2024 Traffic Stop Data Analysis

Suffolk County Police Department

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STONEWALL ANALYTICS

Executive Summary

This report analyzes nearly 160,000 traffic stops conducted in Suffolk County, New York, in 2024, with the goal of assessing whether racial disparities exist in stop, search practices, and traffic stop enforcement. The study applies three key statistical tests: the Veil-of-Darkness test to evaluate racial bias in stop decisions, the Hit Rate test to examine search outcomes, and a regression model examining traffic disposition 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 2024.

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. Although 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.

The analysis of traffic stop enforcement actions found that differences in enforcement outcomes do exist by race and were most evident for moving violations, with minority drivers more likely than White drivers to receive enforcement actions. Differences varied for other traffic stop types, with some groups experiencing lower odds of enforcement. While these results highlight important patterns to analyze further, they do not confirm bias, as unmeasured factors may influence outcomes. Stonewall Analytics will continue to work with the Suffolk County Police Department to identify the root causes of anomalies where possible, including by leveraging data that are outside the scope of this report.

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. There were findings of differences, however, in traffic stop enforcement outcomes by race when controlling for the reason for traffic stop. This work underscores the importance of ongoing monitoring and refinement of data collection practices to ensure transparency and fairness in law enforcement activities.

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Introduction

This report details findings from more than 159,000 traffic stops conducted in Suffolk County, New York, during the 2024 calendar year. Stonewall Analytics—an independent evaluator selected through a competitive process—was engaged to review and analyze both traffic stop and pedestrian stop data. This is the second annual report prepared by Stonewall Analytics. Conducting an annual third-party review of this data equips the Suffolk County Police Department (SCPD) with an essential tool for evaluating organizational performance, improving resource allocation, and flagging unusual traffic stop patterns among officers with comparable assignments. This analysis includes, though is not limited to, stops initiated based on reasonable suspicion of criminal conduct. As with the previous year, due to the limited number of cases, pedestrian stop data were not analyzed.

Since entering into an agreement with the U.S. Department of Justice in 2014, SCPD has been required to collect and analyze traffic stop data. Because traffic stops represent one of the most common interactions between law enforcement and the public, it is vital to conduct a rigorous review of these encounters. Doing so allows for the identification of trends in stop activity and outcomes and helps uncover any disparities that could suggest biased or inequitable policing—particularly those impacting minority groups in Suffolk County.

The findings in this report are presented in two parts. First, the evaluators offer descriptive and summary statistics to help readers understand who is being stopped, under what circumstances, and how often. Second, they assess whether individuals from minority populations face differences in the odds of being stopped relative to a comparison group. In this case, the comparison group is White drivers. This analysis also includes evaluating whether search outcomes differ by race or ethnicity. The report reviews patterns in traffic stop outcome enforcement actions.

Background

A national study examining nearly 100 million traffic stops across the United States revealed notable racial disparities in both stop and search practices (Pierson et al., 2020). Utilizing the Veil-of-Darkness methodology, the researchers assessed whether Black and Hispanic drivers were disproportionately stopped during daylight hours—when a driver's race is more readily observable—compared to after dark. Their analysis found that Black drivers accounted for a smaller share of stops after sunset than during daylight, suggesting that racial perception may play a role in stop decisions. This trend held consistent across both state highway patrol and local police departments, indicating the presence of systemic racial bias in stop practices. Further disparities emerged from an outcome test, which evaluated search rates and their results following traffic stops (Pierson et al., 2020). The study found that Black and Hispanic drivers were searched more frequently than White drivers, yet searches of White drivers were more likely to yield contraband or other evidence. This imbalance suggests that searches of minority drivers may have been conducted using a lower evidentiary threshold. While multiple confounding factors complicate this interpretation, an enhanced method—the threshold test—was able to incorporate both search and success rates. It concluded that searches of Black and Hispanic drivers were, in fact, initiated with less evidence than those of White drivers, pointing to potential discriminatory patterns in post-stop decisions.

A 2020 report by the Finn Institute (Worden et al., 2020) offered a detailed analysis of traffic stop activity in Suffolk County, drawing on data from March 2018 to March 2019. Their work included an assessment of post-stop outcomes and the application of the Veil-of-Darkness test. While searches of drivers or vehicles were infrequent—occurring in only about 3% of stops—the likelihood of being searched varied markedly by race and ethnicity. Black drivers were searched in 6% of stops, Hispanic drivers in 3.4%, and White drivers in just 2%. The majority of these searches were based on probable cause for suspected drug possession, which accounted for over two-thirds of searches carried out by patrol and crime units. Less common justifications included visible evidence of criminal activity or consent-based searches based on founded suspicion.

In applying the Veil-of-Darkness test, the Finn Institute sought to determine whether stop decisions were influenced by a driver's race. The premise of this test is that during darker hours, officers have a harder time perceiving race, thus providing a more race-neutral baseline. The analysis compared daylight and darkness stops for Black and Hispanic drivers, controlling for variables such as time of day, day of the week, and precinct. Across multiple regression models, results indicated no statistically significant differences in daylight versus darkness stop rates for either group. Relative risk ratios hovered around 1.0, and confidence intervals included that value, suggesting an absence of systematic racial bias in the initial stop decision. Although Black and Hispanic drivers were disproportionately represented in stop totals relative to their share of the local population, the Veil-of-Darkness analysis suggested these disparities were likely influenced by factors other than race-based stop decisions.

In 2024, Stonewall Analytics conducted a comprehensive analysis of traffic stop data from 2023, covering nearly 160,000 stops. Utilizing an enhanced methodology, including an updated application of the Veil-of-Darkness test, the review found no evidence of racial bias in officers' decisions to initiate traffic stops. Additionally, the analysis revealed no signs of bias or disparity in traffic stop searches when evaluating search patterns and the corresponding hit rates. The full report is available on the SCPD Transparency Hub.

Together, these national and local findings reinforce the need to distinguish between disparity and bias and emphasize the complexity of analyzing traffic stop data. While disparities in post-stop outcomes—especially in search rates—raise important equity concerns, the Veil-of-Darkness results suggest that racial bias may not be the primary driver of initial stop decisions. Further investigation is needed to better understand the underlying causes of these disparities. Traffic stop data and annual summary statistics are now made publicly available via the Suffolk County Police Department Transparency Hub, supporting independent review and accountability. Over time, considerable effort has been invested in refining the analysis of traffic stop data to detect and respond to inequitable enforcement practices. In the context of this report, such practices are defined as a higher likelihood of being stopped or searched—particularly with a lower success rate—among minority populations as compared to White drivers.

SCPD's data collection infrastructure and methods have advanced significantly in recent years. Legacy paper-based systems have been phased out in favor of more modern digital platforms, with updated data fields that improve clarity and accuracy. In the fourth quarter of 2023, SCPD implemented further enhancements to its data collection practices, aimed at improving transparency and reducing internal barriers—reflecting a continued commitment to fairness, accountability, and equitable policing. These data collection improvements are also evident in the quality of the 2024 traffic stop data.

Methodology

The evaluators obtained a restricted dataset containing traffic stop records from the 2024 calendar year through secure transmission channels. While many of the fields are available to the public via SCPD's Transparency Hub, certain sensitive variables—such as license plate numbers and personally identifiable information about officers—were withheld from public release to maintain privacy and confidentiality.

To assess whether officers disproportionately stop minority drivers compared to White drivers, a refined version of the Veil-of-Darkness test was employed. This approach compares stops made during daylight hours to those made after dark, based on the premise that an officer is less able to determine a driver's race at night. If no significant statistical relationship exists between the time of day and the proportion of minority drivers stopped, this suggests the absence of racial bias in stop decisions. Conversely, a significant difference could point to potential bias, though further analysis would be needed to draw firm conclusions. It is important to emphasize that such statistical associations alone do not confirm or refute the presence of bias.

Race and ethnicity were classified based on officer-reported designations, including White non-Hispanic, Hispanic, Black/African American, Asian/Pacific Islander, and Other. While these classifications do not necessarily reflect individuals' self-identified race or ethnicity, they are the basis for this analysis. Data from the 2020 American Community Survey were also referenced for population context, though these figures are not intended to serve as a benchmark for who should be stopped, since lawful justification—rather than demographics—should guide stop decisions.

The dataset included geographic coordinates and precise timestamps for each traffic stop, allowing for categorization into daytime (sunrise to sunset) and nighttime stops. Nighttime was further refined to the inter-twilight window (approximately 5:00 p.m. to 9:00 p.m.), based on prior research indicating that traffic volume and behavior during this period more closely resemble daytime conditions than those found in late-night or early-morning hours. This refinement enhances the accuracy of comparisons between visibility conditions.

To implement the Veil-of-Darkness test, logistic regression models were used. The dependent variable was whether the driver was a member of a minority group (coded as 1) or not (coded as 0). The primary independent variable was a binary indicator for daylight (1 = day, 0 = night), and the adjusted models also included a variable for pooled officer command category to account for operational variation among police units. The unadjusted model included only the daylight indicator. The adjusted model was structured as follows:

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

All models were assessed at a significance level of $\alpha = 0.05$, and separate models were run for each minority classification.

The second part of the analysis focused on search outcomes—specifically, whether searches resulted in the discovery of contraband or evidence—using the Hit Rate test. This test gauges the effectiveness of searches during traffic stops, which are typically initiated for reasons such as probable cause, visible contraband, or outstanding warrants. Most traffic stops, however, do not result in a search. While it is challenging to determine bias based solely on the decision to conduct a search due to numerous unobservable factors, examining differences in hit rates can reveal possible disparities in outcomes. If searches of minority drivers yield lower hit rates than those of White drivers, this could suggest bias—though differences might also be influenced by infra-marginality, where variation in risk-taking behavior or thresholds for conducting searches may drive observed disparities. Hit rates were compared across hamlets and were stratified by race. A paired, two-sided t-test was used to assess whether the differences in hit rates between White and minority drivers within each hamlet were statistically significant, using $\alpha = 0.05$.

The outcome of a traffic stop was classified into one of two categories based on enforcement action: enforcement or no enforcement. These categories were created by grouping driver disposition codes. An enforcement action was defined as any stop that resulted in an arrest, a summons, or a field appearance ticket. In contrast, stops that resulted in a verbal warning or educational conversation, aid to the driver, issuance of a lights-on voucher, or no police action were categorized as having no enforcement action. A logistic regression model with interaction terms was used to assess whether differences in enforcement outcomes existed, using a binary enforcement variable (1 = enforcement, 0 = no enforcement) and controlling for the reason for the stop. This approach allowed for examination of how combinations of variables may influence enforcement decisions. Traffic stops were grouped into three categories: moving violations, equipment violations, and other. Moving violations included offenses such as speeding, cell phone use, running a stop sign or red light, failure to wear a seat belt, or other moving-related infractions. Equipment violations included issues related to registration, inspection, license plates, or other equipment-related problems. The "other" category included stops based on reasonable suspicion or probable cause of criminal activity. While the data allow for classification of the reason for the traffic stop, the data do not specify the nature of the violation leading to the enforcement action, or the severity of an alleged offense (e.g. unlicensed driver, a speeding driver going 40 miles per hour over the speed limit versus 10 miler per hour over the speed limit). The logistic regression model used for this part of the analysis is presented below.

$$log\left(\frac{P(Enforcement\ Action\ Taken=1)}{P(Enforcement\ Action\ Taken=0)}\right) = \beta_0 + \beta_1(racial\ grouping) + \beta_2(reason\ for\ stop) + \beta_3(reason\ for\ stop\ \times\ racial\ grouping)$$

Additional precinct-level analyses of the Veil-of-Darkness, the Hit Rate tests, and visuals pertainin to traffic stop enforcement actions are included in the appendix. All data processing and analysis were conducted using R (R Core Team, 2023), with the following packages: dplyr for data manipulation (Wickham et al., 2023), ggplot2 for visualization (Wickham, 2016), hms for time handling (Müller, 2023), stringr for string operations (Wickham, 2019), tidyverse for integrated workflows (Wickham et al., 2019), tigris for geographic data (Walker, 2023), sf for spatial analysis (Pebesma, 2018), and ggrepel for refined labeling (Slowikowski, 2023).

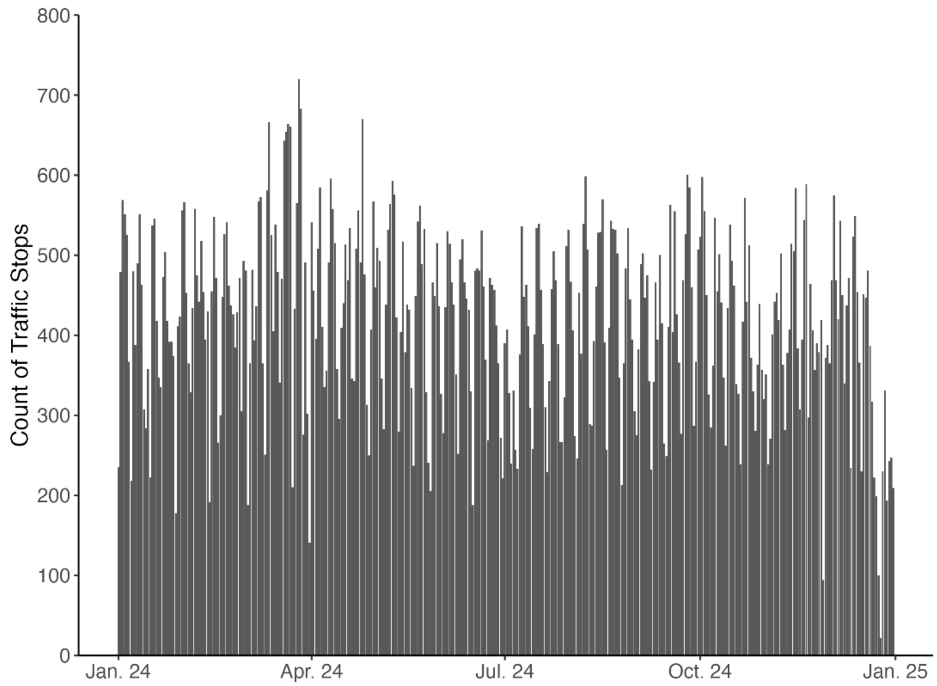
Results

The analysis of traffic stop data is organized into four main sections. First, descriptive and summary statistics provide an overview of key trends and distributions within the dataset. Next, the Veil-of-Darkness test evaluates whether racial disparities in traffic stops are more prevalent during daylight compared to darkness, accounting for differences in visibility. The third section applies the Hit Rate test to determine whether searches conducted during traffic stops yield different outcomes across racial and demographic groups. Finally, the analysis reviews enforcement action outcomes following traffic stops.

Overall Traffic Stops

Figure 1 illustrates the number of traffic stops recorded each day between January and December 2024. The x-axis represents the daily timeline, while the y-axis indicates the daily count of stops. The data show regular day-to-day fluctuations, with some days nearing 700 stops and others falling below 100. Despite this variability, the overall volume of traffic stops remained consistent throughout the year, without any major upward or downward shifts. A slight decrease in stops is observed toward late December 2024, which may reflect seasonal or holiday-related changes in traffic patterns.

Figure 1. Distribution of Traffic Stops Over Time



The distribution of traffic stops by time of day provides important context for analyzing racial disparities and patterns in policing practices. As shown in Table 1, most stops occurred during the daytime, accounting for 70% of all stops (107,445 stops), while nighttime stops comprised nearly 30% (45,256 stops).[1] 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*.

Table 1. Traffic Stops by Time of Day

Time of Day Grouping	Percentage	Count
Daytime	70.3%	107,445
Nighttime	29.7%	45,256

Table 2 presents traffic stops by weekday and highlights that traffic stops occurred more frequently on weekdays than weekends, with the highest volume reported on Tuesday, accounting for 16.7% of all stops (26,539 stops). In contrast, weekend enforcement was noticeably lower, with Saturday comprising 11.4% (18,190 stops) and Sunday just 9.6% (15,217 stops) of the total. The takeaway is that traffic stops are concentrated during the workweek, with reduced activity on weekends.

[1] The total traffic stops analyzed included 159,397 observations; of these observations, 6,696 were missing date time stamps or latitude and/or longitude information which were necessary to determine if the stops were during the day or evening. As a result, these values in Table 1 will only sum to 152,701.

Table 2. Traffic Stops by Weekday

Weekday	Percentage	Count
Monday	14.2%	22,697
Tuesday	16.7%	26,539
Wednesday	16.3%	25,942
Thursday	16.1%	25,751
Friday	15.7%	25,061
Saturday	11.4%	18,190
Sunday	9.6%	15,217

Table 3 presents the demographic breakdown of drivers involved in traffic stops throughout calendar year 2024, based on officer-reported age, gender, and race/ethnicity. The age distribution is concentrated among younger and middle-aged adults, with drivers aged 26 to 35 representing the largest share at 30.2% (48,158 individuals). Drivers under the age of 16 accounted for the smallest group, comprising just 0.1% of stops (133 individuals), which is consistent with expectations. In terms of gender, a substantial majority of traffic stops involved male drivers, who made up 70.9% of the total (112,979 individuals), while female drivers accounted for 29.1% (46,418 individuals). Looking at race and ethnicity, White non-Hispanic drivers represented the largest group, comprising 45.2% of the stopped population (70,484 individuals), followed by Hispanic drivers at 28.5% (45,503 individuals). Black or African American drivers accounted for 18.8% of all stops (29,931 individuals). Drivers classified as Asian or Pacific Islander represented the smallest share at 3.1% (4,951 individuals), while those identified as "Other" made up 5.3% (8,527 individuals). Overall, the data reflect a population of drivers who are predominantly male, largely within the 26 to 45 age range, and primarily identified as White non-Hispanic.

Table 3. Driver Characteristics Overview

Category	Percentage	Count
Age Group (Years)		
Less than 16	0.1%	133
16 to 25	21.0%	33,446
26 to 35	30.2%	48,158
36 to 45	22.1%	35,268
46 to 55	15.0%	23,908
56 to 65	8.7%	13,853
66 and Over	2.9%	4,631
Gender		
Male	70.9%	112,979
Female	29.1%	46,418
Race/Ethnicity		
White non-Hispanic	45.2%	70,484
Hispanic	28.5%	45,503
Black/African American	18.8%	29,931
Other	5.3%	8,527
Asian/Pacific Islander	3.1%	4,951

Table 4 displays race and Hispanic origin estimates for Suffolk County, as reported by the U.S. Census Bureau (2024). When comparing these population estimates to the officer-reported race and ethnicity data for drivers stopped in 2024, several differences emerge. The Census figures show a greater proportion of White residents and a smaller proportion of Black/African American residents than what is reflected in the traffic stop data. However, differences in how race and ethnicity are categorized—particularly the Census Bureau's classification of Hispanic origin as an ethnicity that can span any race—make one-to-one comparisons challenging. As noted by the U.S. Census Bureau (2024), "Hispanics may be of any race, so also are included in applicable race categories," which may help explain these inconsistencies.

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

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

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.

When comparing the racial and ethnic composition of a community—using data sources such as the Census—to the racial makeup reflected in traffic stop data, Ratcliffe and Hyland (2025) caution against drawing straightforward conclusions. The choice of denominator in such comparisons can inadvertently create the appearance of bias, even when none may exist.

Police Department Characteristics

Table 5 presents the distribution of traffic stops by pooled officer command type, providing insight into how stops are allocated across operational units. The pooled categories include Patrol, Highway, Precinct Crime Section, and Other. Patrol officers conducted most stops, accounting for 55.7% (88,711 stops), reflecting their broad responsibility for general traffic enforcement. Highway officers were responsible for 31.5% of stops (50,133), consistent with their role in monitoring major roadways and high-speed areas. Precinct Crime Section units, which support Patrol by targeting violent crime, illegal weapons, gang activity, and quality-of-life offenses, carried out 11.3% of stops (17,950). These units also conduct targeted traffic enforcement, stakeouts, and warrant executions. Stops conducted by officers categorized under “Other” made up just 1.6% (2,603).

Table 5. Traffic Stops by Pooled Officer Command Type

Pooled Category	Percentage	Count
Patrol	55.7%	88,711
Highway	31.5%	50,133
Precinct Crime Section	11.3%	17,950
Other	1.6%	2,603

Table 6 summarizes traffic stops by driver disposition, illustrating the various outcomes following a stop. Nearly half of all traffic stops (49.8%) resulted in a verbal warning, making it the most common disposition, followed closely by summonses, which accounted for 47.4% of stops (75,617). Arrests and entries categorized as "Other" each represented 0.8% of cases, with 1,262 and 1,253 stops respectively. A small number of drivers received Lights-On Vouchers (0.2%, or 301 stops), while 1.6% of stops (2,505) concluded with no police action taken. Field Appearance Tickets were issued in just 0.2% of stops (288), and only four stops (0.0%) involved providing aid to the driver. These figures highlight that most traffic stop outcomes involve either verbal warnings or summonses, with enforcement or assistance-based outcomes occurring far less frequently.

Table 6. Traffic Stops by Driver Disposition

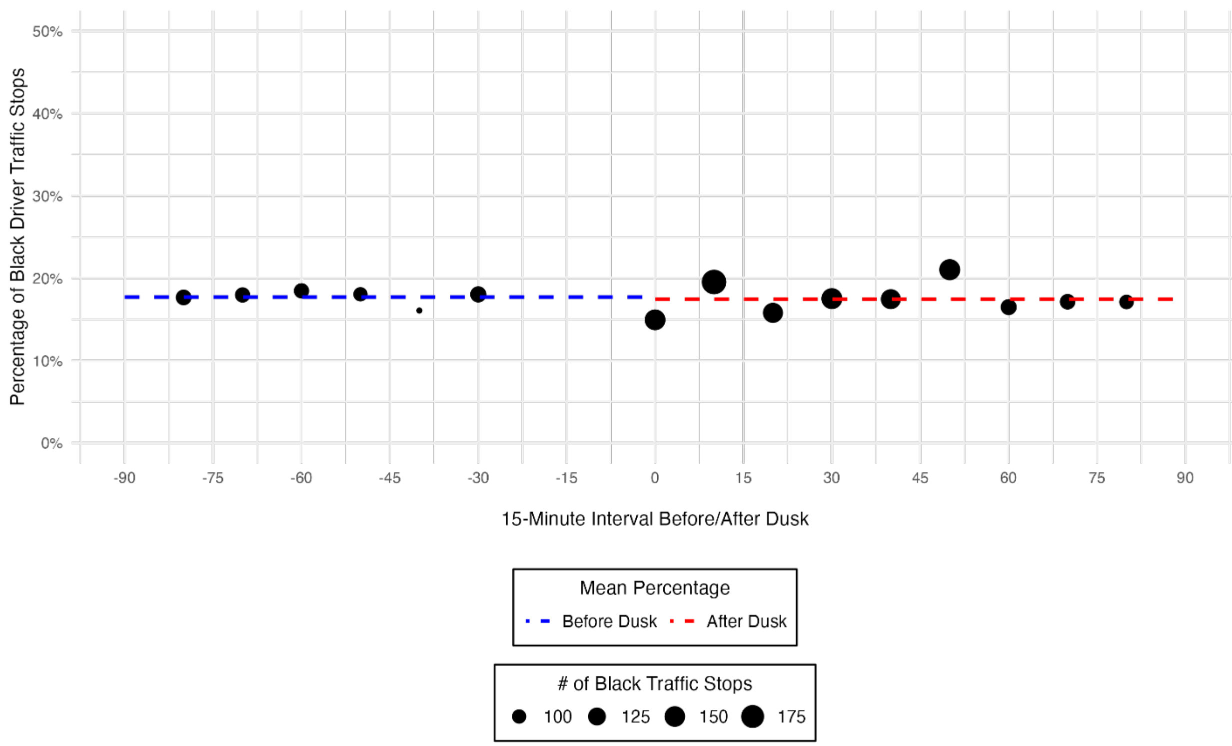
Category	Percentage	Count
Verbal Warning Issued	49.8%	79,420
Summons	47.4%	75,617
Other	0.8%	1,253
Arrest	0.8%	1,262
Lights-On Voucher	0.2%	301
No Police Action Taken	1.6%	2,505
Field Appearance Ticket	0.2%	288
Aided	0.0%	4

The next sub-section addresses results from the analysis of potential bias in traffic stop 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.

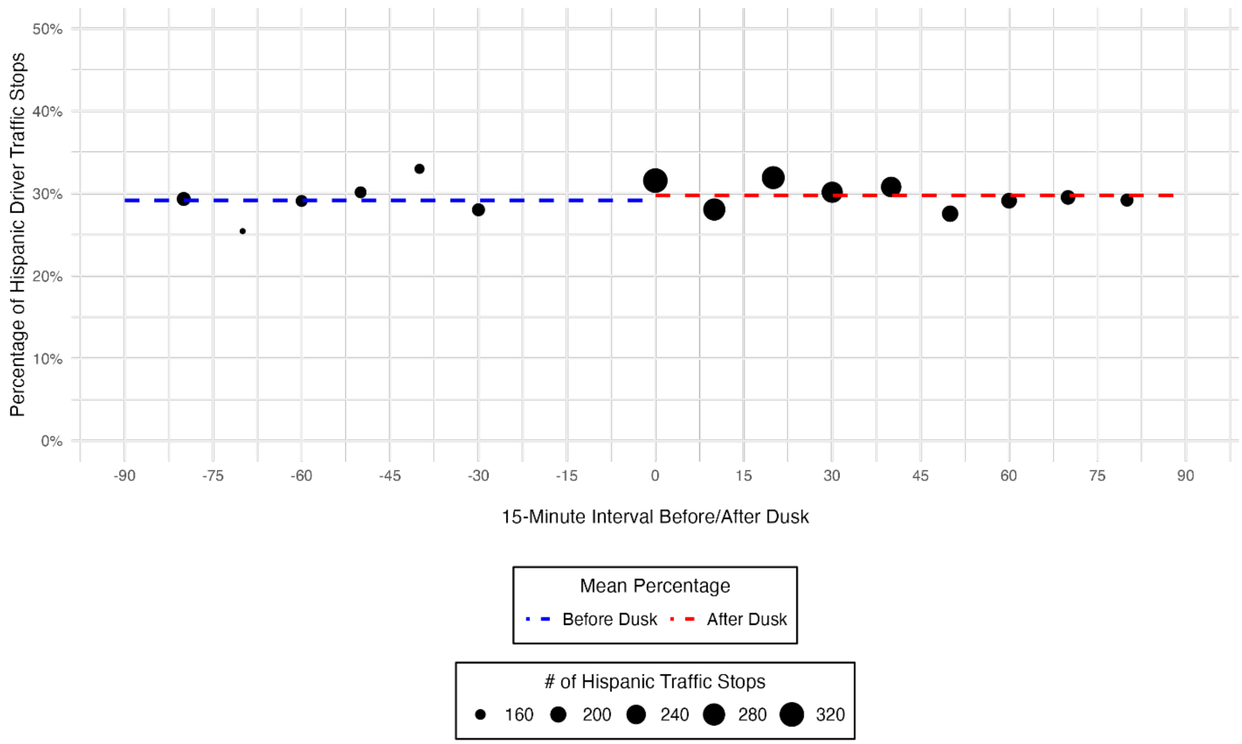
Figure 2. Black Driver Traffic Stops Before and After Dusk



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 very 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 the ability to discern a driver's race in daylight may not significantly influence stop decisions for Hispanic drivers.

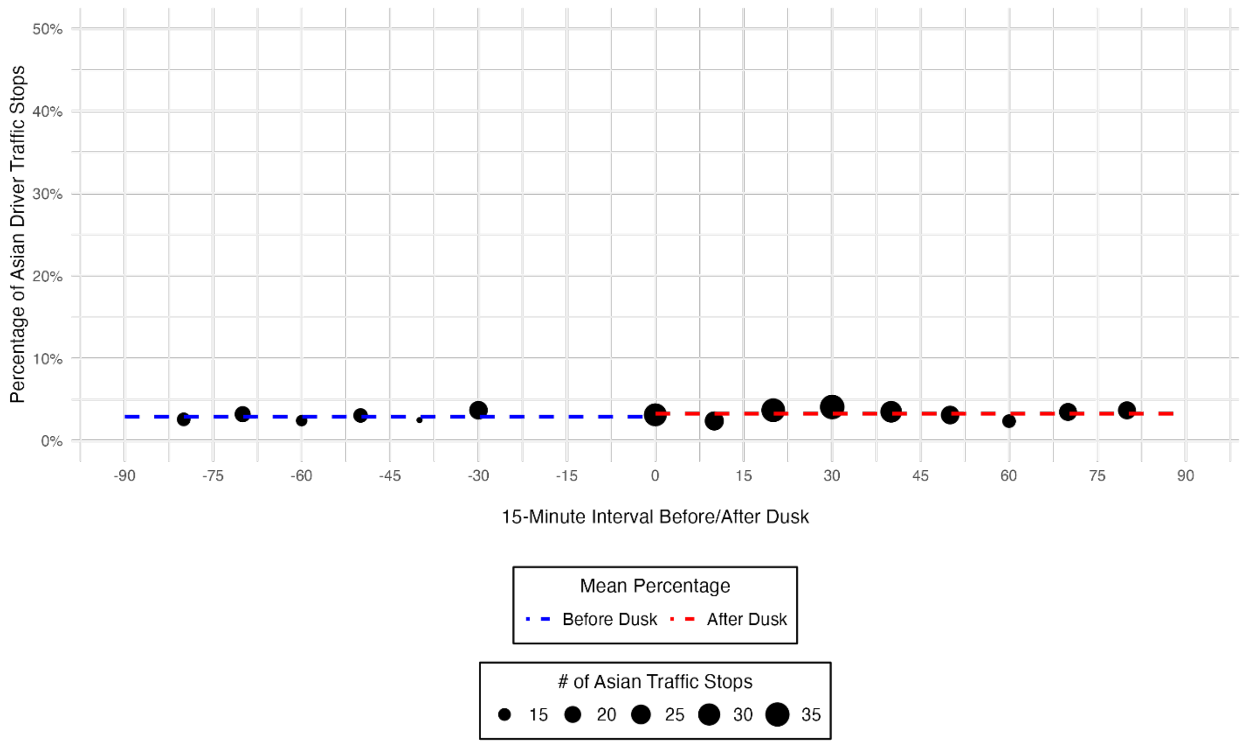
Figure 3. Hispanic Driver Traffic Stops Before and After Dusk



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. Of note, the relatively small size of the data points indicates fewer total stops involving Asian drivers compared to other racial or ethnic groups.

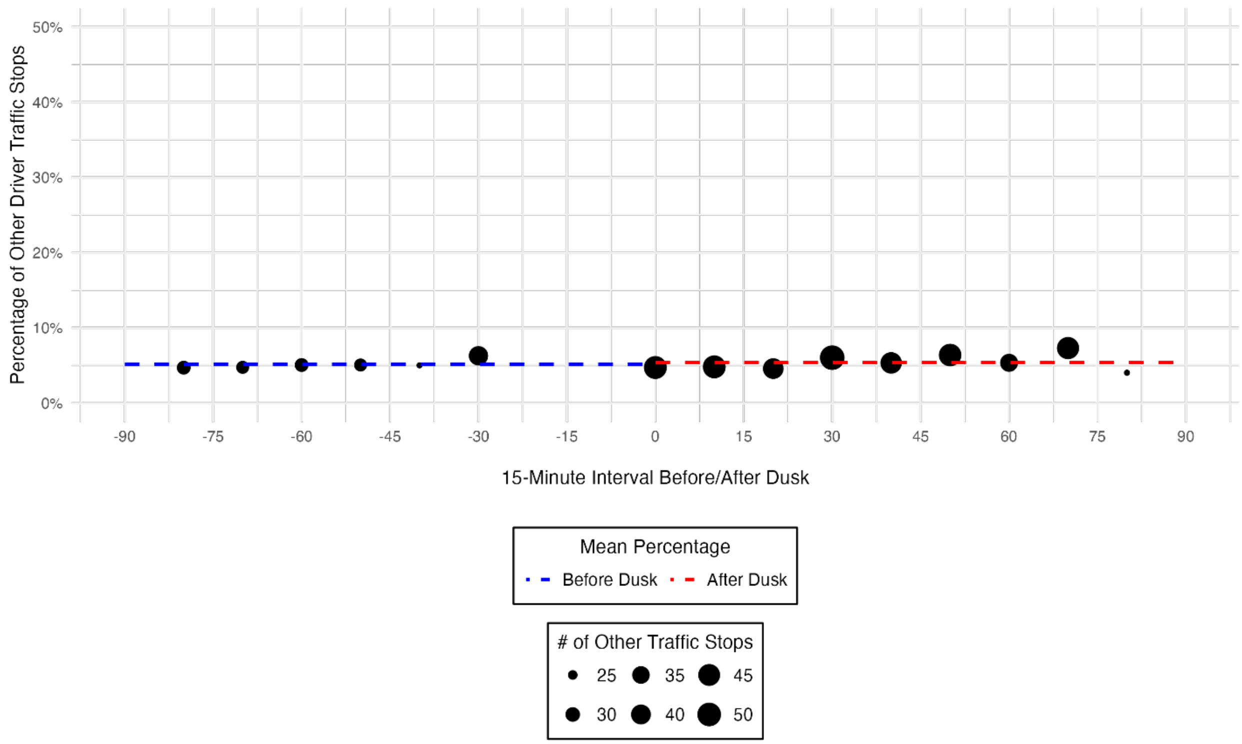
Figure 4. Asian Driver Traffic Stops Before and After Dusk



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 5 reveals little variation in the percentage of "Other" drivers stopped before and after dusk, with the mean percentages remaining 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.

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 likelihood of a traffic stop across racial and ethnic groups, using White drivers as the reference category. These models account for factors such as time of day and officer command type, with nighttime stops and the precinct patrol section serving as the baseline comparison groups. Results are expressed as odds ratios (ORs), which quantify the strength and direction of the association between group membership and the likelihood of being stopped. An OR greater than 1.0 indicates that the odds of the outcome are higher compared to the reference group, while an OR less than 1 means the odds are lower. For instance, an OR of 1.50 implies a 50 percent increase in odds, whereas an OR of 0.75 indicates a 25 percent decrease. In the interpretation of the models to the Veil of Darkness test, an OR greater than 1.0 could imply a bias of stopping minority drivers as compared to White drivers. In the same vein, a value equal to 1.0 would indicate the odds are equal for minority drivers being stopped as compared to White drivers, whereas an OR less than 1.0 would indicate that minority drivers have lower odds of being stopped as compared to White drivers.

To determine whether these associations are statistically meaningful, p-values are used to test the null hypothesis that the OR equals 1.0 (i.e., no difference). A p-value below 0.05 suggests the observed effect is unlikely to be due to random variation. However, statistical significance should not be interpreted as practical importance. Confidence intervals (CIs) provide additional context—if the 95% CI does not include 1, the result is typically considered statistically significant. On the other hand, if the CI spans 1.0, the estimated effect may not be robust or consistently observed across samples.

For all minority drivers, as displayed in Table 7, drivers stopped during the daytime had lower odds of being a minority compared to those stopped at night. Specifically, the odds were about 15% lower during the day (OR = 0.852), and this result was statistically significant, meaning it is unlikely due to chance. Compared to patrol officers, stops made by Precinct Crime units were slightly less likely to involve minority drivers (OR = 0.922), and this difference was also statistically significant. Similarly, stops conducted by Highway officers were about 12% less likely to involve minority drivers (OR = 0.881), again with a statistically significant result. Stops conducted by officers in the "Other" category showed a slightly higher likelihood of involving minority drivers (OR = 1.079), but this result was not statistically significant, indicating the difference could be due to random variation.

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept[2]	1.417	0.017	<0.001	[1.370, 1.466]
Daytime	0.852	0.018	<0.001	[0.822, 0.882]
Precinct Crime	0.922	0.020	<0.001	[0.887, 0.958]
Highway	0.881	0.014	<0.001	[0.857, 0.905]
Other	1.079	0.050	0.133	[0.977, 1.191]

Table 8 presents the results for Black drivers. Stops that occurred during the daytime were about 9% less likely to involve Black drivers than those made at night (OR = 0.906). This difference is statistically significant, meaning it is unlikely to be due to chance. When comparing officer command types to the Patrol reference group, stops made by Precinct Crime officers were slightly less likely to involve Black drivers (OR = 0.935), and this result was statistically significant. Highway officers had a more pronounced difference—stops conducted by this group were about 30% less likely to involve Black drivers (OR = 0.701), a statistically significant finding. For stops involving officers in the "Other" category, the odds of stopping a Black driver were slightly higher (OR = 1.107), but this result was not statistically significant, suggesting the difference may be due to random variation.

[2] 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.

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.476	0.024	<0.001	[0.454, 0.498]
Daytime	0.906	0.025	<0.001	[0.863, 0.951]
Precinct Crime	0.935	0.027	0.012	[0.887, 0.986]
Highway	0.701	0.020	<0.001	[0.674, 0.729]
Other	1.107	0.067	0.129	[0.970, 1.260]

For Hispanic drivers, in Table 9, the model demonstrates that drivers stopped during the daytime were about 15% less likely to be Hispanic than those stopped at night (OR = 0.852), and this result was statistically significant. Stops made by Precinct Crime officers were slightly less likely to involve Hispanic drivers compared to stops by Patrol officers (OR = 0.922), and this finding was statistically significant. Highway officers were even less likely to stop Hispanic drivers, with the odds about 20% lower than those stopped by Patrol officers (OR = 0.803), also statistically significant. Stops conducted by officers in the "Other" category had slightly higher odds of involving Hispanic drivers (OR = 1.065), but this result was not statistically significant, suggesting the difference could be due to chance.

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.755	0.020	<0.001	[0.726, 0.786]
Daytime	0.852	0.021	<0.001	[0.818, 0.888]
Precinct Crime	0.922	0.023	<0.001	[0.881, 0.966]
Highway	0.803	0.017	<0.001	[0.777, 0.830]
Other	1.065	0.059	0.291	[0.947, 1.196]

Table 10 presents the logistic regression results for Asian drivers. Stops conducted during the daytime were about 26% less likely to involve Asian drivers than those made at night (OR = 0.738), and this result was statistically significant. Compared to stops made by Patrol officers, stops by Precinct Crime officers were substantially less likely to involve Asian drivers, with the odds reduced by over 50% (OR = 0.460), a statistically significant result. Stops by Highway officers were also less likely to involve Asian drivers, with odds about 25% lower (OR = 0.753), which was statistically significant as well. Stops by officers in the "Other" category showed slightly lower odds of involving Asian drivers (OR = 0.899), but this result was not statistically significant, suggesting the difference may be due to random variation.

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.098	0.047	<0.001	[0.089, 0.107]
Daytime	0.738	0.050	<0.001	[0.670, 0.814]
Precinct Crime	0.460	0.075	<0.001	[0.396, 0.531]
Highway	0.753	0.042	<0.001	[0.694, 0.817]
Other	0.899	0.151	0.480	[0.660, 1.195]

For Other drivers, Table 11 shows that traffic stops during the daytime were about 24% less likely to involve drivers in the "Other" category than stops made at night (OR = 0.756), and this result was statistically significant. Compared to Patrol officers, stops conducted by Precinct Crime officers were significantly more likely to involve drivers in the "Other" category, with a 39% increase in odds (OR = 1.392). Highway officers showed an even stronger association—stops by this group were over three times more likely to involve drivers in the "Other" category compared to Patrol (OR = 3.076). Both results were statistically significant. Stops by officers in the "Other" command group also showed slightly higher odds of involving drivers in the "Other" racial category (OR = 1.228), but this result was not statistically significant, indicating the difference may be due to chance.

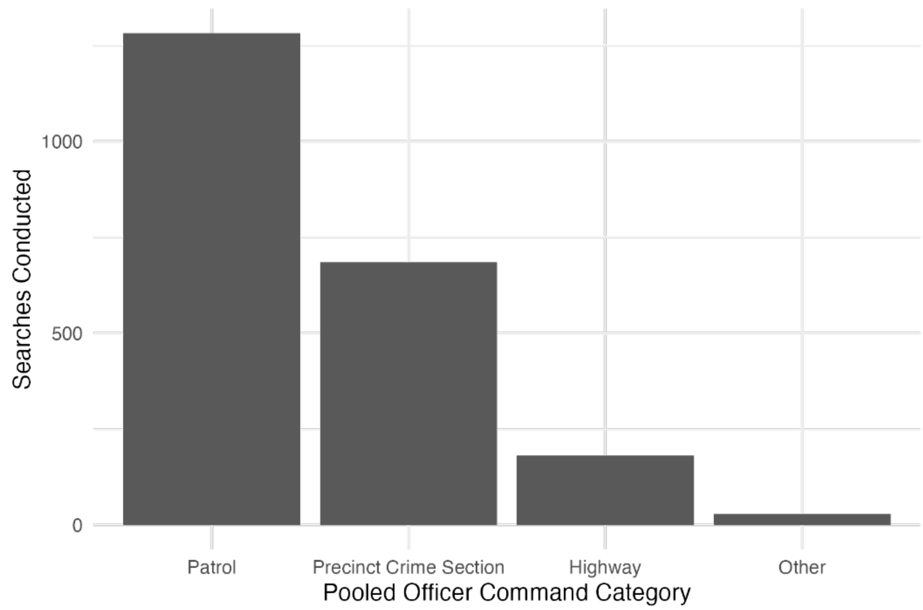
Table 11. Adjusted Logistic Regression Model Results (Other Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.081	0.042	<0.001	[0.074, 0.087]
Daytime	0.756	0.041	<0.001	[0.698, 0.820]
Precinct Crime	1.392	0.052	<0.001	[1.255, 1.541]
Highway	3.076	0.032	<0.001	[2.888, 3.278]
Other	1.228	0.142	0.149	[0.919, 1.607]

Assessing Bias in Traffic Stop Search Decisions

Figure 6 displays the distribution of traffic stops with a search by officer command category. Patrol and Precinct Crime Sections account for most of the traffic stops with a search. 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. The data show that searches were conducted in a small portion of stops—2,176 out of 159,397, or approximately 1.3 percent. Of those, 408 searches (18.7 percent) led to the recovery of illegal drugs, weapons, or other contraband. Nearly 80 percent of searches, had a negative search result.

Table 12. Traffic Stop Searches and Result Outcome Findings

Search Conducted	Positive Search Result	Negative Search Result
Yes	408	1,768
No	0	157,221

Analyzing search outcomes by race and ethnicity can offer insights into potential differences in how traffic stop searches are conducted and what they yield. Table 13 displays the number and percentage of searches that resulted in a positive finding—defined as the recovery of contraband or other evidence—across racial groups. White drivers had the highest positive search rate, with 23.2 percent of searches (161 out of 694) resulting in evidence being found. For Black/African American drivers, 17.5 percent of searches (126 out of 721) were positive, while the rate for Hispanic drivers was slightly lower at 15.8 percent (112 out of 708). Among Asian drivers, 18.2 percent of searches (4 out of 22) yielded a positive result, and drivers categorized as "Other" had a 16.1 percent rate (5 out of 31). These differences in hit rates suggest that searches of minority drivers were, on average, less likely to result in recovered evidence than those of White drivers.

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

Race / Ethnicity	Positive Search Result	Negative Search Result
White	161 (23.2%)	533 (76.8%)
Black / African American	126 (17.5%)	595 (82.5%)
Hispanic	112 (15.8%)	596 (84.2%)
Asian	4 (18.2%)	18 (81.8%)
Other	5 (16.1%)	26 (83.9%)

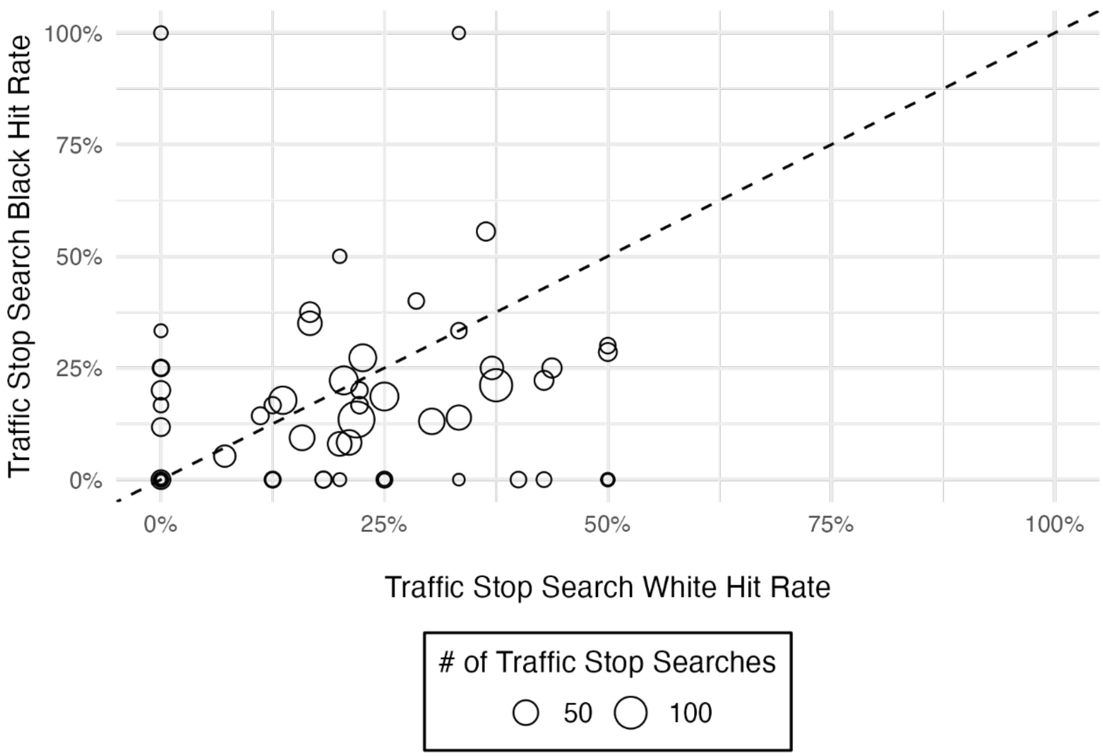
Note: Percentage values may not sum to 100 due to rounding.

The next series of 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. To supplement the figures, a statistical test is performed to examine differences in hit rates by racial category. Tests were not performed if fewer than 30 hamlets had corresponding data.

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.

In Figure 7, the distribution of hamlets and traffic stops with searches is spread across both sides of the diagonal line. There are slightly 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. 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.

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

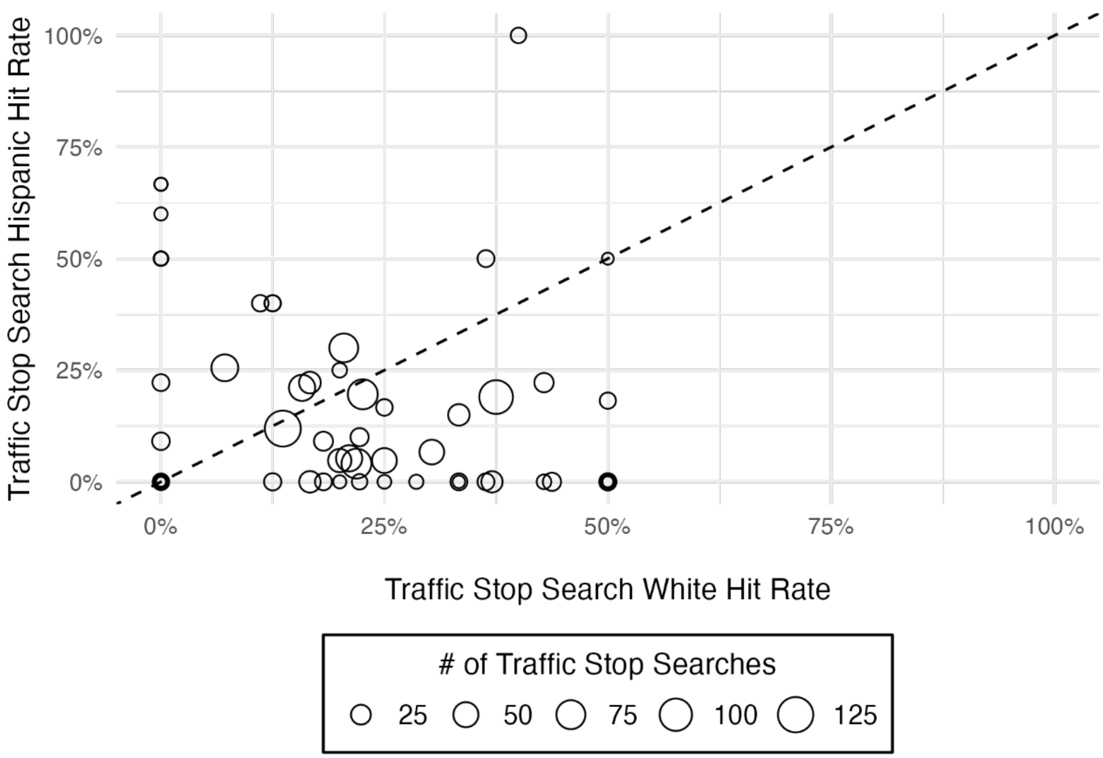


A statistical analysis of the differences in hit rates between Black and White drivers revealed a mean difference[3] of 3.2%. However, the results do not provide sufficient evidence to conclude that this difference is statistically significant ($t = 0.940$, $df = 55$, $p = 0.351$).

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.

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

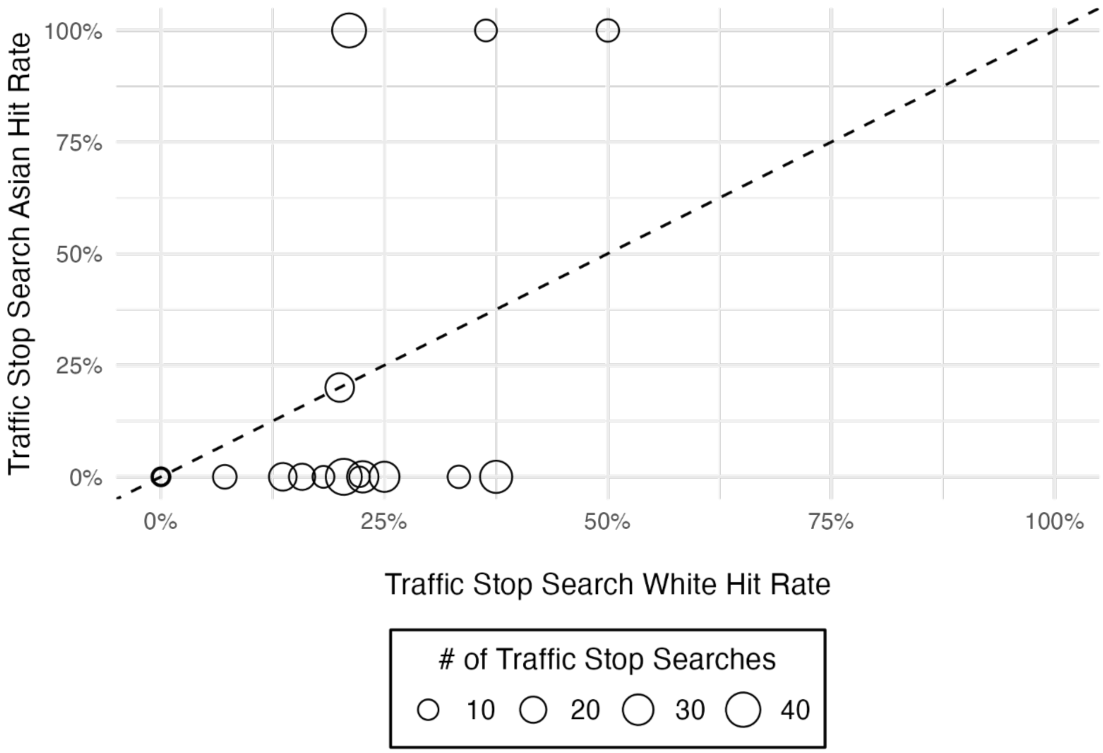
Figure 8. Hispanic Driver and White Drive Hit Rates by Hamlet



A statistical analysis of the differences in hit rates between Hispanic and white drivers revealed a mean difference of 2.8%. However, the results do not provide sufficient evidence to conclude that this difference is statistically significant (t = 0.708, df = 55, p = 0.481).

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. Most hamlets are positioned below the diagonal with two falling exactly on the diagonal. For the points falling below the diagonal line, 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.

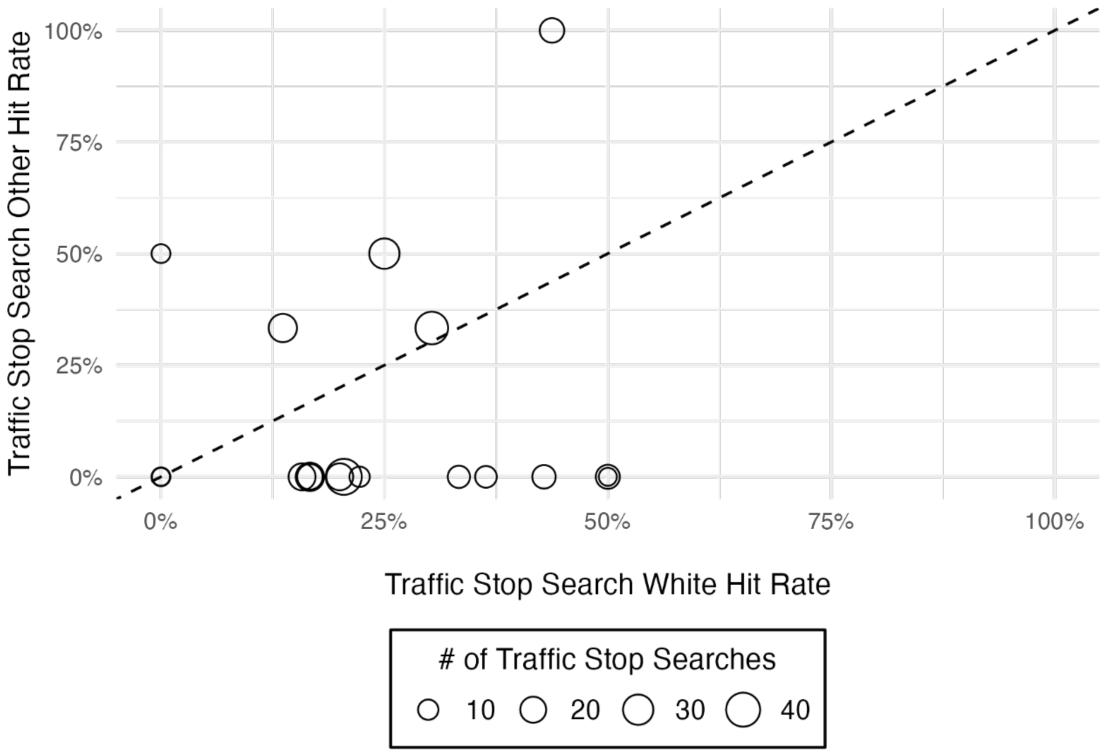
Figure 9. Asian Driver and White Driver Hit Rates by Hamlet



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.

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 data points fall below on both side of the diagonal with no clear pattern. 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.

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



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.

Enforcement Action Outcomes in Traffic Stops

Table 14 presents the pooled categories of the reasons for traffic stops, cross-tabulated by whether the outcome resulted in an enforcement action or no enforcement action. As outlined in the Methodology section, stop reasons are grouped into three main categories: moving violations, equipment violations, and other reasons, such as stops based on probable cause or reasonable suspicion of criminal activity. Similarly, enforcement actions are defined as those that result in a summons, arrest, or field appearance ticket, while non-enforcement actions include verbal warnings, educational interactions, and instances where no formal action was taken.

In Table 14, the data show that moving violations are the most likely to result in enforcement action, with 52.1% of these stops (53,046 out of 101,721) leading to some form of enforcement. The remaining 47.9% (48,675) ended without enforcement. In contrast, equipment violations were more likely to result in non-enforcement outcomes. Just 41.7% (23,747) of stops for equipment-related issues led to enforcement, while a larger share—58.3% (33,139)—ended without enforcement action. Stops classified as “Other,” were more evenly split, with 47.3% (374) resulting in enforcement and 52.7% (416) not resulting in any formal action.

Table 14. Enforcement Action Outcomes by Reason for Traffic Stop

Reason for Traffic Stop	Enforcement Action	No Enforcement Action
Moving Violation	53,046 (52.1%)	48,675 (47.9%)
Equipment Violation	23,747 (41.7%)	33,139 (58.3%)
Other	374 (47.3%)	416 (52.7%)

Figure 11 displays enforcement action outcomes by race through a mosaic plot. The vertical axis reflects the proportion of traffic stops resulting in either enforcement (orange) or no enforcement (green), with each bar summing to 100%. Across almost all groups, most traffic stops did not result in enforcement, as shown by the green portion of each bar. However, the relative size of the orange (enforcement) segment varies by group. Black and Hispanic drivers appear to have higher proportions of enforcement actions compared to White drivers. In contrast, White drivers show a larger share of stops with no enforcement action. The bars also vary in width, representing differences in the total number of stops for each group.

Figure 11. Mosaic Plot of Enforcement Actions by Race

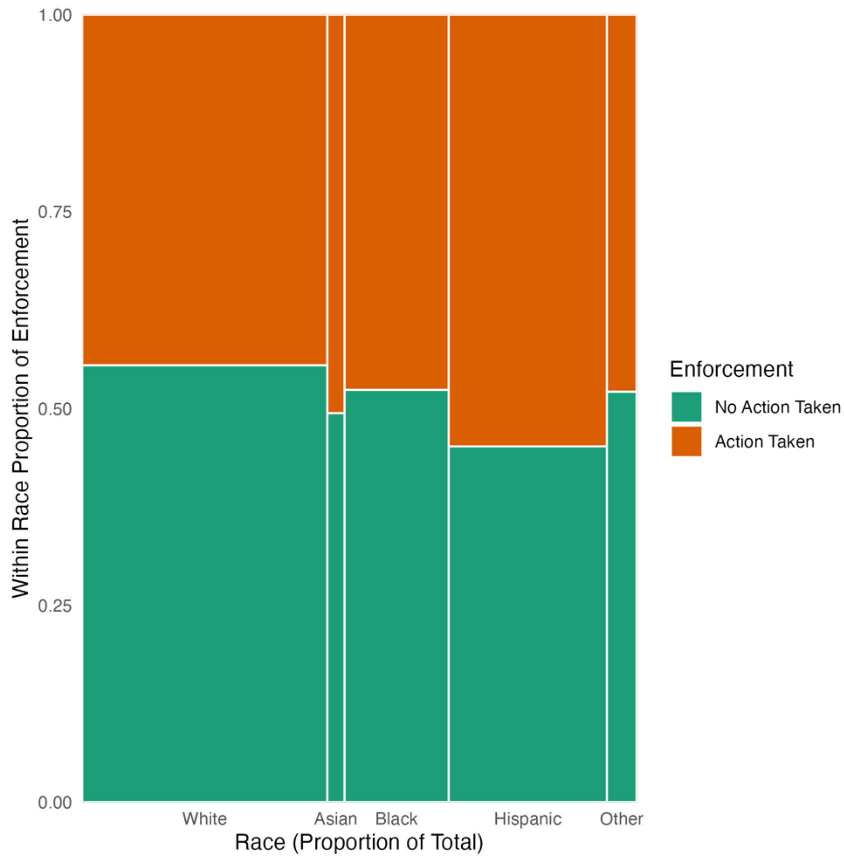


Table 15 presents the model results for enforcement action outcomes in a traffic stop. The logistic regression analysis evaluated the likelihood of enforcement actions—such as arrests, summonses, or field appearance tickets—based on the driver's race and the reason for the stop. The model included both main effects and interaction terms to assess how enforcement patterns varied across different racial and ethnic groups and stop types. Interaction terms allow for the examination of whether the relationship between one variable (e.g., race or ethnicity) and the likelihood of enforcement changes depending on another variable (e.g., the type of stop). This helps identify nuanced patterns—such as whether certain racial or ethnic groups are more or less likely to experience enforcement depending on the context of the stop—that would not be captured by examining each factor independently.

For equipment violations, Black and Hispanic drivers had significantly higher odds of receiving an enforcement action compared to White drivers. Specifically, Black drivers were found to have 11 percent higher odds, while Hispanic drivers had 33 percent higher odds of enforcement. There were no statistically significant differences in enforcement outcomes for Asian or Other race drivers compared to White drivers for this category of stops. The nature of the traffic stop also influenced enforcement likelihood. Among White drivers, those stopped for moving violations had 40 percent higher odds of enforcement compared to those stopped for equipment violations. White drivers stopped for “other” reasons—such as probable cause or reasonable suspicion—faced 53 percent higher odds of enforcement than those stopped for equipment-related reasons. The interaction effects in the model provided further insight into how enforcement patterns shifted when considering both race and stop reason. When examining moving violations, minority drivers consistently experienced higher odds of enforcement compared to White drivers stopped for the same reason. Black drivers stopped for a moving violation had 14 percent higher odds of enforcement, Hispanic drivers had 36 percent higher odds, Asian drivers had 33 percent higher odds, and drivers categorized as Other had 12 percent higher odds. These differences were statistically significant, suggesting that disparities are most pronounced in the context of moving violations. In contrast, for stops categorized as "other," the pattern reversed in most cases. Black drivers had 23 percent lower odds of enforcement than White drivers, and Hispanic drivers had 25 percent lower odds, though neither result reached statistical significance. Drivers identified as Asian had 80 percent lower odds of enforcement compared to White drivers, a result that was statistically significant. Drivers classified as Other had 46 percent lower odds of enforcement for these types of stops, though this difference was not statistically significant.

Table 15. Enforcement Action Outcome Logistic Regression Results

Term	OR Estimate	Standard Error	p-value	95% OR CI
(Intercept)	0.633	0.014	<0.001	[0.616, 0.651]
Asian	1.037	0.057	0.528	[0.927, 1.159]
Black	1.114	0.023	<0.001	[1.066, 1.165]
Hispanic	1.327	0.020	<0.001	[1.276, 1.382]
Other (race)	1.041	0.046	0.387	[0.950, 1.140]
Moving violation	1.396	0.017	<0.001	[1.351, 1.443]
Other (violation)	1.530	0.114	<0.001	[1.222, 1.914]
Asian : moving violation	1.331	0.067	<0.001	[1.168, 1.518]
Black : moving violation	1.143	0.029	<0.001	[1.080, 1.210]
Hispanic : moving violation	1.361	0.026	<0.001	[1.294, 1.431]
Other : moving violation	1.116	0.053	0.041	[1.005, 1.239]
Asian : other (violation)	0.199	0.785	0.040	[0.030, 0.775]
Black : other (violation)	0.770	0.179	0.144	[0.541, 1.093]
Hispanic : other (violation)	0.752	0.174	0.102	[0.534, 1.058]
Other (race) : other (violation)	0.541	0.522	0.240	[0.182, 1.465]

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. From a review of the data and analysis, there is no evidence in the 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. There is insufficient evidence to conclude a significant difference in hit rates between minority and White drivers when compared across geographic areas.

When examining enforcement action outcomes in traffic stops by race, the model suggests that racial and ethnic disparities are most pronounced for moving violations, where minority drivers are more likely than White drivers to receive enforcement outcomes. For other categories of stops, the direction and extent of disparities vary, with some groups experiencing lower odds of enforcement. While these statistical findings offer important insight, they do not definitively confirm whether bias is present. Latent variables not captured in the dataset—such as the severity of the offense (e.g., for a speeding driver, the amount in excess of the speed limit), officer discretion, or contextual circumstances—may provide additional explanatory value.

One of the notable strengths of this analysis is the use of a large dataset containing nearly 160,000 traffic stop records. This volume of data improves the precision of estimates and reduces the influence of random variation. The quality of the data is also a strong point, with complete and well-documented stop records that include variables essential to a robust analysis. A further advantage is the integration of time-stamped data with official sunset times, allowing for an objective classification of stops into day or night conditions—a key requirement for implementing the Veil-of-Darkness methodology. By using an established and widely respected analytical approach, the analysis ensures consistency with best practices in traffic stop research.

At the same time, several limitations should be considered. The analysis depends on officer-reported information, including race and ethnicity classifications that may not always reflect how individuals self-identify. This can introduce some degree of reporting error. The Veil-of-Darkness test, while a powerful tool, does not definitively establish the presence or absence of racial bias, and its findings must be interpreted within a broader context. Similarly, the Hit Rate test is subject to the challenge of infra-marginality—where differences in individual risk profiles across groups may influence search outcomes, even in the absence of biased decision-making. Some traffic stops are triggered by non-discretionary factors, such as warrants, that are unrelated to a driver's race and therefore complicate overall interpretations. This can be a confounding factor when considering outcomes of traffic stop enforcement actions.

Future studies should expand upon this analysis by incorporating additional years of traffic stop data to evaluate trends over time and assess the consistency of observed patterns. One possibility is to look at the amount of change SCPD has undergone in police interactions with the public over a number of years (pending available data). This would allow for ongoing review, an assessment of what has been accomplished and would allow for a clear path as to what could be continuously improved. From a statistical modeling perspective, this would allow for an examination in the rate of change over time. In general, ongoing analysis is essential to identify any shifts in enforcement practices and to monitor for emerging disparities.

Building on this work, future research could also examine more detailed factors influencing traffic stops, such as officer demographics, assignment patterns, or localized geographic variation. Linking traffic stop records with other data sources—such as traffic collision data, citation outcomes, body-worn camera footage, or internal review records—may also enhance understanding of the context surrounding stop decisions and post-stop interactions. This is particularly important in cases where analysis has highlighted potential racial bias or profiling in traffic stops. As an example, traffic enforcement efforts are strategically focused on areas with higher rates of collisions, reflecting the core public safety objective of traffic enforcement: preventing crashes and saving lives. Because these high-collision areas may also reflect underlying demographic patterns, enforcement outcomes can be shaped by geographic and population factors. Implementing a sustained, structured approach to data collection and analysis is essential to ensure transparency, support accountability, and guide evidence-based policy and practice across both agency operations and community engagement.

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Appendix

Precinct # 1

Assessing Bias in Traffic Stop Decisions

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	1.018	0.053	0.742	[0.917, 1.130]
Daytime	0.953	0.058	0.407	[0.851, 1.068]
Precinct Crime	0.814	0.088	0.019	[0.684, 0.966]
Highway	0.690	0.068	<0.001	[0.604, 0.789]
Other	0.817	0.175	0.249	[0.579, 1.150]

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	1.078	0.053	0.153	[0.972, 1.196]
Daytime	0.905	0.057	0.081	[0.809, 1.012]
Precinct Crime	0.605	0.095	<0.001	[0.501, 0.728]
Highway	0.850	0.065	0.012	[0.749, 0.964]
Other	0.844	0.173	0.324	[0.600, 1.182]

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.130	0.113	<0.001	[0.103, 0.161]
Daytime	0.775	0.124	0.040	[0.610, 0.993]
Precinct Crime	0.785	0.211	0.250	[0.507, 1.164]
Highway	0.556	0.182	0.001	[0.383, 0.783]
Other	1.381	0.327	0.324	[0.688, 2.515]

Table 19. Precinct # 1 Adjusted Logistic Regression Model Results (Other Driver)

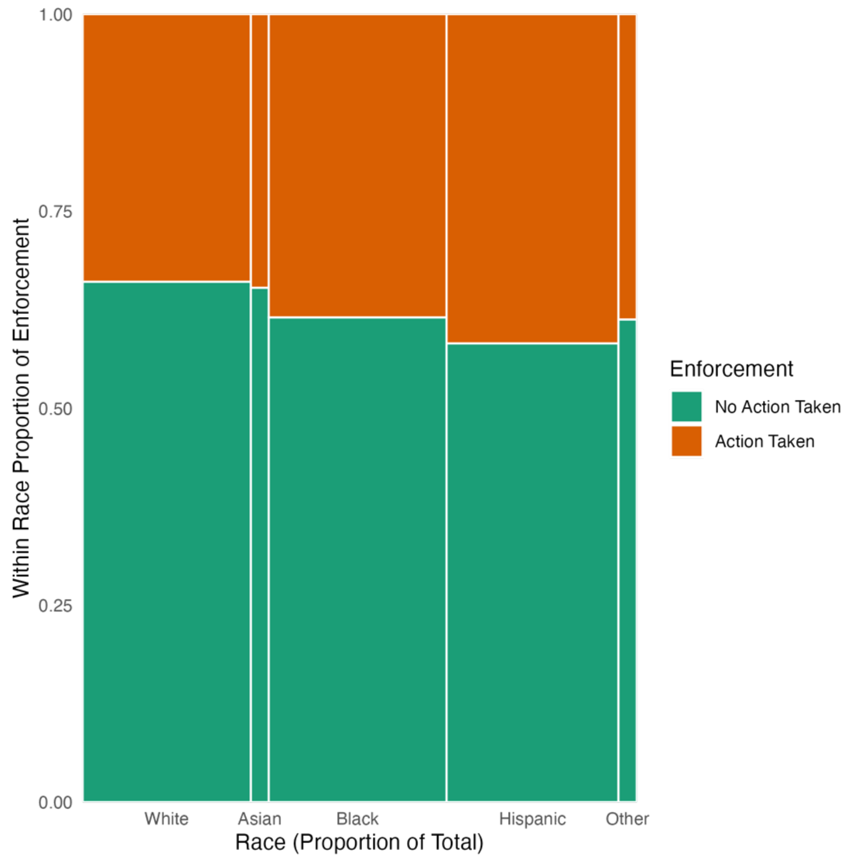
Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.111	0.116	<0.001	[0.088, 0.139]
Daytime	0.722	0.127	0.011	[0.565, 0.932]
Precinct Crime	0.185	0.454	<0.001	[0.066, 0.406]
Highway	3.117	0.107	<0.001	[2.522, 3.843]
Other	0.623	0.517	0.360	[0.189, 1.513]

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: 14 hamlets for Black–White, 14 for Hispanic–White, 6 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.

Enforcement Action Outcomes in Traffic Stops

Figure 12. Precinct # 1 Mosaic Plot of Enforcement Actions by Race



Precinct # 2

Assessing Bias in Traffic Stop Decisions

In the models involving Black, Hispanic, and Asian drivers for Precinct 2, model instability from the "Other" officer command category (due to too few observations) prevented the results of the full model from being published here. The unadjusted model, however, with the main variable of interest (daytime) is included.

Table 20. Precinct # 2 Unadjusted Logistic Regression Model Results (Black Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.325	0.069	<0.001	[0.284, 0.372]
Daytime	0.990	0.075	0.898	[0.855, 1.150]

Table 21. Precinct # 2 Unadjusted Logistic Regression Model Results (Hispanic Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.834	0.051	<0.001	[0.755, 0.921]
Daytime	0.780	0.056	<0.001	[0.699, 0.871]

Table 22. Precinct # 2 Unadjusted Logistic Regression Model Results (Asian Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.165	0.091	<0.001	[0.138, 0.196]
Daytime	0.576	0.104	<0.001	[0.471, 0.709]

Table 23. Precinct #2 Adjusted Logistic Regression Model Results (Other Driver)

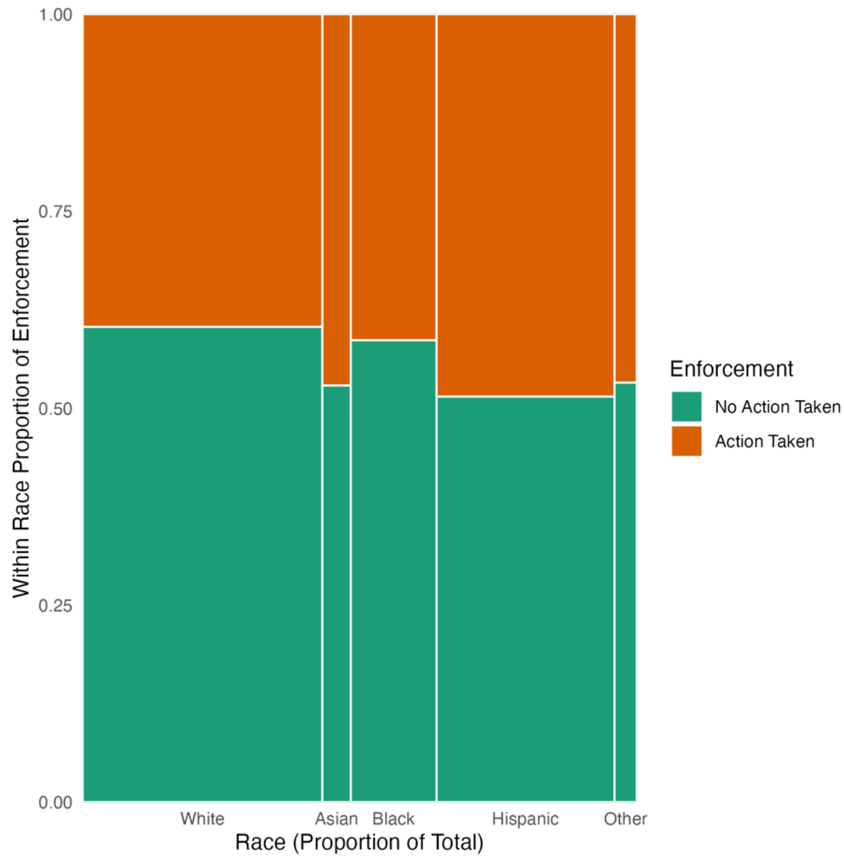
Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.066	0.133	<0.001	[0.050, 0.084]
Daytime	0.971	0.143	0.834	[0.739, 1.293]
Precinct Crime	1.760	0.173	0.001	[1.239, 2.445]
Highway	2.463	0.127	<0.001	[1.912, 3.151]
Other	3.855	1.121	0.229	[0.196, 26.271]

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: 6 hamlets for Black–White, 6 for Hispanic–White, 2 for Asian–White, and 1 for Other–White comparisons. With such limited data, statistical power is reduced, increasing the chance that meaningful differences go undetected and results become misleading.

Enforcement Action Outcomes in Traffic Stops

Figure 13. Precinct # 2 Mosaic Plot of Enforcement Actions by Race



Precinct # 3

Assessing Bias in Traffic Stop Decisions

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.952	0.076	0.519	[0.819, 1.106]
Daytime	1.108	0.081	0.207	[0.945, 1.300]
Precinct Crime	1.121	0.093	0.220	[0.934, 1.347]
Highway	0.542	0.092	<0.001	[0.452, 0.648]
Other	0.987	0.222	0.953	[0.638, 1.528]

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	2.705	0.062	<0.001	[2.398, 3.056]
Daytime	0.909	0.066	0.147	[0.798, 1.033]
Precinct Crime	1.398	0.078	<0.001	[1.203, 1.631]
Highway	0.865	0.068	0.033	[0.757, 0.989]
Other	1.619	0.177	0.006	[1.158, 2.317]

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.115	0.174	<0.001	[0.081, 0.160]
Daytime	0.920	0.189	0.661	[0.643, 1.351]
Precinct Crime	0.346	0.347	0.002	[0.163, 0.645]
Highway	0.273	0.315	<0.001	[0.139, 0.483]
Other	0.677	0.603	0.518	[0.163, 1.883]

Table 27. Precinct #3 Adjusted Logistic Regression Model Results (Other Driver)

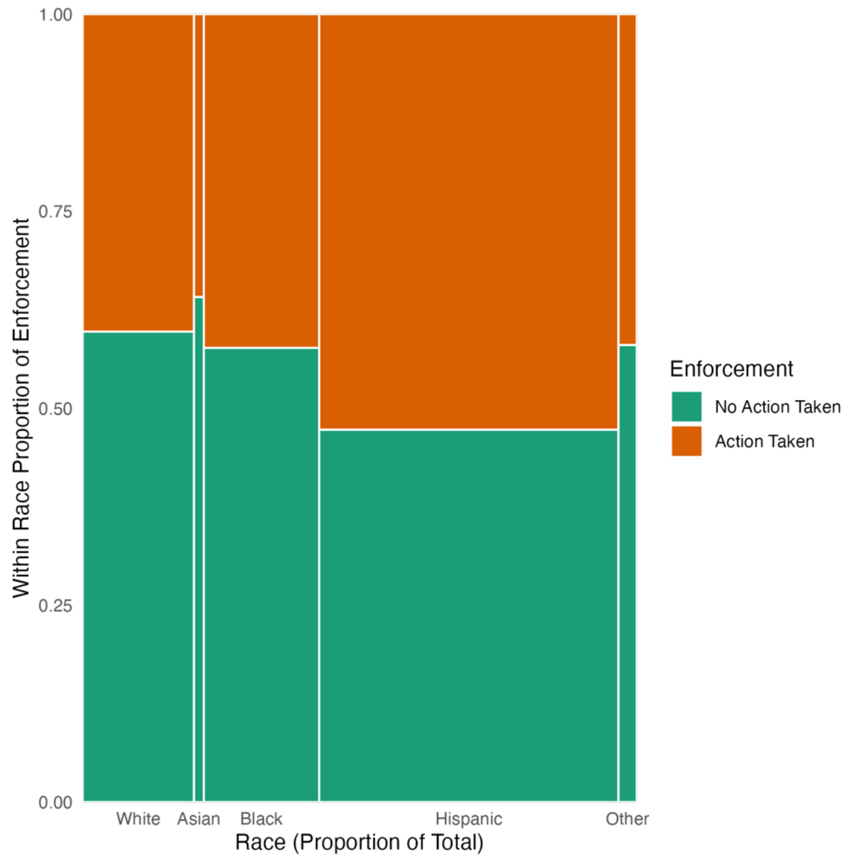
Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.128	0.146	<0.001	[0.095, 0.169]
Daytime	0.627	0.155	0.003	[0.465, 0.857]
Precinct Crime	3.070	0.162	<0.001	[2.221, 4.203]
Highway	2.539	0.147	<0.001	[1.895, 3.379]
Other	0.270	1.016	0.198	[0.015, 1.257]

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: 9 hamlets for Black–White, 8 for Hispanic–White, 2 for Asian–White, and 2 for Other–White comparisons. With such limited data, statistical power is reduced, increasing the likelihood that meaningful differences go undetected and results become misleading.

Enforcement Action Outcomes in Traffic Stops

Figure 14. Precinct # 3 Mosaic Plot of Enforcement Actions by Race



Precinct # 4

Assessing Bias in Traffic Stop Decisions

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.208	0.115	<0.001	[0.166, 0.260]
Daytime	0.731	0.118	0.008	[0.582, 0.925]
Precinct Crime	1.314	0.106	0.010	[1.065, 1.612]
Highway	1.067	0.102	0.526	[0.871, 1.301]
Other	1.115	0.366	0.765	[0.509, 2.175]

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.399	0.088	<0.001	[0.335, 0.473]
Daytime	0.768	0.090	0.003	[0.645, 0.917]
Precinct Crime	1.448	0.079	<0.001	[1.239, 1.688]
Highway	1.539	0.070	<0.001	[1.341, 1.765]
Other	2.265	0.222	<0.001	[1.456, 3.488]

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.100	0.162	<0.001	[0.072, 0.135]
Daytime	0.828	0.167	0.258	[0.602, 1.162]
Precinct Crime	1.199	0.144	0.209	[0.897, 1.581]
Highway	0.500	0.180	<0.001	[0.346, 0.703]
Other	1.410	0.437	0.432	[0.537, 3.072]

Table 31. Precinct #4 Adjusted Logistic Regression Model Results (Other Driver)

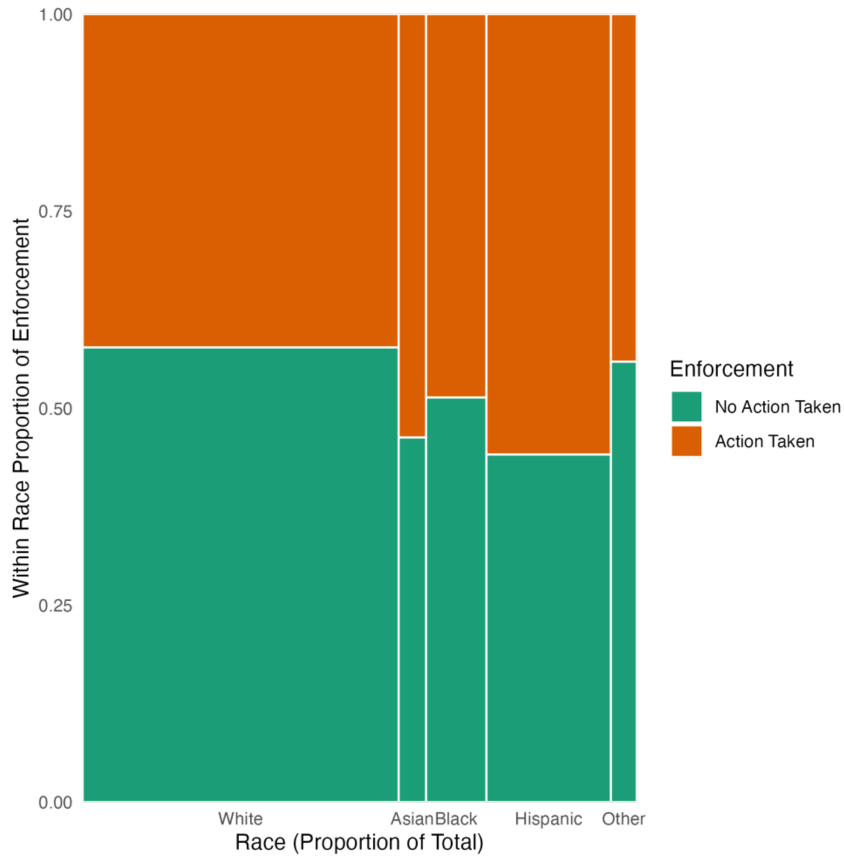
Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.048	0.215	<0.001	[0.031, 0.071]
Daytime	1.128	0.217	0.579	[0.752, 1.767]
Precinct Crime	1.088	0.187	0.652	[0.745, 1.551]
Highway	2.313	0.130	<0.001	[1.789, 2.980]
Other	0.758	0.726	0.703	[0.123, 2.473]

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, 7 for Hispanic–White, 1 for Asian–White, and 2 for Other–White comparisons. Such sparse data reduce statistical power, increasing the risk that meaningful differences go undetected and results become misleading.

Enforcement Action Outcomes in Traffic Stops

Figure 15. Precinct # 4 Mosaic Plot of Enforcement Actions by Race



Precinct # 5

Assessing Bias in Traffic Stop Decisions

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.272	0.080	<0.001	[0.232, 0.318]
Daytime	1.005	0.081	0.951	[0.859, 1.180]
Precinct Crime	0.880	0.061	0.035	[0.781, 0.991]
Highway	0.808	0.085	0.012	[0.683, 0.953]
Other	1.636	0.294	0.094	[0.897, 2.866]

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.471	0.066	<0.001	[0.414, 0.536]
Daytime	0.973	0.066	0.677	[0.855, 1.109]
Precinct Crime	0.852	0.050	0.001	[0.773, 0.940]
Highway	0.867	0.068	0.037	[0.758, 0.991]
Other	1.028	0.288	0.923	[0.572, 1.781]

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.051	0.195	<0.001	[0.034, 0.073]
Daytime	1.011	0.204	0.955	[0.690, 1.537]
Precinct Crime	0.359	0.172	<0.001	[0.254, 0.498]
Highway	0.320	0.265	<0.001	[0.183, 0.521]
Other	0.512	1.016	0.510	[0.029, 2.383]

Table 35. Precinct #5 Adjusted Logistic Regression Model Results (Other Driver)

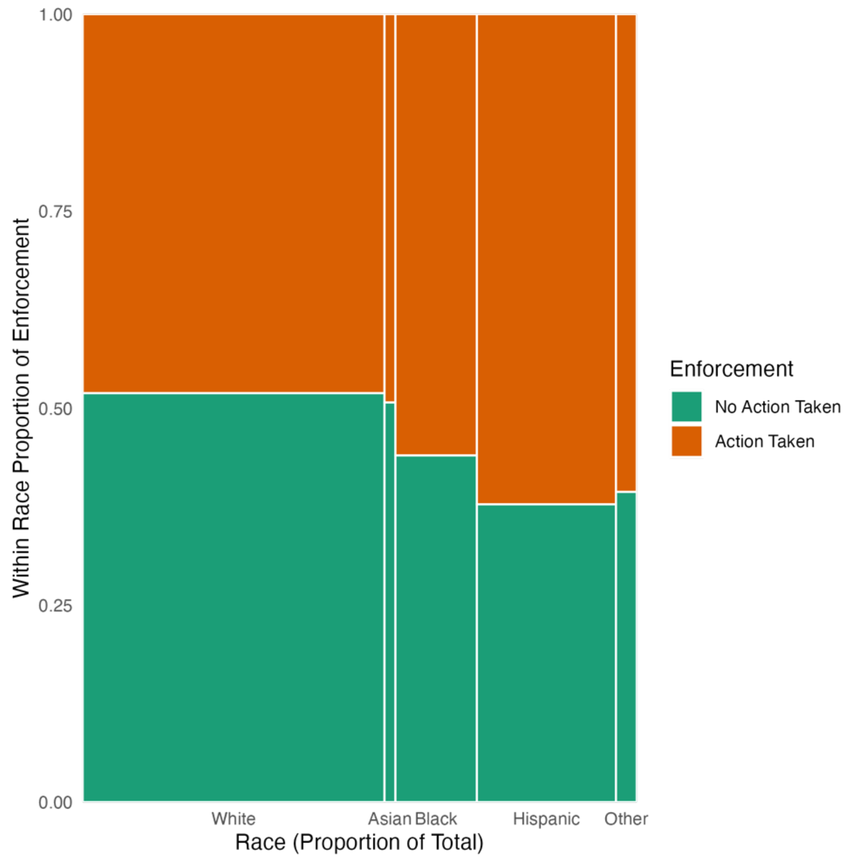
Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.055	0.149	<0.001	[0.040, 0.072]
Daytime	0.940	0.144	0.666	[0.714, 1.258]
Precinct Crime	1.473	0.112	<0.001	[1.183, 1.836]
Highway	1.632	0.142	<0.001	[1.232, 2.147]
Other	0.000	236.089	0.957	[0.000, 0.158]

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, 8 for Hispanic–White, 2 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.

Enforcement Action Outcomes in Traffic Stops

Figure 16. Precinct # 5 Mosaic Plot of Enforcement Actions by Race



Precinct # 6

Assessing Bias in Traffic Stop Decisions

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.351	0.069	<0.001	[0.306, 0.401]
Daytime	0.773	0.072	<0.001	[0.672, 0.890]
Precinct Crime	1.787	0.062	<0.001	[1.582, 2.018]
Highway	0.714	0.088	<0.001	[0.598, 0.847]
Other	0.297	0.521	0.020	[0.090, 0.732]

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.422	0.065	<0.001	[0.371, 0.479]
Daytime	0.809	0.068	0.002	[0.709, 0.925]
Precinct Crime	1.404	0.061	<0.001	[1.245, 1.582]
Highway	1.254	0.068	<0.001	[1.097, 1.430]
Other	0.835	0.305	0.556	[0.443, 1.478]

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.097	0.134	<0.001	[0.074, 0.125]
Daytime	0.641	0.146	0.002	[0.485, 0.860]
Precinct Crime	0.182	0.286	<0.001	[0.099, 0.305]
Highway	0.539	0.192	0.001	[0.363, 0.773]
Other	1.535	0.474	0.366	[0.529, 3.537]

Table 39. Precinct #6 Adjusted Logistic Regression Model Results (Other Driver)

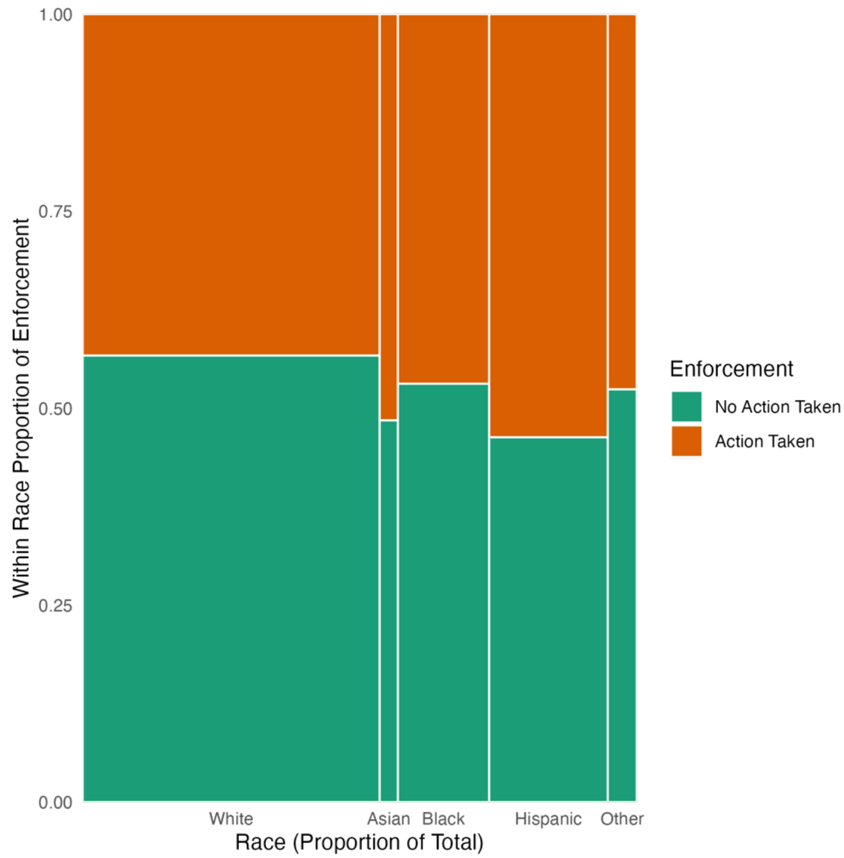
Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.100	0.115	<0.001	[0.079, 0.125]
Daytime	0.718	0.120	0.006	[0.570, 0.913]
Precinct Crime	1.446	0.113	0.001	[1.154, 1.799]
Highway	1.687	0.115	<0.001	[1.340, 2.109]
Other	0.555	0.724	0.416	[0.090, 1.801]

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: 12 hamlets for Black–White, 14 for Hispanic–White, 1 for Asian–White, and 2 for Other–White comparisons. Such sparse data reduce statistical power, increasing the likelihood that meaningful differences go undetected and results become misleading.

Enforcement Action Outcomes in Traffic Stops

Figure 17. Precinct #6 Mosaic Plot of Enforcement Actions by Race



Precinct # 7

Assessing Bias in Traffic Stop Decisions

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.365	0.067	<0.001	[0.320, 0.416]
Daytime	0.922	0.070	0.243	[0.805, 1.058]
Precinct Crime	1.448	0.070	<0.001	[1.262, 1.660]
Highway	0.750	0.070	<0.001	[0.653, 0.859]
Other	1.346	0.173	0.086	[0.951, 1.879]

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.395	0.065	<0.001	[0.348, 0.449]
Daytime	0.801	0.069	0.001	[0.701, 0.917]
Precinct Crime	1.220	0.074	0.007	[1.054, 1.410]
Highway	0.811	0.069	0.002	[0.707, 0.928]
Other	1.219	0.182	0.277	[0.844, 1.730]

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.033	0.195	<0.001	[0.022, 0.047]
Daytime	0.776	0.207	0.221	[0.526, 1.187]
Precinct Crime	0.991	0.245	0.970	[0.596, 1.563]
Highway	0.931	0.206	0.729	[0.611, 1.375]
Other	1.766	0.467	0.223	[0.615, 3.993]

Table 43. Precinct #7 Adjusted Logistic Regression Model Results (Other Driver)

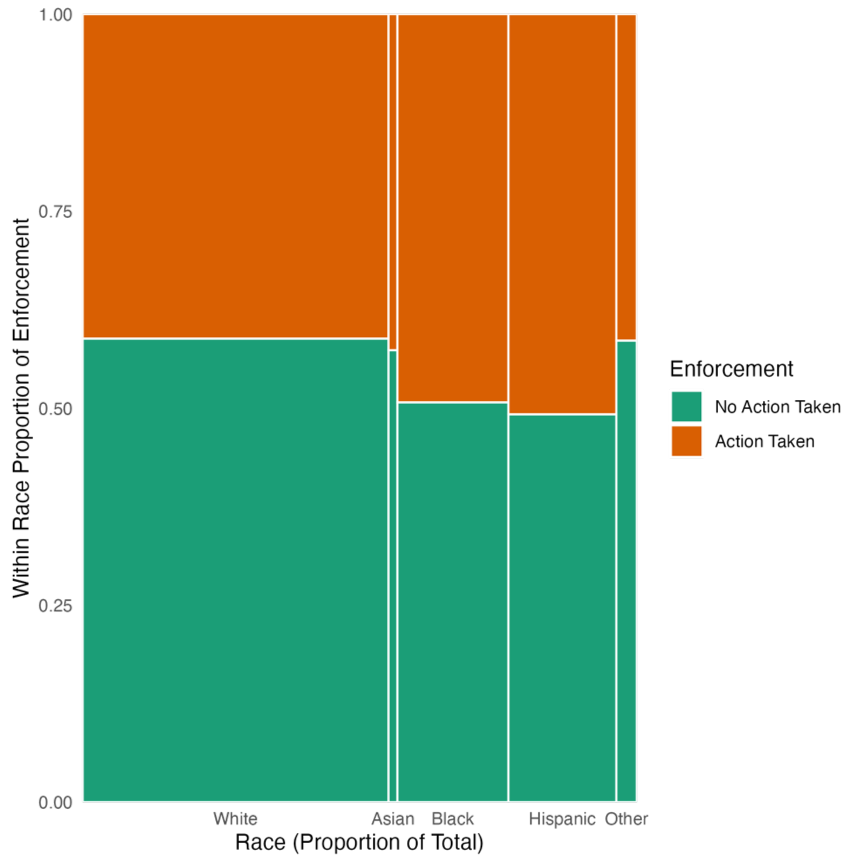
Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.049	0.149	<0.001	[0.036, 0.065]
Daytime	0.818	0.154	0.192	[0.610, 1.117]
Precinct Crime	2.209	0.146	<0.001	[1.649, 2.927]
Highway	1.376	0.144	0.027	[1.031, 1.816]
Other	1.130	0.464	0.792	[0.396, 2.532]

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: 4 hamlets for Black–White, 6 for Hispanic–White, none for Asian–White, and 1 for Other–White comparisons. Such sparse data reduce statistical power, increasing the risk that meaningful differences go undetected and results become misleading.

Enforcement Action Outcomes in Traffic Stops

Figure 18. Precinct # 7 Mosaic Plot of Enforcement Actions by Race



Precinct # 9

Assessing Bias in Traffic Stop Decisions

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.293	0.097	<0.001	[0.242, 0.354]
Daytime	0.945	0.060	0.345	[0.842, 1.063]
Precinct Crime	0.975	0.658	0.970	[0.219, 3.169]
Highway	1.104	0.093	0.287	[0.922, 1.329]
Other	1.670	0.132	<0.001	[1.289, 2.164]

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.405	0.085	<0.001	[0.342, 0.477]
Daytime	0.959	0.051	0.412	[0.868, 1.060]
Precinct Crime	1.628	0.490	0.320	[0.592, 4.189]
Highway	1.284	0.082	0.002	[1.094, 1.511]
Other	1.172	0.125	0.205	[0.916, 1.498]

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

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.055	0.203	<0.001	[0.036, 0.080]
Daytime	0.900	0.115	0.359	[0.722, 1.134]
Precinct Crime	3.660	0.793	0.102	[0.549, 14.492]
Highway	1.344	0.197	0.134	[0.930, 2.020]
Other	0.989	0.315	0.972	[0.523, 1.815]

Table 47. Precinct #9 Adjusted Logistic Regression Model Results (Other Driver)

Term	OR Estimate	Standard Error	p-value	95% OR CI
Intercept	0.063	0.194	<0.001	[0.042, 0.090]
Daytime	0.707	0.065	<0.001	[0.623, 0.804]
Precinct Crime	1.986	1.062	0.519	[0.107, 10.767]
Highway	4.948	0.193	<0.001	[3.454, 7.383]
Other	2.529	0.254	<0.001	[1.541, 4.196]

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: 8 hamlets for Black–White, 7 for Hispanic–White, 1 for Asian–White, and 4 for Other–White comparisons. Such sparse data reduce statistical power, increasing the likelihood that meaningful differences go undetected and results become misleading.

Enforcement Action Outcomes in Traffic Stops

Figure 19. Precinct # 9 Mosaic Plot of Enforcement Actions by Race