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INSTITUTE FOR MUNICIPAL AND REGIONAL POLICY

TRAFFIC STOP DATA ANALYSIS AND FINDINGS, 2023-2024

METROPOLITAN POLICE DEPARTMENT WASHINGTON, D.C.

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UCONN

INSTITUTE FOR MUNICIPAL AND REGIONAL POLICY

DC Highway Safety Office
250 M St SE
Washington, DC, 20003

Dear DC Highway Safety Office,

Enclosed is our evaluation of traffic stops conducted by the Metropolitan Police Department (MPD) between 2019 and 2024. This report represents our second analysis of MPD's traffic stop data and builds on similar evaluations we have conducted for law enforcement agencies and jurisdictions across the country since 2013.

The primary focus of this report is on the more than 37,000 traffic stops conducted between July 2023 and June 2024. These findings build on our prior analysis of more than 190,000 stops conducted between July 2019 and June 2023. As detailed in the report, MPD's traffic enforcement activity reached its highest level since the COVID-19 pandemic during the period from July through September 2023. However, enforcement activity declined during the final quarter of 2023, and the first two quarters of 2024 remained below the study-period average.

Overall, the findings present a mixed but encouraging picture, with continued progress in reducing racial and ethnic differences in traffic enforcement. Using the most rigorous statistical methods available, we found no evidence that MPD was more likely to stop Black or Hispanic drivers during daylight hours than during darkness between 2019 and 2024. The analysis identified some differences involving Hispanic motorists in the most recent study year, from July 2023 through June 2024. While small disparities in certain post-stop outcomes, including arrest and ticketing rates, were observed using a commonly applied but less rigorous test, those differences declined steadily through most of the study period before increasing slightly in the most recent year. In addition, we found no statistically significant differences in contraband discovery rates across racial and ethnic groups.

We commend MPD for its continued commitment to transparency and accountability in traffic enforcement. The department has demonstrated a meaningful willingness to engage in an open and honest review of its practices, enabling us to produce a rigorous and independent assessment. We are grateful for MPD's collaboration and constructive feedback throughout this process.

This report reflects MPD's commitment to fair and effective traffic enforcement and sets a strong example for agencies across the country. We look forward to continuing this partnership and supporting MPD's ongoing efforts to strengthen its operations in the years ahead.

Sincerely,

Kenneth Barone

Kenneth Barone
Associate Director

Disclaimer

The Institute for Municipal and Regional Policy (IMRP) at the University of Connecticut (UConn) is the author of this report. The Representations, opinions, findings, and/or conclusions contained in this report are those of the authors and do not necessarily reflect the official policies or positions of the Metropolitan Police Department or the Government of the District of Columbia.

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EXECUTIVE SUMMARY OF FINDINGS

In October 2024, the DC Highway Safety Office[1], with funds made available from the National Highway Traffic and Safety Administration (NHTSA), provided a grant to the Institute for Municipal and Regional Policy (IMRP) at the University of Connecticut (UConn) to independently analyze traffic stop data collected by the Metropolitan Police Department (MPD). This report aims to understand stop patterns in the district better.

The IMRP research team is particularly well-known for developing the technical framework of the "Connecticut Model," a pioneering approach designed to promote fairness and consistency in police traffic stops. Their approach has been adopted by multiple states, endorsed by stakeholder organizations, and is nationally recognized as the gold standard approach for analyzing traffic stop data. The influence of the Connecticut Model extends far beyond Connecticut's borders, significantly shaping the national discourse on police effectiveness. As early as 2015, the authors of this report offered detailed guidance to states interested in enacting data collection laws, conducting analyses, and implementing similar interventions. To date, the research team has provided guidance and technical assistance to states including Alabama, California, Colorado, Maine, Maryland, Minnesota, Nevada, New Jersey, New York, Oregon, Ohio, and Rhode Island. Additionally, the U.S. Department of Justice (DOJ) has integrated its analytical framework into its enforcement activities and has invited Dr. Matt Ross, one of the report's authors, to serve as a subject matter expert.

In July 2019, the MPD and the Department of Motor Vehicles launched a new data system, forms, policy, and training to allow for the collection of police stop data in a more detailed manner. This new data system allows MPD to conduct greater data analysis of police stops. MPD has publicly stated its commitment to transparency and ensuring that stops meet the highest standards for fair and constitutional policing. The data system received an additional update in October 2022 as MPD worked to enhance data collection capabilities.

E.1: SUMMARY OF DATA ANALYZED

Since September 2019, MPD has published three reports reviewing stop data from July 2019 through December 2020. This is the second analysis of traffic stop data conducted by IMRP, expanding upon our earlier work by adding an additional year of stops, now covering the period from July 2019 through June 2024. The dataset includes all MPD traffic stops, encompassing vehicle, pedestrian, bicycle, and harbor stops. A stop may involve a ticket (citation or warning), investigatory detention, protective pat-down, search, or arrest. In March 2023, MPD introduced a new data field to better identify stops resulting specifically from traffic enforcement. For this analysis, researchers examined only those stops determined to be traffic-related.[2] Street stops of individuals and their outcomes are not included in this report.

For each traffic stop, MPD officers recorded the demographic information of the individual stopped. Demographic information was recorded in 88 percent of all traffic stops. This report focuses on differences in stops based on a driver's race and ethnicity, but this information is rarely included on official government identification cards, and it is not on DC Driver's Licenses. As a result, the race and ethnicity data used for this report were most commonly gathered based on the officer's observations.

When presented with an official government identification card, officers rely on that card to document the stopped individual's age and gender. If an official government identification card was not presented, officers

[1] The DC Highway Safety Office is within the Office of the City Administrator.
[2] A traffic stop is defined as a stop identified in the dataset as "traffic-involved" but excludes stops made as a response to a crash.

were instructed to ask for this information if possible. Beginning in June 2021, officers were instructed to document age and gender based on government identification, their observations, or a respectful query.

Our analysis covers traffic stops conducted between July 2019 and June 2024, with particular attention to the most recent year of publicly available data. During the most recent year (July 2023 to June 2024), MPD conducted more than 37,000 traffic stops. Fifteen (15) percent of the individuals stopped were White, 60 percent were Black, 10 percent were Hispanic, and 3 percent were some other race. Between July 2023 and June 2024, MPD made an average of 3,132 monthly traffic stops. Notably, the third quarter of 2023 (July–September) recorded the highest number of stops outside the pre-pandemic period.

E.2: SUMMARY OF METHODS

For the past two decades, analyzing racial disparities in policing data has been a key policy tool for evaluating the potential presence of racial and ethnic bias within various jurisdictions. This report presents a statistical assessment of traffic stop data from the MPD, intending to provide a clear, transparent, and unbiased evaluation. The report is structured to guide the reader through three analytical tests, each differing in assumptions and levels of scrutiny.

- **Solar Visibility Analysis**: Solar visibility analysis compares the rate at which White and non-White drivers are stopped during daylight to the rate at which they are stopped in darkness when it is harder for the officer to observe the driver's race. When there is a higher relative rate of non-White drivers stopped in daytime than in darkness, it indicates differences that warrant additional review. This method is the most rigorous method that could be applied to the MPD's traffic data.
- **Post-stop Enforcement Action Analysis**: This method examines each traffic stop conducted and then compares the outcomes of the stop between White and non-White drivers. Outcomes can include arrests and other discretionary law enforcement actions (searches, tickets, warnings, amount of time stopped). When there is a *different* rate of a specific outcome for non-White drivers compared to White drivers who were stopped under similar circumstances, it can again indicate differences that warrant review. We could not apply this method in its most rigorous and conclusive form, so we urge caution in interpreting the results.
- **Search Hit Rate Analysis**: This method examines each traffic stop where *a search* is conducted and then compares the rates of contraband found between White and non-White drivers. "Contraband" is an illegal item, such as drugs, weapons, and stolen property. When there is a *lower* rate of contraband found for non-White drivers compared to White drivers who were stopped under similar circumstances, it can indicate differences that warrant review.

We use this multi-test approach to safeguard against potential errors, reducing the possibility of (1) false positives- where a difference is detected where none exists, and (2) false negatives- where a real difference goes undetected. Each method has inherent drawbacks based on the volume and structure of the data available for this analysis. However, if we find consistent racial and ethnic differences across DC or within specific MPD Police Districts, it indicates an area for MPD to investigate further to determine if the differences result from specific policing practices that can be changed.

E.3: SUMMARY OF FINDINGS

The analysis of MPD traffic stops between July 2019 and June 2024 reveals a mixed but overall encouraging picture, with progress in reducing racial and ethnic differences.

The statewide Solar Visibility Analysis showed that, on average, MPD was not any more likely to stop Black or non-White drivers between 2019 and 2024 in daylight compared to darkness. The analysis did show differences in the rate at which Hispanic motorists were stopped in daylight compared to darkness in the most recent year (July 2023–June 2024). These differences were statistically significant, and the estimated effect indicated a modest change in the likelihood that a stopped driver is Hispanic in daylight compared to darkness[3].

When examining outcomes such as arrest rates, ticketing, and stop duration, differences persist, although they have decreased since 2020. Citywide, Black and Hispanic motorists were more likely to be arrested or ticketed compared to White motorists. Arrest differences were consistently significant for Black, Hispanic, and non-White motorists across all years, though the magnitude declined until a slight uptick in the most recent year. Ticketing differences were significant for both Black and Hispanic drivers in most years. For stop duration, the most recent year showed shorter stop times for Black and Hispanic motorists relative to White drivers, a reversal of earlier trends. The aggregate analysis also found no consistent evidence of differences in contraband discovery following discretionary searches. We do find differences in specific MPD districts when we apply these methods. Those differences are highlighted below and in the body of the report.

All communities would benefit from an independent, routine review of their stop data. The MPD should be commended for their commitment to this project and willingness to examine their data critically. Addressing racial and ethnic differences requires a collective effort of all law enforcement and community stakeholders. An atmosphere of open-mindedness, empathy, and honesty from all stakeholders remains necessary to create sustained police legitimacy and a safer, more just society. The authors of this report are hopeful that the information contained herein will be valuable to the citizens of DC. We are both humbled and grateful for the opportunity to be part of this important effort.

E. 3.A: Highlights from the Analysis

Solar Visibility Analysis:
Used to identify differences in stops between daylight and darkness periods.

Citywide Estimates

- All non-White and Black drivers: No evidence of increased stops in daylight.
- Hispanic drivers were stopped more often in daylight than in darkness across several statistical models in the most recent year (July 2023-June 2024)[4]. These differences were statistically significant, indicating a modest change in the likelihood that a stopped driver is Hispanic in daylight compared to darkness.

District Estimates

- July 2023 – June 2024
    - Black drivers: One district showed a small increase in daylight stops involving Black drivers.

[3] When we say the differences are statistically significant, we mean they are unlikely to be due to random chance and instead likely reflect a real pattern in the data. When we say the differences are modest in magnitude, we mean the size of the difference is meaningful but not large in practical terms. For example, a difference of about 9 percentage points indicates a noticeable shift between daylight and darkness conditions, but not a dramatic one. Statistical significance reflects our confidence that the difference is real, while magnitude reflects the size of the difference itself.

[4] The share of Hispanic drivers stopped in daylight was 9 percentage points greater than in darkness.

    - Hispanic drivers: One district showed a modest increase in daylight stops involving Hispanic drivers.
- July 2021 – June 2024
    - Black drivers: Three districts showed modest increases in daylight stops involving Black drivers.
    - Hispanic drivers: One district showed a modest increase in daylight stops involving Hispanic drivers.

<u>Post-Stop Enforcement Action Analysis:</u>
Investigated differences in post-stop outcomes such as arrests and other discretionary enforcement actions (searches, tickets, stop duration).

- Differences were found in the outcomes of stops, including arrests, ticketing rates, and stop durations. However, the differences have decreased each year.
- Black and Hispanic drivers were more likely to be arrested or ticketed than White drivers across all years, although the differences declined between 2020 and 2023 before rising slightly again in 2023–2024.

We caution the reader not to place a causal interpretation on this test because we could not adequately control for selection into different types of circumstances that necessitate a search, ticket, or stop duration.

<u>Search Hit-Rate Analysis:</u>
Examined differences in the likelihood of a discretionary search resulting in contraband (e.g., drugs, stolen property, or a weapon) being found.

- We found no evidence of a statistically significant difference in contraband finding rates in the most recent year or the three-year aggregate sample.
- In 2023–2024, one district's searches of Black and non-White motorists were significantly less successful than searches of White motorists. Across the three-year period (2021–2024), two districts showed differences, with searches of Black and non-White drivers yielding contraband at lower rates than searches of White drivers.

I: METHODOLOGICAL APPROACH UNDERLYING THE ANALYSIS

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

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

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

The report is organized to lead the reader through a host of descriptive and statistical tests that vary in their assumptions and level of scrutiny. This approach intends to apply multiple tests as a screening filter for the possibility that any one test (1) produces false positive results or (2) reports a false negative. In the analysis, the demography of individuals was grouped into four overlapping categories to ensure a large enough sample size for the statistical analysis. Although much of the analysis focuses on stops made of Black and Hispanic individuals, the analysis was also conducted for aggregated groupings of all non-White individuals. Regarding identifying districts in individual tests, the estimated difference (i.e., the higher likelihood of stopping a non-White individual) must have been estimated with at least a 95 percent level of statistical confidence for either Black or Hispanic individuals alone. Put simply, under the rigorous conditions set by each test, there must have been at least a 95 percent chance that another random sample would have shown that either Black or Hispanic individuals were more likely to be stopped (or searched) at a higher rate relative to non-White individuals.

The analysis begins by presenting a method referred to as the Solar Visibility analysis, which was used to assess the existence of racial and ethnic differences in stop data. This test, developed by Grogger and Ridgeway (2006), examines a restricted sample of stops occurring during the "inter-twilight window," defined as the fixed window of time throughout the year during which visibility varies due to seasonality and the discrete Daylight Savings Time shift. It assesses relative differences in the ratio of non-White to White stops that occur in daylight as compared to darkness. This technique relies on the assumption that if police officers are profiling motorists, they are better able to do so during daylight hours when race and ethnicity are more easily observed. After restricting the sample of stops to the inter-twilight window and controlling for things like the time of day and day of the week, any remaining difference in the likelihood that a non-White motorist is stopped during daylight may be attributed to disparate treatment. This analytical approach is considered the most rigorous and broadly applicable of all the tests presented in this report.

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

Lastly, we conduct an analysis of post-stop outcomes using a hit-rate approach developed by Knowles, Persico and Todd (2001). The hit-rate approach relies on the idea that individuals rationally adjust their propensity to carry contraband in response to their likelihood of being searched by police. Similarly, police officers rationally decide whether to search a motorist based on visible indicators of guilt and an expectation of the likelihood that a given motorist might have contraband. According to the model, a demographic group of individuals would be searched by police more often than White non-Hispanic individuals if they were more likely to carry contraband. However, the higher level of searches should be exactly proportional to the higher propensity for this group to carry contraband. Thus, in the absence of racial animus, we should expect the rate of successful searches (i.e. the hit-rate) to be equal across different demographic groups regardless of differences in their propensity to carry contraband. [5] In this test, discrimination is interpreted as a preference for searching non-White individuals that shows up statistically as a lower hit-rate relative to White individuals. Note that this test inherently says nothing about disparate treatment in the decision to stop individuals as it is limited in scope to vehicular searches.

In short, we aim to identify the statistically significant racial and ethnic differences in MPD policing data. Various statistical tests are applied to the data to provide a comprehensive approach based on the lessons learned from academic and policy applications. Our explanations of the mechanisms and assumptions underlying each test are intended to provide policymakers and the public with enough information to assess the data and draw their own conclusions from the findings. Finally, we emphasize that any statistical test can only truly identify racial and ethnic differences. Such findings cannot, without further investigation, provide sufficient evidence that racial profiling exists.

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

II: CHARACTERISTICS OF TRAFFIC STOP DATA

This section examines general patterns of traffic enforcement activities in D.C. from July 1, 2023, to June 30, 2024. For this report, we used only the stop records likely to result from a traffic stop. Those included all stops that MPD defined as "traffic involved" but excluded stops that were only a response to a crash. This information can be used to identify variations in traffic stop patterns to help law enforcement and the local community understand more about traffic enforcement. Although some comparisons can be made between similar patrol districts, we caution against comparing the districts' data in this report section.

In D.C., more than 37,000 traffic stops were conducted between July 2023 and June 2024. This builds on the prior report, which analyzed over 190,000 stops between July 2019 and June 2023. With this update, researchers examined an additional year of data, covering a total of 20 quarters (60 months), including roughly three quarters—or nine months—before the COVID-19 pandemic. During the most recent year, stops averaged 9,396 per quarter. Notably, the third quarter of 2023 (July–September) recorded the highest number of stops outside the pre-pandemic period. However, the following quarter saw a 36% decline, with stops remaining below the quarterly average for the rest of the 2019–2024 study period. Figure 2.1 presents the aggregate number of traffic stops by quarter, broken down by demographic category.

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

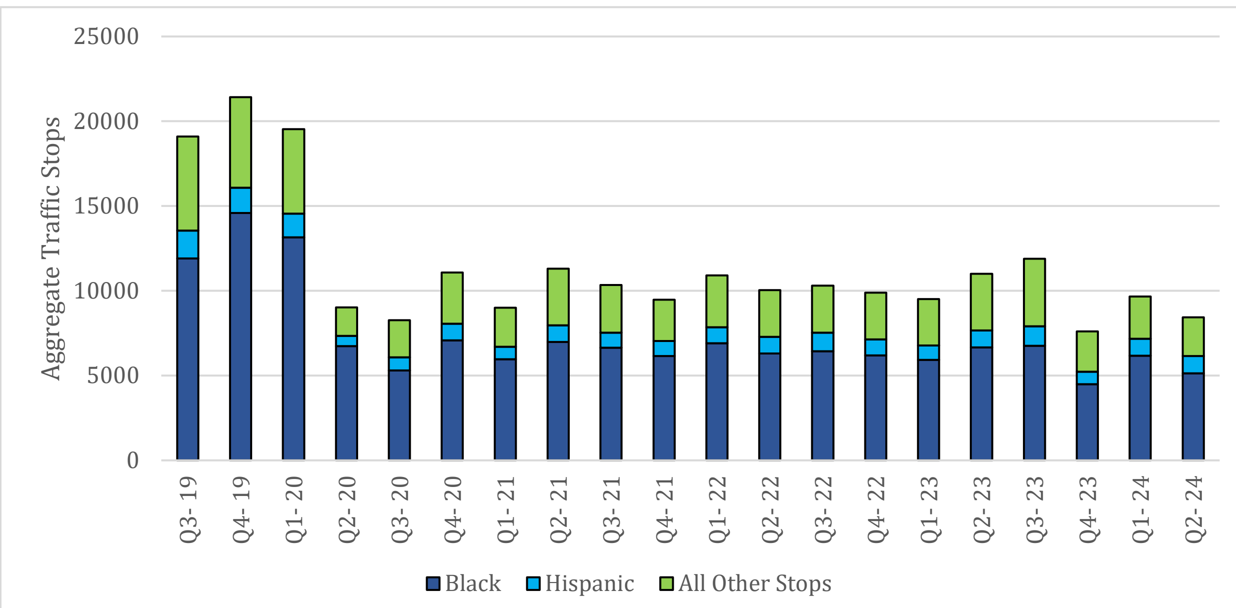


Figure 2.2 shows the distribution of traffic stops by time of day over the analysis period. Stop volume varied considerably throughout the day, with peaks between 12:00–2:00 PM and again from 8:00 PM to midnight. The single highest hourly volume occurred between 9:00–10:00 PM, accounting for 9 percent of all stops. This marks a shift from the previous report, where the busiest hour was 5:00–6:00 PM. The evening surge, spanning 8:00 PM to 1:00 AM, represents a concentrated period of traffic enforcement and comprises 35 percent of all stops. A smaller increase was also observed between 4:00–5:00 AM, while the lowest stop volume occurred between 7:00–8:00 AM.

Figure 2. 2: Aggregate Traffic Stops by Time of Day (2023-24)

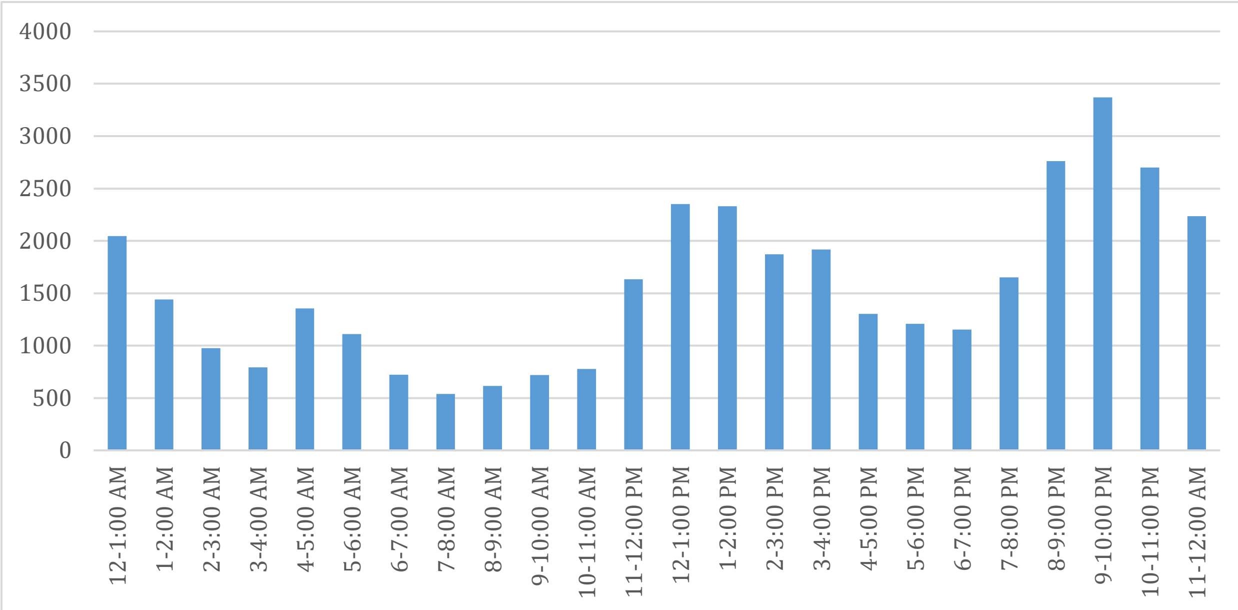


Figure 2.3 illustrates the distribution of traffic stops by patrol district during the study period. While the average district recorded 5,239 stops, enforcement activity varied widely. District 3 stood out with the highest share—22 percent of all stops—more than double the proportion in District 7, which had the lowest at just 8 percent. Districts 1, 2, and 5 reported similar volumes, falling between these two stop totals.

Figure 2. 3: Total Number of Traffic Stops by Patrol District (2023-24)

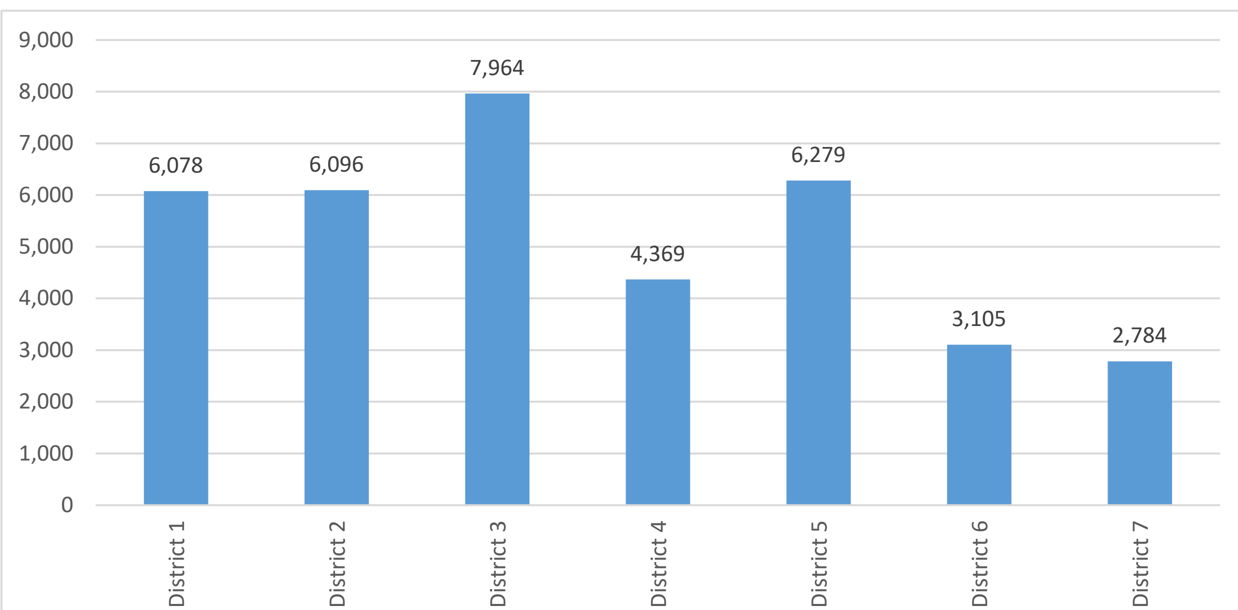


Figure 2.4 displays traffic stops by day of the week for the analysis period. This figure shows that traffic stops increase throughout the week and peak on Thursdays. Traffic stops decline substantially on the weekends, with the smallest number occurring on Sundays.

Figure 2. 4: Traffic Stops by Day of Week (2023-24)

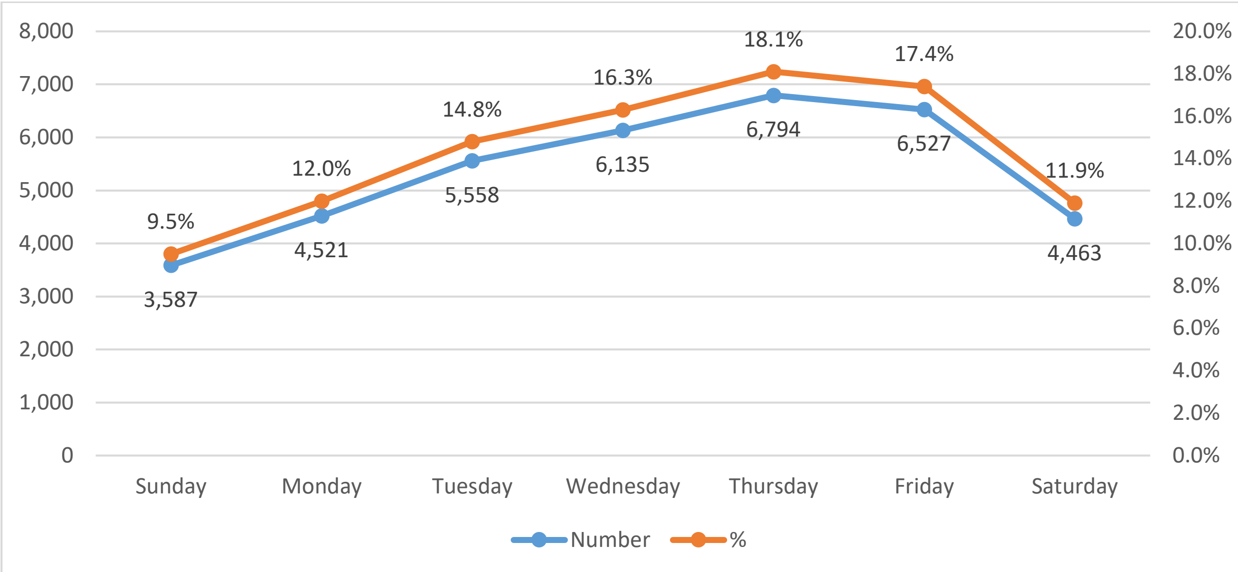


Table 2.1 provides demographic data on individuals involved in traffic stops in the district between July 1, 2023, and June 30, 2024. Officers relied on information gathered from an official government identification card to document stopped individuals' demographic information. Alternatively, if an official government identification card was not presented, officers were instructed to ask for this information if possible.[6] Overall, two-thirds (67 percent) of those stopped were male. Age patterns showed that about one-third were under 30, while only 18 percent were over 50. A majority of stops (60 percent) involved Black individuals, compared with 15 percent White, 10 percent Hispanic, and 3 percent categorized as other races. Demographic information on race or ethnicity was missing for 12 percent of stops—an increase from prior reporting years.

Table 2. 1: Traffic Stop Characteristics (2023-24)

Race and Ethnicity		Gender		Age	
White	14.9%	Male	66.9%	18 to 20	2.3%
Black	60.0%			21 to 30	27.9%
Hispanic	10.4%	Female	30.2%	31 to 40	25.8%
Asian	1.6%			41 to 50	15.1%
Other	1.0%	Unknown	2.9%	51 to 60	10.3%
Not Reported	12.1%			61 +	7.4%
				Unknown	11.3%

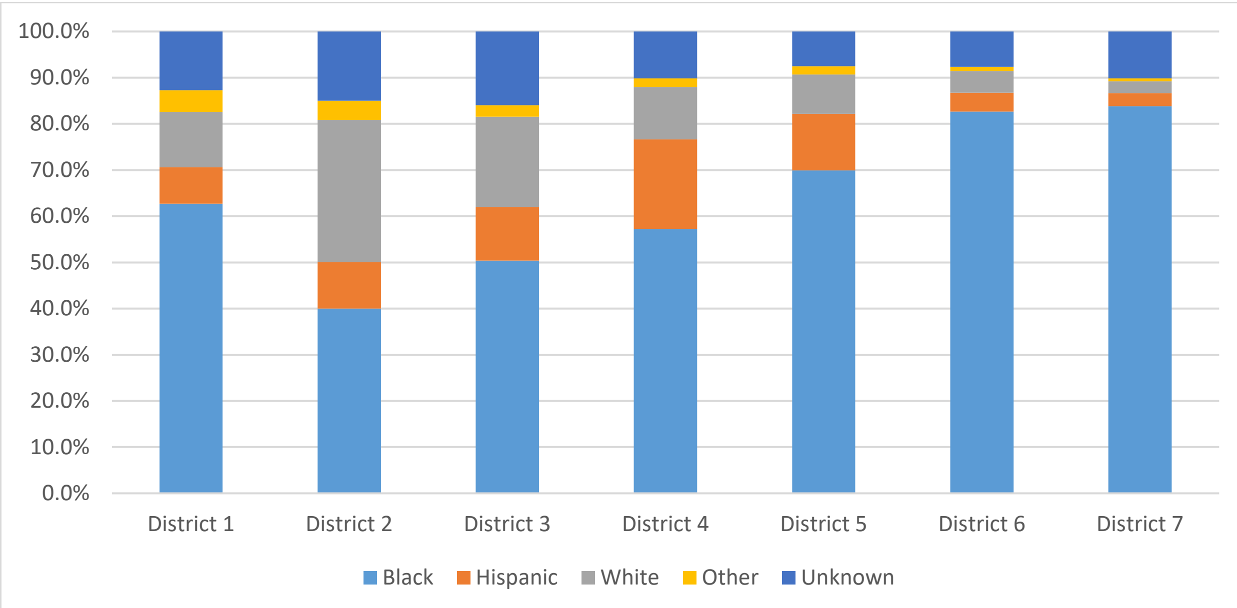
The racial composition of traffic stops varied considerably across patrol districts. Districts 6 and 7 reported the highest shares of stops involving Black individuals (83 percent and 84 percent, respectively), while District 4 recorded the largest share of stops involving Hispanic individuals (19 percent). District 2 reported the highest percentage of stops involving White individuals (31 percent). These patterns largely reflect the residential demographics of each district[7]: Districts 6 and 7, located in the southern part of the city, have higher

[6] After this study period, officers were instructed to document this information based on their observations beginning in September 2023.

[7] Researchers aligned census tract boundaries with police patrol district boundaries to estimate the demographic composition of each patrol area. In most cases, census tracts and patrol district boundaries closely

concentrations of Black residents; District 4, in the north, has the city's largest share of Hispanic residents; and District 2, also in the north, has the largest White population. Figure 2.5 displays the percentage of stops by race and ethnicity across all patrol districts.

Figure 2. 5: Racial and Ethnic Composition of Stopped Drives by District (2023-24)

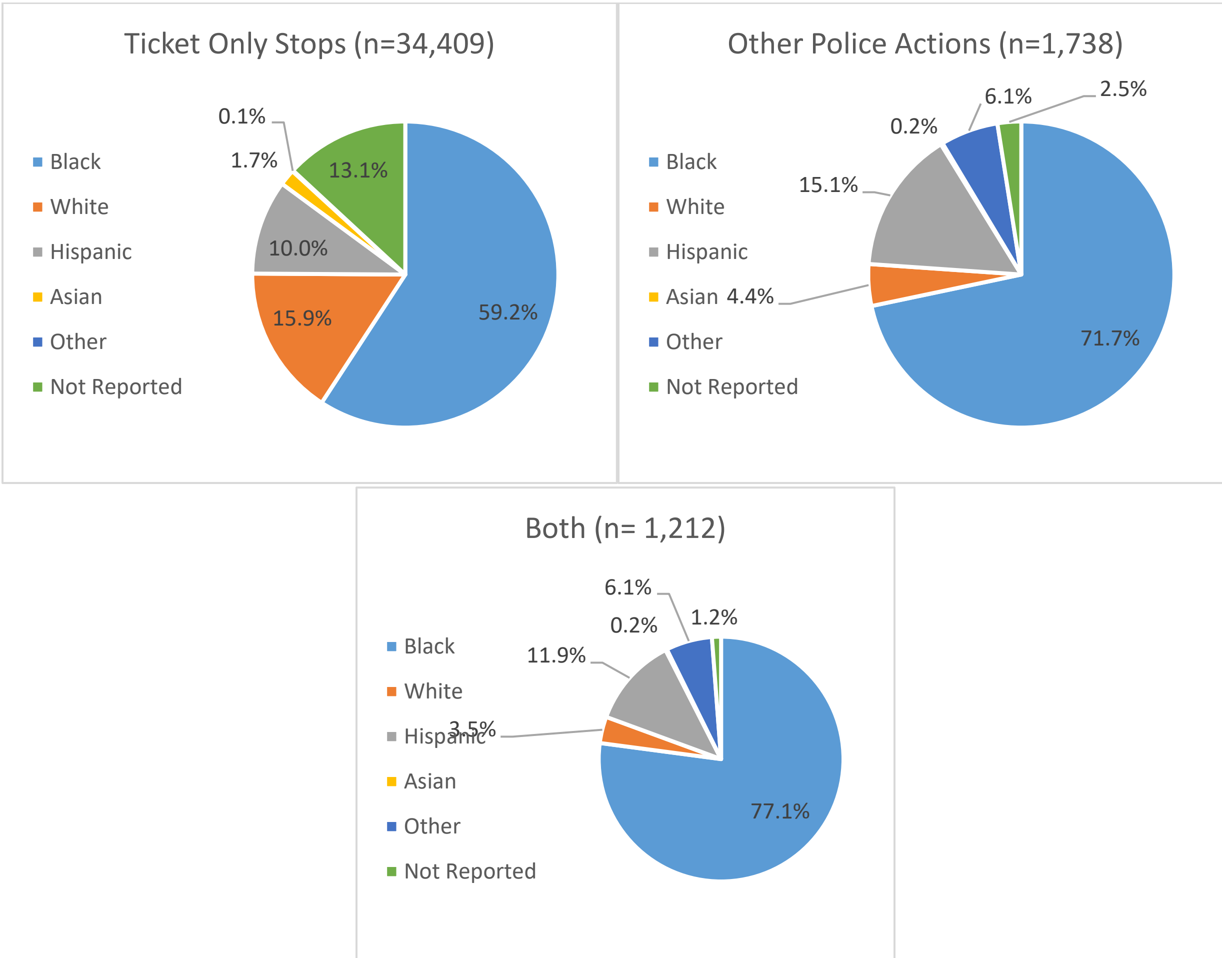


The department recorded the outcome of traffic stops as resulting in a ticket (actual or warning), some other police action such as a search or arrest, or both a ticket and other police action. A ticket can be an actual or warning ticket, but it serves as official documentation of the stop. Other police actions that result from a traffic stop may include an arrest or search. Of the stops that resulted from a traffic stop, approximately 92 percent resulted in only a ticket, 4.6 percent in other police actions, 3.2 percent in both, and 0.6 percent in harbor activity[8]. Figure 2.6 shows the number of traffic stops that result in a ticket, other police action, or both by race and ethnicity.

overlapped, allowing tract-level demographic data to serve as a reasonable approximation of patrol area demographics.

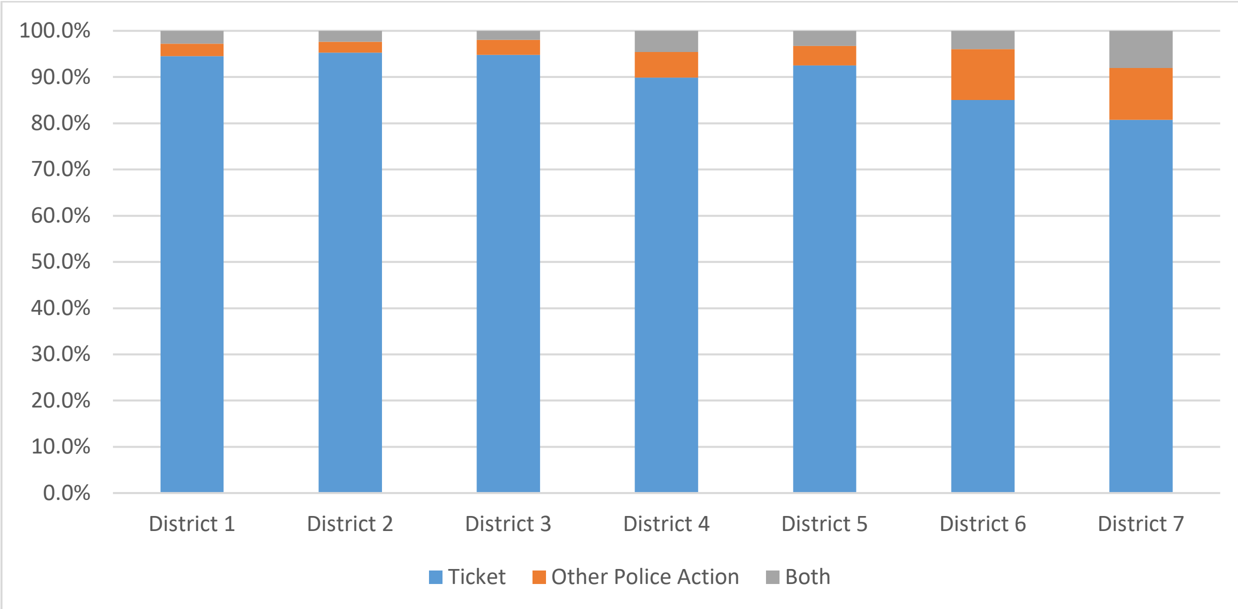
[8] There were 226 records recorded at "Harbor" and were excluded from this analysis.

Figure 2. 6: Traffic Stop Outcome by Type and Race and Ethnicity (2023-24)



Enforcement activity may vary from district to district depending on calls for services, crime rates, traffic crashes, and other local factors. Traffic stops in District 2 resulted in only a ticket at the highest rate (95 percent of stops), whereas stops in District 7 resulted in the lowest rate (81 percent). Districts 6 and 7 had the highest rate of stops that resulted in some other police action, but not a ticket. District 7 also had the highest proportion of traffic stops that resulted in the driver receiving both a ticket and some other action occurring. Figure 2.7 shows the percentage of traffic stops that result in a ticket, other police action, or both by District.

Figure 2. 7: Traffic Stop Outcome by District (2023-24)



Stops that resulted in only a ticket or only some other police action varied by race and ethnicity across patrol districts. For example, over 80 percent of tickets issued in Districts 6 and 7 were issued to Black individuals, whereas in District 2, only 40 percent of tickets were issued to Black individuals. The outcome of ticket stops by race and ethnicity by district generally reflects the overall stop demographics within each district, and no significant difference was identified.

Tables 2.2 and 2.3 present the percentage of traffic stops resulting in a ticket or other police action but no ticket by race, ethnicity, and patrol district. These percentages are calculated by dividing the number of stops involving each racial or ethnic group within a district by the total number of stops in that district. In other words, percentages were calculated using the total number of stops within each patrol district as the denominator; therefore, percentages in each district column sum to 100%.

Table 2. 2: Percentage of Traffic Stops Resulting in Only a Ticket by Race and Ethnicity

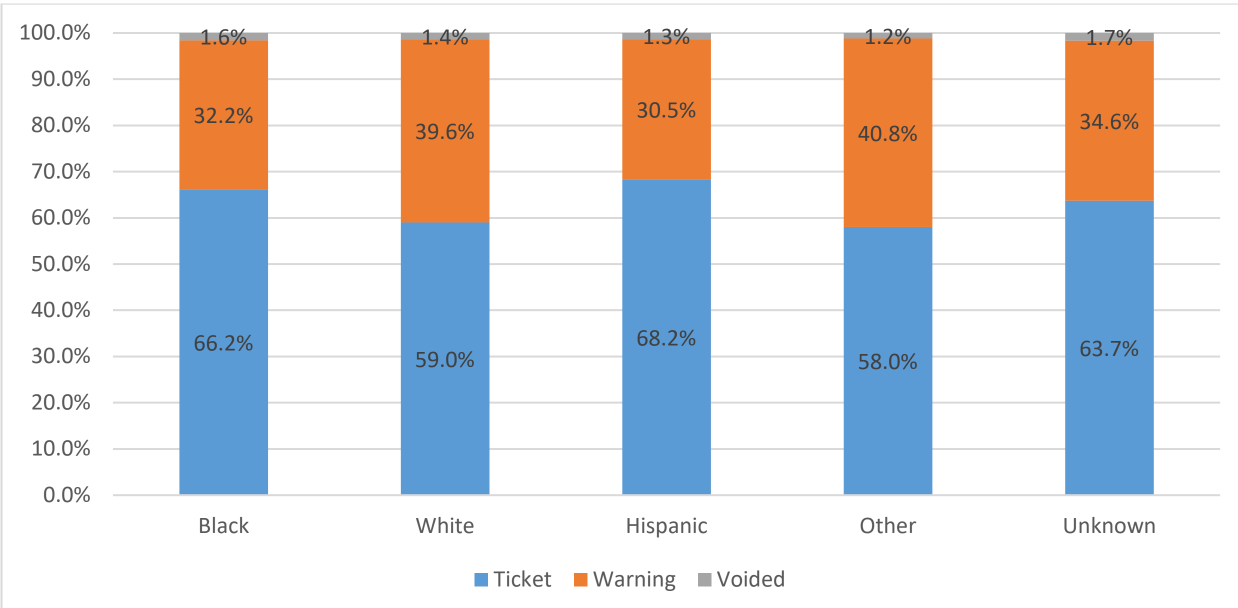
Race/Ethnicity	1D	2D	3D	4D	5D	6D	7D	Citywide
Black	64.4	39.6	49.9	57.2	69.6	80.8	81.6	59.2
White	13.0	31.6	20.3	12.0	9.0	5.4	2.8	15.9
Hispanic	7.0	9.6	11.0	18.1	12.2	4.2	2.9	10.0
Asian	1.6	3.5	2.1	1.3	1.0	0.7	0.4	1.7
Other/Unknown	14.0	15.6	16.7	11.3	8.1	8.9	12.2	13.1

Table 2. 3: Percentage of Traffic Stops Resulting in Some Other Police Action but No Ticket by Race and Ethnicity

Race/Ethnicity	1D	2D	3D	4D	5D	6D	7D	Citywide
Black	76.7	40.6	54.0	47.1	74.7	92.4	92.3	71.7
White	4.4	15.4	5.7	6.6	3.3	0.9	1.6	4.4
Hispanic	11.3	21.7	25.9	38.0	11.5	3.2	3.2	15.1
Asian	0.0	2.1	0.4	0.0	0.0	0.0	0.0	0.2
Other/Unknown	7.5	20.3	14.1	8.3	10.4	3.5	2.9	8.5

Traffic stops recorded as resulting in a ticket can be an actual ticket, a warning, or, in some instances, the ticket was voided. It should be noted that some traffic stops, such as for expired insurance, mandate the issuance of a ticket and do not allow for a warning. Over 64 percent of stops recorded as tickets were actual tickets, 34 percent resulted in a warning, and 2 percent of tickets were voided. Black and Hispanic individuals received an actual ticket (excluding a warning and a voided ticket) at a higher rate than White individuals (66 and 68 percent, respectively, compared to 59 percent). Figure 2.8 shows the outcome of traffic stops recorded as a result of a ticket, warning, or voided ticket by race and ethnicity.

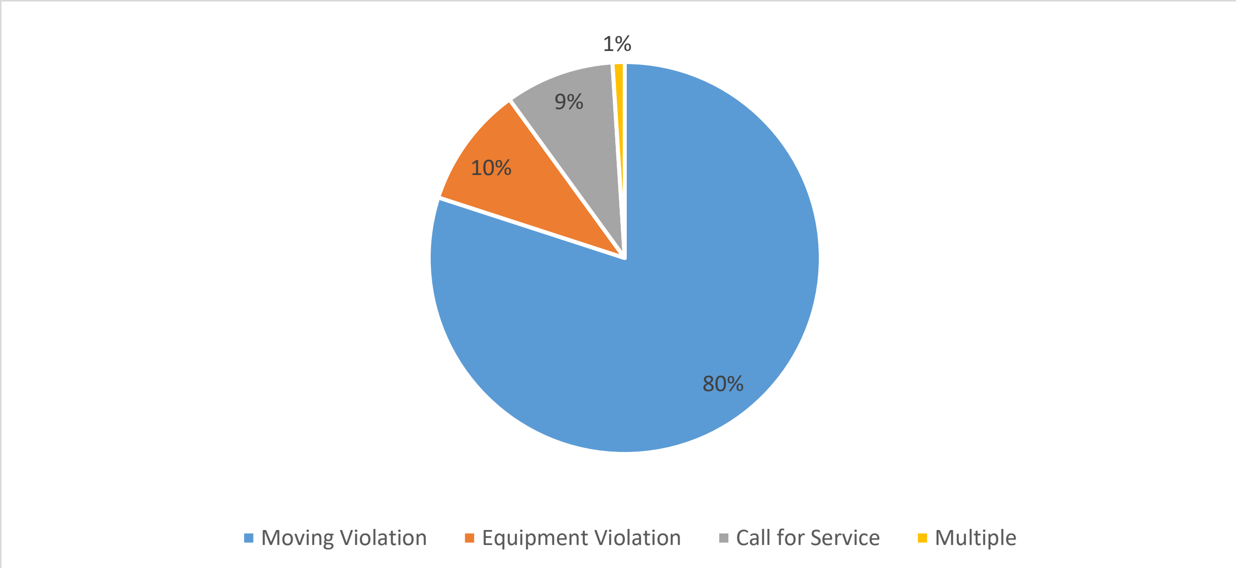
Figure 2. 8: Traffic Stop Outcome for Ticket, Warning, or Voided Ticket by Race and Ethnicity (2023-24)



In addition to whether the traffic stop resulted in a ticket or some other police action, such as an arrest or search, the department also recorded general categories outlining the stop outcome. For example, a traffic stop may have resulted from a call for service, the observation of a moving or equipment violation, or for some other reason.[9] For this section, we will only focus on traffic stops that resulted in a ticket and not stops that resulted in some other police action. Most tickets resulted from the officer observing a moving violation (80 percent). Approximately 10 percent resulted from observing an equipment violation, 9 percent from a call for service, and the remaining 1 percent were a combination of multiple factors. Figure 2.9 shows the reason for the traffic stop that resulted in only a ticket.

[9] We removed stops resulting from only a response to a crash from this analysis.

Figure 2. 9: Reason for Traffic Stop Resulting in a Ticket Only



Officers appear to issue tickets for different reasons, from district to district. Some of these differences may result from specific crime, disorder, traffic, or other related issues being addressed at a more localized level. For example, police in Districts 1, 2, 3, and 5 issued tickets for moving violations at a higher rate than in the other districts. On the other hand, District 7 issues tickets for equipment violations at the highest rate of all patrol districts. Table 2.4 shows the reason for a traffic stop that resulted in a ticket by the patrol district.

Table 2. 4: Reason for Traffic Stop Resulting in a Ticket Only by District (Percent)

Ticket Reason	1D	2D	3D	4D	5D	6D	7D
Moving Violation	81.6	81.1	82.9	74.9	83.7	78.5	63.8
Equipment Violation	11.9	6.1	9.2	13.2	7.9	6.4	22.2
Call for Service	5.3	11.1	5.7	10.8	7.0	13.6	11.6
Multiple	1.2	1.7	2.2	1.1	1.4	1.6	2.3

In addition to providing data on the reason for a traffic stop that resulted in a ticket, MPD also provided more detailed information in the form of a "t-code." The t-code is a reference to the specific traffic code violation that is cited on a ticket. An officer in the district can cite more than 500 traffic code violations, ranging from speeding to failure to yield and other violations. Officers can issue more than one ticket during a traffic stop for multiple violations. Of the stops that resulted in a ticket, approximately 70 percent resulted in only one violation being cited. However, in 17 percent of stops, two violations were cited; in 8 percent of stops, three violations were cited; and in 5 percent of stops, four or more violations were cited. Two stops resulted in 15 violations being cited, the most listed for an individual stop that resulted in a ticket. Of the stops that resulted in a warning, 77 percent resulted in only one violation being cited. However, two violations were cited in 14 percent of stops, and three or more violations were cited in 9 percent of warning stops. Of all the stops that resulted in a ticket (actual or warning), 49,051 t-code violations were cited.

Researchers reviewed the code violations and categorized them into several groups. It is important to note that officers report the violation listed on the ticket, not the violation that led to the stop. Although it is reasonable to assume that officers observed the moving violation prior to stopping the vehicle, we cannot make that same assumption with administrative or other violations. Drivers involved in stops that resulted in a ticket for an administrative violation may have also committed a moving violation, which led to the stop, but were not cited for that violation.

Speeding, traffic light, and other moving violations comprised a significant percentage of tickets issued. Over 7 percent of tickets were issued for speeding, 14 percent for traffic light violations, and 17 percent for some other moving violation. Administrative violations, particularly failure to produce proof of insurance, were also a significant violation category, with almost 15 percent of tickets issued for administrative offenses. An administrative violation, such as failure to produce proof of insurance, would likely not be the reason for stopping the vehicle. In most cases, the officer would observe another violation and identify the administrative violation after the stop was made. The DC traffic code requires officers to demand proof of insurance from the operator of a motor vehicle during a traffic stop. If the operator fails to show proof of insurance, the officer must issue two tickets. Tickets are issued for failure to have insurance and failure to show proof of insurance. Table 2.5 lists the number of traffic stops made by the t-code violation category.

Table 2. 5: Ticket Code Violation Reported (2023-24)

T-Code Violation Category	Number	%
Administrative (Other)	4,286	12.0
Administrative (Insurance)	993	2.8
Cell Phone	1,206	3.4
Equipment	3,547	9.9
Other Moving	6,026	16.9
Plate/Tag	3,053	8.6
Seatbelt	1,947	5.5
Speed	2,605	7.3
Stop Sign	4,029	11.3
Traffic Control Signal	5,128	14.4
Other	2,801	7.9

Patrol districts issue tickets for different reasons. The most notable differences are comparing ticket outcomes in District 2 to District 7. A ticket for an administrative violation is greatest in Districts 6 and 7. Stops resulting in a ticket for speeding occur at the highest rates in Districts 1 through 3, where the average rate is more than twice that of patrol districts 4 and 5. There is more than five times as much speed enforcement in District 2 compared to District 7. Tickets for equipment violations are highest in Districts 4 and 7, three times higher than in District 2. More tickets are issued for administrative and equipment violations in the southeastern patrol districts (5, 6, and 7), and more moving and hazardous driving violation tickets are issued in the northwestern patrol districts (2 and 3). Figure 2.6 shows the ticket code violation by the patrol district.

Table 2. 6: Ticket Code Violation Reported by Patrol District as a Percent (2023-24)

T-Code Violation Category	1D	2D	3D	4D	5D	6D	7D
Administrative (Other)	13.4	10.5	11.1	10.9	10.5	15.6	17.8
Administrative (Insurance)	2.4	3.2	1.9	2.2	3.3	4.0	4.1
Cell Phone	2.0	3.9	4.9	3.7	3.6	1.8	1.4
Equipment	7.1	6.1	9.1	17.2	9.9	9.2	18.0
Moving	15.1	20.8	14.7	15.7	15.1	32.1	7.8
Plate/Tag	6.4	9.6	10.1	10.1	5.0	7.7	13.1
Seatbelt	4.3	3.0	5.7	5.5	8.6	5.6	5.7
Speed	9.4	11.1	10.1	4.7	5.7	1.6	1.3
Stop Sign	8.3	3.8	18.4	10.2	12.6	7.6	13.3
Traffic Control Signal	25.5	18.2	7.8	9.6	16.9	7.5	9.7

T-Code Violation Category	1D	2D	3D	4D	5D	6D	7D
Other	6.2	9.7	6.1	10.1	8.8	7.3	7.7

The reasons cited on a ticket also varied by race and ethnicity. Black and Hispanic individuals were 1.6 times more likely to receive a ticket for an administrative violation compared to White individuals. On the other hand, White individuals were almost twice as likely to receive a ticket for speeding. Again, officers have little to no discretion in issuing a ticket for an administrative offense. Although it may be fair to assume that a speed stop is because the officer observed a speed violation, we cannot make that same assumption for administrative offenses. Although Black and Hispanic motorists are cited for an administrative violation at a higher rate, we do not fully understand the initial reason for the stop. Therefore, comparisons between racial groups may be inappropriate. Figure 2.7 shows the ticket code violation by race and ethnicity.

Table 2. 7: Ticket Code Violation Reported by Race and Ethnicity as a Percent (2023-24)

T-Code Violation Category	Black	Hispanic	White	Asian	Other	Not Reported
Administrative (Other)	12.7	12.2	7.7	6.8	25.0	14.3
Administrative (Insurance)	3.1	2.6	2.5	2.3	0.9	2.0
Cell Phone	3.0	4.0	4.4	3.6	0.9	3.7
Equipment	11.9	10.0	4.5	6.5	7.1	7.8
Moving	16.4	16.0	19.9	22.4	12.5	16.0
Plate/Tag	8.4	6.8	7.5	6.6	13.4	12.4
Seatbelt	6.9	5.0	2.6	3.3	5.4	2.9
Speed	6.8	6.2	12.6	5.1	1.8	4.5
Stop Sign	10.6	10.4	14.7	16.4	8.9	10.5
Traffic Control Signal	13.5	16.2	15.9	16.9	13.4	15.2
Other	6.7	10.6	7.8	10.0	10.7	10.7

This section focuses on traffic stops that did not result in a ticket but only resulted in some other police action. The MPD records management system allows officers to select multiple reasons for a stop that results in some other police action.[10] A total of 13 categories can be listed as the reason for the stop that results in some other police actions.[11] Of the 1,738 cases reported as only some other police action and no ticket, most were reported for only one reason (88%). There were 14 cases with five or more reasons listed, with the most being six reasons, which occurred in one case. The largest share of these stops resulted from the officer observing a traffic violation (41 percent). Table 2.8 lists the categories provided for the outcome of a traffic stop that resulted in only some other police action.

Table 2. 8: Reason for Traffic Stops Reported as Resulting in Some Other Police Action but No Ticket (2023-24)

Reason for Stop Category	Number	%
Call for Service	404	23.2
Individual’s actions	185	10.6
Traffic Violation	711	40.9

[10] When a stop only results in a ticket, data is collected and recorded on the ticket through a system provided by DMV. However, if any other police action is taken, such as an arrest or search, officers must complete more extensive reports through the departments records management system.
[11] Stops that resulted from a response to a crash were removed from this analysis.

Reason for Stop Category	Number	%
Be on the Lookout (BOLO)	66	3.8
Suspicion of criminal activity	63	3.6
Warrant/Court Order	20	1.1
Information obtained from LEO source	39	2.2
Individual's characteristics	4	0.2
Information obtained from witness or informants	7	0.4
Prior Knowledge	14	0.8
Demeanor during field contact	19	1.1
Observed a weapon	2	0.1
Multiple	201	11.6

The reason for traffic stops that resulted in other police actions varied notably by patrol district. In District 2, nearly one-third (32 percent) of such stops stemmed from a call for service, compared with just 18 percent in District 7. District 2 also accounted for both observed weapon cases during the study period. By contrast, traffic violations were cited more frequently in District 6, while stops related to a BOLO were least common in District 2. Table 2.9 summarizes the distribution of reasons for these stops across all patrol districts.

Table 2. 9: Reason for Traffic Stops Reported as Resulting in Some Other Police Action but No Ticket by District (2023-24)

Reason for Stop Category	1D	2D	3D	4D	5D	6D	7D
Call for Service	23.9	32.2	23.2	27.3	23.4	21.3	17.9
Individual's actions	8.2	10.5	12.2	7.0	12.6	10.2	12.5
Traffic Violation	35.8	44.8	41.1	42.1	36.4	50.6	33.3
Be on the Lookout (BOLO)	2.5	0.7	4.2	3.7	4.1	4.1	5.1
Suspicion of criminal activity	5.7	1.4	4.2	2.1	2.6	2.3	6.7
Warrant/Court Order	4.4	0.0	0.4	1.2	0.4	0.6	1.9
Information obtained from LEO source	4.4	0.7	1.1	1.2	3.7	3.2	1.3
Individual's characteristics	0.0	0.0	1.1	0.0	0.0	0.0	0.3
Information obtained from witness or informants	0.0	0.0	1.1	0.8	0.0	0.6	0.0
Prior Knowledge	0.6	0.0	0.4	1.7	0.7	0.3	1.3
Demeanor during field contact	1.3	0.7	1.9	1.7	0.7	0.6	1.0
Observed a weapon	0.0	1.4	0.0	0.0	0.0	0.0	0.0
Multiple	13.2	7.7	9.1	11.2	15.2	6.1	18.6

Some traffic stops also result in an arrest. A stop that results in an arrest can also result in the issuance of a ticket or some other police action taking place. For the purposes of this section, all traffic stops that resulted in an arrest, regardless of whether they also resulted in a ticket, were included in the total number of arrests. Of the more than 37,000 traffic stops, approximately 2,700 resulted in an arrest (7 percent). An arrest could result in multiple charges for an individual. The most an individual was charged with was 14 criminal arrest charges. There were several arrest citations listed in the dataset, from driving under the influence of alcohol or drugs to fleeing from law enforcement and possession of a firearm, among others. Officers made the largest number of arrests for drivers not having a permit (42 percent of all arrests) and driving under the influence of alcohol or drugs (19 percent of all arrests). District 7 had the highest number of arrests resulting from traffic stops, accounting for 18 percent of all arrests and the highest arrest rate per stop. Specifically, 18 percent of stops in

District 7 resulted in an arrest, which is 2.5 times the department's arrest rate. Table 2.10 shows the number of arrests from a traffic stop by the patrol district.

Table 2. 10: Arrests by Patrol District

District	Number	Percent of All Arrests	Percent of Stops
1	297	10.7	4.9
2	275	9.9	4.5
3	387	13.8	4.8
4	426	15.3	9.7
5	442	15.9	7.0
6	439	15.8	14.0
7	500	18.0	18.0

Arrests resulting from a traffic stop varied by race and ethnicity. Excluding individuals recorded as "other", Hispanic individuals were arrested at the highest rate resulting from a traffic stop and were arrested at a rate more than five times greater than White individuals. Black individuals were arrested at a lower rate when compared to Hispanic individuals, but at a rate 4 times greater than White individuals. Based on the largest percentage of arrests occurring in Districts 6 and 7, this racial and ethnic disparity is not surprising, given the demographics of stops in those areas. Table 2.11 shows arrests by race and ethnicity and as a percentage of the overall traffic stops.

Table 2. 11: Arrests by Race and Ethnicity

Race/Ethnicity	Number	Arrests as a % of Stops
Black	2,001	8.9
Hispanic	412	10.5
White	117	2.1
Other	186	18.6
Unknown	58	1.3

III: ANALYSIS OF TRAFFIC STOPS, SOLAR VISIBILITY

Solar visibility analysis looks at how changing sunset times throughout the year can help understand differences in police traffic stops across racial and ethnic groups. The purpose of the solar visibility analysis is to determine the role of visibility and officer perception in traffic-related stops by law enforcement.

The method of the solar visibility analysis is based on the assumption that police officers are marginally better at observing certain characteristics of drivers, including race and ethnicity, during daylight compared to darkness (Grogger and Ridgeway 2006; Ridgeway 2009; Horace and Rohlin 2020; Kalinowski et al. 2018, 2022a, 2022b)[12].The timing of sunset and sunrise varies throughout the year due to two primary factors: (1) seasonal changes caused by the Earth's axial tilt and elliptical orbit around the sun, and (2) discrete shifts resulting from the spring and fall transitions to and from Daylight Saving Time. Leveraging these two sources of variation, we can effectively compare stops made in darkness versus daylight, at the same time of day and on the same day of the week. Unlike methods that use population-based benchmarks, solar visibility analysis does not require assumptions about the underlying risk-set of individuals on the road. Instead, it presumes that the composition of individuals and police enforcement behavior does not vary in response to visibility changes[13]. By comparing the racial composition of stops in darkness to those in daylight within a fixed window where sunset timing varies throughout the year, we can use stops made in darkness as a comparison point for those made in daylight, helping to provide insights into how visibility may play a role in traffic stop patterns. The solar visibility test specifically examines whether the probability that a stopped driver is non-White increases from darkness to daylight, relative to the change in probability for a White non-Hispanic driver. In other words, this test examines the probability of a stopped driver belonging to a specific racial group across daylight and darkness. Our ultimate goal, however, is to make an inference about whether there are changes to the probability that a driver is stopped given their race, not the probability of race given being stopped. While we can directly calculate the probability of race given being stopped using traffic stop data, we unfortunately cannot directly calculate the probability of being stopped conditional on race without detailed information on the underlying driving population. Importantly, Grogger and Ridgeway (2006) demonstrate that under certain conditions, the likelihood of stopping a non-White individual in daylight versus darkness is equivalent to the likelihood of a

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[12] Statewide multi-agency studies relying on Solar Visibility, also known as the Veil Of Darkness (VOD), include Connecticut (Ross et al. 2015, 2016, 2017a, 2017b, 2018, 2020a, 2020b, 2020, 2022, 2022), Rhode Island (Ross et al. 2020, 2020, 2022), California (Sanchagrin et al. 2020, 2020, 2022), Oregon (Oregon DOJ dashboard), and Massachusetts (Salem State 2020, 2022, Ross 2023). Agency-specific studies relying on the VOD include in Oakland, CA (Grogger and Ridgeway 2006); Cincinnati, OH (Ridgeway 2009); Minneapolis, MN (Ritter and Bael 2009 and Ritter 2017); Syracuse, NY (Worden, McLean, and Wheeler 2010, 2012; Horace and Rohlin 2016); Portland, OR (Renauer, Henning, and Covelli 2009); Durham Greensboro, Raleigh, and Fayetteville, North Carolina (Taniguchi et al. 2016a, 2016b, 2016c, 2016d); New Orleans, LA (Asher 2016); San Diego, CA (Chanin et al. 2016); Corvallis PD (Criminal Justice Policy Research Institute 2017); Columbia, MO (Milyo 2017); San Jose, CA (Smith et al. 2017); Maricopa, AZ (Wallace et al. 2017); Portland, ME (McDevitt et al. 2023), Douglas Co, KS (McDevitt et al. 2023); Tennessee State Police (Kalinowski et al. 2023); Texas Highway Patrol (Kalinowski et al. 2023, Mello et al. 2024); Massachusetts State Police (Kalinowski et al. 2023); and New Jersey State Police (Ross 2023). There has also been a highly cited national application of Veil of Darkness on 100 million traffic stops from 21 state patrol agencies and 35 municipal police agencies published in Nature Human Behavior (Pierson et al. 2020).

[13] This assumption allows for the existence of differential rates of traffic stops across racial groups, as well as potential differences in guilt and driving behavior. This assumption has been rigorously tested in numerous scholarly publications employing this methodology through "balancing tests." These tests demonstrate that characteristics of White drivers (e.g., sex/gender, age, and vehicle characteristics) do not significantly vary between daylight and darkness conditions (see Kalinowski et al., 2023).

stopped individual being non-White in daylight versus darkness[14]. Practically, this assumes that variations in travel and enforcement patterns occur similarly across racial groups and are not influenced by differences in lighting conditions.

To meet these conditions, the estimates are adjusted for the time, day of the week, and location. Additionally, to account for inherent differences between daylight and darkness, the sample is restricted to the inter-twilight window—a period during the day when solar visibility varies throughout the year (i.e., between the earliest eastern sunset and the latest western end of civil twilight, as well as the earliest eastern beginning of civil twilight and the latest western sunrise). Conveniently, these two windows overlap with the morning and evening commutes, when the risk set of individuals is also least likely to be affected by seasonal variation. The assumptions inherent to this method have been tested in a number of peer-reviewed scholarly papers and have been shown to hold in a variety of settings[15]. However, the analysis includes a number of additional robustness tests to ensure that they are met in the present context.

III.A: AGGREGATE ANALYSIS WITH SOLAR VISIBILITY TEST

Figures 3.1 to 3.3 present the results of applying the solar visibility test to the aggregate sample of traffic stops made within the inter-twilight sample in D.C. between July 2019 and June 2024. The vertical axis on the figure plots a 95 percent confidence interval around the coefficient estimate of a linear regression of motorist race/ethnicity on daylight and includes controls for time of day, day of week, and year. The reference group across all specifications is held constant and consists of stops made of White drivers. We cluster standard errors on the day of the week by hour by district. In Figure 3.1, we report estimates of changes in the likelihood that a Black driver will be stopped in daylight relative to darkness. In all of the periods analyzed, none of the coefficient estimates for Black drivers were positive in magnitude and statistically significant at conventional levels.[16] In Figure 3.2, we report estimates of changes to the likelihood of a Hispanic driver being stopped in daylight relative to darkness. In all of the periods analyzed except for July 2023 to June 2024, none of the coefficient estimates for Hispanic drivers were positive in magnitude and statistically significant at conventional levels.[17] During the period spanning July 2023 to June 2024, we estimate a statistically significant difference, indicating that Hispanic motorists were more frequently stopped by MPD during daylight compared to darkness. In Figure 3.3, we report estimates of changes to the likelihood that any individual who is a non-White driver is stopped in daylight relative to darkness. In all the periods analyzed, none of the coefficient estimates were positive in magnitude and statistically significant at conventional levels.[18] Coefficient estimates, standard errors, and sample sizes are contained in Table B.1 of Appendix B for Figures 3.1 to 3.3.

The main estimates presented in Figures 3.1 through 3.3 may be subject to several sources of bias. First, certain types of equipment violations, such as those related to lighting, may be correlated with both visibility and race/ethnicity through underlying socioeconomic factors. Second, the analysis may be affected by a violation of the assumption that the relative risk set of individuals remains invariant to changes in visibility. Third, seasonal variation in the driving population could influence the results.

[14] See the appendix for a formal mathematical explanation.
[15] Refer to footnote 9.
[16] In the period from July 2019 to June 2020, we estimate a statistically significant negative disparity. As shown in Kalinowski et al. (2023), this is potentially also a result consistent with disparate treatment.
[17] In the period from July 2021 to June 2022, we estimate a statistically significant negative disparity. As shown in Kalinowski et al. (2023), this is potentially also a result consistent with disparate treatment.
[18] In the period from July 2019 to June 2020, we estimate a statistically significant negative disparity. As shown in Kalinowski et al. (2023), this is potentially also a result consistent with disparate treatment.

To address these concerns, we conduct a series of robustness tests, the details of which are provided in Table B.2 through B.4 of Appendix B. Overall, the findings from these tests are consistent with the main estimates. Specifically, we find no evidence of statistically significant differences across the years analyzed, with the exception of Hispanic drivers during the period from July 2023 to June 2024. Additionally, results from a restricted-sample robustness test designed to account for seasonal variation show no statistically significant differences across any of the periods examined.

Figure 3. 1: Aggregate Solar Visibility Analysis by Year for Black Individuals, All Stops 2019-24

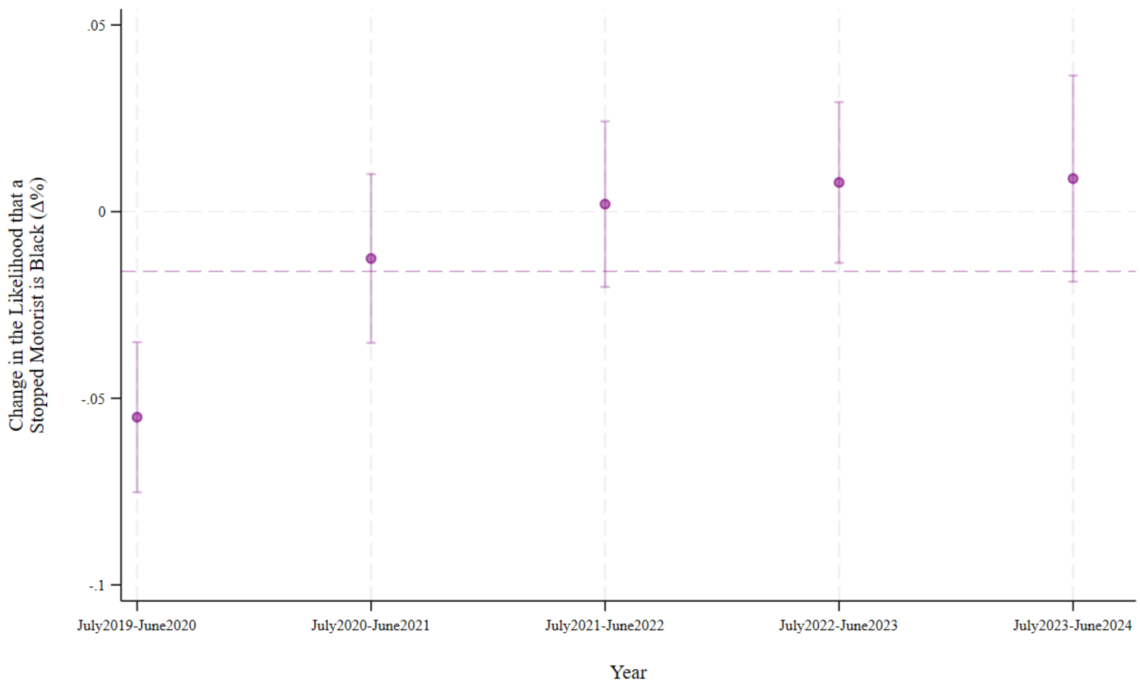


Figure 3. 2: Aggregate Solar Visibility Analysis by Year for Hispanic Individuals, All Stops 2019-24

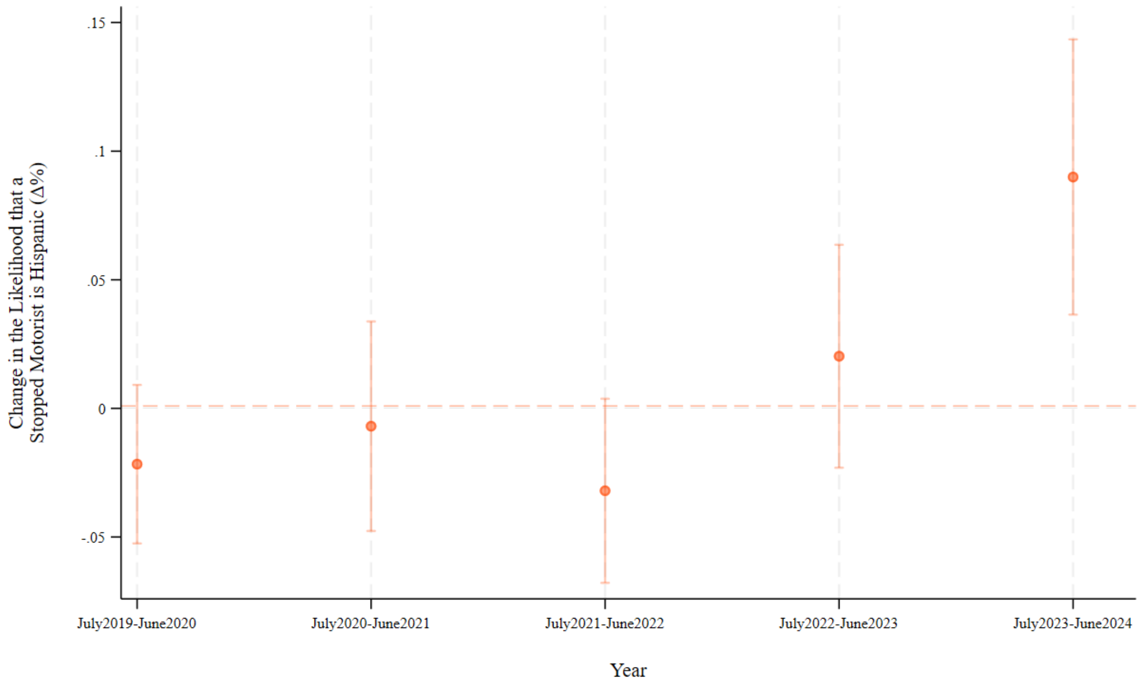
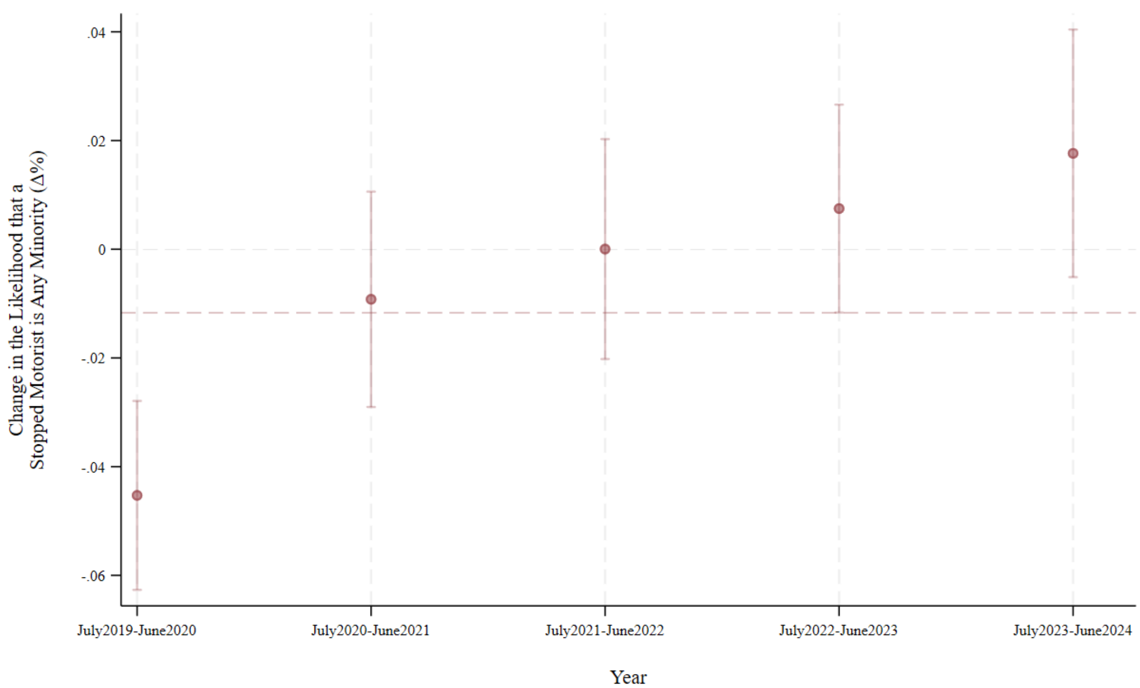


Figure 3. 3: Aggregate Solar Visibility Analysis by Year for Non-White Individuals, All Stops 2019-24



III.B: DISTRICT ANALYSIS WITH SOLAR VISIBILITY TEST

Figures 3.4 to 3.6 report the results of applying the solar visibility analysis to each of the seven patrol districts from July 2023 through June 2024. These figures present the estimated changes in the likelihood that Black, Hispanic, and non-White drivers are stopped in daylight compared to darkness during this period. As shown below, we find statistically significant differences in District 3 (Hispanic: β=15.97pp or 0.51%, $p<0.01$; Any non-White: β=6.5pp or 0.42%, $p<0.01$) and District 7 (Black: β=3.72pp or 0.18%, $p<0.01$; Any non-White: β=3.5pp or 0.25%, $p<0.01$). In these two districts, the results indicate that racial/ethnic minority drivers were more likely to be stopped in daylight relative to darkness for the period from July 2023 to June 2024. While these results do not necessarily indicate racial bias, they suggest that these districts may engage in enforcement practices that result in stop differences, even if they are prima facie race-neutral. Coefficient estimates, standard errors, and sample sizes are contained in Table B.5 of Appendix B for Figures 3.4 to 3.6.

Figure 3. 4: Solar Visibility Analysis by District for Black Individuals, July 2023- June 2024

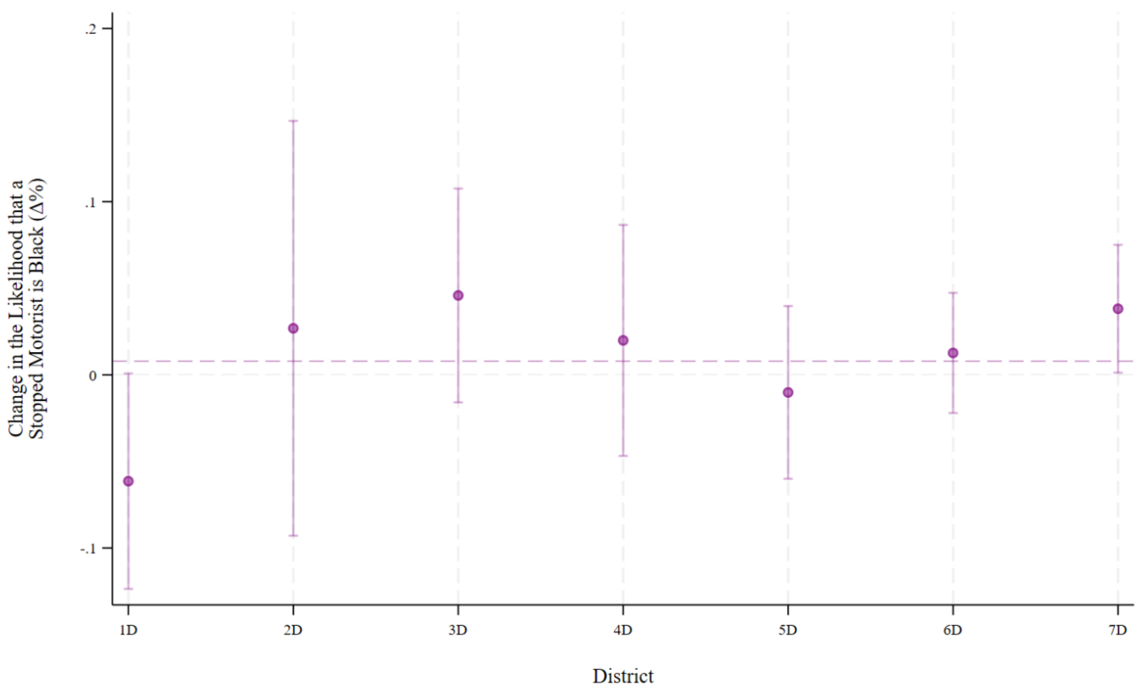


Figure 3. 5: Solar Visibility Analysis by District for Hispanic Individuals, July 2023-June 2024

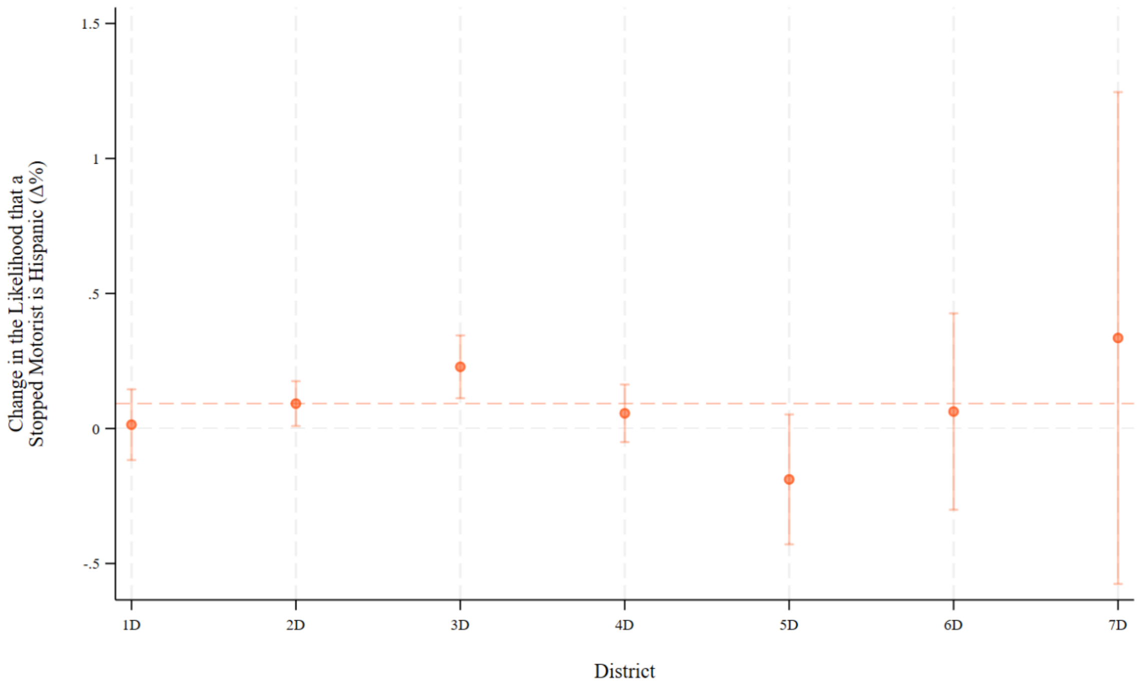
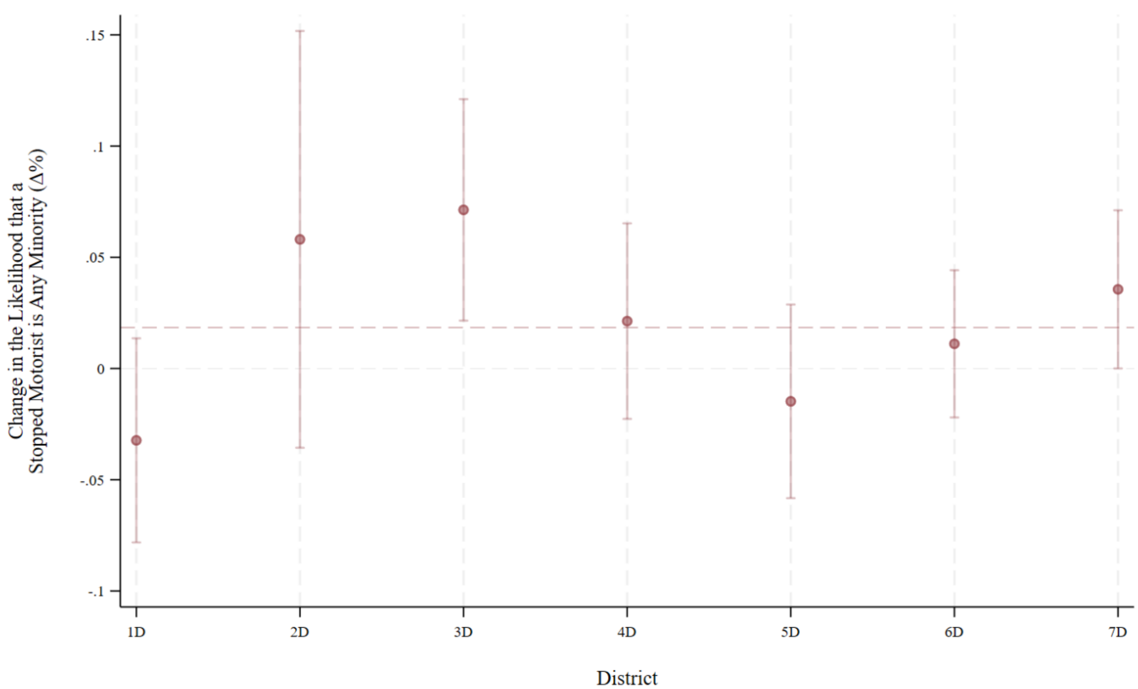


Figure 3. 6: Solar Visibility Analysis by District for Non-White Individuals, July 2023-June 2024



Figures 3.7 to 3.9 report the results of applying the solar visibility analysis to each of the seven patrol districts during the combined three-year period from July 2021 through June 2024. Figures 3.7 to 3.9 present the estimated changes in the likelihood that Black, Hispanic, and non-White drivers are stopped in daylight compared to darkness during this period. As shown below, we find statistically significant differences in District 1 (Hispanic: β=9.47pp or 28.58%, p<0.01), District 3 (Black: β=3.42pp or 4.73%, p<0.04; Any non-White: β=3.05pp or 4%, p<0.04), District 4 (Black: β=3.75pp or 4.49%, p<0.03; Any non-White: β=2.97pp or 3.4%, p<0.03), and District 5 (Black: β=4.33pp or 4.87%, p<0.01; Any non-White: β=3.59pp or 3.97%, p<0.01). In these four districts, the results indicate that racial/ethnic minority individuals are more likely to be stopped in daylight relative to darkness. As discussed with respect to the one-year district results, these results do not necessarily indicate racial bias, but they suggest that these districts may engage in enforcement practices that result in stop differences. Coefficient estimates, standard errors, and sample sizes are contained in Table B.6 of Appendix B for Figures 3.7 to 3.9.

Figure 3. 7: Solar Visibility Analysis by District for Black Individuals, Three-Year Aggregate

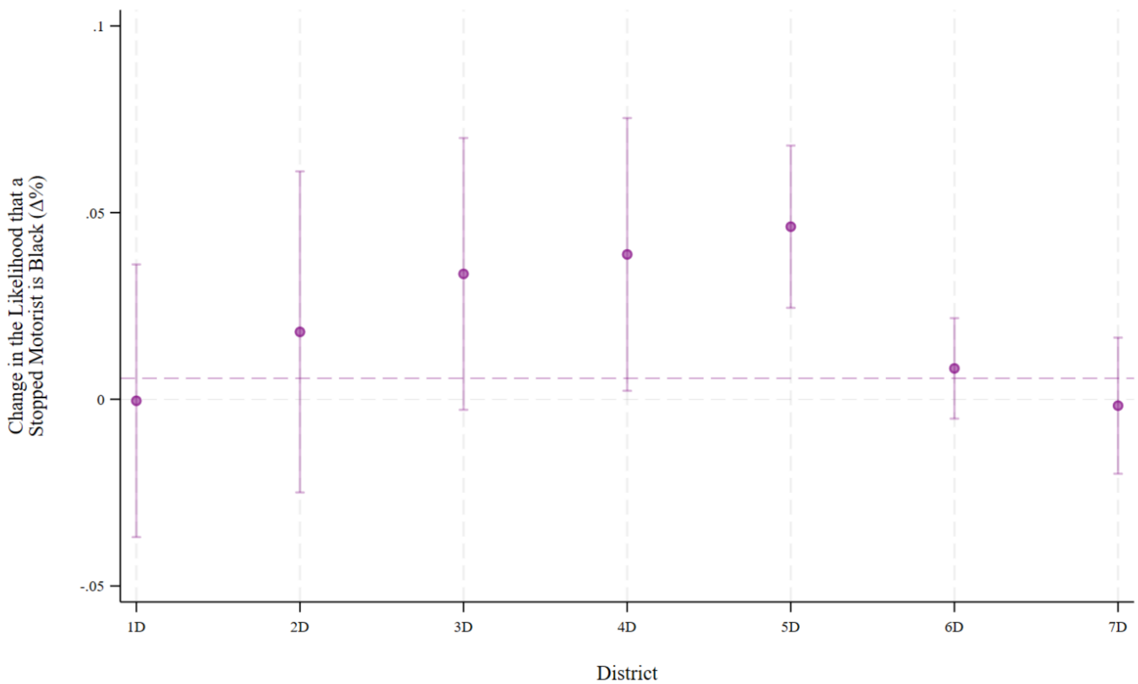


Figure 3. 8: Solar Visibility Analysis by District for Hispanic Individuals, Three-Year Aggregate

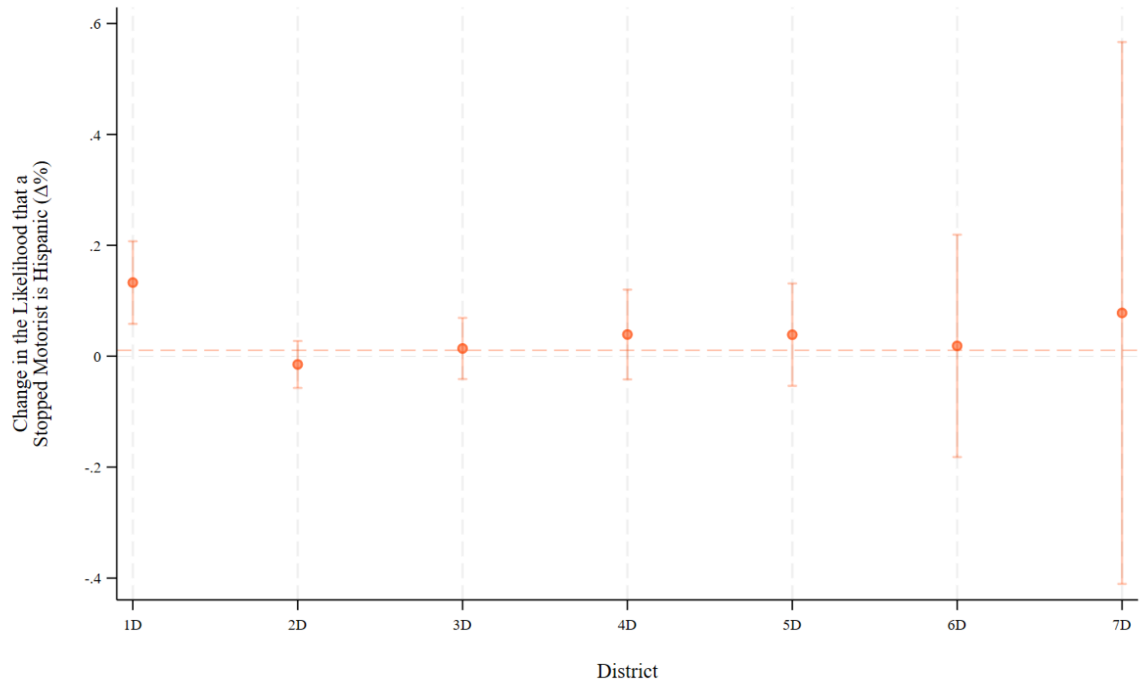
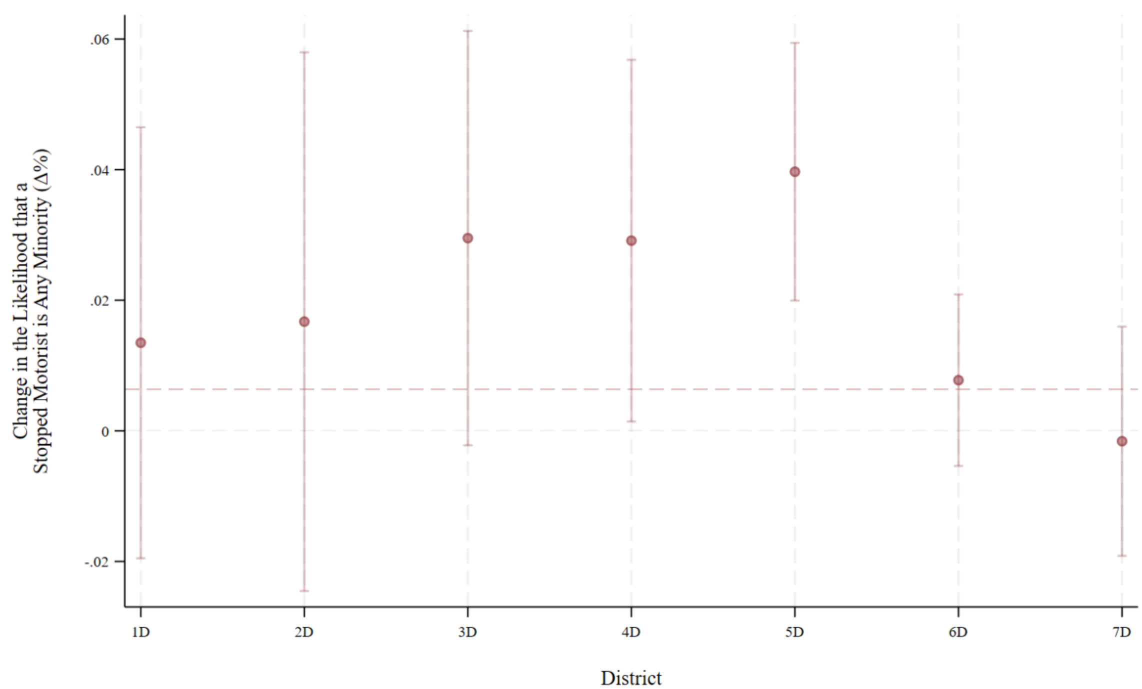


Figure 3. 9: Solar Visibility Analysis by District for Non-White Individuals, Three-Year Aggregate



IV. ANALYSIS OF POST-STOP ENFORCEMENT ACTION

In this section, we test for differences in the outcomes of traffic stops using a model that examines the distribution of outcomes conditional on race, time of day, and day of week. Specifically, we test whether traffic stops made of non-White individuals result in different outcomes relative to their White peers. Since ex-ante it is unclear whether discrimination would create more or less severe stop outcomes, we simply test for equality in the distribution of outcomes ex-post. On the one hand, discriminatory police officers might treat non-White individuals more harshly conditional on the reason they were stopped. However, discriminatory police might also make more pretextual traffic stops for lower-level offenses motivated by the fact that they may observe evidence of a more severe crime once the vehicle is stopped. Rather than making untestable assumptions, we simply assume that the overall distribution of outcomes will be equal across race/ethnicity in the absence of disparate treatment. The intuition is similar to that of hit-rate style tests like those presented in a subsequent section, but we are unable to sign the direction that we expect bias to take. In terms of possible outcomes, we test for differences in arrest rates, ticketing rates, and the duration of the stop. We caution the reader not to place a causal interpretation on this test because we do not have adequately detailed data to allow us to control for selection into different types of circumstances and locations.

IV.A: AGGREGATE ANALYSIS OF POST-STOP ENFORCEMENT ACTION

Figures 4.1 to 4.3 report results from applying the conditional outcome test focusing on arrests in each of the five years between July 2019 and June 2024. We use ordinary least squares to regress a binary indicator variable of a stop, resulting in an arrest on an indicator for race/ethnicity as well as controls for time of day and day of week. We cluster standard errors on the day of the week by hour by district. As mentioned in the introduction to this section, the ideal formulation of this test would also include granular geographic controls for location and the circumstances motivating a stop. Since the current data do not contain sufficient information to build these additional controls, we caution the reader about placing any causal interpretation of the results of this analysis and instead recommend that they are used only for identifying trends in the data.

In Figure 4.1, we report estimates of the likelihood that a stop of a Black driver results in an arrest. Across all years in the sample, we estimate that Black drivers are statistically more likely to be arrested (β=6.16pp or 94.8%, $p<0.01$) following a stop. Similarly, in Figures 4.2 and 4.3, we find that Hispanic (β=4.36pp or 67.08%, $p<0.01$) and any non-White (β=5.79pp or 89.07%, $p<0.01$) individuals were also statistically more likely to be arrested following a stop. As shown below, all of the differences decrease in each of the years between 2020 and 2024 but increase in the most recent year. As noted, we caution the reader not to place a causal interpretation on this test because we cannot adequately control for selection into different types of circumstances that necessitate an arrest. Coefficient estimates, standard errors, and sample sizes are contained in Table C.1 of Appendix C for Figures 4.1 to 4.3.

Figure 4. 1: Aggregate Analysis of Decision to Arrest by Year for Black Individuals

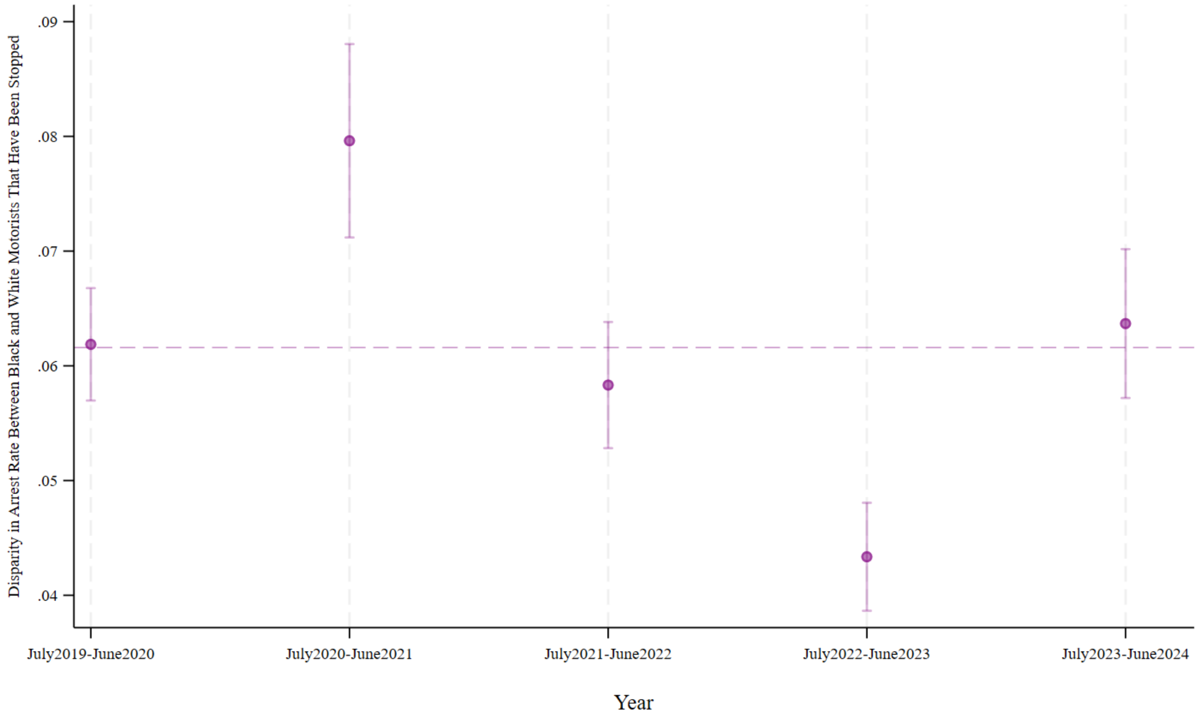


Figure 4. 2: Aggregate Analysis of Decision to Arrest by Year for Hispanic Individuals

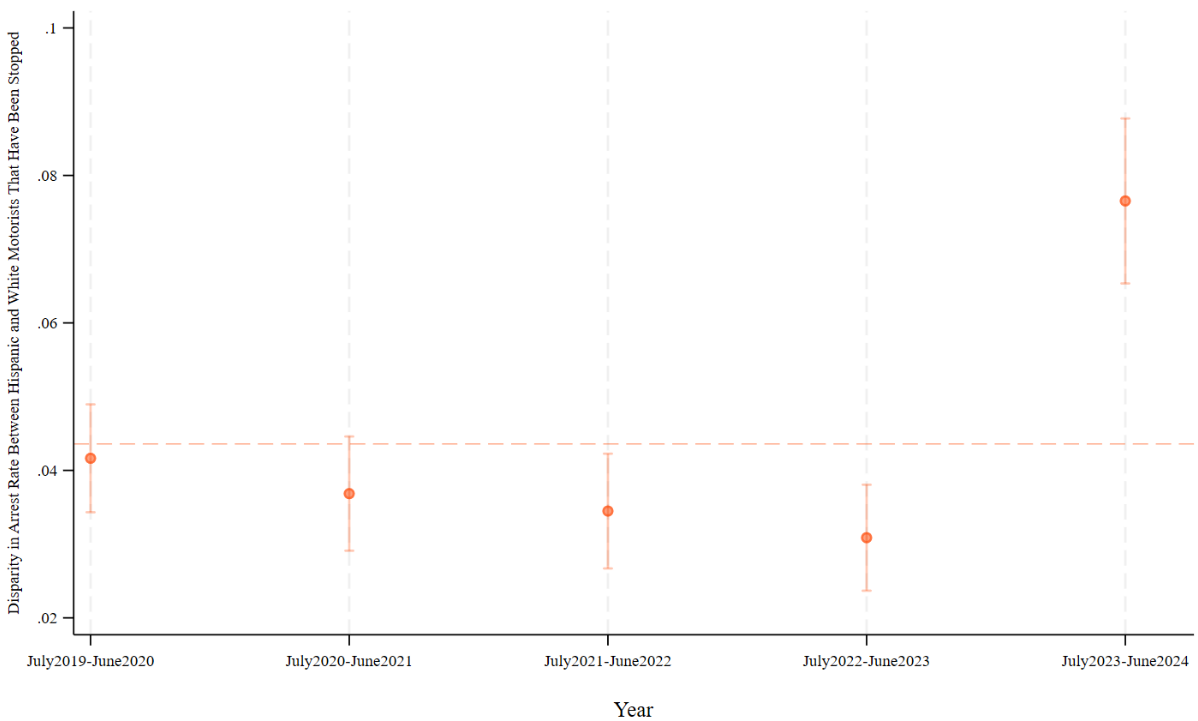
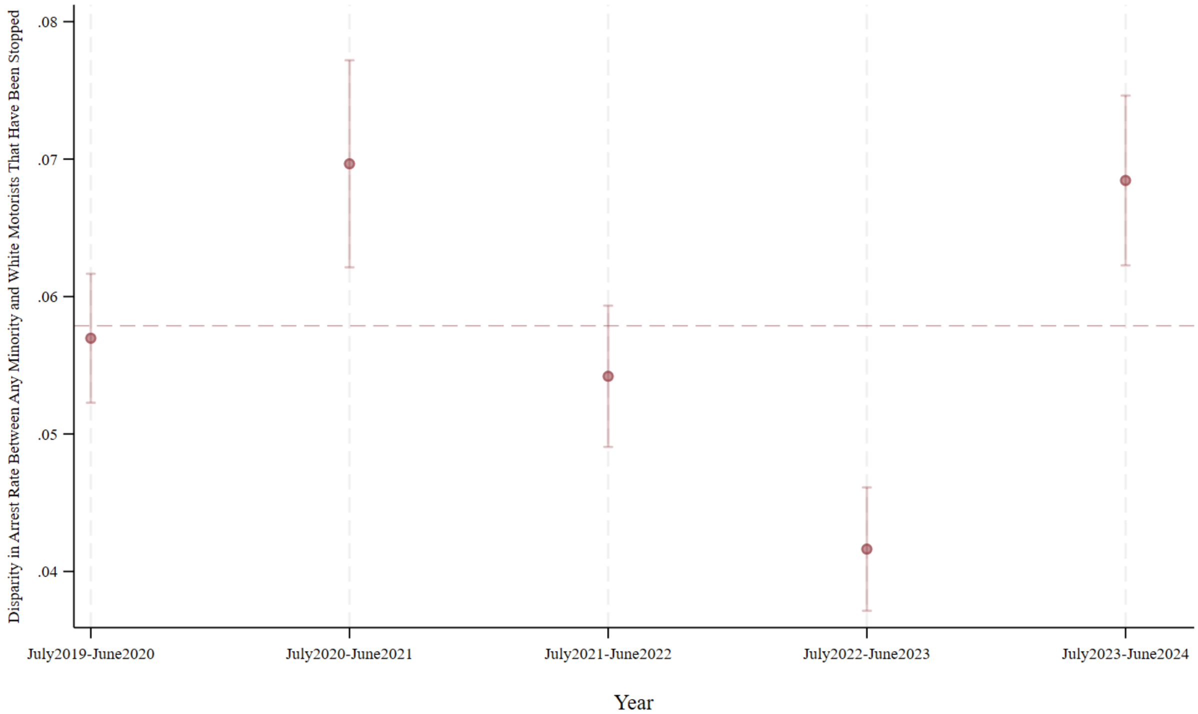


Figure 4. 3: Aggregate Analysis of Decision to Arrest by Year for Non-White Individuals



Figures 4.4 to 4.6 report results from applying the conditional outcome test focusing on the decision to ticket for each of the five years between July 2019 and June 2024. We use ordinary least squares to regress a binary indicator variable of a stop, resulting in a ticket on an indicator for race/ethnicity and controls for the time of day and day of the week. We cluster standard errors on the day of the week by hour by district. We again make the necessary caveat that the ideal formulation of this test would also include granular geographic controls for location and the circumstances motivating a stop. In Figure 4.4, we report estimates of the likelihood that a stop of a Black driver results in a ticketed offense. Across all years in the sample except July 2019 to June 2020, we estimate that Black drivers are statistically more likely to receive a ticket (β=3pp or 4.5%, $p<0.01$) following a stop. In Figure 4.5, we find that Hispanic individuals are more likely to receive a ticket (β=7.08pp or 10.61%, $p<0.01$) in all five years examined. In Figure 4.6, we find that any non-White driver was statistically more likely to receive a ticket (β=3.44pp or 5.16%, $p<0.01$) in all years but July 2019 to June 2020. As noted again, we caution the reader not to place a causal interpretation on this test because we are unable to adequately control for selection into different types of circumstances that necessitate a ticket. Coefficient estimates, standard errors, and sample sizes are contained in Table C.2 of Appendix C for Figures 4.4 to 4.6.

Figure 4. 4: Aggregate Analysis of Decision to Ticket by Year for Black Individuals

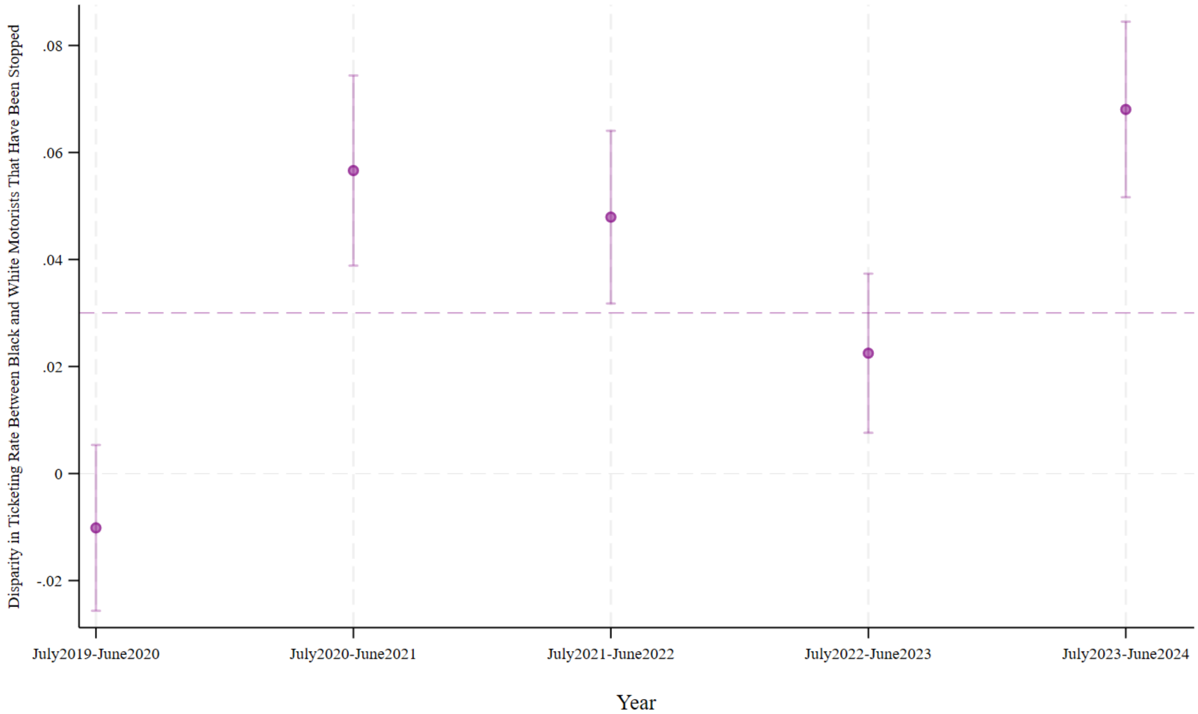


Figure 4. 5: Aggregate Analysis of Decision to Ticket by Year for Hispanic Individuals

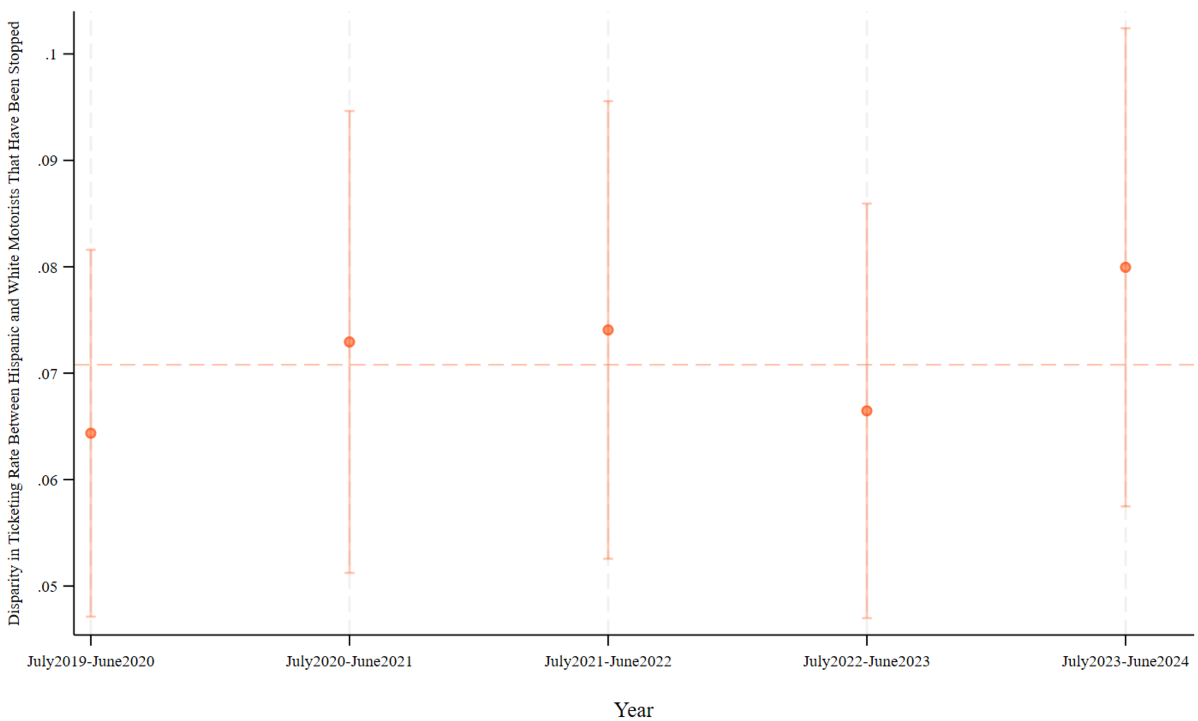
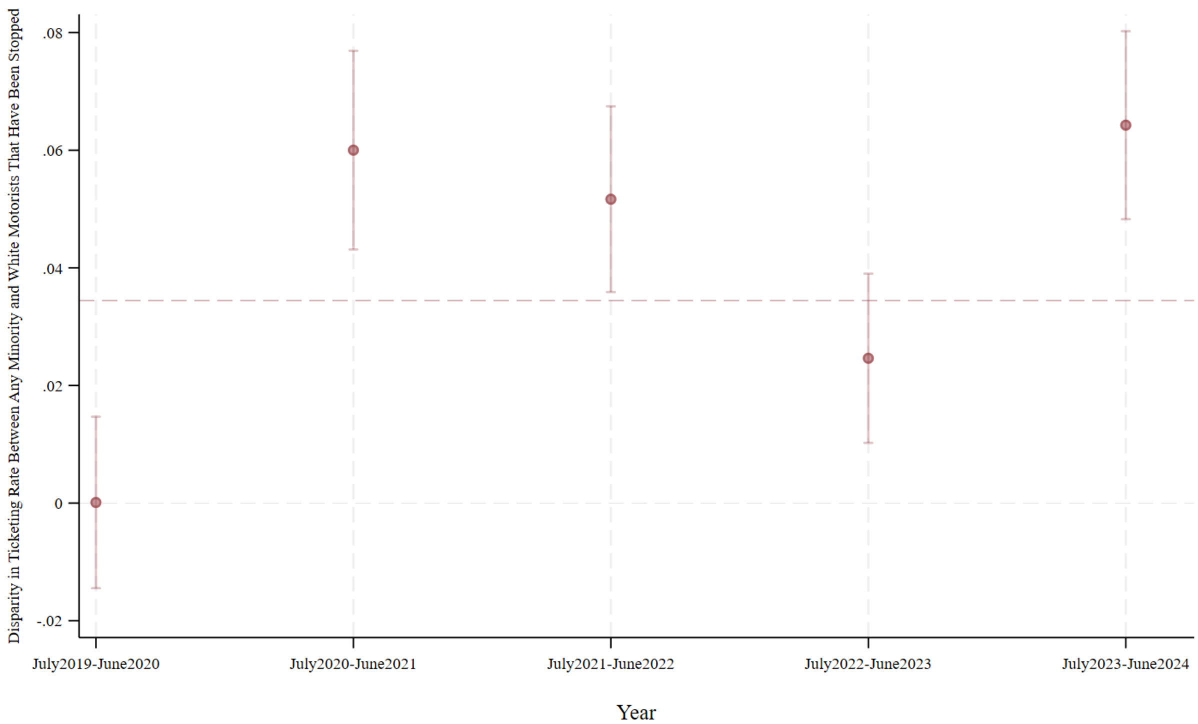


Figure 4. 6: Aggregate Analysis of Decision to Ticket by Year for Non-White Individuals



Figures 4.7 to 4.9 report results from applying the conditional outcome test focusing on the duration of a stop for each of the five years between July 2019 and June 2024. We use ordinary least squares to regress a variable reporting the length of a stop (in minutes) on an indicator for race/ethnicity, as well as controls for the time of day and day of the week.[19] We cluster standard errors on the day of the week by hour by district. Again, we make the necessary caveat that the ideal formulation of this test would also include granular geographic controls for location and the circumstances motivating a stop. In Figure 4.7, we report estimates of the difference in the duration of a stop involving a Black driver. In the most recent year of data from July 2023 to June 2024, we estimate a statistically significant lower stop duration (β=-12.2min or -18.23%, p<0.01) for Black drivers. In Figures 4.8, we also estimate a statistically significant lower stop duration for Hispanic (b=-17.93min or -26.79%, p<0.01) in the most recent year. In Figure 4.9, we also estimate a statistically significant lower stop duration for any non-White motorists (b=-13.35min or -19.95%, p<0.01) in the most recent year. As noted again, we caution the reader not to place a causal interpretation on this test because we cannot adequately control for selection into different types of circumstances that necessitate a longer stop duration. Coefficient estimates, standard errors, and sample sizes are contained in Table C.3 of Appendix C for Figures 4.7 to 4.9.

[19] Note that for durations listed as longer than 24-hours, we top code duration at 1,440 minutes.

Figure 4. 7: Aggregate Analysis of Stop Duration by Year for Black Individuals

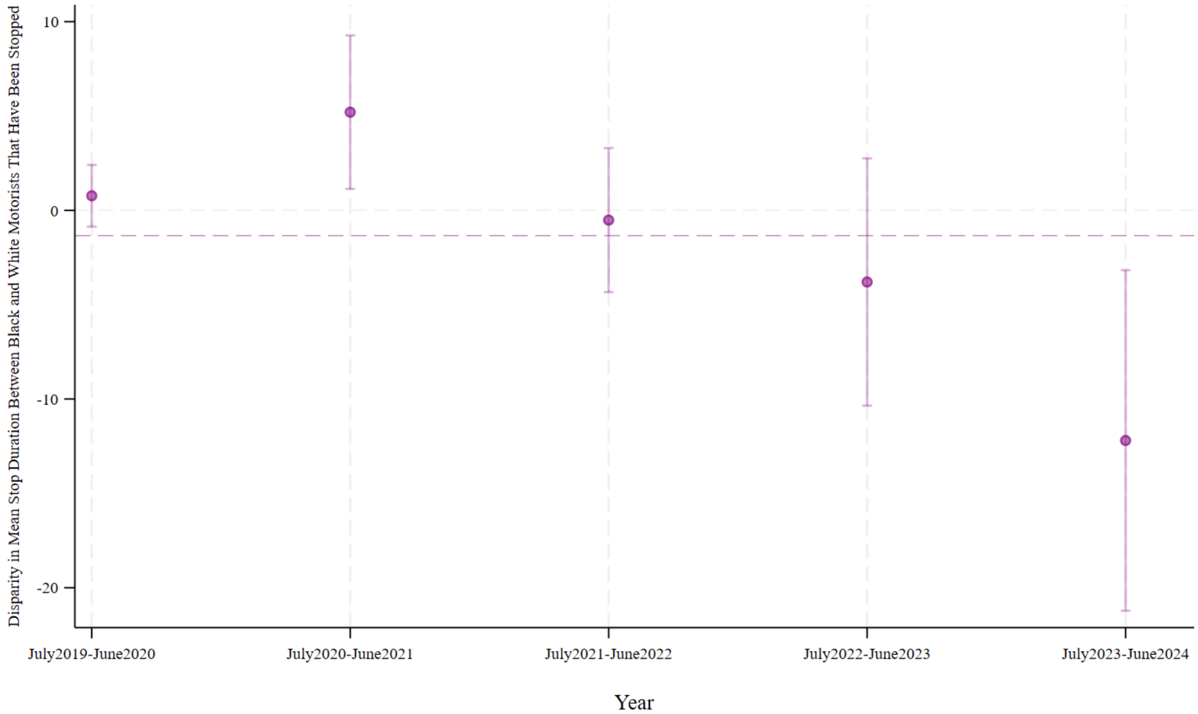


Figure 4. 8: Aggregate Analysis of Stop Duration by Year for Hispanic Individuals

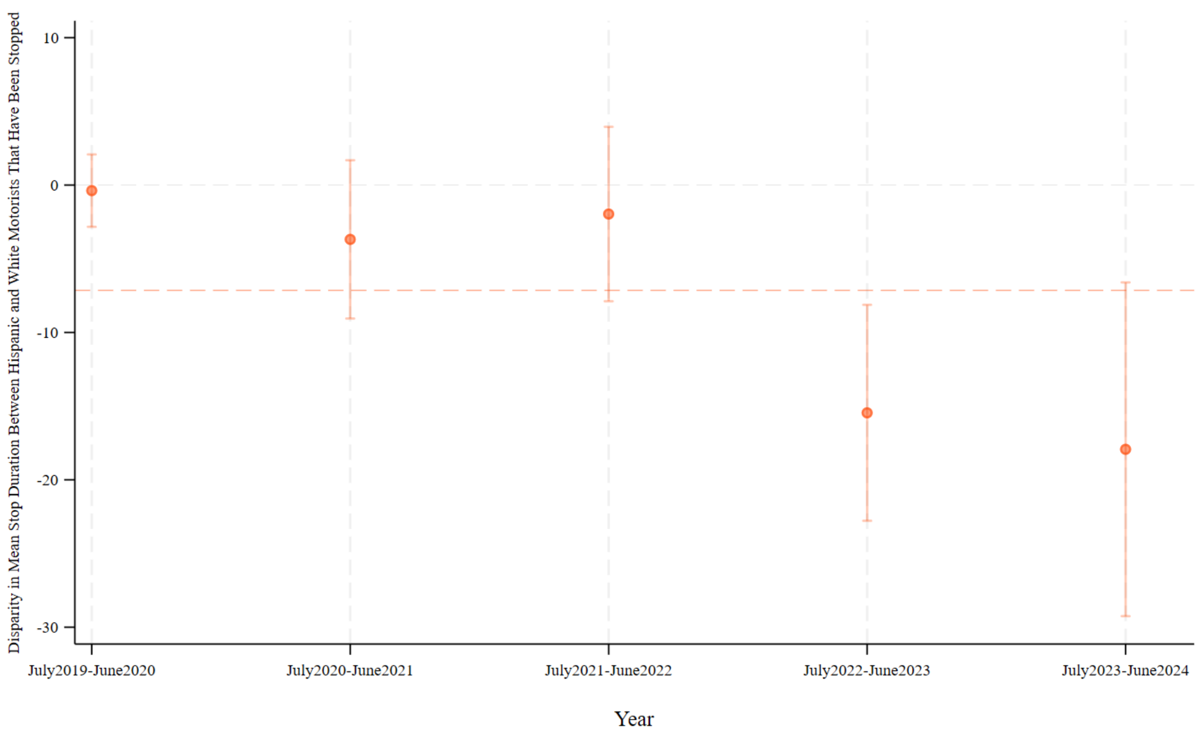
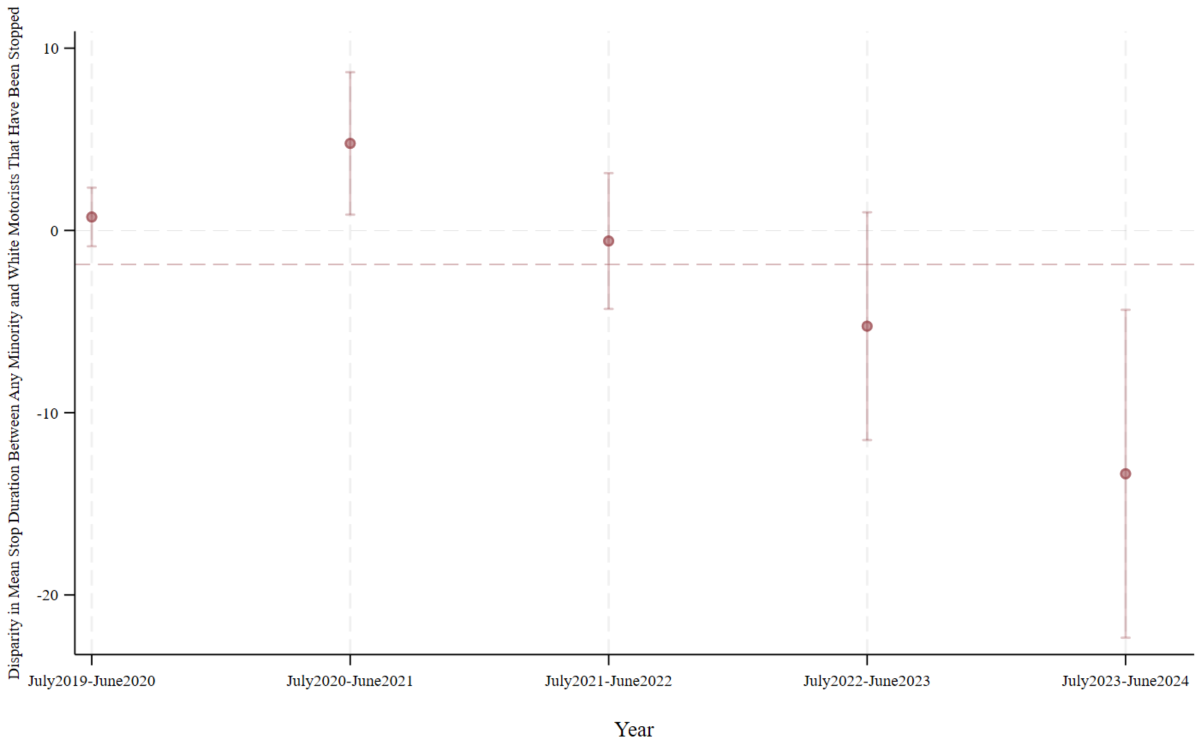


Figure 4. 9: Aggregate Analysis of Stop Duration by Year for Non-White Individuals



IV.B: DISTRICT ANALYSIS OF POST-STOP ENFORCEMENT ACTION

Figures 4.10 to 4.12 report the results of applying the conditional outcome test for the decision to arrest in each of the seven patrol districts from July 2023 through June 2024. Figures 4.10 to 4.12 present differences in arrest rates for White individuals relative to Black, Hispanic, and any non-White individuals during this period. As shown below, we find statistically significant higher arrest rates across all districts for Black, Hispanic, and Any non-White motorists. The only exception is that we do not find a statistically significant difference for Hispanic motorists in District 7. We again caution the reader not to place a causal interpretation on this test because we are unable to adequately control for selection into different types of circumstances that necessitate an arrest. Coefficient estimates, standard errors, and sample sizes are contained in Table C.4 of Appendix C for Figures 4.10 to 4.12. We also applied the conditional outcome test for the decision to arrest for each of the seven patrol districts for a three-year period (July 2021 to June 2024). These results are contained in Table C.5 of Appendix C.

Figure 4. 10: Analysis of Decision to Arrest by District for Black Individuals, July 2023- June 2024

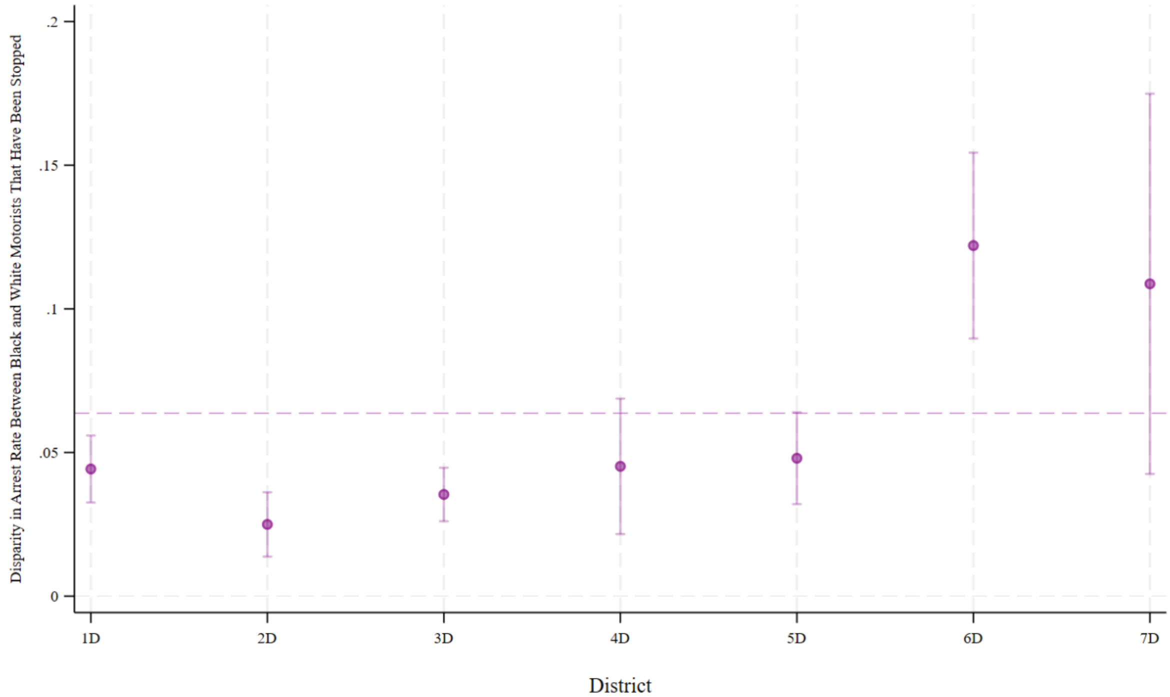


Figure 4. 11: Analysis of Decision to Arrest by District for Hispanic Individuals, July 2023- June 2024

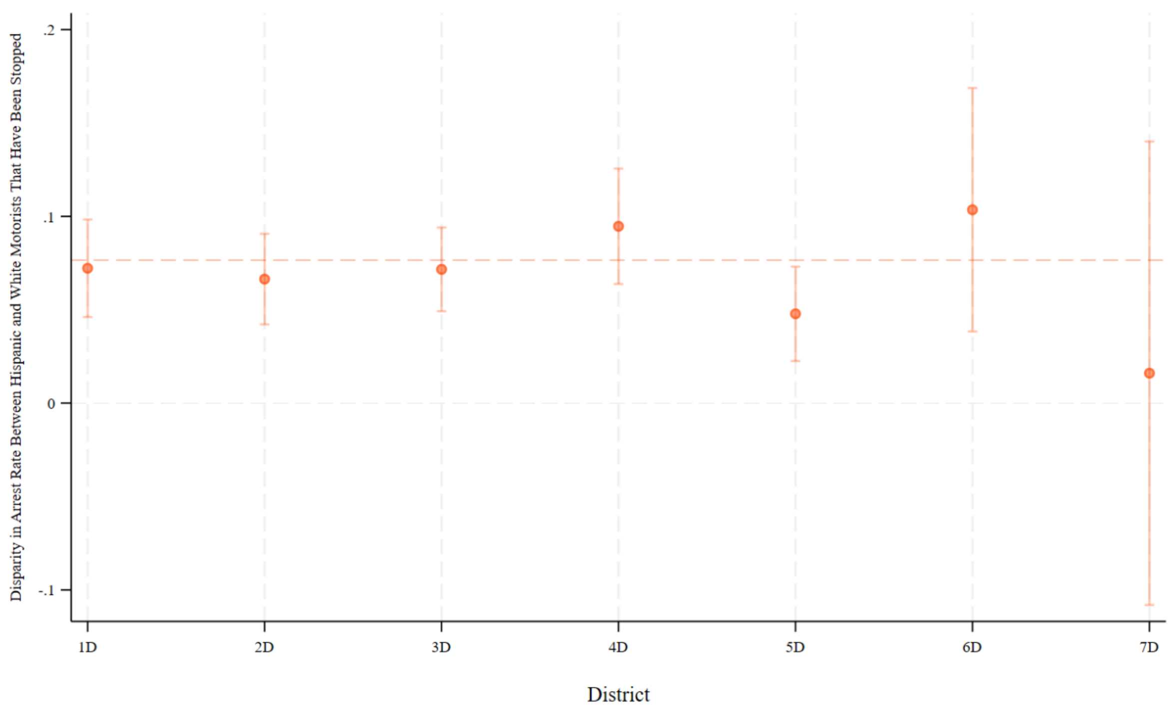
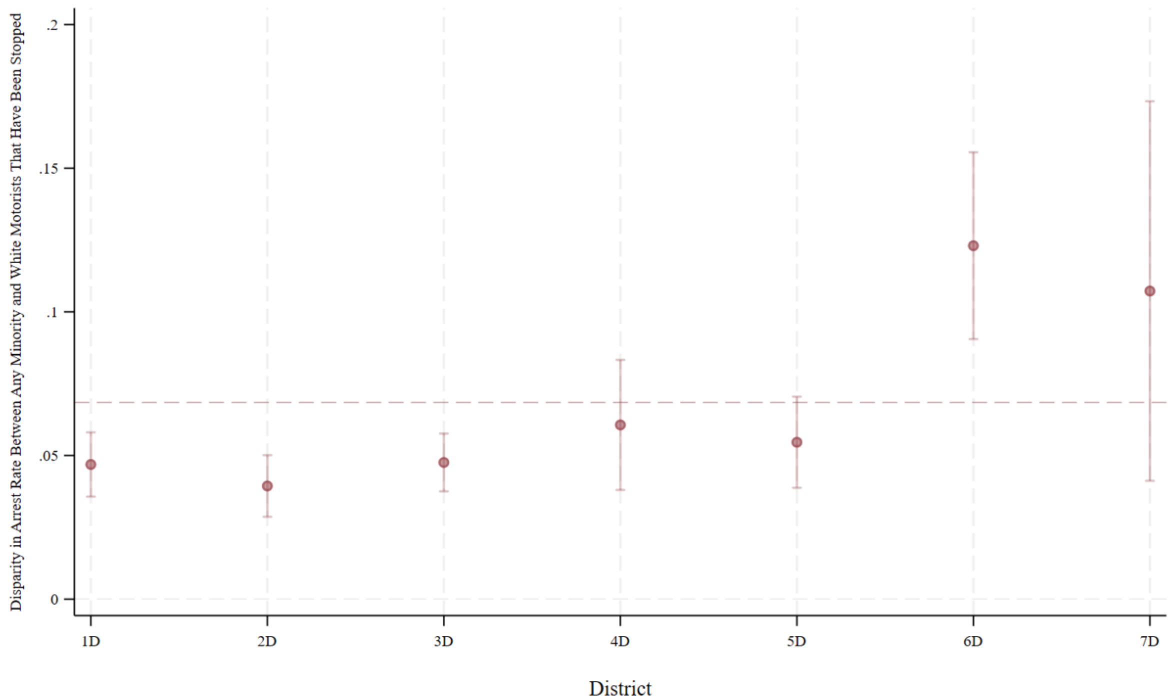


Figure 4. 12: Analysis of Decision to Arrest by District for Non-White Individuals, July 2023- June 2024



Figures 4.13 to 4.15 report the results of applying the conditional outcome test for the decision to ticket in each of the seven patrol districts from July 2023 through June 2024. Figures 4.16 to 4.18 present differences in the likelihood of receiving a ticket for White drivers relative to Black, Hispanic, and any non-White drivers during this period. As shown below, we find statistically significant differences in District 1 (Black: β=7.7pp or 9.85%, p<0.01; Any Non-White: β=4.3pp or 5.5%, p<0.03), District 2 (Hispanic: β=6.51pp or 10.23%, p<0.01; Any Non-White: β=3pp or 4.71%, p<0.02), District 3 (Any Non-White: β=5.77pp or 11.55%, p<0.01), District 4 (Hispanic β=7.03pp or 11%, p<0.03), District 5 (Black: β=5.33pp or 7.44%, p<0.02; Hispanic: β=12.97pp or 18.1%, p<0.01; Any Non-White: β=6.42pp or 8.96%, p<0.01), and District 6 (Black: β=-8pp or 7.44%, p<0.02; Any Non-White: β=-7.5pp or -9.97%, p<0.03). We again caution the reader not to place a causal interpretation on this test because we are unable to adequately control for selection into different types of circumstances that necessitate a ticket. Coefficient estimates, standard errors, and sample sizes are contained in Table C.6 of Appendix C for Figures 4.13 to 4.15. We also applied the conditional outcome test for the decision to ticket for each of the seven patrol districts for a three-year period (July 2021 to June 2024). These results are contained in Table C.7 of Appendix C.

Figure 4. 13: Analysis of Decision to Ticket by District for Black Individuals, July 2023-June 2024

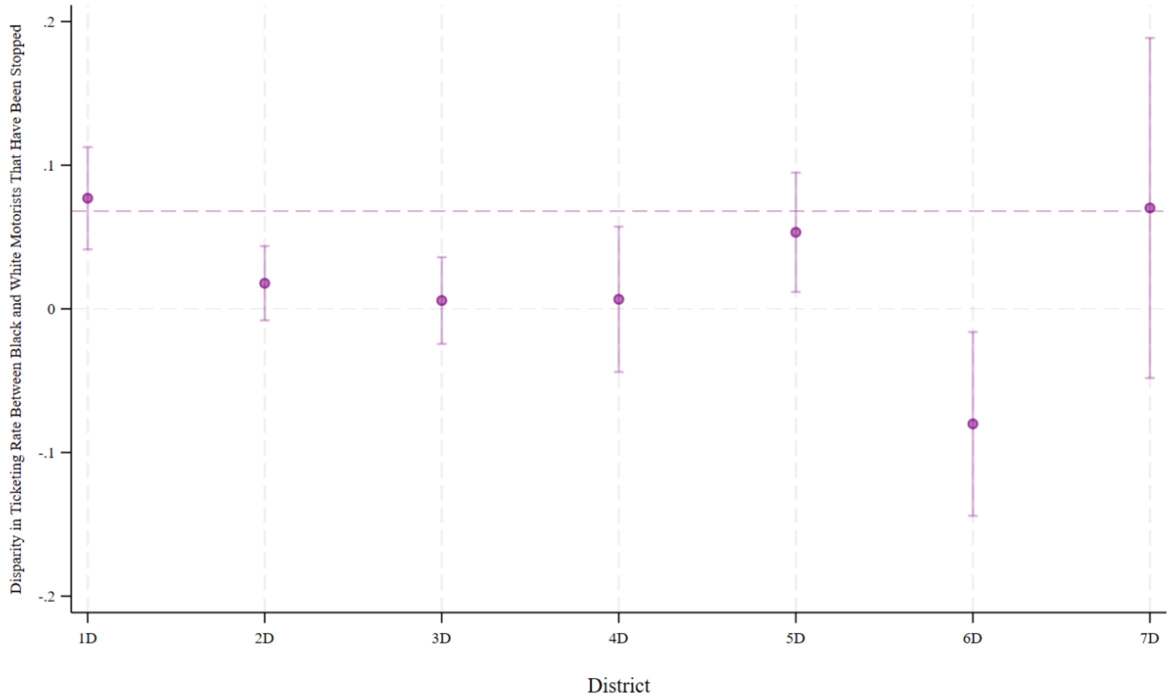


Figure 4. 14: Analysis of Decision to Ticket by District for Hispanic Individuals, July 2023- June 2024

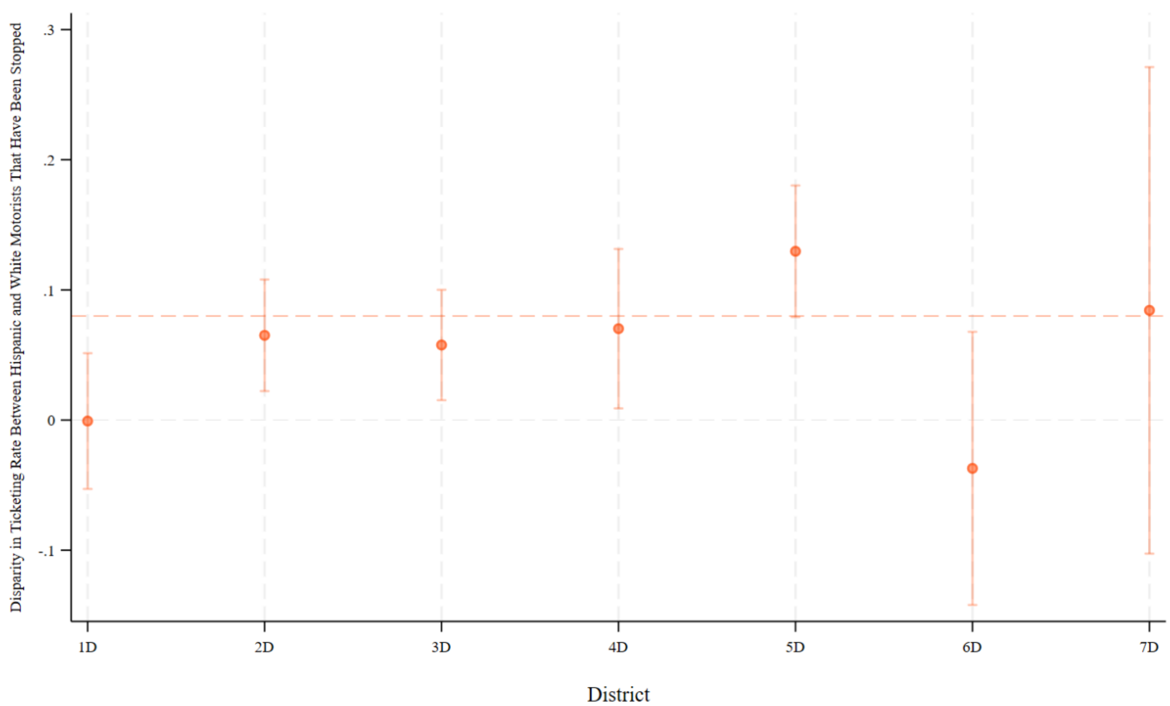
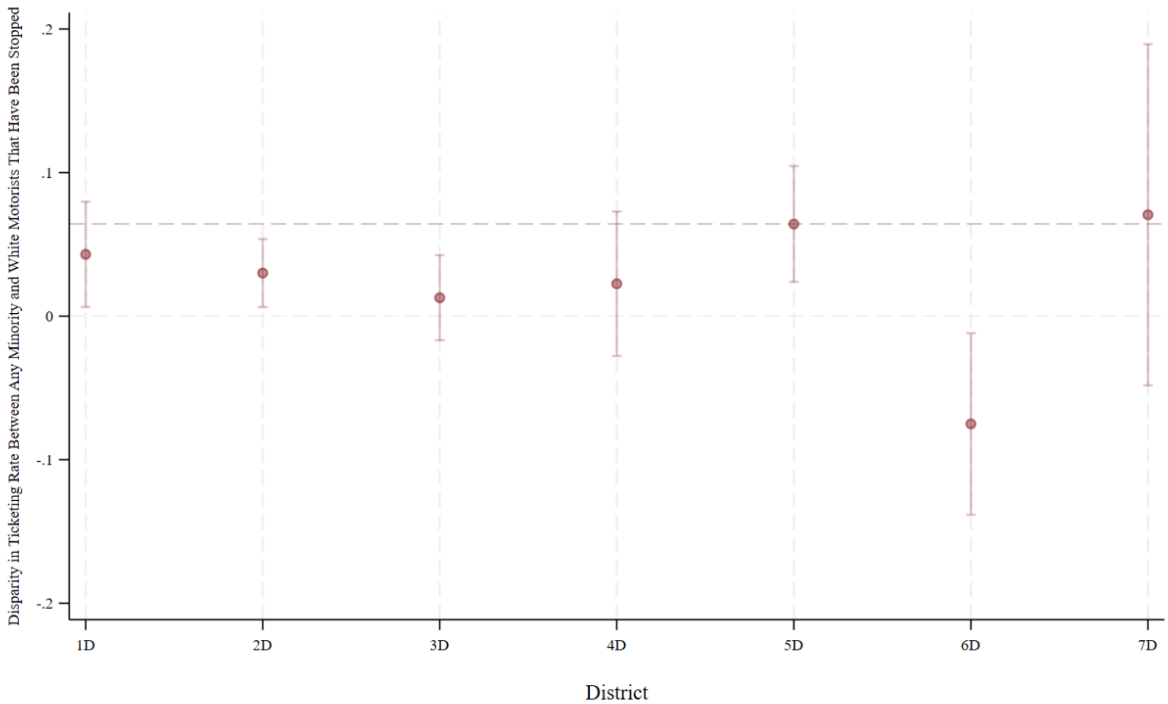


Figure 4. 15: Analysis of Decision to Ticket by District for Non-White Individuals, July 2023- June 2024



Figures 4.16 to 4.18 report the results of applying the conditional outcome test to stop duration in each of the seven patrol districts from July 2023 through June 2024. Figures 4.16 to 4.18 present differences in the length of a stop (in minutes) for White drivers relative to Black, Hispanic, and any non-White drivers during this period. As shown below, we find statistically significant differences in District 1 (Hispanic: β=-51.74min or -63.37%, $p<0.01$; Any non-White: β=-26.42min or -32.36%, $p<0.04$). Again, we caution the reader not to place a causal interpretation on this test because we are unable to adequately control for selection into different types of circumstances that necessitate a longer stop duration. Coefficient estimates, standard errors, and sample sizes are contained in Table C.8 of Appendix C for Figures 4.22 to 4.24. We also applied the conditional outcome test to stop duration for each of the seven patrol districts for a three-year period (July 2021 to June 2024). These results are contained in Table C.9 of Appendix C.

Figure 4. 16: Analysis of Stop Duration by District for Black Individuals, July 2023-June 2024

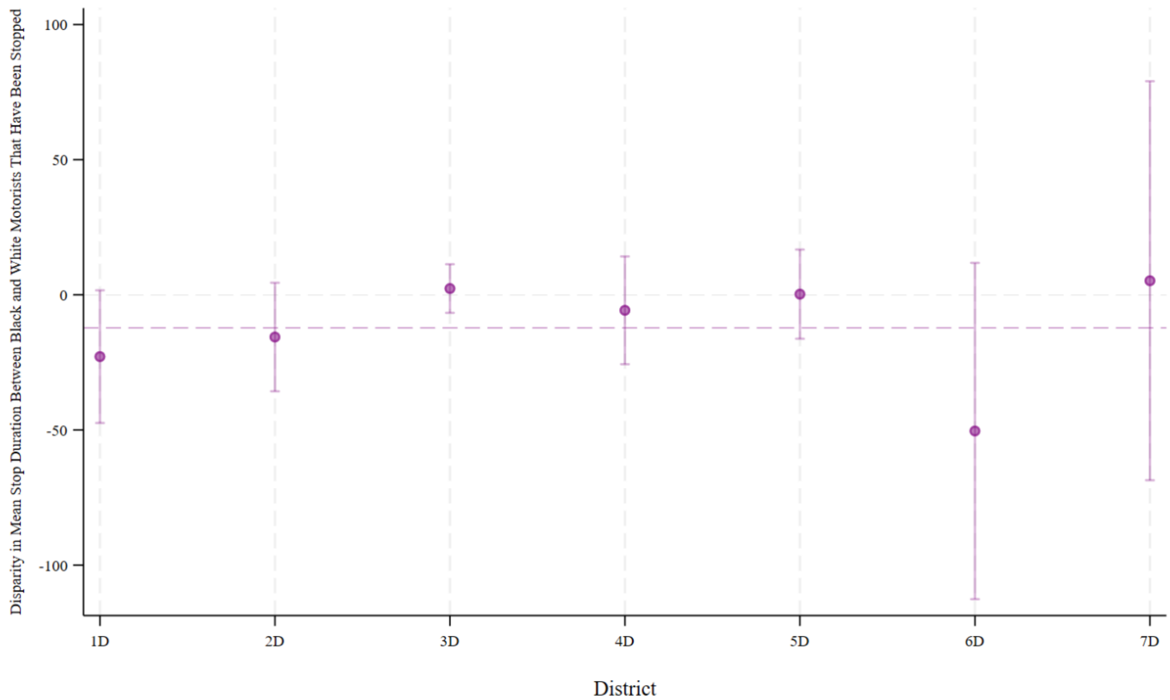


Figure 4. 17: Analysis of Stop Duration by District for Hispanic Individuals, July 2023-June 2024

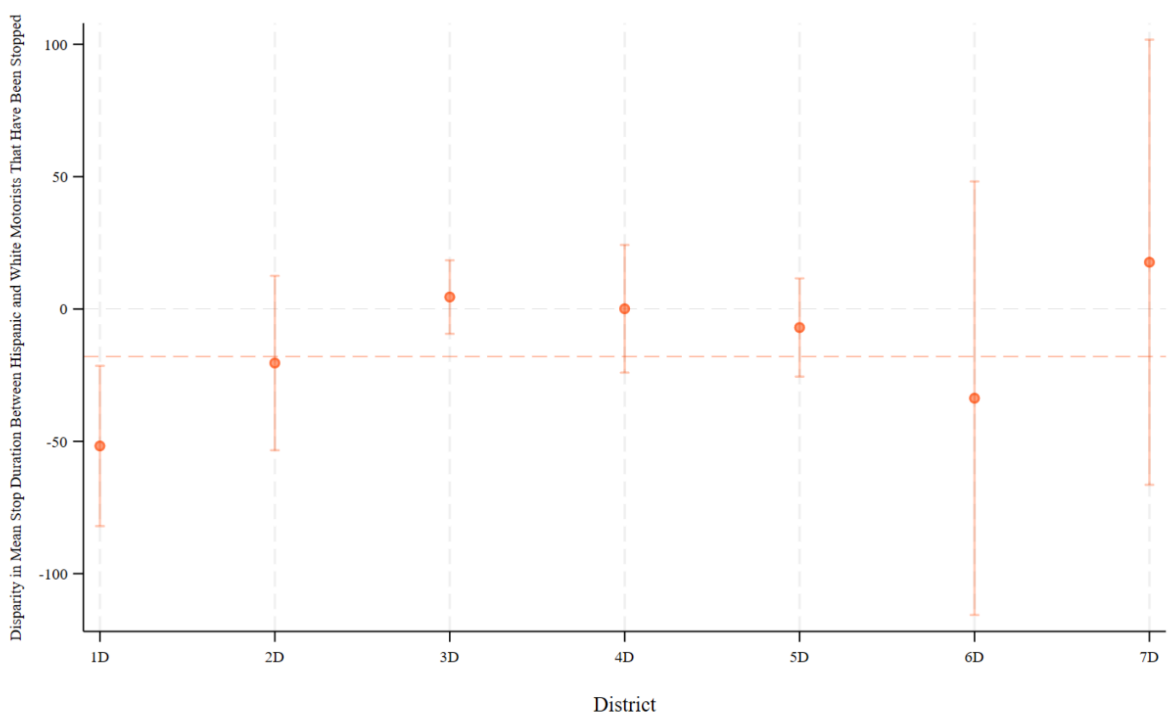
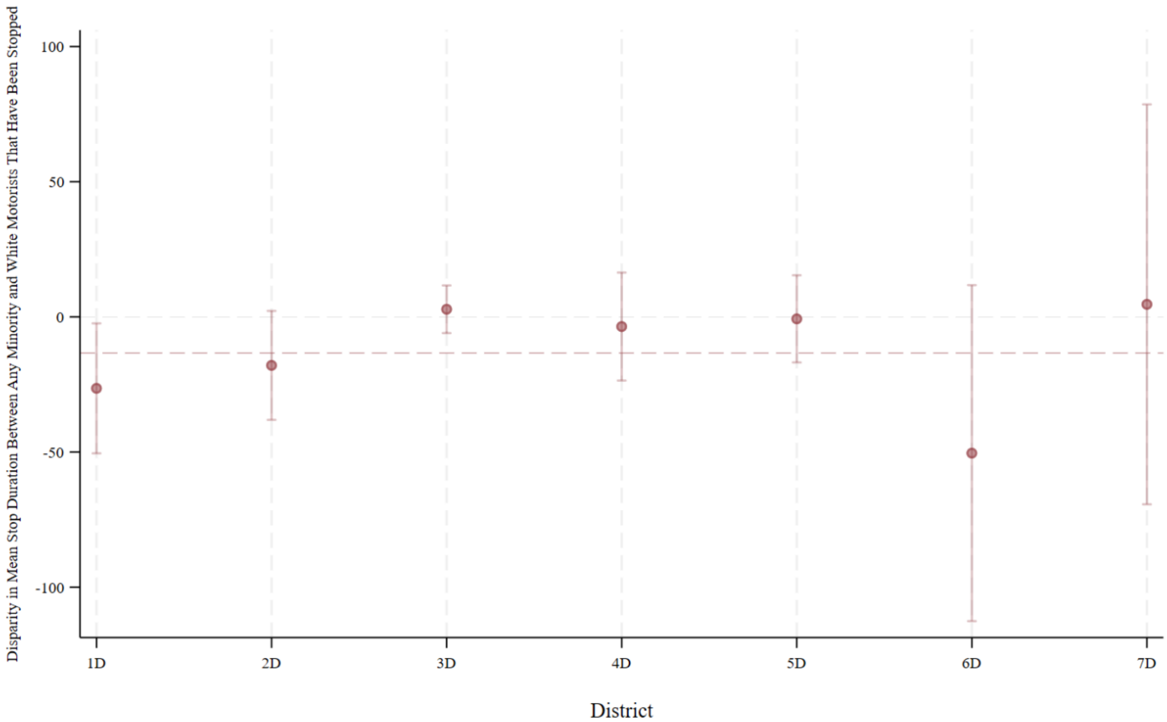


Figure 4. 18: Analysis of Stop Duration by District for Non-White Individuals, July 2023- June 2024



V. ANALYSIS OF VEHICULAR SEARCHES

This section contains the results of an analysis of post-stop outcomes using a hit-rate approach following Knowles, Persico and Todd (2001). The hit-rate approach relies on the idea that individuals rationally adjust their propensity to carry contraband in response to their likelihood of being searched by police. Similarly, police officers rationally decide whether to search an individual based on visible indicators of guilt and an expectation of the likelihood that a given individual might have contraband. According to the model, we should expect the police to search a demographic group of individuals more often than Whites if they were also more likely to carry contraband. However, the higher level of searches should be exactly proportional to the higher propensity of this group to carry contraband. Thus, in the absence of racial animus, we should expect the rate of successful searches (i.e., the hit rate) to be equal across different demographic groups regardless of differences in their propensity to carry contraband. [20]

In this test, discrimination is interpreted as a preference for searching non-White motorists that shows up in the data as a statistically lower hit rate relative to White motorists. In technical terms, the testable implication derived from this model is that the equilibrium search strategy, in the absence of group bias, will result in an equalization of the rate of contraband that is found relative to the total number of searches (i.e., the hit-rate) across motorist groups. In our application, we test for the presence of a disparity in the rate of successful searches by regression indicator for a contraband hit (i.e., finding drugs, weapons, or money) on an indicator for the race/ethnicity of the subject for a sample of discretionary searches. Note that this test inherently says nothing about disparate treatment in the decision to stop motorists, as it is limited in scope to vehicular searches. We limit our analysis to discretionary searches, defined as pat-downs, consent searches, and probable cause searches. We exclude warrant searches from the analysis of discretionary searches. We also exclude a small number of stops coded as both pat-down and warrant searches.

V.A: AGGREGATE ANALYSIS OF VEHICULAR SEARCHES

Figures 5.1 to 5.3 report results from applying the search hit-rate test to each of the five years between July 2019 through June 2024. We use ordinary least squares to regress a binary indicator variable of contraband being found on an indicator for race/ethnicity using a sample consisting of discretionary searches. The reference group across all specifications is held constant and consists of stops made of White individuals. We calculate standard errors using the Huber-White bias correction for robust variance. In Figure 5.1, we report estimates of the likelihood that a search of a Black individual yields contraband. Only in the period from July 2019 to June 2020 do we estimate a marginally significant ($p<0.10$) lower contraband finding rate ($\beta=16.5$pp or 52.77%) for searched Black individuals. In Figure 5.2, we report estimates of the likelihood that a search of a Hispanic individual yields contraband where we find no evidence of a statistically significant difference in contraband finding rates. In Figure 5.3, we report estimates of the likelihood that a search of any individual who is a racial/ethnic minority yields contraband where we find no evidence of a statistically significant difference in contraband finding rates. Coefficient estimates, standard errors, and sample sizes are contained in Table D.1 of Appendix D for Figures 5.1 to 5.3.

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

Figure 5. 1: Aggregate Hit-Rate Analysis by Year, Black Individuals

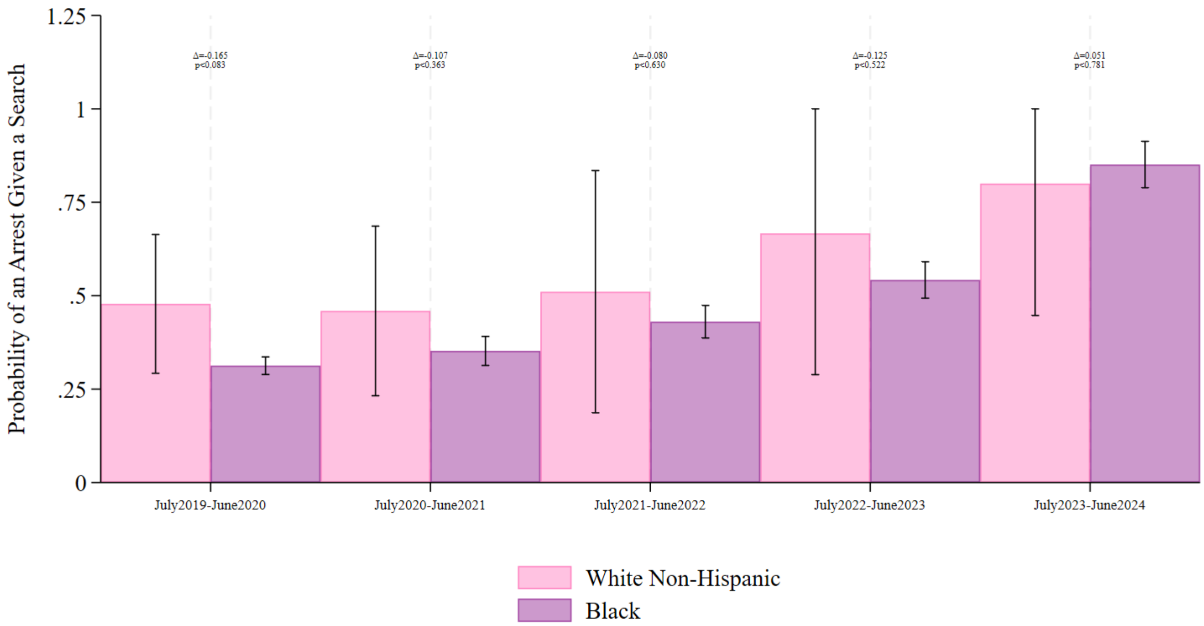


Figure 5. 2: Aggregate Hit-Rate Analysis by Year, Hispanic Individuals

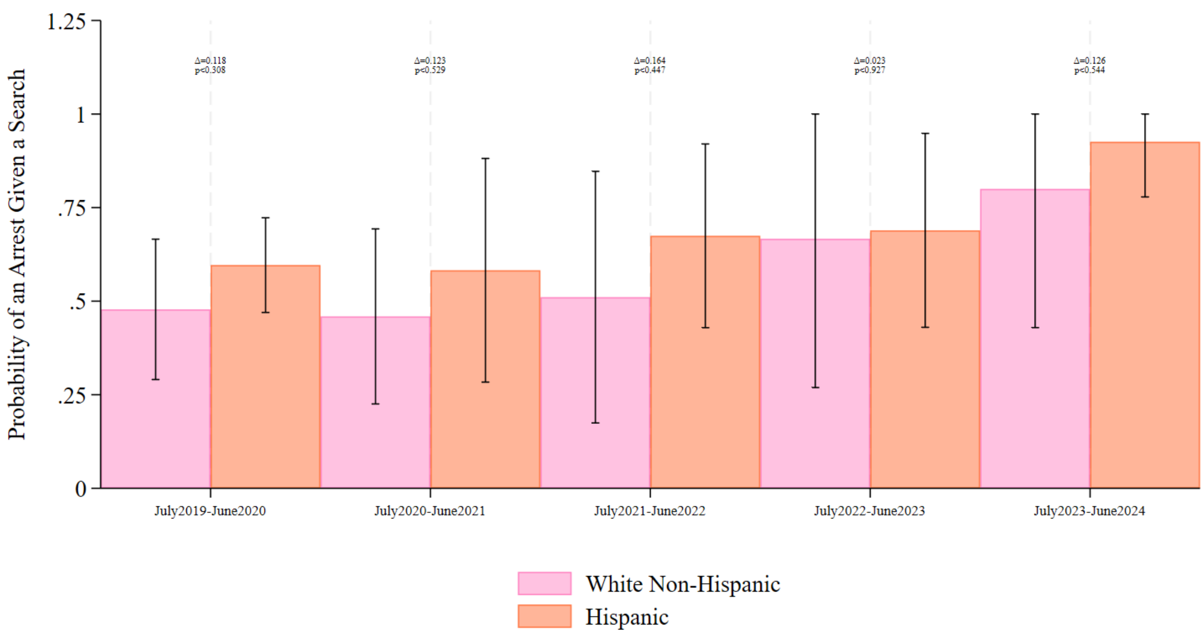
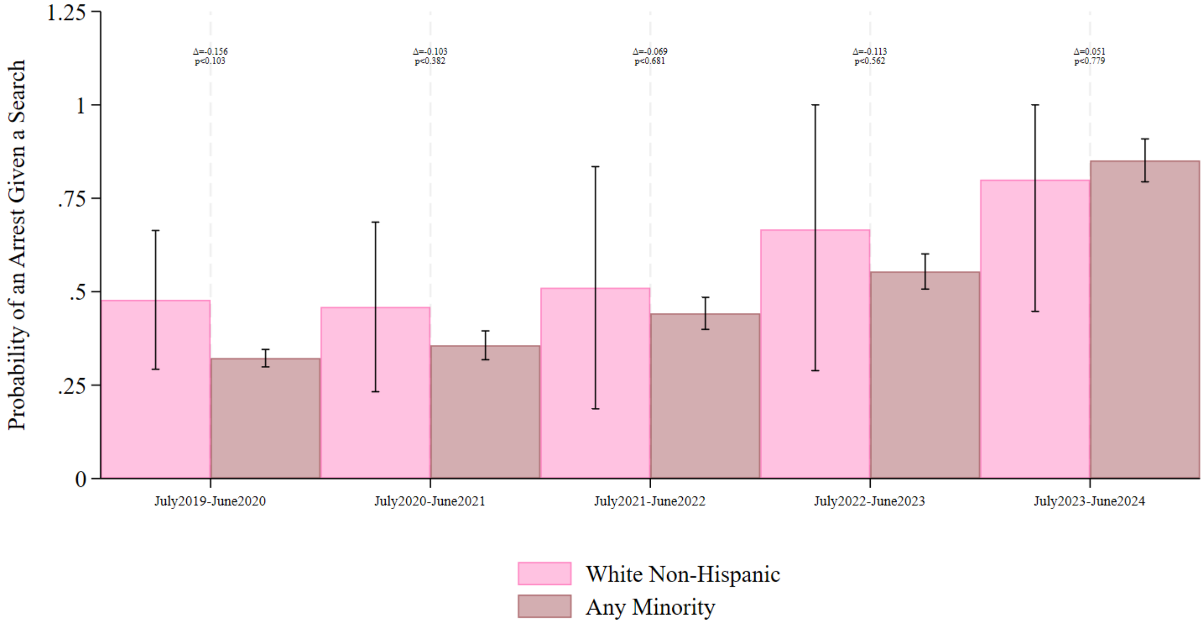


Figure 5. 3: Aggregate Hit-Rate Analysis by Year, Non-White Individuals



V.B: DISTRICT ANALYSIS OF VEHICULAR SEARCHES

Figures 5.4 to 5.6 report the results of applying the hit-rate analysis to each of the seven patrol districts from July 2023 through June 2024. Figures 5.4 to 5.6 present differences in hit rates for White individuals relative to Black individuals, Hispanic individuals, and any non-White individuals during this period. For most districts, there was not a sufficiently large enough sample to run the test. There was statistically significant ($p<0.05$) evidence of a difference in District 6 where there was a -18.5pp difference (-22.7%) between the success rate of searches of White and Black as well as Any non-White motorists. Coefficient estimates, standard errors, and sample sizes are contained in Table D.2 of Appendix D for Figures 5.4 to 5.6.

Figure 5. 4: Aggregate Hit-Rate Analysis by District, July 2023 to June 2024, Black Individuals

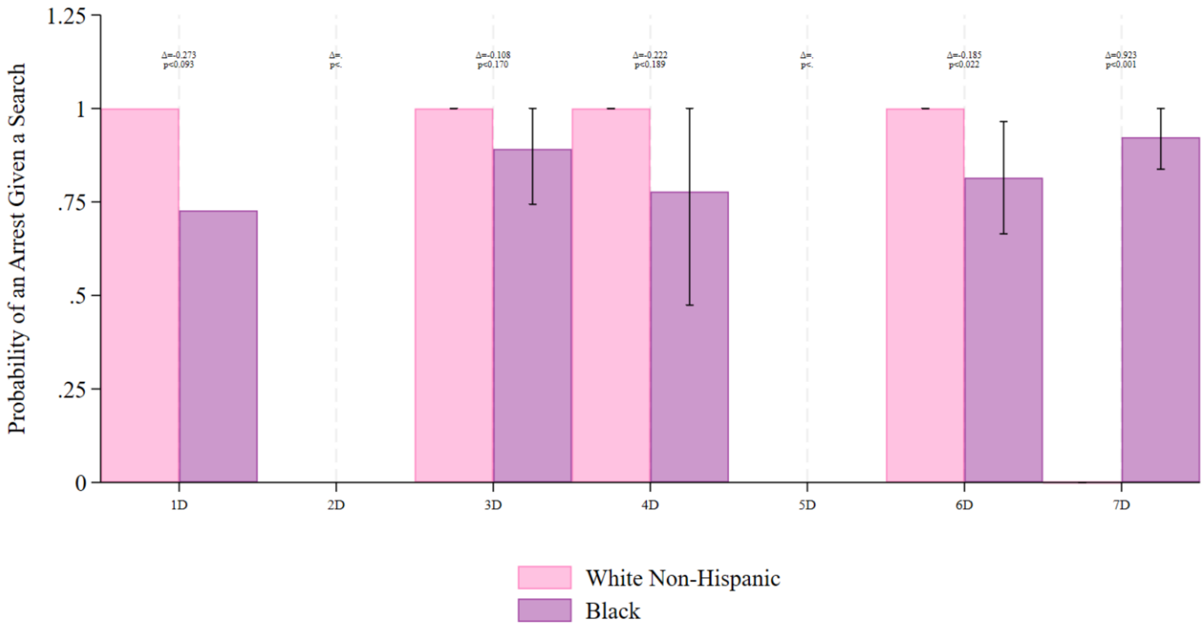


Figure 5. 5: Aggregate Hit-Rate Analysis by District, July 2023 to June 2024, Hispanic Individuals

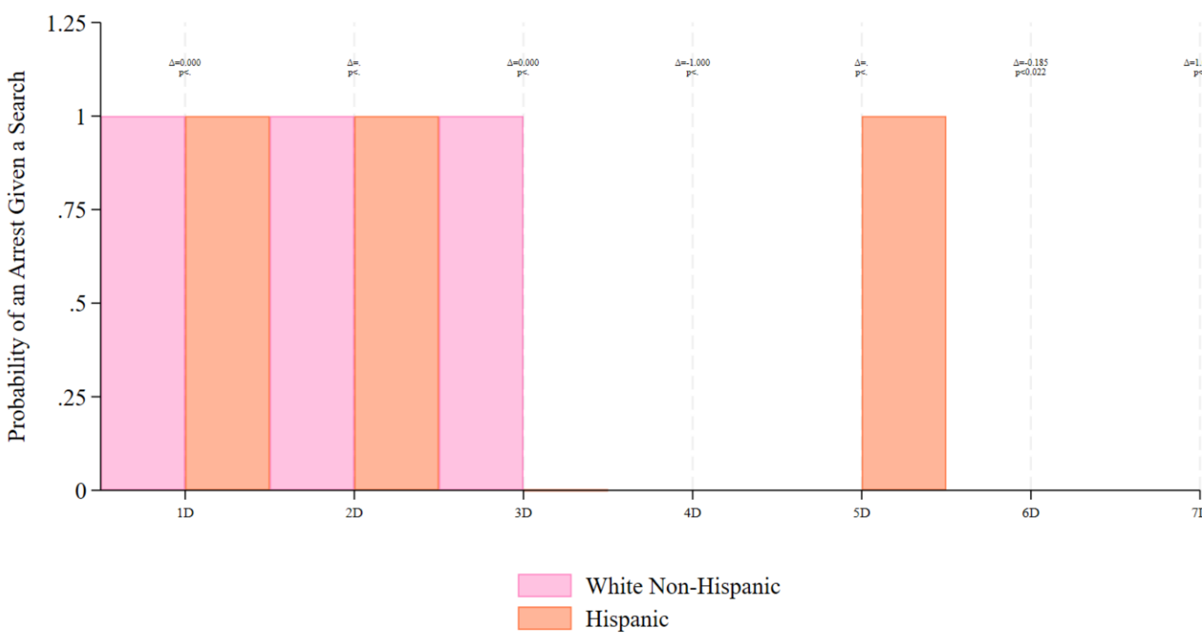
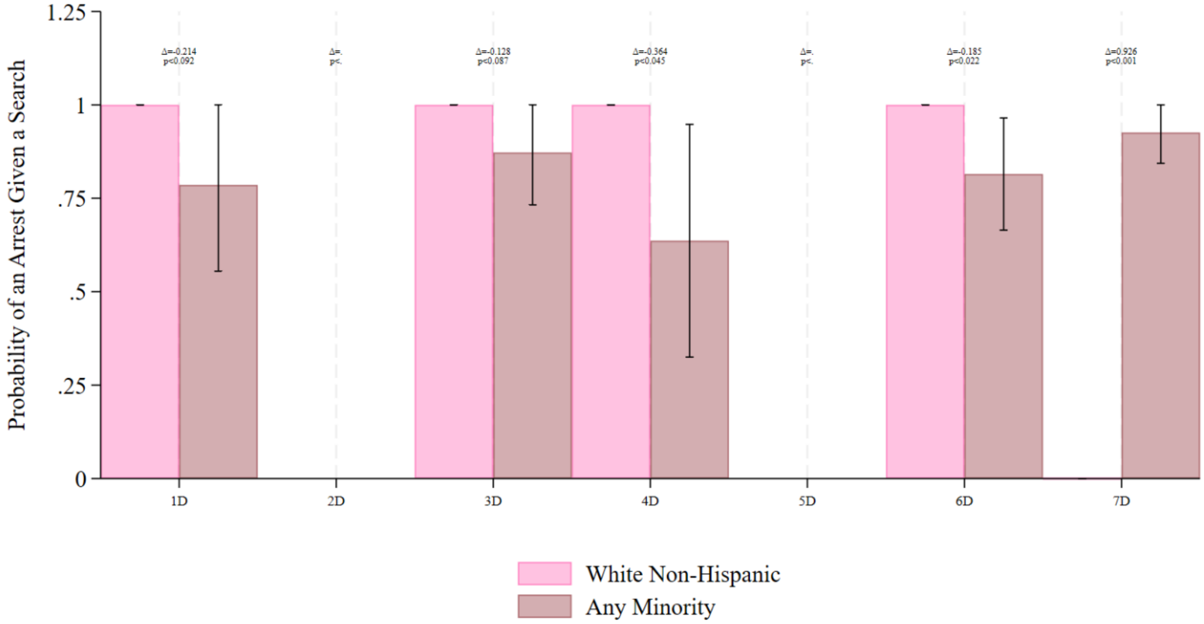


Figure 5. 6: Aggregate Hit-Rate Analysis by District, July 2023 to June 2024, Non-White Individuals



Figures 5.7 to 5.9 report the results of applying the hit-rate analysis to each of the seven patrol districts from July 2021 through June 2024. They present differences in hit rates for White individuals relative to Black, Hispanic, and any non-White individuals during this period. In District 4, there was a statistically significant (p<0.01) evidence of a difference of -50.1pp difference (-100.5%) between the success rate of searches of White and Black motorists. In District 4, there was also a statistically significant (p<0.01) evidence of a difference of -45.2pp difference (-82.5%) between the success rate of searches of White and Any non-White motorists. In District 6, there was a statistically significant (p<0.01) evidence of a difference of -40.6pp difference (-89.9%) between the success rate of searches of White and Black motorists. In District 6, there was also a statistically significant (p<0.01) evidence of a difference of -40.3pp difference (-88.8%) between the success rate of searches of White and Any non-White motorists. Table D. 3 of Appendix D contains coefficient estimates, standard errors, and sample sizes for Figures 5.7 to 5.9.

Figure 5. 7: Aggregate Hit-Rate Analysis by District, July 2021 to June 2024, Black Individuals

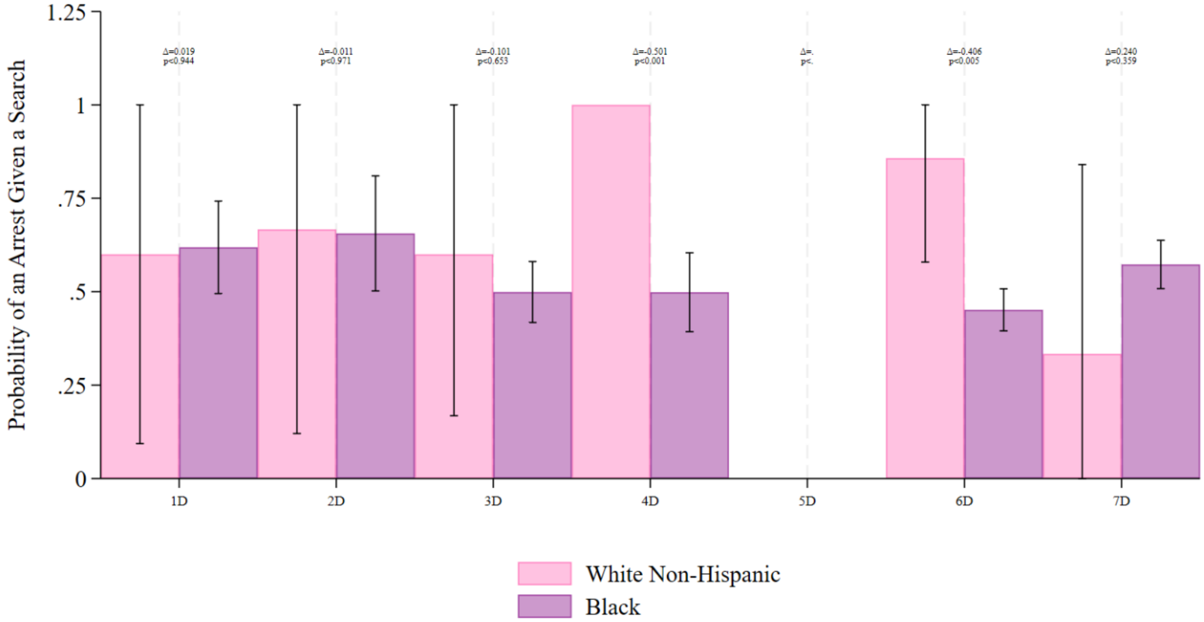


Figure 5. 8: Aggregate Hit-Rate Analysis by District, July 2021 to June 2024, Hispanic Individuals

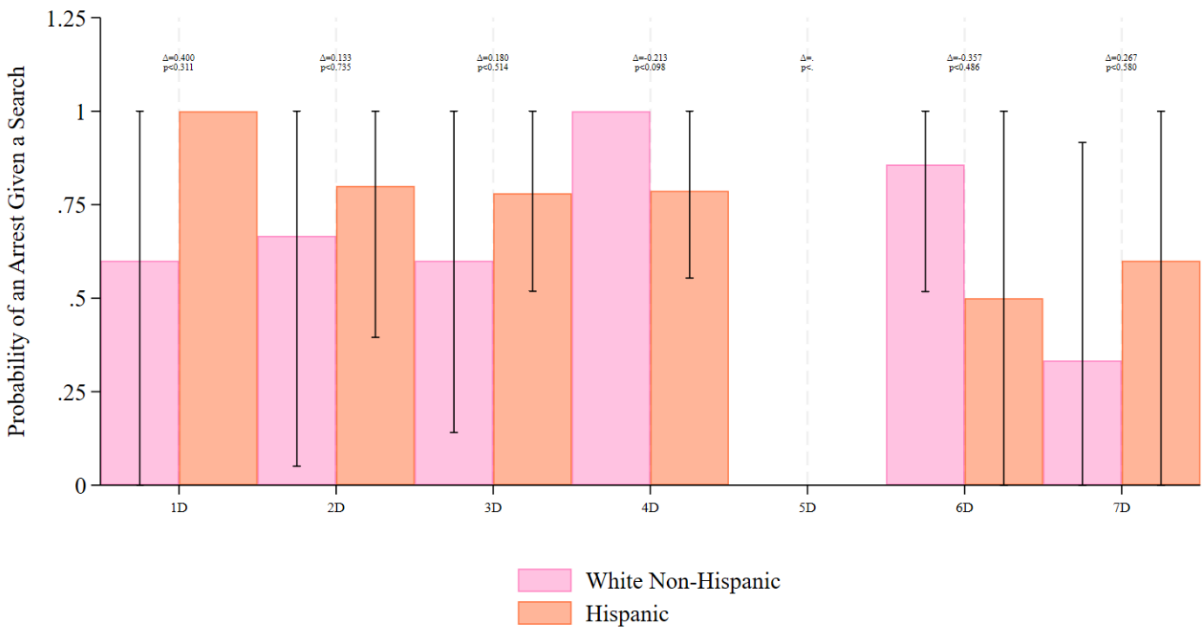
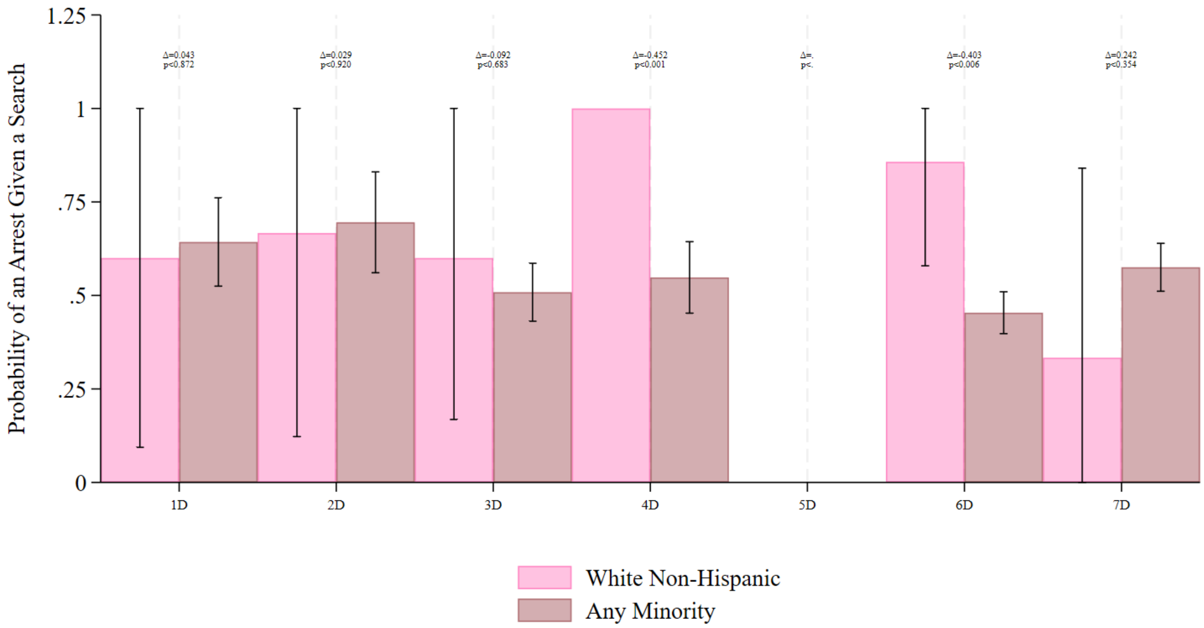


Figure 5. 9: Aggregate Hit-Rate Analysis by District, July 2021 to June 2024, Non-White Individuals



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GLOSSARY OF TERMS

Bias: In a statistical context, bias refers to a systematic error in a study or analysis that can lead to misleading results. For example, it can be caused by unobserved factors, such as those that give rise to unobserved variable bias, which are not included in the model's estimate. It can also be introduced by a flawed selection process, leading to selection bias, where the chosen sample does not accurately represent the intended population.

Benchmark: A benchmark is a standard used for comparison. It can be a real-world reference, like the general population, or a more specific standard created for the study. While a benchmark is useful for measuring how one group compares to another, it does not necessarily have a causal interpretation. In contrast, a counterfactual is a hypothetical scenario that helps researchers understand what would have happened if a specific event had not occurred, which is necessary to establish a causal link.

Causal Link: A causal link is a connection between two things where one is directly responsible for causing the other. It is different from an association or a correlation, which simply means two things are related without proving that one caused the other.

Coefficient (Beta): In a statistical model, the beta or coefficient is a numerical value that represents the strength and direction of the relationship between a predictor variable and the outcome variable. For example, a positive beta value indicates that as the predictor variable increases, the outcome variable also increases.

Conditional Outcomes: This term refers to the results of an event, such as a traffic stop, that are analyzed while taking into account or "conditioning on" various circumstances of that event. The analysis looks for differences in outcomes (like arrests or searches) between different groups, assuming that if all other circumstances were equal, the outcomes should be similar.

Confidence Interval: A confidence interval is a range of values that likely contains the true value of a population parameter, such as the mean. It provides a measure of how precise an estimate is. A 95% confidence interval, for example, means that if the study were repeated many times, 95% of the calculated intervals would contain the true population value.

Contraband Hit-Rate Test: This test is used to determine if there are racial disparities in police search practices. It works by comparing the success rate of searches (the "hit rate") across different racial or ethnic groups. If officers are searching non-White drivers more frequently but are less successful in finding illegal items, it suggests they have a lower standard for searching these drivers.

Control Variable: A factor that is accounted for in a statistical analysis to ensure the results are not due to that factor. For example, when analyzing traffic stops, a researcher might use time of day or location as a control variable to isolate the effect of other factors.

Counterfactual: A counterfactual is a concept used in research and statistics to describe what would have happened in a different, alternative world. It is a hypothetical scenario that allows researchers to consider what would have occurred in the absence of a particular event or intervention. Unlike a benchmark, which is used for simple comparison, a counterfactual is essential for establishing causation by providing a basis to infer what would have happened if the event had not occurred.

Disparate Impact: This refers to a policy or practice that is neutral on its face but has a disproportionately negative effect on a particular racial or ethnic group.

Disparate Treatment (Discrimination): This is a form of discrimination that occurs when an individual or group is intentionally treated differently than others based on a protected characteristic, such as race or ethnicity.

Disparity: A statistical overrepresentation of one group compared to another in a specific outcome or action. It highlights an imbalance that may be caused by a neutral policy with a disproportionate effect (disparate impact) or by intentional bias (disparate treatment).

Endogeneity: In a statistical model, endogeneity refers to a situation where a variable is correlated with the error term of the model, which can lead to biased and unreliable results. This can happen for several reasons, including when important variables are missing from the model (omitted variable bias), when there is a two-way causal relationship between variables (simultaneity), or when variables are measured with error.

Estimate: In a statistical context, an estimate is a value or range calculated from a data sample to approximate a characteristic of a larger population. When working with observational data, this assumes the population is a realization of a data-generating process. It is not a casual guess, but a precise calculation derived from a statistical model.

Fixed Effects: A statistical approach used in regression analysis to control for unobserved variables that do not change over time or across specific groups. This technique can be used to account for the unique characteristics of each individual, such as a police officer, that might influence their behavior, ensuring that the results are not just due to differences between individuals.

Hypothesis Test A hypothesis test is a statistical method used to determine whether there is enough evidence in a sample of data to infer a particular conclusion about an entire population. The process involves two competing ideas: the null hypothesis, which states there is no effect or relationship, and the alternative hypothesis, which states there is a real effect or relationship. The goal of the test is to see if there is enough evidence to reject the null hypothesis in favor of the alternative.

Inter-Twilight Period: This refers to a specific time window around sunrise and sunset when the amount of daylight changes significantly throughout the year. Researchers focus on this period because it is when the difference in visibility between full daylight and full darkness is most pronounced, making it ideal for solar visibility analysis.

Inverse Propensity Score Weighting: A statistical technique that creates a fair comparison between different groups by assigning a weight to each observation based on how similar it is to the observations in the other group.

Mean (or Average): The mean, or average, is a statistical measure of the central tendency of a data set. It is calculated by summing all the values and dividing by the number of values.

Propensity Score: A propensity score is a statistical measure of similarity. It represents the likelihood of a person or observation being in a certain group based on a set of observed characteristics.

P-Value: The p-value is a statistical measure used to determine if a finding is statistically significant. It represents the probability of observing a result as extreme as the one found, assuming that there is no real effect. A low p-value (typically less than 0.05) is often used as a threshold to reject the idea that the result is due to random chance.

Q-Value or False Discovery Rate: The q-value or False Discovery Rate (FDR) is a statistical measure used when performing many statistical tests at the same time. It helps to control the proportion of "false positives"—results that appear to be significant but are not—among all the findings that are deemed statistically significant. For example, a q-value of 0.1 means that you expect 10% of your significant findings to be false positives. Researchers typically set a low threshold for the q-value to ensure the findings are reliable.

Regression Analysis: his is a statistical technique used to understand the relationship between different variables. For example, it can be used to see if factors like the time of day, location, or an officer's characteristics are related to the likelihood of a traffic stop or a particular outcome. It helps to isolate the effect of one factor while accounting for others. Two common types of regression are:

- Ordinary Least Squares (OLS) Regression: This technique finds the line of best fit for a set of data by minimizing the sum of the squared differences between the observed data points and the values predicted by the model.
- Linear Probability Model (LPM): This is a straightforward method that uses linear regression to model a binary outcome. It is a simpler alternative to Logistic Regression, but it can under certain conditions, produce non-sensical results with predicted probabilities that are less than 0 or greater than 1.
- Logistic (Logit) Regression: This technique is used to model the probability of an outcome that can only have two results (e.g., yes/no, arrest/no arrest). It uses a logistic function to ensure that the estimated probabilities always fall between 0 and 1.

<u>Regression Discontinuity Design:</u> A statistical method used to estimate the effect of an intervention when people or things are assigned to a treatment or control group based on whether a specific cutoff point is met. This technique allows researchers to analyze data around the cutoff, providing a strong basis for inferring a causal effect.

<u>Robustness Tests:</u> These are additional analyses performed to verify that the results of a study are reliable and not simply a result of the specific methods or assumptions used. If a result passes robustness tests, it means the findings are consistent and dependable.

<u>Sample:</u> A sample is a subset of a population selected for analysis. In research, a sample is used to draw conclusions about the entire population without having to study every single person or instance. When working with observational data, the entirety of the data can be considered a sample because it is a representation of a larger data-generating process.

<u>Solar Visibility Analysis:</u> Also known as the "veil of darkness" test, this is a method used to study racial disparities in police traffic stops. The underlying assumption is that in the daytime, an officer can more easily see a driver's race before deciding to pull them over, but in darkness, this is more difficult. By comparing the racial makeup of stopped drivers during the day versus at night, researchers can see if there is a difference in the likelihood of a non-White driver being stopped when their race is visible. A statistically significant difference in stop rates between daylight and darkness suggests the presence of bias or disparate treatment.

<u>Standard Deviation</u>: A measure of how spread out the numbers in a data set are from the average (mean). It is the square root of the variance. A low standard deviation indicates that the data points tend to be very close to the mean, while a high standard deviation indicates that the data points are spread out over a wider range.

<u>Standard Error:</u> The standard error is a measure of the statistical accuracy of an estimate. It is an estimate of the standard deviation of the sampling distribution of a statistic, and it provides a measure of how much the estimate is likely to vary from one sample to another. A smaller standard error means the estimate is more precise.

<u>Statistical Significance:</u> This is a term used in statistics to describe the likelihood that a research result is due to chance. If a result is "statistically significant," it means there is a very low probability that the finding occurred by random chance. Researchers use this to highlight which findings are likely to be real differences rather than just random variations.

<u>Synthetic Control Analysis:</u> This is a method that creates a "synthetic," or artificial, control group to estimate the effect of an event. It works by weighting a combination of unaffected units (e.g., other cities or states) to

create a control group that closely resembles the unit that was affected by the event. This synthetic control provides a benchmark for comparison, which is essential for determining if a particular action had an impact.

<u>Type I and Type II Errors:</u> A Type I Error occurs when a researcher incorrectly rejects a true null hypothesis. In simpler terms, it's a "false positive" or a mistaken conclusion that there is a significant effect when there is not. A Type II Error occurs when a researcher fails to reject a false null hypothesis. This is a "false negative," meaning a missed opportunity to find a real effect or relationship.

<u>Unobservable Differences:</u> These are characteristics or factors that influence an outcome but are not captured in the data available for analysis. Researchers may use specific statistical methods, such as fixed effects, to try and account for these missing variables.

<u>Variance:</u> A measure of how far a set of numbers are spread out from their average value. It is calculated as the average of the squared differences from the mean. It is the square of the standard deviation and is used in many statistical calculations.

APPENDIX A

A.1: METHODOLOGY FOR THE SOLAR VISIBILITY TEST

Following Grogger and Ridgeway (2006), let the parameter K_{ideal} capture the true level of disparate treatment for minority group *m* relative to majority group *w:*

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

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

Applying Baye's rule to Equation 1 such that:

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

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

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

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

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

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

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

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

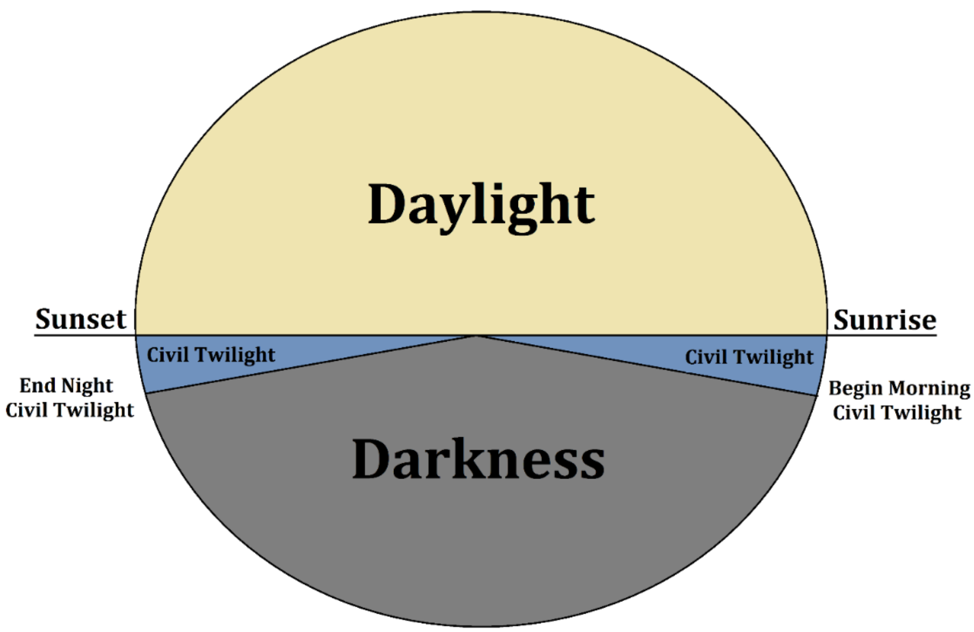
Assuming that the assumptions outlined above hold, Equation 4 can be estimated using a linear probability model

$$1[minority_i] = \beta + \delta 1[daylight_i] + \mu_i \quad (4)$$

where the dependent variable is an indicator for one if a stopped individual is a racial/ethnic minority, β is a constant, δ is an indicator for daylight, and μ_i is an idiosyncratic error term. In practice, it is unlikely that the third assumption (a constant relative risk-set) will hold without including additional controls in Equation 4. Thus, we amend Equation 4 by including controls for hour of day by year and day of the week by year.

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

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



In this analysis, we rely primarily on a combined inter-twilight window that includes traffic stops made at both dawn and dusk. The dawn inter-twilight window is constructed from astronomical data and occurs in the morning hours. The dusk inter-twilight window, on the other hand, is constructed from the same astronomical data but occurs in the evening hours. The combined inter-twilight window relies on a sample that is created by pooling these timeframes and including an additional control variable that identifies the period.

A.2: METHODOLOGY FOR THE STOP DISPOSITION TEST

In this section, we describe the methodology for a simple test of equality in the distribution of outcomes for individuals of different races conditional on the reason that they were stopped. Specifically, we test whether traffic stops made of minority individuals result in different outcomes relative to their non-Hispanic Caucasian peers. Since ex-ante it is unclear whether discrimination would create more or less severe traffic stop outcomes in the data, we simply test for equality in the distribution of outcomes ex-post. On the one hand, discriminatory police officers might treat minority individuals more harshly conditional on the reason they were stopped. However, discriminatory police might also make more pretextual traffic stops for lower-level offenses motivated by the fact that they may observe evidence of a more severe crime once the vehicle is stopped. Rather than making untestable assumptions, we simply assume that the overall distribution of outcomes will be equal across race in the absence of disparate treatment. The intuition is similar to hit-rate style tests but where we are unable to ex-ante sign the direction that we expect bias to take.

We provide one important cautionary note about interpreting our test as causal evidence of discrimination. Ideally, this test would be performed on data containing detailed location information as well as information on the circumstances surrounding a stop. The data we were provided does not contain either piece of necessary information. We present the results of these tests in an effort to highlight key trends in the underlying data but caution the reader not to place a causal interpretation on the results. In the future, we would recommend that more detailed data is collected so that these tests can be refined and provide more informative results.

A.3: METHODOLOGY FOR THE VEHICULAR SEARCH TEST

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

Knowles et al. (2001) introduce disparate treatment via search costs incurred by officers that differ across demographic groups. An officer with a lower search cost for a specific demographic group will be more likely to search individuals from that group. The result of this action will be an observable increase in the number of targeted searches for that group. As above, the targeted group will respond rationally and reduce their exposure by carrying less contraband. Eventually, the added benefit associated with a higher probability of finding contraband in the non-targeted group will offset the lower cost of search for that group. As a result, one would expect the hit-rates to differ across demographic groups in the presence of disparate treatment.

Knowles et al. (2001) developed a theoretical model with testable implications that can be used to evaluate statistical disparities in the rate of searches across demographic groups. Following Knowles et al., an empirical test of the null hypothesis (that no racial or ethnic disparity exists) in Equation 9 is presented.

$$P(H = 1|m, S) = P(H = 1|S) \ \forall \ r, c \tag{9}$$

Equation 9 computes the probability of a search resulting in a hit across different demographic groups. If the null hypothesis was true and there was no racial or ethnic disparity across these groups, one would expect the hit-rates across minority and non-minority groups to reach equilibrium. As discussed previously, this expectation stems from a game-theoretic model where officers and individuals optimize their behaviors based on knowledge of the other party's actions. In more concrete terms, one would expect individuals to lower their propensity to carry contraband as searches increase while officers would raise their propensity to search vehicles that are more likely to have contraband. Essentially, the model allows for statistical discrimination but finds if there is bias-based discrimination.

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

APPENDIX B: SOLAR VISBILITY ANALYSIS DATA TABLES

Table B.1: Solar Visibility Analysis by Year and Race/Ethnicity

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
7/2023- 6/2024	Black vs. White	0.0088638	0.0140907	0.5297593	0.7933954	4,637
7/2023- 6/2024	Hispanic vs. White	0.0899534	0.0273025	0.0011368	0.4238489	1,666
7/2023- 6/2024	Any Minority vs. White	0.0176432	0.0116187	0.1298606	0.8267046	5,536
7/2022- 6/2023	Black vs. White	0.0078237	0.010987	0.4769159	0.8086099	9,214
7/2022- 6/2023	Hispanic vs. White	0.0202719	0.0221098	0.3600721	0.3562768	2,735
7/2022- 6/2023	Any Minority vs. White	0.007483	0.0097533	0.4434937	0.8317801	10,487
7/2021- 6/2022	Black vs. White	0.0020118	0.0113141	0.8589775	0.7814057	9,702
7/2021- 6/2022	Hispanic vs. White	-0.0320276	0.0182638	0.0806581	0.3067742	3,050
7/2021- 6/2022	Any Minority vs. White	0.0000343	0.0103201	0.997353	0.8077989	11,036
7/2020- 6/2021	Black vs. White	-0.0125497	0.011535	0.2774209	0.7957603	9,273
7/2020- 6/2021	Hispanic vs. White	-0.0069289	0.0207763	0.7390251	0.3100691	2,744
7/2020- 6/2021	Any Minority vs. White	-0.0092088	0.0101072	0.3629136	0.8196675	10,500
7/2019- 6/2020	Black vs. White	-0.0550691	0.0102612	0.000000151	0.8120142	13,702
7/2019- 6/2020	Hispanic vs. White	-0.0216777	0.0157244	0.1691496	0.2807115	3,590
7/2019- 6/2020	Any Minority vs. White	-0.0452871	0.008866	0.000000551	0.8314226	15,283
ALL	Black vs. White	-0.0160064	0.0052494	0.0023315	0.7998555	46,528
ALL	Hispanic vs. White	0.0009551	0.0090917	0.9163496	0.3248727	13,785
ALL	Any Minority vs. White	-0.0116942	0.0045938	0.0109981	0.8237364	52,842

Table B.2: Solar Visibility Analysis by Year and Race/Ethnicity for All Moving Violations

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
7/2023- 6/2024	Black vs. White	0.01926	0.017617	0.2751252	0.7619899	3,284
7/2023- 6/2024	Hispanic vs. White	0.0791903	0.0292718	0.0073505	0.3844376	1,273
7/2023- 6/2024	Any Minority vs. White	0.0267148	0.0143983	0.0644747	0.8012932	3,940
7/2022- 6/2023	Black vs. White	0.0016628	0.0123038	0.8925805	0.7879518	7,277
7/2022- 6/2023	Hispanic vs. White	0.0085649	0.0231508	0.711723	0.3380694	2,329
7/2022- 6/2023	Any Minority vs. White	0.0019301	0.0110794	0.8618091	0.814585	8,328
7/2021- 6/2022	Black vs. White	-0.0074864	0.012274	0.5423295	0.7683402	7,839
7/2021- 6/2022	Hispanic vs. White	-0.0449651	0.0197294	0.0234788	0.2975963	2,583
7/2021- 6/2022	Any Minority vs. White	-0.010248	0.0112558	0.363248	0.7965971	8,931
7/2020- 6/2021	Black vs. White	-0.0245714	0.0126166	0.0523408	0.7838343	6,940
7/2020- 6/2021	Hispanic vs. White	-0.0151066	0.0227294	0.5068924	0.2989739	2,139
7/2020- 6/2021	Any Minority vs. White	-0.0188487	0.0111173	0.0909535	0.8092397	7,864
7/2019- 6/2020	Black vs. White	-0.0552926	0.0118183	0.00000424	0.7876045	10,009
7/2019- 6/2020	Hispanic vs. White	-0.0331885	0.0172743	0.0557874	0.2668269	2,905
7/2019- 6/2020	Any Minority vs. White	-0.0455668	0.0103295	0.000014	0.8108611	11,243
ALL	Black vs. White	-0.0200913	0.0058642	0.0006278	0.7802622	35,349
ALL	Hispanic vs. White	-0.0109444	0.0097526	0.261993	0.3084096	11,229
ALL	Any Minority vs. White	-0.0156685	0.0051817	0.0025352	0.8072188	40,306

Table B.3: Solar Visibility Analysis by Year and Race/Ethnicity with Controls of Individual Characteristics

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
7/2023- 6/2024	Black vs. White	0.009241	0.0141045	0.5128183	0.7933954	4,637
7/2023- 6/2024	Hispanic vs. White	0.0728046	0.0267406	0.0069601	0.4238489	1,666
7/2023- 6/2024	Any Minority vs. White	0.017567	0.0116362	0.1321013	0.8267046	5,536
7/2022- 6/2023	Black vs. White	0.0076265	0.0110094	0.4889741	0.8086099	9,214
7/2022- 6/2023	Hispanic vs. White	0.012844	0.0221813	0.5630658	0.3562768	2,735
7/2022- 6/2023	Any Minority vs. White	0.0070732	0.0097883	0.4704288	0.8317801	10,487
7/2021- 6/2022	Black vs. White	0.0020242	0.0112556	0.8573854	0.7814057	9,702
7/2021- 6/2022	Hispanic vs. White	-0.0296759	0.0174547	0.0902777	0.3067742	3,050
7/2021- 6/2022	Any Minority vs. White	0.0000647	0.0102222	0.9949555	0.8077989	11,036
7/2020- 6/2021	Black vs. White	-0.0123477	0.0115008	0.2837897	0.7957603	9,273
7/2020- 6/2021	Hispanic vs. White	-0.0012027	0.0209808	0.9543315	0.3100691	2,744
7/2020- 6/2021	Any Minority vs. White	-0.0088004	0.0100876	0.3836324	0.8196675	10,500
7/2019- 6/2020	Black vs. White	-0.056058	0.0102933	0.000000101	0.8120142	13,702
7/2019- 6/2020	Hispanic vs. White	-0.0261209	0.0151938	0.0867181	0.2807115	3,590
7/2019- 6/2020	Any Minority vs. White	-0.0464759	0.0088828	0.000000298	0.8314226	15,283
ALL	Black vs. White	-0.0162512	0.0052622	0.0020469	0.7998555	46,528
ALL	Hispanic vs. White	-0.0016897	0.0089121	0.8496552	0.3248727	13,785
ALL	Any Minority vs. White	-0.0121156	0.0046059	0.0086067	0.8237364	52,842

Table B.4: Solar Visibility Analysis by Year and Race/Ethnicity with Controls for Daylight Savings Time

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
Spring 2024	Black vs. White	0.0068437	0.0807279	0.9325497	0.8041431	529
Spring 2024	Hispanic vs. White	-0.0256953	0.1755113	0.8840184	0.3658537	164
Spring 2024	Any Minority vs. White	0.0057522	0.0722556	0.9366472	0.8295082	608
Fall 2023	Black vs. White	-0.1048107	0.0890377	0.241303	0.76	336
Fall 2023	Hispanic vs. White	-0.1468801	0.1949667	0.4537967	0.3636364	129
Fall 2023	Any Minority vs. White	-0.0905142	0.0754263	0.2322277	0.7971014	399
Spring 2023	Black vs. White	0.0254324	0.0487252	0.6023613	0.7953964	1,139
Spring 2023	Hispanic vs. White	0.0676907	0.1083898	0.5336331	0.2429022	309
Spring 2023	Any Minority vs. White	0.0292274	0.0459652	0.5256941	0.8130841	1,249
Fall 2022	Black vs. White	0.0230211	0.0482241	0.6337243	0.8051823	1,028
Fall 2022	Hispanic vs. White	0.0103597	0.1206748	0.9317418	0.3867069	326
Fall 2022	Any Minority vs. White	0.0171899	0.0428148	0.6885632	0.8301255	1,181
Spring 2022	Black vs. White	-0.0707777	0.0592108	0.2336149	0.8113027	1,023
Spring 2022	Hispanic vs. White	-0.0902263	0.1195556	0.4524111	0.2649254	255
Spring 2022	Any Minority vs. White	-0.063257	0.053135	0.2354276	0.8301724	1,137
Fall 2021	Black vs. White	-0.0251327	0.0696521	0.7186624	0.7591463	970
Fall 2021	Hispanic vs. White	-0.0780109	0.1048681	0.458617	0.2967359	330
Fall 2021	Any Minority vs. White	-0.0327842	0.0610649	0.5920277	0.7885816	1,106
Spring 2021	Black vs. White	-0.0527822	0.0462784	0.2555617	0.8294509	1,202
Spring 2021	Hispanic vs. White	-0.1227594	0.1336594	0.360393	0.3166667	300
Spring 2021	Any Minority vs. White	-0.0483106	0.0412582	0.2431399	0.8481482	1,350
Fall 2020	Black vs. White	-0.043918	0.0605518	0.4692853	0.7826923	1,035
Fall 2020	Hispanic vs. White	-0.0899271	0.1736602	0.6058173	0.3067485	323
Fall 2020	Any Minority vs. White	-0.0408895	0.0558135	0.464805	0.8089603	1,176
Spring 2020	Black vs. White	-0.0101632	0.0549799	0.8535421	0.7592329	1,408
Spring 2020	Hispanic vs. White	0.0247975	0.0787226	0.7533703	0.2116279	430
Spring 2020	Any Minority vs. White	-0.0001204	0.0506168	0.9981043	0.7835249	1,566
Fall 2019	Black vs. White	-0.0443673	0.0341287	0.195185	0.8437687	1,670
Fall 2019	Hispanic vs. White	0.1042283	0.1070899	0.3324578	0.2722222	359
Fall 2019	Any Minority vs. White	-0.0374089	0.0327845	0.2552767	0.8571429	1,827
ALL	Black vs. White	-0.0239562	0.017207	0.1641787	0.7993494	10,340
ALL	Hispanic vs. White	-0.0103365	0.0369514	0.7797706	0.2927487	2,925
ALL	Any Minority vs. White	-0.0199354	0.0155867	0.2012051	0.8210292	11,599

Table B.5: Solar Visibility Analysis by District and Race/Ethnicity (July 2023 to June 2024)

District	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	0.0372423	0.0112064	0.0017743	0.9726444	329
7D	Hispanic vs. White	0.3245077	0.3613114	0.3867776	0.64	24
7D	Any Minority vs. White	0.0350374	0.0108988	0.0024171	0.9742121	349
6D	Black vs. White	-0.0147352	0.0179884	0.4171171	0.9397089	481
6D	Hispanic vs. White	0.0638903	0.1603402	0.6955529	0.4081633	47
6D	Any Minority vs. White	-0.0146937	0.017284	0.3998527	0.9428008	507
5D	Black vs. White	0.0028355	0.0225679	0.9005628	0.8985115	739
5D	Hispanic vs. White	-0.1009005	0.1143896	0.3852447	0.5454546	163
5D	Any Minority vs. White	-0.0019022	0.0193526	0.922128	0.9124854	857
4D	Black vs. White	0.0187464	0.0245304	0.4487309	0.8566667	600
4D	Hispanic vs. White	0.0771872	0.0557474	0.1734902	0.7084746	295
4D	Any Minority vs. White	0.0208169	0.0186124	0.2693137	0.8955042	823
3D	Black vs. White	0.0500439	0.0252513	0.053363	0.755531	904
3D	Hispanic vs. White	0.1597141	0.0488323	0.0020895	0.4075067	373
3D	Any Minority vs. White	0.0650011	0.0210308	0.0033512	0.7953704	1,080
2D	Black vs. White	0.0196517	0.0457956	0.6698402	0.5388769	926
2D	Hispanic vs. White	0.0663464	0.0398961	0.1032672	0.2650602	581
2D	Any Minority vs. White	0.0358695	0.0351237	0.3124849	0.6234568	1,134
1D	Black vs. White	-0.0496659	0.0283465	0.0867233	0.837386	658
1D	Hispanic vs. White	0.0632153	0.0542923	0.2528895	0.3988764	177
1D	Any Minority vs. White	-0.0230545	0.0204991	0.2668306	0.8638677	786
ALL	Black vs. White	0.0088638	0.0140907	0.5297593	0.7933954	4,637
ALL	Hispanic vs. White	0.0899534	0.0273025	0.0011368	0.4238489	1,666
ALL	Any Minority vs. White	0.0176432	0.0116187	0.1298606	0.8267046	5,536

Table B.6: Solar Visibility Analysis by District and Race/Ethnicity (July 2021 to June 2024)

District	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	0.0031602	0.0085039	0.7107565	0.9783491	1,478
7D	Hispanic vs. White	0.050208	0.2145548	0.8164227	0.5076923	62
7D	Any Minority vs. White	0.0031973	0.0082439	0.6987466	0.9790576	1,528
6D	Black vs. White	0.0033086	0.005998	0.5821036	0.9665563	3,020
6D	Hispanic vs. White	0.0115197	0.0918282	0.9005562	0.4820513	192
6D	Any Minority vs. White	0.0031135	0.0058275	0.594019	0.9678242	3,139
5D	Black vs. White	0.0433191	0.0100358	0.0000293	0.8899862	5,063
5D	Hispanic vs. White	0.0331999	0.0296219	0.2646157	0.5156522	1,148
5D	Any Minority vs. White	0.0358653	0.0087309	0.0000667	0.9031304	5,750
4D	Black vs. White	0.0375034	0.0174226	0.0331308	0.8356097	2,050
4D	Hispanic vs. White	0.0527733	0.0360018	0.1451792	0.6108545	866
4D	Any Minority vs. White	0.0296775	0.0135665	0.0303978	0.8725416	2,644
3D	Black vs. White	0.0342039	0.0165397	0.0404305	0.7226834	4,457
3D	Hispanic vs. White	0.0238126	0.0246582	0.3359438	0.3087248	1,788
3D	Any Minority vs. White	0.0304669	0.0143685	0.0356872	0.7623077	5,200
2D	Black vs. White	0.0154904	0.0175972	0.3801848	0.5490987	4,216
2D	Hispanic vs. White	-0.0080185	0.019084	0.6750405	0.2108759	2,409
2D	Any Minority vs. White	0.0153504	0.0168306	0.3632779	0.6220676	5,030
1D	Black vs. White	0.001055	0.0150784	0.9443196	0.7999388	3,269
1D	Hispanic vs. White	0.0946711	0.0319119	0.0036235	0.3312883	977
1D	Any Minority vs. White	0.0114344	0.0130665	0.3830113	0.8264331	3,768
ALL	Black vs. White	0.0057089	0.0069083	0.408787	0.7944635	23,553
ALL	Hispanic vs. White	0.0146558	0.0130341	0.2611908	0.351145	7,451
ALL	Any Minority vs. White	0.006627	0.0061287	0.2798238	0.8210071	27,059

APPENDIX C: STOP DISPOSITION ANALYSIS DATA TABLES

Table C.1: Stop Disposition Test for Decision to Arrest by Year and Race/Ethnicity

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
7/2023- 6/2024	Black vs. White	0.0636844	0.0033102	0	0.0737794	27,469
7/2023- 6/2024	Hispanic vs. White	0.0765447	0.0057071	7.52E-38	0.0737794	9,249
7/2023- 6/2024	Any Minority vs. White	0.0684474	0.0031524	0	0.0737794	32,287
7/2022- 6/2023	Black vs. White	0.0433567	0.0024024	0	0.04901	31,052
7/2022- 6/2023	Hispanic vs. White	0.0308767	0.0036663	1.37E-16	0.04901	10,292
7/2022- 6/2023	Any Minority vs. White	0.0416263	0.0022901	0	0.04901	35,878
7/2021- 6/2022	Black vs. White	0.0583246	0.0028058	0	0.0618453	32,633
7/2021- 6/2022	Hispanic vs. White	0.0344885	0.003972	1.65E-17	0.0618453	10,636
7/2021- 6/2022	Any Minority vs. White	0.0541999	0.0026215	0	0.0618453	37,419
7/2020- 6/2021	Black vs. White	0.0796207	0.0043008	0	0.0736763	32,359
7/2020- 6/2021	Hispanic vs. White	0.0368546	0.0039518	6.90E-20	0.0736763	10,637
7/2020- 6/2021	Any Minority vs. White	0.0696599	0.0038426	0	0.0736763	37,133
7/2019- 6/2020	Black vs. White	0.0618747	0.0024997	0	0.0664351	57,499
7/2019- 6/2020	Hispanic vs. White	0.0416442	0.0037332	1.98E-27	0.0664351	16,793
7/2019- 6/2020	Any Minority vs. White	0.0569674	0.0023932	0	0.0664351	64,661
ALL	Black vs. White	0.0615939	0.0014038	0	0.0649725	181,012
ALL	Hispanic vs. White	0.043582	0.0019138	0	0.0649725	57,607
ALL	Any Minority vs. White	0.0578736	0.0013057	0	0.0649725	207,378

Table C.2: Stop Disposition Test for Decision to Ticket by Year and Race/Ethnicity

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
7/2023- 6/2024	Black vs. White	0.0680455	0.0083699	1.09E-15	0.6550575	26,073
7/2023- 6/2024	Hispanic vs. White	0.0799525	0.0114625	5.59E-12	0.6550575	8,892
7/2023- 6/2024	Any Minority vs. White	0.0642673	0.0081506	7.15E-15	0.6550575	30,510
7/2022- 6/2023	Black vs. White	0.0224946	0.0075861	0.0030861	0.6857246	29,332
7/2022- 6/2023	Hispanic vs. White	0.0664626	0.0099394	3.92E-11	0.6857246	10,046
7/2022- 6/2023	Any Minority vs. White	0.0246301	0.0073391	0.0008162	0.6857246	33,931
7/2021- 6/2022	Black vs. White	0.0479233	0.0082346	7.61E-09	0.6683871	30,024
7/2021- 6/2022	Hispanic vs. White	0.0740645	0.0109718	2.59E-11	0.6683871	10,304
7/2021- 6/2022	Any Minority vs. White	0.0516719	0.0080576	2.07E-10	0.6683871	34,559
7/2020- 6/2021	Black vs. White	0.056622	0.0090649	5.87E-10	0.6710818	29,527
7/2020- 6/2021	Hispanic vs. White	0.0729386	0.0110742	7.39E-11	0.6710818	10,314
7/2020- 6/2021	Any Minority vs. White	0.0600185	0.008617	5.45E-12	0.6710818	34,092
7/2019- 6/2020	Black vs. White	-0.010148	0.0079067	0.199577	0.6594633	52,819
7/2019- 6/2020	Hispanic vs. White	0.0643612	0.0087968	5.00E-13	0.6594633	16,232
7/2019- 6/2020	Any Minority vs. White	0.0001072	0.007438	0.9885007	0.6594633	59,613
ALL	Black vs. White	0.030031	0.0038143	4.09E-15	0.6670789	167,775
ALL	Hispanic vs. White	0.0707929	0.0046222	0	0.6670789	55,788
ALL	Any Minority vs. White	0.0344405	0.0036487	5.3E-21	0.6670789	192,705

Table C.3: Stop Disposition Test for Stop Duration by Year and Race/Ethnicity

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
7/2023- 6/2024	Black vs. White	-12.19772	4.604758	0.008183	66.91528	27,469
7/2023- 6/2024	Hispanic vs. White	-17.92798	5.777481	0.0019687	66.91528	9,249
7/2023- 6/2024	Any Minority vs. White	-13.34934	4.590029	0.003702	66.91528	32,287
7/2022- 6/2023	Black vs. White	-3.795481	3.34377	0.2565703	70.90073	31,052
7/2022- 6/2023	Hispanic vs. White	-15.45202	3.738662	0.000039	70.90073	10,292
7/2022- 6/2023	Any Minority vs. White	-5.251963	3.187819	0.0997221	70.90073	35,878
7/2021- 6/2022	Black vs. White	-0.5146751	1.948624	0.7917323	50.52263	32,633
7/2021- 6/2022	Hispanic vs. White	-1.963687	3.0191	0.5155765	50.52263	10,636
7/2021- 6/2022	Any Minority vs. White	-0.57856	1.901618	0.7609946	50.52263	37,419
7/2020- 6/2021	Black vs. White	5.20472	2.074831	0.0122585	38.19743	32,359
7/2020- 6/2021	Hispanic vs. White	-3.684794	2.739439	0.178902	38.19743	10,637
7/2020- 6/2021	Any Minority vs. White	4.776575	1.993134	0.0167075	38.19743	37,133
7/2019- 6/2020	Black vs. White	0.7738063	0.8352937	0.3544345	21.1176	57,499
7/2019- 6/2020	Hispanic vs. White	-0.3760167	1.253386	0.7642341	21.1176	16,793
7/2019- 6/2020	Any Minority vs. White	0.7391135	0.8218499	0.3686617	21.1176	64,661
ALL	Black vs. White	-1.342412	1.070066	0.2097058	45.80462	181,012
ALL	Hispanic vs. White	-7.144391	1.478898	0.0000014	45.80462	57,607
ALL	Any Minority vs. White	-1.864301	1.047966	0.0752963	45.80462	207,378

Table C.4: Stop Disposition Test for Decision to Arrest by Year and Race/Ethnicity (July 2023 to June 2024)

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	0.1087043	0.0337588	0.0015405	0.1788793	2,406
7D	Hispanic vs. White	0.0160442	0.0633185	0.8005396	0.1788793	150
7D	Any Minority vs. White	0.1072529	0.0337094	0.0017461	0.1788793	2,502
6D	Black vs. White	0.1220275	0.0165047	6.83E-12	0.1446055	2,712
6D	Hispanic vs. White	0.1035476	0.0332649	0.002372	0.1446055	273
6D	Any Minority vs. White	0.1230339	0.0165846	5.93E-12	0.1446055	2,867
5D	Black vs. White	0.0480077	0.0081523	2.08E-08	0.0708712	4,928
5D	Hispanic vs. White	0.0478482	0.0128969	0.0002895	0.0708712	1,303
5D	Any Minority vs. White	0.0546198	0.0080914	2.32E-10	0.0708712	5,808
4D	Black vs. White	0.0451794	0.0120336	0.0002395	0.0954452	2,997
4D	Hispanic vs. White	0.0947011	0.0157629	0.000000012	0.0954452	1,343
4D	Any Minority vs. White	0.0606467	0.0115466	0.000000452	0.0954452	3,926
3D	Black vs. White	0.0353966	0.0047515	4.78E-12	0.0480914	5,571
3D	Hispanic vs. White	0.0716376	0.01144	3.14E-09	0.0480914	2,478
3D	Any Minority vs. White	0.0475831	0.0051335	9.28E-17	0.0480914	6,695
2D	Black vs. White	0.0249613	0.0057119	0.0000218	0.0454396	4,316
2D	Hispanic vs. White	0.0664344	0.0123713	0.000000264	0.0454396	2,492
2D	Any Minority vs. White	0.0393931	0.005478	2.05E-11	0.0454396	5,184
1D	Black vs. White	0.0442604	0.0059474	4.99E-12	0.0487002	4,539
1D	Hispanic vs. White	0.0722261	0.0133184	0.000000224	0.0487002	1,210
1D	Any Minority vs. White	0.0468801	0.0057135	5.91E-14	0.0487002	5,305
ALL	Black vs. White	0.0636844	0.0033102	0	0.0737794	27,469
ALL	Hispanic vs. White	0.0765447	0.0057071	7.52E-38	0.0737794	9,249
ALL	Any Minority vs. White	0.0684474	0.0031524	0	0.0737794	32,287

Table C.5: Stop Disposition Test for Decision to Arrest by Year and Race/Ethnicity (July 2021 to June 2024)

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	0.0575713	0.0236273	0.0151734	0.172926	6,410
7D	Hispanic vs. White	0.0145916	0.0435367	0.7378383	0.172926	343
7D	Any Minority vs. White	0.0580794	0.023506	0.0138136	0.172926	6,624
6D	Black vs. White	0.0819562	0.0084359	1.48E-20	0.1014311	11,466
6D	Hispanic vs. White	0.0488801	0.0145977	0.0009121	0.1014311	872
6D	Any Minority vs. White	0.0822446	0.0084069	8.43E-21	0.1014311	11,995
5D	Black vs. White	0.035018	0.0036877	9.04E-20	0.0552256	16,939
5D	Hispanic vs. White	0.026756	0.0054663	0.00000138	0.0552256	4,220
5D	Any Minority vs. White	0.0367786	0.0036182	3.47E-22	0.0552256	19,566
4D	Black vs. White	0.0492271	0.0060998	5.2E-15	0.0783931	8,346
4D	Hispanic vs. White	0.0632816	0.0078603	6.41E-15	0.0783931	3,616
4D	Any Minority vs. White	0.0544774	0.0057744	1.45E-19	0.0783931	10,732
3D	Black vs. White	0.0357782	0.0024466	0	0.0419395	18,056
3D	Hispanic vs. White	0.0435635	0.0053491	3.3E-15	0.0419395	7,311
3D	Any Minority vs. White	0.03907	0.0024931	0	0.0419395	21,376
2D	Black vs. White	0.0447369	0.0030745	0	0.042452	16,979
2D	Hispanic vs. White	0.0517067	0.0053413	2.2E-20	0.042452	10,174
2D	Any Minority vs. White	0.0450193	0.0028018	0	0.042452	20,425
1D	Black vs. White	0.0315703	0.003405	5.41E-19	0.0403299	12,958
1D	Hispanic vs. White	0.0373367	0.006752	5.34E-08	0.0403299	3,636
1D	Any Minority vs. White	0.0313801	0.0033066	9.29E-20	0.0403299	14,866
ALL	Black vs. White	0.0547606	0.0016498	0	0.0612243	91,154
ALL	Hispanic vs. White	0.0468105	0.0026591	0	0.0612243	30,177
ALL	Any Minority vs. White	0.0540609	0.0015753	0	0.0612243	105,584

Table C.6: Stop Disposition Test for Decision to Ticket by Year and Race/Ethnicity (July 2023 to June 2024)

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	0.070238	0.0603942	0.2464917	0.7197556	2,101
7D	Hispanic vs. White	0.0843285	0.09536	0.3790191	0.7197556	135
7D	Any Minority vs. White	0.0706337	0.0606386	0.2457485	0.7197556	2,183
6D	Black vs. White	-0.0800757	0.0326607	0.0152651	0.7528172	2,383
6D	Hispanic vs. White	-0.0370954	0.0535519	0.4900568	0.7528172	258
6D	Any Minority vs. White	-0.0750641	0.0322559	0.0211727	0.7528172	2,520
5D	Black vs. White	0.0533064	0.0211985	0.0128613	0.7164329	4,704
5D	Hispanic vs. White	0.129708	0.0257902	0.00000139	0.7164329	1,258
5D	Any Minority vs. White	0.0641879	0.0205902	0.0021489	0.7164329	5,528
4D	Black vs. White	0.006662	0.0258206	0.7967165	0.638774	2,856
4D	Hispanic vs. White	0.0702451	0.031248	0.0259349	0.638774	1,232
4D	Any Minority vs. White	0.0225374	0.0256618	0.3810714	0.638774	3,675
3D	Black vs. White	0.0058006	0.015397	0.7068507	0.499414	5,405
3D	Hispanic vs. White	0.0576876	0.0216418	0.00845	0.499414	2,392
3D	Any Minority vs. White	0.0127976	0.0151176	0.3984644	0.499414	6,433
2D	Black vs. White	0.0178431	0.0131855	0.1778087	0.6365628	4,227
2D	Hispanic vs. White	0.0651347	0.0218688	0.0033373	0.6365628	2,434
2D	Any Minority vs. White	0.0299954	0.0121007	0.0141746	0.6365628	5,037
1D	Black vs. White	0.0770207	0.018157	0.0000366	0.78196	4,397
1D	Hispanic vs. White	-0.0007453	0.0266027	0.9776856	0.78196	1,182
1D	Any Minority vs. White	0.0430366	0.0187153	0.0227122	0.78196	5,134
ALL	Black vs. White	0.0680455	0.0083699	1.09E-15	0.6550575	26,073
ALL	Hispanic vs. White	0.0799525	0.0114625	5.59E-12	0.6550575	8,892
ALL	Any Minority vs. White	0.0642673	0.0081506	7.15E-15	0.6550575	30,510

Table C.7: Stop Disposition Test for Decision to Ticket by Year and Race/Ethnicity (July 2021 to June 2024)

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	-0.0249817	0.0422849	0.5549269	0.6439225	5,199
7D	Hispanic vs. White	0.0748023	0.0710199	0.2935893	0.6439225	290
7D	Any Minority vs. White	-0.0234081	0.0423293	0.5805129	0.6439225	5,377
6D	Black vs. White	-0.0512716	0.0186317	0.0061412	0.7277367	10,106
6D	Hispanic vs. White	-0.0046863	0.0276261	0.8654128	0.7277367	839
6D	Any Minority vs. White	-0.0478813	0.0184622	0.0097789	0.7277367	10,592
5D	Black vs. White	0.0151076	0.0117505	0.1991487	0.7090864	16,075
5D	Hispanic vs. White	0.1033949	0.014978	1.78E-11	0.7090864	4,109
5D	Any Minority vs. White	0.0263773	0.0116179	0.0236116	0.7090864	18,582
4D	Black vs. White	-0.0035514	0.0144996	0.8066077	0.610617	7,843
4D	Hispanic vs. White	0.0646327	0.0169826	0.0001595	0.610617	3,375
4D	Any Minority vs. White	0.0124167	0.0141699	0.3812995	0.610617	9,999
3D	Black vs. White	0.006412	0.0088903	0.4710989	0.6208506	17,302
3D	Hispanic vs. White	0.0454337	0.0121599	0.0002092	0.6208506	7,121
3D	Any Minority vs. White	0.0128168	0.0086483	0.1389626	0.6208506	20,427
2D	Black vs. White	0.043832	0.0078794	4.33E-08	0.6397771	16,478
2D	Hispanic vs. White	0.0567933	0.0122173	0.00000431	0.6397771	9,961
2D	Any Minority vs. White	0.0484745	0.0075236	2.76E-10	0.6397771	19,759
1D	Black vs. White	0.0406238	0.0102855	0.0000895	0.7584006	12,426
1D	Hispanic vs. White	0.0574643	0.0155771	0.0002518	0.7584006	3,539
1D	Any Minority vs. White	0.0275298	0.0101918	0.0071431	0.7584006	14,264
ALL	Black vs. White	0.0450842	0.0046777	1.02E-21	0.6701173	85,429
ALL	Hispanic vs. White	0.0733173	0.0062212	2.45E-31	0.6701173	29,242
ALL	Any Minority vs. White	0.0460486	0.0045658	1.34E-23	0.6701173	99,000

Table C.8: Stop Disposition Test for Stop Duration by Year and Race/Ethnicity (July 2023 to June 2024)

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	5.230648	37.65815	0.889698	85.26041	2,406
7D	Hispanic vs. White	17.67677	42.91016	0.681346	85.26041	150
7D	Any Minority vs. White	4.649148	37.73654	0.9020967	85.26041	2,502
6D	Black vs. White	-50.37479	31.741	0.1144142	86.15008	2,712
6D	Hispanic vs. White	-33.70963	41.78545	0.4215944	86.15008	273
6D	Any Minority vs. White	-50.38874	31.70895	0.1139518	86.15008	2,867
5D	Black vs. White	0.2630283	8.415962	0.9751047	51.41312	4,928
5D	Hispanic vs. White	-6.990885	9.46835	0.4614374	51.41312	1,303
5D	Any Minority vs. White	-0.7223318	8.222255	0.9301005	51.41312	5,808
4D	Black vs. White	-5.725462	10.17214	0.5742869	51.78027	2,997
4D	Hispanic vs. White	0.0970586	12.30749	0.9937176	51.78027	1,343
4D	Any Minority vs. White	-3.565344	10.19563	0.7270094	51.78027	3,926
3D	Black vs. White	2.341166	4.59025	0.6107038	44.15482	5,571
3D	Hispanic vs. White	4.535034	7.079953	0.522701	44.15482	2,478
3D	Any Minority vs. White	2.826727	4.497025	0.5304846	44.15482	6,695
2D	Black vs. White	-15.60977	10.24299	0.1294135	94.18569	4,316
2D	Hispanic vs. White	-20.40572	16.8192	0.2267721	94.18569	2,492
2D	Any Minority vs. White	-17.92968	10.28785	0.0832091	94.18569	5,184
1D	Black vs. White	-22.85464	12.52246	0.0697737	81.64643	4,539
1D	Hispanic vs. White	-51.74116	15.44985	0.0010213	81.64643	1,210
1D	Any Minority vs. White	-26.42183	12.26067	0.0325937	81.64643	5,305
ALL	Black vs. White	-12.19772	4.604758	0.008183	66.91528	27,469
ALL	Hispanic vs. White	-17.92798	5.777481	0.0019687	66.91528	9,249
ALL	Any Minority vs. White	-13.34934	4.590029	0.003702	66.91528	32,287

Table C.9: Stop Disposition Test for Stop Duration by Year and Race/Ethnicity (July 2021 to June 2024)

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	-33.45217	23.87181	0.1617398	75.9623	6,410
7D	Hispanic vs. White	-24.55638	31.02328	0.4295098	75.9623	343
7D	Any Minority vs. White	-33.97743	23.91598	0.1560298	75.9623	6,624
6D	Black vs. White	-43.38853	16.65551	0.009459	90.934	11,466
6D	Hispanic vs. White	-24.25661	20.78118	0.2440049	90.934	872
6D	Any Minority vs. White	-42.88443	16.56818	0.0099235	90.934	11,995
5D	Black vs. White	1.035318	3.478958	0.7661368	41.67636	16,939
5D	Hispanic vs. White	-1.736775	4.584126	0.7049656	41.67636	4,220
5D	Any Minority vs. White	0.847933	3.434498	0.8050972	41.67636	19,566
4D	Black vs. White	-7.907846	5.566654	0.1560601	63.98896	8,346
4D	Hispanic vs. White	-4.976138	6.256746	0.4268143	63.98896	3,616
4D	Any Minority vs. White	-6.783114	5.480666	0.2164254	63.98896	10,732
3D	Black vs. White	2.192446	2.050221	0.2854156	40.20431	18,056
3D	Hispanic vs. White	0.6370146	3.117259	0.8381656	40.20431	7,311
3D	Any Minority vs. White	2.213798	1.993689	0.2673559	40.20431	21,376
2D	Black vs. White	-5.134991	3.831297	0.1807659	70.66929	16,979
2D	Hispanic vs. White	-13.5781	5.790848	0.0194413	70.66929	10,174
2D	Any Minority vs. White	-7.193275	3.619174	0.047407	70.66929	20,425
1D	Black vs. White	-15.80494	5.254793	0.0027642	66.99464	12,958
1D	Hispanic vs. White	-24.73754	7.563389	0.001152	66.99464	3,636
1D	Any Minority vs. White	-16.62137	5.204443	0.0014929	66.99464	14,866
ALL	Black vs. White	-5.073301	1.917005	0.0081699	62.66526	91,154
ALL	Hispanic vs. White	-11.72856	2.484107	0.00000245	62.66526	30,177
ALL	Any Minority vs. White	-5.928369	1.876868	0.0015985	62.66526	105,584

APPENDIX D: SEARCH ANALYSIS DATA TABLES

Table D.1: Hit-Rate Analysis (Contraband) by Year and Race/Ethnicity

Period	Comparison	Race	B=	Upper_Bound=	Lower_Bound=	B_Difference=	P=	N=
7/2019- 6/2020	Black vs. White	White	0.4781022	0.6637651	0.2924393	-0.165	0.083	1,866
7/2019- 6/2020	Black vs. White	Black	0.3126696	0.3362241	0.2891151	-0.165	0.083	1,866
7/2020- 6/2021	Black vs. White	White	0.4591837	0.6861405	0.2322269	-0.107	0.363	724
7/2020- 6/2021	Black vs. White	Black	0.3521459	0.3910558	0.313236	-0.107	0.363	724
7/2021- 6/2022	Black vs. White	White	0.5106383	0.8346806	0.186596	-0.08	0.63	573
7/2021- 6/2022	Black vs. White	Black	0.4302569	0.47378	0.3867337	-0.08	0.63	573
7/2022- 6/2023	Black vs. White	White	0.6666667	1	0.2886101	-0.125	0.522	443
7/2022- 6/2023	Black vs. White	Black	0.5420018	0.5907729	0.4932307	-0.125	0.522	443
7/2023- 6/2024	Black vs. White	White	0.8	1	0.4469241	0.051	0.781	144
7/2023- 6/2024	Black vs. White	Black	0.8509804	0.9129956	0.7889652	0.051	0.781	144
7/2019- 6/2020	Hispanic vs. White	White	0.4781022	0.6656087	0.2905957	0.118	0.308	97
7/2019- 6/2020	Hispanic vs. White	Hispanic	0.5962963	0.7228196	0.469773	0.118	0.308	97
7/2020- 6/2021	Hispanic vs. White	White	0.4591837	0.6930236	0.2253438	0.123	0.529	33
7/2020- 6/2021	Hispanic vs. White	Hispanic	0.5825243	0.881376	0.2836726	0.123	0.529	33
7/2021- 6/2022	Hispanic vs. White	White	0.5106383	0.8468047	0.1744719	0.164	0.447	27
7/2021- 6/2022	Hispanic vs. White	Hispanic	0.6745562	0.9199528	0.4291596	0.164	0.447	27
7/2022- 6/2023	Hispanic vs. White	White	0.6666667	1	0.2690607	0.023	0.927	20
7/2022- 6/2023	Hispanic vs. White	Hispanic	0.6891892	0.948348	0.4300304	0.023	0.927	20
7/2023- 6/2024	Hispanic vs. White	White	0.8	1	0.4293334	0.126	0.544	19
7/2023- 6/2024	Hispanic vs. White	Hispanic	0.9259259	1	0.7783414	0.126	0.544	19
7/2019- 6/2020	Any Minority vs. White	White	0.4781022	0.6637616	0.2924428	-0.156	0.103	1,934
7/2019- 6/2020	Any Minority vs. White	Any Minority	0.3221638	0.3454847	0.2988428	-0.156	0.103	1,934
7/2020- 6/2021	Any Minority vs. White	White	0.4591837	0.6861345	0.2322328	-0.103	0.382	738
7/2020- 6/2021	Any Minority vs. White	Any Minority	0.3565198	0.3951568	0.3178827	-0.103	0.382	738
7/2021- 6/2022	Any Minority vs. White	White	0.5106383	0.8346615	0.1866151	-0.069	0.681	593
7/2021- 6/2022	Any Minority vs. White	Any Minority	0.4419699	0.4848158	0.399124	-0.069	0.681	593
7/2022- 6/2023	Any Minority vs. White	White	0.6666667	1	0.2886594	-0.113	0.562	470
7/2022- 6/2023	Any Minority vs. White	Any Minority	0.5539749	0.6010867	0.5068631	-0.113	0.562	470
7/2023- 6/2024	Any Minority vs. White	White	0.8	1	0.4472401	0.051	0.779	165
7/2023- 6/2024	Any Minority vs. White	Any Minority	0.8513514	0.9088227	0.79388	0.051	0.779	165

Table D.2: Hit-Rate Analysis (Contraband) by District and Race/Ethnicity (July 2023 to June 2024)

District	Comparison	Race	B=	Upper_Bound=	Lower_Bound=	B_Difference=	P=	N=
1D	Black vs. White	White	1	1	.	-0.273	0.093	12
1D	Black vs. White	Black	0.7272727	1	.	-0.273	0.093	12
2D	Black vs. White	White	.	1	.	.	.	4
2D	Black vs. White	Black	.	1	.	.	.	4
3D	Black vs. White	White	1	1	1	-0.108	0.17	21
3D	Black vs. White	Black	0.8918919	1	0.7434971	-0.108	0.17	21
4D	Black vs. White	White	1	1	0.9999999	-0.222	0.189	10
4D	Black vs. White	Black	0.7777778	1	0.4741012	-0.222	0.189	10
5D	Black vs. White	White	.	1	.	.	.	21
5D	Black vs. White	Black	.	1	.	.	.	21
6D	Black vs. White	White	1	1	1	-0.185	0.022	32
6D	Black vs. White	Black	0.8148148	0.9648643	0.6647654	-0.185	0.022	32
7D	Black vs. White	White	1.31E-14	5.63E-08	0	0.923	0.001	43
7D	Black vs. White	Black	0.9230769	1	0.837567	0.923	0.001	43
1D	Hispanic vs. White	White	1	1	.	0	.	2
1D	Hispanic vs. White	Hispanic	1	1	.	0	.	2
2D	Hispanic vs. White	White						
2D	Hispanic vs. White	Hispanic						
3D	Hispanic vs. White	White	1	1	.	0	.	5
3D	Hispanic vs. White	Hispanic	1	1	.	0	.	5
4D	Hispanic vs. White	White	1	1	.	-1	.	2
4D	Hispanic vs. White	Hispanic	-2.22E-16	1	.	-1	.	2
5D	Hispanic vs. White	White	.	1	.	.	.	6
5D	Hispanic vs. White	Hispanic	.	1	.	.	.	6
6D	Hispanic vs. White	White						
6D	Hispanic vs. White	Hispanic						
7D	Hispanic vs. White	White	0	1	.	1	.	3
7D	Hispanic vs. White	Hispanic	1	1	.	1	.	3
1D	Any Minority vs. White	White	1	1	0.9999999	-0.214	0.092	15
1D	Any Minority vs. White	Any Minority	0.7857143	1	0.5548297	-0.214	0.092	15
2D	Any Minority vs. White	White	.	1	.	.	.	4
2D	Any Minority vs. White	Any Minority	.	1	.	.	.	4
3D	Any Minority vs. White	White	1	1	0.9999999	-0.128	0.087	26

Table D.2: Hit-Rate Analysis (Contraband) by District and Race/Ethnicity (July 2023 to June 2024)

District	Comparison	Race	B=	Upper_Bound=	Lower_Bound=	B_Difference=	P=	N=
3D	Any Minority vs. White	Any Minority	0.8723404	1	0.7322345	-0.128	0.087	26
4D	Any Minority vs. White	White	1	1	0.9999999	-0.364	0.045	12
4D	Any Minority vs. White	Any Minority	0.6363636	0.9477766	0.3249507	-0.364	0.045	12
5D	Any Minority vs. White	White	.	1	.	.	.	30
5D	Any Minority vs. White	Any Minority	.	1	.	.	.	30
6D	Any Minority vs. White	White	1	1	1	-0.185	0.022	32
6D	Any Minority vs. White	Any Minority	0.8148148	0.9648643	0.6647654	-0.185	0.022	32
7D	Any Minority vs. White	White	1.22E-14	1.33E-14	1.11E-14	0.926	0.001	45
7D	Any Minority vs. White	Any Minority	0.9259259	1	0.8435557	0.926	0.001	45

Table D.3: Hit-Rate Analysis (Contraband) by District and Race/Ethnicity (July 2021 to June 2024)

District	Comparison	Race	B=	Upper_Bound=	Lower_Bound=	B_Difference=	P=	N=
1D	Black vs. White	White	0.6	1	0.0934477	0.019	0.944	67
1D	Black vs. White	Black	0.6186441	0.7423403	0.4949478	0.019	0.944	67
2D	Black vs. White	White	0.6666667	1	0.1203663	-0.011	0.971	43
2D	Black vs. White	Black	0.6559633	0.8098755	0.5020511	-0.011	0.971	43
3D	Black vs. White	White	0.6	1	0.1679751	-0.101	0.653	166
3D	Black vs. White	Black	0.499056	0.5805922	0.4175198	-0.101	0.653	166
4D	Black vs. White	White	1	1	.	-0.501	0.001	95
4D	Black vs. White	Black	0.498605	0.6042238	0.3929862	-0.501	0.001	95
5D	Black vs. White	White	.	1	.	.	.	185
5D	Black vs. White	Black	.	1	.	.	.	185
6D	Black vs. White	White	0.8571429	1	0.579196	-0.406	0.005	340
6D	Black vs. White	Black	0.4514768	0.5077273	0.3952263	-0.406	0.005	340
7D	Black vs. White	White	0.3333333	0.8402459	0	0.24	0.359	252
7D	Black vs. White	Black	0.5728559	0.6374986	0.5082133	0.24	0.359	252
1D	Hispanic vs. White	White	0.6	1	0	0.4	0.311	5
1D	Hispanic vs. White	Hispanic	1	1	.	0.4	0.311	5
2D	Hispanic vs. White	White	0.6666667	1	0.0506981	0.133	0.735	8
2D	Hispanic vs. White	Hispanic	0.8	1	0.3951441	0.133	0.735	8
3D	Hispanic vs. White	White	0.6	1	0.1409366	0.18	0.514	16
3D	Hispanic vs. White	Hispanic	0.7804878	1	0.5185496	0.18	0.514	16
4D	Hispanic vs. White	White	1	1	.	-0.213	0.098	14
4D	Hispanic vs. White	Hispanic	0.7868853	1	0.5538666	-0.213	0.098	14
5D	Hispanic vs. White	White	.	1	.	.	.	9
5D	Hispanic vs. White	Hispanic	.	1	.	.	.	9
6D	Hispanic vs. White	White	0.8571429	1	0.5177316	-0.357	0.486	6
6D	Hispanic vs. White	Hispanic	0.5	1	0	-0.357	0.486	6
7D	Hispanic vs. White	White	0.3333333	0.9163382	0	0.267	0.58	8
7D	Hispanic vs. White	Hispanic	0.6	1	0	0.267	0.58	8
1D	Any Minority vs. White	White	0.6	1	0.0938862	0.043	0.872	71
1D	Any Minority vs. White	Any Minority	0.6428571	0.7609177	0.5247965	0.043	0.872	71
2D	Any Minority vs. White	White	0.6666667	1	0.1224445	0.029	0.92	51
2D	Any Minority vs. White	Any Minority	0.6954888	0.8303193	0.5606582	0.029	0.92	51
3D	Any Minority vs. White	White	0.6	1	0.1682065	-0.092	0.683	182
3D	Any Minority vs. White	Any Minority	0.508465	0.5859668	0.4309632	-0.092	0.683	182

Table D.3: Hit-Rate Analysis (Contraband) by District and Race/Ethnicity (July 2021 to June 2024)

District	Comparison	Race	B=	Upper_Bound=	Lower_Bound=	B_Difference=	P=	N=
4D	Any Minority vs. White	White	1	1	.	-0.452	0.001	114
4D	Any Minority vs. White	Any Minority	0.5480962	0.6436569	0.4525355	-0.452	0.001	114
5D	Any Minority vs. White	White	.	1	.	.	.	199
5D	Any Minority vs. White	Any Minority	.	1	.	.	.	199
6D	Any Minority vs. White	White	0.8571429	1	0.5792032	-0.403	0.006	343
6D	Any Minority vs. White	Any Minority	0.4537865	0.5097786	0.3977945	-0.403	0.006	343
7D	Any Minority vs. White	White	0.3333333	0.8402143	0	0.242	0.354	256
7D	Any Minority vs. White	Any Minority	0.5752864	0.6393375	0.5112354	0.242	0.354	256