that searches are conducted in a very small proportion of traffic stops, and when they do occur, a small proportion yield results consisting of illegal weapons, illegal

drugs, or other contraband or evidence. Out of 162,895 total traffic stops, only 1,678, or approximately 1.03 percent, resulted in a search. Among the 1,678 searches conducted, only 393, or 23.4 percent, yielded a positive search result. This means that nearly 77 percent of searches, or 1,285 cases, had a negative search result. To assess if searches are conducted disproportionately on certain racial or ethnic groups without a correspondingly higher rate of positive results, it may indicate potential bias or systemic disparities in search practices. The next results present findings of the outcome, or "hit rate," of searches—measured by the proportion of searches that yield positive search results.

By comparing traffic stops with searches and their outcomes by race/ethnicity, potential bias could exist if there are wide differences in outcome percentages. Table 13 shows that the likelihood of a positive search result—where an item of interest is found—varies by race and ethnicity. White drivers had the highest positive search result rate at 30.6 percent, meaning nearly one in three searches yielded a positive result. In contrast, Black/African American drivers had a lower positive result rate at 21.1 percent, while Hispanic drivers had a rate of 18.1 percent. Asian drivers had the lowest positive result rate at 15.7 percent, and individuals categorized as "Other" had a rate of 20.0 percent.

Based strictly on the counts, searches of minority drivers resulted in lower positive search results compared to searches of white drivers. In an ideal scenario where search decisions are based solely on objective indicators of illegal activity, hit rates might be expected to be more consistent across racial and ethnic groups. The differences in recovery rates suggest that various factors, such as differences in driving patterns, search justifications, or infra-marginality, may contribute to these findings.

Race / Ethnicity	Positive Search Result	Negative Search Result
White	175 (30.6%)	396 (69.3%)
Black / African American	117 (21.1%)	435 (78.8%)
Hispanic	92 (18.1%)	414 (81.8%)
Asian	3 (15.7%)	16 (84.2%)
Other	6 (20.0%)	24 (80.0%)

Table 13. Traffic Stop with Searches and Search Outcome Results by Race/Ethnicity

Note: Percentage values may not sum to 100 due to rounding.

Examining search outcomes by hamlet is necessary to account for any race/ethnicity differences in Suffolk County and the following results present findings where enough observations were present to compare minority drivers to White drivers.

The next several figures (7-10) examine hit rates by specific races and ethnicities. Each data point represents a different hamlet, with the x-axis showing the percentage of total stops that

resulted in a search that yielded a positive search result for White drivers, and the y-axis indicating the proportion of those traffic stops with searches where a positive search result was yielded for a minority driver. The size of each bubble corresponds to the number of traffic stop searches in each hamlet. Only hamlets with greater than or equal to 30 stops with searches are labeled.

If all conditions were uniform across the hamlets, we would expect each data point to align closely along the dotted line that runs across the plot. A uniform distribution along this line would imply that the likelihood of a specific outcome from a search is consistent across different hamlets, regardless of the number of stops conducted. Essentially, it would suggest that no single hamlet is experiencing disproportionately higher or lower outcomes relative to the search rates compared to other hamlets when comparing race and ethnicity.

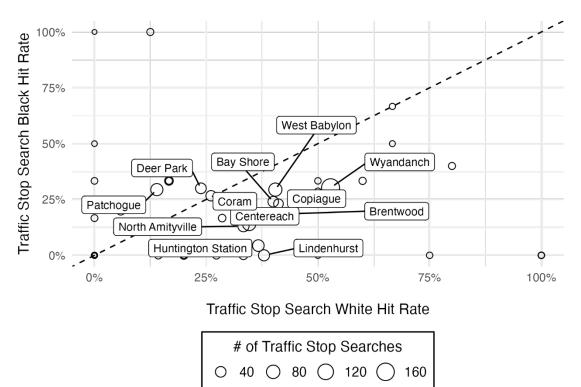
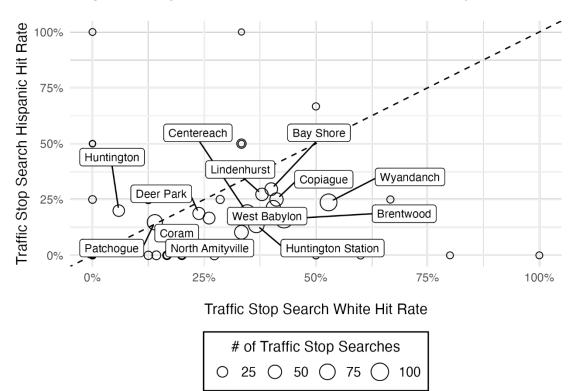


Figure 7. Black Driver and White Driver Hit Rates by Hamlet

In Figure 7, the distribution of hamlets and traffic stops with searches is spread across both sides of the diagonal line. However, there are more hamlets positioned below the diagonal, indicating that White drivers tend to have higher hit rates—meaning a greater proportion of traffic stops with searches result in a positive search result. This suggests that, on average, Black drivers experience a higher percentage of traffic stops with searches that do not yield a positive search result as compared to white drivers. The presence of this imbalance implies a potential disparity in search efficiency, where Black drivers may be subjected to a higher rate of unnecessary or unproductive searches. The varying bubble sizes indicate differences in the

volume of searches conducted across hamlets, adding further nuance to the overall distribution and the potential for localized enforcement patterns contributing to these trends.

A statistical analysis of the differences in hit rates between Black and White drivers revealed a mean difference² of 8.3%. However, the results do not provide sufficient evidence to conclude that this difference is statistically significant (t = 1.918, df = 48, p = 0.061).





With Figure 8, the distribution of hamlets and their associated search outcomes is spread across both sides of the diagonal line, which represents equal hit rates between Hispanic and White drivers. However, a greater number of hamlets also fall below this line, meaning that searches of White drivers are more likely to uncover a positive search result compared to searches of Hispanic drivers. This pattern indicates that Hispanic drivers experience a higher proportion of searches that do not result in a positive search result.

A statistical analysis of the differences in hit rates between Hispanic and white drivers revealed a mean difference of 6.4%. However, the results do not provide sufficient evidence to conclude that this difference is statistically significant (t = 1.264, df = 46, p = 0.210).

² Testing both the mean and standard deviation between groups will determine whether the mean difference is statistically significant between two groups.

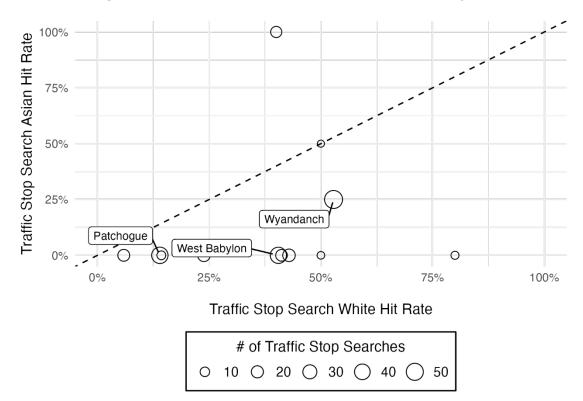


Figure 9. Asian Driver and White Driver Hit Rates by Hamlet

In Figure 9, the data points represent traffic stops with searches involving Asian drivers, with their distribution relative to the diagonal line indicating differences in hit rates compared to White drivers. Almost all the hamlets are positioned below the diagonal, meaning that traffic stops with searches of White drivers are more likely to yield positive search results than searches of Asian drivers. This suggests that Asian drivers are subjected to a relatively higher proportion of searches that do not result in a positive search result, indicating potential disparities in search effectiveness. The smaller number of data points and relatively small bubble sizes suggest that searches of Asian drivers occur less frequently compared to other racial and ethnic groups.

A statistical analysis was not performed between Asian and White drivers due to the limited sample size of less than 30 observations, which is insufficient to conduct a reliable test.

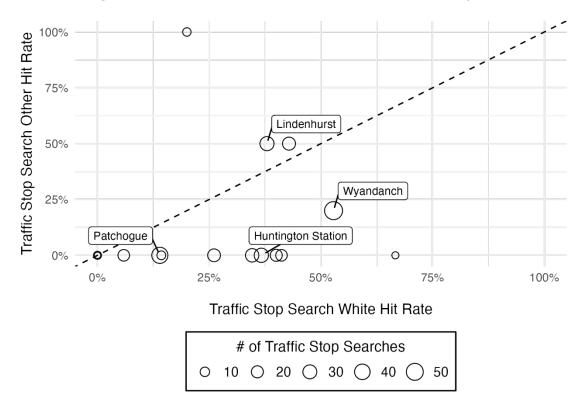


Figure 10. Other Driver and White Driver Hit Rates by Hamlet

In Figure 10, the data represents searches involving drivers classified as "Other," with the diagonal line serving as the reference point for equal hit rates compared to White drivers. The distribution of hamlets shows that most data points fall below the diagonal, suggesting that searches of White drivers are more likely to result in positive search results than searches of "Other" drivers in this category. This pattern implies that drivers classified as "Other" may be experiencing a higher rate of searches that yield negative results. The bubble sizes vary, indicating differences in the number of searches conducted across hamlets, though overall, the volume appears relatively low compared to other demographic groups.

A statistical analysis was not performed between Other and white drivers due to the limited sample size of less than 30 observations, which is insufficient to conduct a reliable test.

Conclusions

The results of the statistical models in the Veil-of-Darkness tests indicate that traffic stop patterns vary by race and ethnicity, with all minority groups experiencing lower odds of being stopped during the day compared to nighttime stops, relative to White drivers. There is no evidence in the calendar year 2023 traffic stop data to suggest potential bias or discrimination by the Suffolk County Police Department against minority drivers when compared to White drivers involved in traffic stops.

An analysis of traffic stops involving vehicle and driver searches reveals variation in hit rates across racial and ethnic groups. However, there is insufficient evidence to conclude a significant difference in hit rates between minority and White drivers when compared across geographic areas.

One of the key strengths of this study is the large sample size, consisting of more than 160,000 traffic stop observations. A dataset of this magnitude provides robust statistical power, allowing for more precise estimates and reducing the likelihood that findings are driven by random variation. Additionally, the data quality is strong, with well-documented traffic stop records that include key variables necessary for rigorous analysis. Another significant strength is the linkage of date and time stamps with official sunset times, enabling a precise classification of stops as occurring during daylight or nighttime periods. This approach ensures an objective measure of visibility conditions, which is central to the Veil-of-Darkness methodology. Furthermore, the analysis employs an established framework widely used in the literature to assess potential biases in traffic stops. By applying this well-validated methodology, the study enhances the credibility and comparability of its findings, ensuring that conclusions are grounded in rigorous and widely accepted analytical techniques.

Several limitations of this analysis stem from the reliance on officer-reported data. For instance, accurately discerning a White driver from a Hispanic driver can be challenging, potentially leading to inaccuracies in the recorded race and ethnicity of drivers. Furthermore, while the tests employed in this analysis are methodologically robust, they are subject to well-documented limitations.

First, the Veil-of-Darkness test, though widely used, does not definitively confirm or refute the presence of racial bias in traffic stops. Previous research has shown that statistical associations—or the lack thereof—may fail to fully capture underlying biases. Second, the Hit Rate test is constrained by the issue of infra-marginality. Infra-marginality refers to differences in the likelihood that individuals from different demographic groups carry illegal weapons, illegal drugs, or contraband or other evidence and are willing to assume the associated risk of being searched during a traffic stop. Police officers, in turn, may set a threshold probability for conducting searches based on observed behaviors or circumstances, irrespective of race.

To illustrate this, consider the following hypothetical example:

- White drivers have probabilities of carrying illegal drugs, illegal weapons, or contraband or other evidence at 10% and 80%.
- Black drivers have probabilities of carrying illegal drugs, illegal weapons, or contraband or other evidence at 10% and 50%.

If officers were to only search individuals with a probability above 20%, they would search drivers with 80% probability in the White group and 50% probability in the Black group. This race-neutral approach could result in lower hit rates for Black drivers, simply due to differences in risk distribution. However, such differences might be misinterpreted as evidence of racial bias when, in fact, they are driven by these probabilistic variations.

Additionally, some traffic stops are conducted for reasons unrelated to the driver's race, such as when officers recognize a vehicle or individual with an active warrant. In such cases, the decision to stop is not influenced by race, which complicates interpretations of overall racial disparities in stop data.

Future studies should continue to build on this analysis by incorporating additional years of traffic stop data to assess trends over time and ensure the robustness of findings. While this study did not find evidence of bias in stop patterns using the Veil-of-Darkness methodology, ongoing data monitoring remains essential to detect any emerging disparities and to evaluate the impact of policy changes or shifts in enforcement practices. Future research could also explore more granular factors influencing traffic stops, such as officer characteristics, geographic variations, or stop outcomes beyond searches. Additionally, integrating other data sources, such as body-worn camera footage or citation records, could provide further insight into the context of stops and post-stop interactions. Establishing a systematic approach to data collection and analysis will help law enforcement agencies and policymakers ensure transparency, accountability, and fairness in traffic enforcement practices.

References

Müller, K. (2023). *hms: Pretty time of day* (Version 1.1.3) [R package]. CRAN. https://CRAN.R-project.org/package=hms

Pebesma, E. (2018). Simple features for R: Standardized support for spatial vector data. *The R Journal, 10*(1), 439–446. https://doi.org/10.32614/RJ-2018-009

Pierson, E., Simoiu, C., Overgoor, J., Corbett-Davies, S., Jenson, D., Shoemaker, A., Ramachandran, V., Barghouty, P., Phillips, C., Shroff, R., & Goel, S. (2020). A large-scale analysis of racial disparities in police stops across the United States. *Nature Human Behaviour, 4*(7), 736–745. https://doi.org/10.1038/s41562-020-0858-1

R Core Team. (2023). *R: A language and environment for statistical computing* [Software]. R Foundation for Statistical Computing. https://www.R-project.org/

Slowikowski, K. (2023). ggrepel: Automatically position non-overlapping text labels with 'ggplot2' (Version 0.9.3) [R package]. CRAN. https://CRAN.R-project.org/package=ggrepel

U.S. Census Bureau. (2024). *QuickFacts: Suffolk County, New York*. U.S. Department of Commerce. https://www.census.gov/quickfacts/fact/table/suffolkcountynewyork/PST045223

Walker, K. (2023). *tigris: Load Census TIGER/Line Shapefiles* (Version 2.1.1) [R package]. CRAN. https://CRAN.R-project.org/package=tigris

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. Springer-Verlag. https://ggplot2.tidyverse.org

Wickham, H. (2019). *stringr: Simple, consistent wrappers for common string operations* (Version 1.5.0) [R package]. CRAN. https://CRAN.R-project.org/package=stringr

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D. A., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., ... Yutani, H. (2019). Welcome to the tidyverse. *Journal of Open Source Software*, 4(43), 1686. https://doi.org/10.21105/joss.01686

Wickham, H., François, R., Henry, L., & Müller, K. (2023). *dplyr: A grammar of data manipulation* (Version 1.1.3) [R package]. CRAN. https://CRAN.R-project.org/package=dplyr

Worden, R. E., Worden, K. M., & Cochran, H. (2020). *Traffic stops by Suffolk County police*. The John F. Finn Institute for Public Safety, Inc.

Appendix

Pooled Officer Command	Officer Command	Percentage	Count
Patrol	110 - 1st Patrol Section	10.3%	16,990
Precinct Crime Section	120 - 1st Precinct Crime Section	1.7%	2,849
Patrol	200 - 2nd Precinct Command	0.0%	23
Patrol	210 - 2nd Patrol Section	8.6%	14,140
Precinct Crime Section	220 - 2nd Precinct Crime Section	2.2%	3,552
Patrol	300 - 3rd Precinct Command	0.0%	20
Patrol	310 - 3rd Patrol Section	8.5%	13,889
Precinct Crime Section	320 - 3rd Precinct Crime Section	2.3%	3,722
Patrol	400 - 4th Precinct Command	0.0%	66
Patrol	410 - 4th Patrol Section	4.3%	7,128
Precinct Crime Section	420 - 4th Precinct Crime Section	1.7%	2,753
Patrol	500 - 5th Precinct Command	0.0%	21
Patrol	510 - 5th Patrol Section	5.7%	9,358
Precinct Crime Section	520 - 5th Precinct Crime Section	3.7%	6,094
Patrol	530 - 5th C.O.P.E. Section	0.1%	97
Patrol	600 - 6th Precinct Command	0.0%	2
Patrol	610 - 6th Patrol Section	7.4%	12,073
Precinct Crime Section	620 - 6th Precinct Crime Section	2.5%	4,109
Patrol	700 - 7th Precinct Command	0.0%	29
Patrol	710 - 7th Patrol Section	6.9%	11,313
Precinct Crime Section	720 - 7th Precinct Crime Section	2.2%	3,612
Other	1000 - Office Of Commissioner	0.0%	9
Other	1500 - Internal Affairs Bureau	0.0%	1
Other	1700 - Strategic Initiatives Bureau	0.0%	1
Other	1900 - Community Relations Bureau	0.1%	131
Precinct Crime Section	3110 - 1st Squad Section	0.0%	17
Precinct Crime Section	3120 - 2nd Squad Section	0.0%	55
Precinct Crime Section	3130 - 3rd Squad Section	0.0%	51
Precinct Crime Section	3140 - 4th Squad Section	0.0%	3
Precinct Crime Section	3160 - 6th Squad Section	0.1%	88
Precinct Crime Section	3170 - 7th Squad Section	0.0%	13
Other	3211 - Financial Crimes Unit	0.1%	153

Table 14. Traffic Stops by Officer Command (Pooled and Non-Pooled)

Pooled Officer Command	Officer Command	Percentage	Coun
Other	3212 - Digital Forensics Unit	0.0%	75
Precinct Crime Section	3320 - Special Victims Section	0.0%	4
Precinct Crime Section	3420 - Narcotics Section	0.0%	3
Precinct Crime Section	4020 - Warrant Enforcement Section	0.3%	429
Precinct Crime Section	4110 - Canine Section	0.1%	186
Other	4120 - Aviation Section	0.1%	193
Other	4130 - Emergency Service Section	0.0%	20
Precinct Crime Section	4140 - Crime Scene Section	0.0%	51
Other	4150 - Airport Operations Section	0.0%	5
Other	4160 - Medical Crisis Action Section	0.4%	662
Highway	4200 - Highway Patrol Bureau	0.4%	591
Highway	4210 - Highway Enforcement Section	13.1%	21,47
Highway	4220 - Motorcycle Section	2.7%	4,466
Highway	4230 - Motor Carrier Safety Section	3.3%	5,498
Highway	4240 - Safe-T Section	1.3%	2,095
Highway	4250 - Suffolk Intensified Traffic Enforcement	8.2%	13,49
Precinct Crime Section	4310 - Marine Patrol Section	0.5%	817
Precinct Crime Section	4410 - Homeland Security Section	0.0%	1
Other	4440 - Behavioral Health Section	0.0%	16
Other	5040 - Applicant Investigation Section	0.1%	110
Other	5361 - Court Liaison TPVA Unit	0.0%	1
Other	5400 - Police Academy Bureau	0.0%	2
Precinct Crime Section	5410 - Recruit Training Section	0.0%	6
Other	5420 - In-Service Training Section	0.1%	184
Other	5430 - Firearms Training Section	0.0%	1
Other	5530 - Medical Evaluation Section	0.6%	981
Precinct Crime Section	5610 - Property Section	0.0%	20
Precinct Crime Section	5620 - Impound Section	0.1%	90
Other	5700 - Police Technology Bureau	0.0%	71
N/A	Missing	0.2%	271

Precinct # 1

Assessing Bias in Traffic Stop Decisions

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	1.342	0.030	<0.001	[1.266, 1.423]
Daytime	0.697	0.035	<0.001	[0.651, 0.747]
Precinct Crime	1.702	0.048	<0.001	[1.551, 1.868]
Highway	0.720	0.060	<0.001	[0.641, 0.810]
Other	1.225	0.130	0.118	[0.951, 1.584]

Table 15. Precinct # 1 Adjusted Logistic Regression Model Results (Black Driver)

Table 16. Precinct # 1 Adjusted Logistic Regression Model Results (Hispanic Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	1.176	0.031	<0.001	[1.107, 1.249]
Daytime	0.760	0.037	<0.001	[0.707, 0.816]
Precinct Crime	1.169	0.051	0.002	[1.057, 1.293]
Highway	0.891	0.058	0.046	[0.796, 0.998]
Other	0.838	0.145	0.225	[0.630, 1.114]

Table 17. Precinct # 1 Adjusted Logistic Regression Model Results (Asian Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.105	0.074	<0.001	[0.091, 0.122]
Daytime	0.678	0.090	<0.001	[0.569, 0.810]
Precinct Crime	1.283	0.122	0.041	[1.005, 1.622]
Highway	0.673	0.173	0.022	[0.472, 0.933]
Other	1.433	0.299	0.229	[0.761, 2.481]

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.140	0.065	<0.001	[0.123, 0.159]
Daytime	0.751	0.078	<0.001	[0.646, 0.876]
Precinct Crime	0.915	0.119	0.454	[0.720, 1.149]
Highway	2.193	0.094	<0.001	[1.819, 2.634]
Other	0.621	0.370	0.198	[0.277, 1.203]

Table 18. Precinct # 1 Adjusted Logistic Regression Model Results (Other Driver)

Assessing Bias in Traffic Stop Search Decisions

In Precinct 1, limited traffic stop search observations at the hamlet level undermine the reliability of the analysis. The sample sizes were small: 13 hamlets for Black–White, 14 for Hispanic–White, 5 for Asian–White, and 3 for Other–White comparisons. Such limited data reduce statistical power, meaning differences may go undetected, and results could be misleading.

Assessing Bias in Traffic Stop Decisions

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.354	0.042	<0.001	[0.326, 0.384]
Daytime	0.767	0.047	<0.001	[0.699, 0.842]
Precinct Crime	1.926	0.053	<0.001	[1.734, 2.138]
Highway	0.996	0.078	0.958	[0.854, 1.158]
Other	1.328	0.174	0.103	[0.935, 1.855]

Table 19. Precinct #2 Adjusted Logistic Regression Model Results (Black Driver)

Table 20. Precinct #2 Adjusted Logistic Regression Model Results (Hispanic Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.766	0.033	<0.001	[0.718, 0.817]
Daytime	0.777	0.037	<0.001	[0.723, 0.836]
Precinct Crime	1.748	0.043	<0.001	[1.606, 1.903]
Highway	0.833	0.062	0.003	[0.737, 0.940]
Other	1.259	0.138	0.096	[0.958, 1.649]

Table 21. Precinct #2 Adjusted Logistic Regression Model Results (Asian Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.110	0.071	<0.001	[0.095, 0.126]
Daytime	0.729	0.084	<0.001	[0.619, 0.861]
Precinct Crime	0.724	0.123	0.009	[0.566, 0.915]
Highway	0.578	0.164	<0.001	[0.413, 0.788]
Other	0.747	0.368	0.428	[0.334, 1.440]

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.120	0.065	<0.001	[0.106, 0.136]
Daytime	0.769	0.074	<0.001	[0.666, 0.890]
Precinct Crime	1.189	0.095	0.070	[0.983, 1.429]
Highway	2.177	0.092	<0.001	[1.813, 2.603]
Other	1.740	0.240	0.021	[1.057, 2.725]

Table 22. Precinct #2 Adjusted Logistic Regression Model Results (Other Driver)

Assessing Bias in Traffic Stop Search Decisions

In Precinct 2, a limited number of traffic stop search observations at the hamlet level weakens the reliability of the analysis. The sample sizes were small: 4 hamlets for Black–White, 5 for Hispanic–White, 1 for Asian–White, and 2 for Other–White comparisons. With such limited data, statistical power is reduced, increasing the chance that meaningful differences go undetected and results become misleading.

Assessing Bias in Traffic Stop Decisions

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	1.173	0.043	<0.001	[1.078, 1.276]
Daytime	0.762	0.049	<0.001	[0.692, 0.839]
Precinct Crime	1.513	0.057	<0.001	[1.353, 1.693]
Highway	0.483	0.078	<0.001	[0.415, 0.562]
Other	0.944	0.171	0.736	[0.674, 1.319]

Table 23. Precinct #3 Adjusted Logistic Regression Model Results (Black Driver)

Table 24. Precinct #3 Adjusted Logistic Regression Model Results (Hispanic Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	2.745	0.037	<0.001	[2.557, 2.950]
Daytime	0.758	0.042	<0.001	[0.699, 0.822]
Precinct Crime	1.590	0.050	<0.001	[1.444, 1.754]
Highway	0.817	0.056	<0.001	[0.733, 0.912]
Other	1.292	0.136	0.060	[0.995, 1.697]

Table 25. Precinct #3 Adjusted Logistic Regression Model Results (Asian Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.091	0.113	<0.001	[0.072, 0.112]
Daytime	0.800	0.132	0.090	[0.620, 1.040]
Precinct Crime	0.681	0.189	0.041	[0.463, 0.971]
Highway	0.482	0.228	0.001	[0.300, 0.736]
Other	1.962	0.331	0.042	[0.972, 3.600]

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.191	0.078	< 0.001	[0.163, 0.221]
Daytime	0.675	0.090	< 0.001	[0.567, 0.806]
Precinct Crime	1.226	0.114	0.074	[0.977, 1.527]
Highway	1.563	0.111	< 0.001	[1.255, 1.936]
Other	1.459	0.288	0.190	[0.799, 2.494]

Table 26. Precinct #3 Adjusted Logistic Regression Model Results (Other Driver)

Assessing Bias in Traffic Stop Search Decisions

In Precinct 3, a limited number of traffic stop search observations at the hamlet level weakens the reliability of the analysis. The sample sizes were small: 5 hamlets for Black–White, 4 for Hispanic–White, 3 for Asian–White, and 4 for Other–White comparisons. With such limited data, statistical power is reduced, increasing the likelihood that meaningful differences go undetected and results become misleading.

Assessing Bias in Traffic Stop Decisions

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.211	0.062	<0.001	[0.187, 0.238]
Daytime	0.692	0.067	<0.001	[0.607, 0.791]
Precinct Crime	1.753	0.070	<0.001	[1.529, 2.009]
Highway	1.156	0.086	0.092	[0.975, 1.366]
Other	1.158	0.241	0.543	[0.703, 1.818]

Table 27. Precinct #4 Adjusted Logistic Regression Model Results (Black Driver)

Table 28. Precinct #4 Adjusted Logistic Regression Model Results (Hispanic Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.433	0.048	<0.001	[0.394, 0.476]
Daytime	0.753	0.052	<0.001	[0.680, 0.834]
Precinct Crime	1.231	0.057	<0.001	[1.101, 1.375]
Highway	1.317	0.061	<0.001	[1.168, 1.484]
Other	1.401	0.166	0.043	[1.005, 1.930]

Table 29. Precinct #4 Adjusted Logistic Regression Model Results (Asian Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.074	0.104	<0.001	[0.060, 0.091]
Daytime	0.871	0.114	0.222	[0.699, 1.091]
Precinct Crime	1.141	0.116	0.256	[0.905, 1.429]
Highway	0.394	0.195	<0.001	[0.264, 0.568]
Other	1.052	0.371	0.891	[0.468, 2.042]

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.079	0.094	<0.001	[0.065, 0.095]
Daytime	0.735	0.100	0.002	[0.605, 0.896]
Precinct Crime	1.375	0.113	0.005	[1.100, 1.710]
Highway	2.515	0.103	<0.001	[2.054, 3.073]
Other	0.989	0.395	0.977	[0.414, 1.992]

Table 30. Precinct #4 Adjusted Logistic Regression Model Results (Other Driver)

Assessing Bias in Traffic Stop Search Decisions

In Precinct 4, limited traffic stop search observations at the hamlet level weaken the reliability of the analysis. The sample sizes were small: 7 hamlets for Black–White, 5 for Hispanic–White, and none for Asian–White or Other–White comparisons. Such sparse data reduce statistical power, increasing the risk that meaningful differences go undetected and results become misleading.

Assessing Bias in Traffic Stop Decisions

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.353	0.043	<0.001	[0.324, 0.384]
Daytime	0.674	0.047	<0.001	[0.614, 0.739]
Precinct Crime	0.988	0.048	0.804	[0.900, 1.085]
Highway	0.814	0.068	0.003	[0.712, 0.930]
Other	0.664	0.211	0.052	[0.430, 0.986]

Table 31. Precinct #5 Adjusted Logistic Regression Model Results (Black Driver)

Table 32. Precinct #5 Adjusted Logistic Regression Model Results (Hispanic Driver)

OR Estimate	Standard Error	p-value	95% OR CI
0.480	0.038	<0.001	[0.446, 0.517]
0.828	0.041	<0.001	[0.765, 0.897]
0.935	0.041	0.096	[0.863, 1.012]
1.128	0.052	0.021	[1.018, 1.250]
0.699	0.169	0.034	[0.496, 0.965]
	Estimate 0.480 0.828 0.935 1.128	Estimate Error 0.480 0.038 0.828 0.041 0.935 0.041 1.128 0.052	EstimateErrorp-value0.4800.038<0.001

Table 33. Precinct #5 Adjusted Logistic Regression Model Results (Asian Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.054	0.103	<0.001	[0.044, 0.066]
Daytime	0.667	0.119	<0.001	[0.529, 0.844]
Precinct Crime	0.508	0.137	<0.001	[0.386, 0.661]
Highway	0.569	0.185	0.002	[0.390, 0.805]
Other	0.645	0.512	0.391	[0.197, 1.544]

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.068	0.082	<0.001	[0.058, 0.079]
Daytime	0.820	0.084	0.018	[0.697, 0.967]
Precinct Crime	1.204	0.088	0.034	[1.013, 1.429]
Highway	2.206	0.096	<0.001	[1.824, 2.662]
Other	0.326	0.586	0.056	[0.080, 0.866]

Table 34. Precinct #5 Adjusted Logistic Regression Model Results (Other Driver)

Assessing Bias in Traffic Stop Search Decisions

In Precinct 5, limited traffic stop search observations at the hamlet level weaken the reliability of the analysis. The sample sizes were small: 9 hamlets for Black–White, 9 for Hispanic–White, 2 for Asian–White, and 3 for Other–White comparisons. With such limited data, statistical power is reduced, increasing the chance that meaningful differences go undetected and results become misleading.

Assessing Bias in Traffic Stop Decisions

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.297	0.039	<0.001	[0.275, 0.321]
Daytime	0.787	0.045	<0.001	[0.721, 0.859]
Precinct Crime	2.111	0.047	<0.001	[1.926, 2.313]
Highway	0.792	0.072	0.001	[0.686, 0.911]
Other	0.769	0.274	0.338	[0.433, 1.279]

Table 35. Precinct #6 Adjusted Logistic Regression Model Results (Black Driver)

Table 36. Precinct #6 Adjusted Logistic Regression Model Results (Hispanic Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.387	0.036	<0.001	[0.360, 0.415]
Daytime	0.808	0.041	<0.001	[0.745, 0.876]
Precinct Crime	1.426	0.046	<0.001	[1.302, 1.560]
Highway	1.145	0.057	0.019	[1.022, 1.280]
Other	1.245	0.205	0.284	[0.823, 1.843]

Table 37. Precinct #6 Adjusted Logistic Regression Model Results (Asian Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.074	0.078	<0.001	[0.063, 0.086]
Daytime	0.862	0.094	0.115	[0.718, 1.039]
Precinct Crime	0.449	0.139	<0.001	[0.339, 0.585]
Highway	0.251	0.216	<0.001	[0.160, 0.375]
Other	1.446	0.373	0.323	[0.641, 2.826]

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.113	0.060	<0.001	[0.100, 0.127]
Daytime	0.659	0.070	< 0.001	[0.575, 0.756]
Precinct Crime	1.309	0.083	0.001	[1.112, 1.537]
Highway	1.729	0.089	< 0.001	[1.449, 2.056]
Other	1.023	0.396	0.954	[0.428, 2.071]

Table 38. Precinct #6 Adjusted Logistic Regression Model Results (Other Driver)

Assessing Bias in Traffic Stop Search Decisions

-

In Precinct 6, limited traffic stop search observations at the hamlet level weaken the reliability of the analysis. The sample sizes were small: 6 hamlets for Black–White, 6 for Hispanic–White, and none for Asian–White or Other–White comparisons. Such sparse data reduce statistical power, increasing the likelihood that meaningful differences go undetected and results become misleading.

Assessing Bias in Traffic Stop Decisions

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.378	0.042	<0.001	[0.347, 0.410]
Daytime	0.693	0.046	<0.001	[0.633, 0.759]
Precinct Crime	1.723	0.047	<0.001	[1.570, 1.890]
Highway	0.779	0.069	<0.001	[0.679, 0.891]
Other	1.358	0.241	0.205	[0.830, 2.148]

Table 39. Precinct #7 Adjusted Logistic Regression Model Results (Black Driver)

Table 40. Precinct #7 Adjusted Logistic Regression Model Results (Hispanic Driver)

OR Estimate	Standard Error	p-value	95% OR CI
0.387	0.043	<0.001	[0.356, 0.420]
0.703	0.047	<0.001	[0.642, 0.771]
1.319	0.050	<0.001	[1.196, 1.454]
0.808	0.067	0.002	[0.707, 0.921]
0.923	0.275	0.769	[0.522, 1.542]
	Estimate 0.387 0.703 1.319 0.808	Estimate Error 0.387 0.043 0.703 0.047 1.319 0.050 0.808 0.067	EstimateErrorp-value0.3870.043<0.001

Table 41. Precinct #7 Adjusted Logistic Regression Model Results (Asian Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.042	0.118	<0.001	[0.033, 0.052]
Daytime	0.589	0.135	<0.001	[0.454, 0.771]
Precinct Crime	0.865	0.164	0.376	[0.620, 1.182]
Highway	0.556	0.232	0.012	[0.343, 0.856]
Other	2.301	0.522	0.110	[0.693, 5.659]

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.100	0.076	<0.001	[0.086, 0.116]
Daytime	0.435	0.089	<0.001	[0.366, 0.517]
Precinct Crime	1.019	0.111	0.865	[0.816, 1.263]
Highway	1.300	0.120	0.028	[1.023, 1.636]
Other	1.526	0.470	0.368	[0.530, 3.474]

Table 42. Precinct #7 Adjusted Logistic Regression Model Results (Other Driver)

Assessing Bias in Traffic Stop Search Decisions

In Precinct 7, limited traffic stop search observations at the hamlet level weaken the reliability of the analysis. The sample sizes were small: 5 hamlets for Black–White, 3 for Hispanic–White, and none for Asian–White or Other–White comparisons. Such sparse data reduce statistical power, increasing the risk that meaningful differences go undetected and results become misleading.

Assessing Bias in Traffic Stop Decisions

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.678	0.079	<0.001	[0.579, 0.791]
Daytime	0.704	0.033	<0.001	[0.659, 0.752]
Precinct Crime	1.585	0.364	0.205	[0.768, 3.239]
Highway	0.647	0.078	<0.001	[0.556, 0.755]
Other	0.821	0.121	0.105	[0.647, 1.041]

Table 43. Precinct #9 Adjusted Logistic Regression Model Results (Black Driver)

Table 44. Precinct #9 Adjusted Logistic Regression Model Results (Hispanic Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.675	0.074	<0.001	[0.583, 0.780]
Daytime	0.955	0.031	0.137	[0.899, 1.015]
Precinct Crime	0.983	0.393	0.965	[0.442, 2.101]
Highway	0.748	0.072	<0.001	[0.649, 0.863]
Other	0.962	0.109	0.720	[0.776, 1.191]

Table 45. Precinct #9 Adjusted Logistic Regression Model Results (Asian Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.127	0.156	<0.001	[0.093, 0.171]
Daytime	0.680	0.067	<0.001	[0.597, 0.776]
Precinct Crime	1.162	0.764	0.844	[0.181, 4.231]
Highway	0.674	0.153	0.010	[0.505, 0.922]
Other	0.446	0.296	0.006	[0.242, 0.779]

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.182	0.117	<0.001	[0.144, 0.228]
Daytime	1.053	0.048	0.282	[0.959, 1.157]
Precinct Crime	0.313	1.030	0.260	[0.017, 1.553]
Highway	0.875	0.114	0.242	[0.704, 1.100]
Other	1.180	0.165	0.316	[0.853, 1.628]

Table 46. Precinct #9 Adjusted Logistic Regression Model Results (Other Driver)

Assessing Bias in Traffic Stop Search Decisions

In Precinct 9, limited traffic stop search observations at the hamlet level weaken the reliability of the analysis. The sample sizes were small: 4 hamlets for Black–White, 7 for Hispanic–White, and none for Asian–White or Other–White comparisons. Such sparse data reduce statistical power, increasing the likelihood that meaningful differences go undetected and results become misleading.