UCONN
INSTITUTE FOR MUNICIPAL
AND REGIONAL POLICY

TRAFFIC STOP DATA ANALYSIS AND FINDINGS, 2019-2023

METROPOLITAN POLICE DEPARTMENT WASHINGTON, D.C.

May 2025

UCONN
INSTITUTE FOR MUNICIPAL AND REGIONAL POLICY

DC Highway Safety Office
2000 14th Street NW, 8th floor
Washington, DC, 20009

Dear DC Highway Safety Office,

Enclosed is our evaluation of traffic stops conducted by the Metropolitan Police Department (MPD) between 2019 and 2023. While this marks our first analysis of MPD's traffic stop data, we have produced similar evaluations for agencies and jurisdictions nationwide since 2013.

This analysis reviewed more than 190,000 traffic stops conducted between July 1, 2019, and June 30, 2023. As noted in the report, traffic enforcement activity was significantly affected by the COVID-19 pandemic, with the volume of stops decreasing by 38% in the period following the onset of the pandemic.

Overall, the findings are encouraging and indicate positive progress in reducing disparities over time. Using the most rigorous statistical methods, we found no evidence that MPD was more likely to stop Black or Hispanic drivers during daylight hours compared to darkness. While small disparities in stop outcomes, such as arrest and ticketing rates, were observed using a commonly applied but less rigorous test, these differences steadily declined throughout the study period. Additionally, between 2021 and 2023, we found no statistically significant disparities in contraband discovery rates across racial and ethnic groups.

We commend MPD for its ongoing commitment to transparency and equity in traffic enforcement. The department has shown a commendable willingness to engage in an open and honest review of its practices, which has allowed us to produce a rigorous and independent assessment. We are grateful for MPD's collaboration and feedback throughout this process.

This report reflects MPD's dedication to enforcing traffic laws fairly and equitably, setting a strong example for agencies across the country. We look forward to continuing our partnership and supporting MPD's efforts to further enhance 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 2023, 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 stop data collected by the Metropolitan Police Department (MPD). This report aims to determine if non-White drivers are stopped by MPD at disparate rates than White drivers, if there are disparate outcomes of the stops conducted, and if there are disparate rates of seizure of contraband (e.g., drugs, stolen property, or a weapon).

The IMRP research team is particularly well-known for developing the technical framework of the "Connecticut Model," a pioneering approach designed to identify and mitigate racial and ethnic disparities in police traffic stops. Their approach has been adopted by multiple states, endorsed by advocacy organizations, and is nationally recognized as the gold standard approach for analyzing traffic stop data for evidence of disparate treatment. The influence of the Connecticut Model extends far beyond Connecticut's borders, significantly shaping the national discourse on police reform. 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.

The Section 1906 Racial Profiling Prohibition Grant provides grants to encourage states to maintain and allow public inspection of statistical information on the race and ethnicity of the driver for all motor vehicle stops made on all public roads. 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 between July 2019 and December 2020.[2] This report builds upon the agency's previous work and analyzes traffic stops between July 22, 2019, and June 30, 2023. The data provided for this report covers all MPD traffic stops, including vehicle, pedestrian, bicycle, and harbor stops. A traffic stop may involve a ticket (actual or warning), investigatory stop, protective pat down, search, or arrest. In March 2023, MPD added a traffic stop field to more easily identify stops that result from traffic enforcement. For this report, researchers analyzed

[1] The DC Highway Safety Office is within the Office of the City Administrator.
[2] These reports analyzed all stop data reported, not just traffic stops.

only what we determined to be a traffic stop.[3] This report does not address street stops of individuals or any outcomes from street stops.

For each traffic stop, MPD officers recorded the demographic information of the individual stopped. Demographic information was recorded in 93 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 was 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 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 22, 2019, and June 30, 2023. During that time period, MPD conducted more than 190,000 traffic stops. Seventeen (17) percent of the individuals stopped were White, 65 percent were Black, 8.5 percent were Hispanic, and 7.5 percent were some other race. Traffic stops declined 38 percent between the months before the COVID-19 pandemic (July 2019 to March 2020) and after (April 2020 to June 2023). Around March 2020, across the nation, residents began working from home in large numbers, retail and entertainment establishments were temporarily closed, schools were closed, and there were far fewer drivers on the roads. In many jurisdictions, police departments were trying to reduce contact with the public, where appropriate, to reduce the potential transmission of COVID-19. Both of these trends are likely reflected in MPD's traffic stop data. Between July 2019 and March 2020, MPD made an average of 7,200 monthly traffic stops. Since April 2020, MPD has made an average of 3,300 monthly traffic stops. Although traffic enforcement increased in the last quarter of 2020, it remained relatively suppressed for the rest of the year, and that trend appears to have become the new normal.

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 racial bias. This method is the most rigorous and conclusive method that could be applied to the MPD's traffic data.

[3] 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.

- **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 indicate racial bias. 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 racial bias.

We use this multi-test approach to safeguard against potential errors, reducing the possibility of (1) false positives- where a disparity is detected where none exists, and (2) false negatives- where a real disparity 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 disparities across DC or within specific MPD Police Districts, it indicates an area for MPD to investigate further to determine if the disparities result from specific policing practices that can be changed.

E.3: SUMMARY OF FINDINGS

The overarching results of the analyses in this report are encouraging and show positive trends in reducing racial and ethnic disparities over the four-year study period analyzed. Using the most rigorous method we could apply to the data, Solar Visibility Analysis, we found that, on average, MPD was not any more likely to stop Black or Hispanic drivers between 2019 and 2023 in daylight compared to darkness. When using the Post-Stop Enforcement Action Analysis to compare outcomes of traffic stops, such as arrests, tickets, and stop duration, we found a statistically significant disparity for Black and Hispanic drivers in some of the years between 2020 and 2023, but the disparity decreased in each of the years since 2020. Lastly, the Search Hit Rate Analysis revealed a lower likelihood of contraband being found during searches of Black individuals compared to White individuals between July 2019 and June 2020, indicating that police searches of Black individuals were less successful. This difference is marginally statistically significant. We found no evidence of a statistically significant difference in contraband finding rates in any other year or for any other racial and ethnic group. We do find disparities in specific MPD districts when we apply these methods. Those disparities 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 disparities 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 racial disparities in stops between daylight and darkness periods.

- We find no evidence of a statistically significant positive disparity in any of the years analyzed. In other words, MPD was not any more likely to stop non-White drivers in daylight compared to darkness.
- Five of the seven patrol districts were identified with a statistical disparity in either the one-year or three-year analysis. In other words, non-White drivers were more likely to be stopped in daylight than in darkness in these districts.

Post-Stop Enforcement Action Analysis:
Investigated racial disparities in post-stop outcomes such as arrests and other discretionary enforcement actions (searches, tickets, stop duration).

- Disparities were found in the outcomes of stops, including arrests, ticketing rates, and stop durations. However, the disparity has decreased each year.
- Black individuals were more likely to be arrested, especially in Districts 1 and 2. Hispanic individuals also had higher arrest rates compared to White peers.

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.

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

- Between July 2019 and June 2020, MPD was less successful in searches of Black individuals. We found no evidence of a statistically significant difference in contraband finding rates in any other year or for any other racial and ethnic group.
- In the three-year sample (July 2020 to June 2023), we found a statistically significant disparity in District 5 for searches of Black and Hispanic individuals. Black searches were 66 percent less successful, and Hispanic individuals' searches were 80 percent less successful than White searches.

I: METHODOLOGICAL APPROACH UNDERLYING THE ANALYSIS

Assessing racial disparities in policing data has been used for the last two decades as a policy tool to evaluate whether racial bias exists within a given jurisdiction. Although 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 disparities indicative of racial and ethnic bias but that, in the absence of a formal procedural investigation, cannot be considered comprehensive evidence.*
>
> *Principle 2: Apply a holistic approach for assessing racial and ethnic disparities in 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 disparity (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 disparities 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 is attributed to disparate treatment. This analytical approach is considered the most rigorous and broadly applicable of all the tests presented in this report.

The next analytical tool used in the analysis tests for disparities in the outcomes of traffic stops using a model that examines the distribution of dispositions conditional on race and the reason for the stop. Specifically, we test whether traffic stops made of 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. [4] 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 disparities 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

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

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 disparities. Such findings provide a mechanism to indicate possible racial profiling, but they cannot, without further investigation, provide sufficient evidence that racial profiling exists.

II: CHARACTERISTICS OF TRAFFIC STOP DATA

This section examines general patterns of traffic enforcement activities in D.C. from July 22, 2019, to June 30, 2023. 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 districts' data in this report section.

In D.C., more than 190,000 traffic stops were conducted between July 2019 and June 2023. In the most recent year in the sample (July 2022 to June 2023), there were approximately 41,000 traffic stops. Researchers examined 16 quarters or 48 months, including approximately three quarters or nine months before the COVID-19 pandemic. Overall, there was an average of 3,963 monthly stops and 11,890 stops per quarter. Traffic stops decreased by 38% on average between the months before COVID-19 and after[5]. Traffic enforcement has remained depressed since the second quarter of 2020. Figure 2.1 shows the aggregate number of traffic stops by quarter and each demographic category.

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

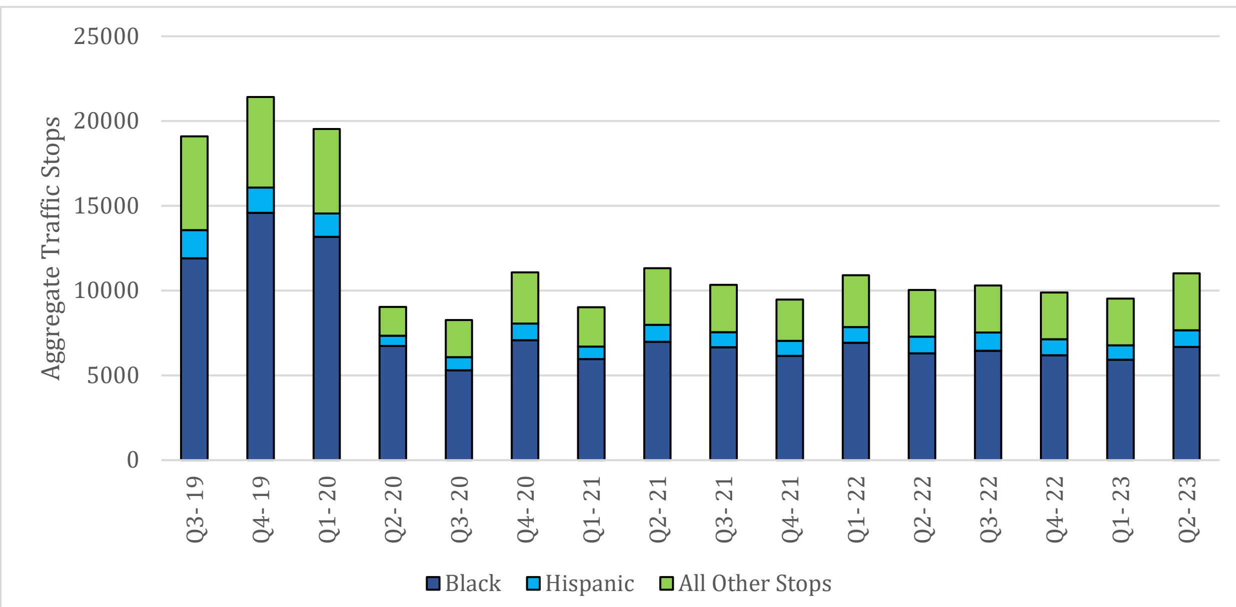


Figure 2.2 displays traffic stops by time of day for the analysis period. As can be seen from the figure, the total volume of traffic stops fluctuates significantly across different times of the day, with two peaks associated with peak commutation. The sample's highest hourly volume of traffic stops occurred from 5:00 PM to 6:00 PM and accounted for 9 percent of all stops. The surge between 4:00 PM and 7:00 PM represents a significant traffic enforcement period. In aggregate, stops occurring between these hours represented 25 percent of total stops. Unsurprisingly, traffic stops increase between these hours, as this is a peak commuting time in the District. In addition to the evening commute enforcement peak, there is

[5] The months before the COVID-19 pandemic include July 2019 through March 2020. The months after include April 2020 to June 2023.

a smaller peak during the morning commuting period. Approximately 19 percent of all traffic enforcement occurs between 7:00 AM and 10:00 AM. The lowest volume of traffic stops occurs between 3:00 AM and 4:00 AM.

Figure 2. 2: Aggregate Traffic Stops by Time of Day (2019-23)

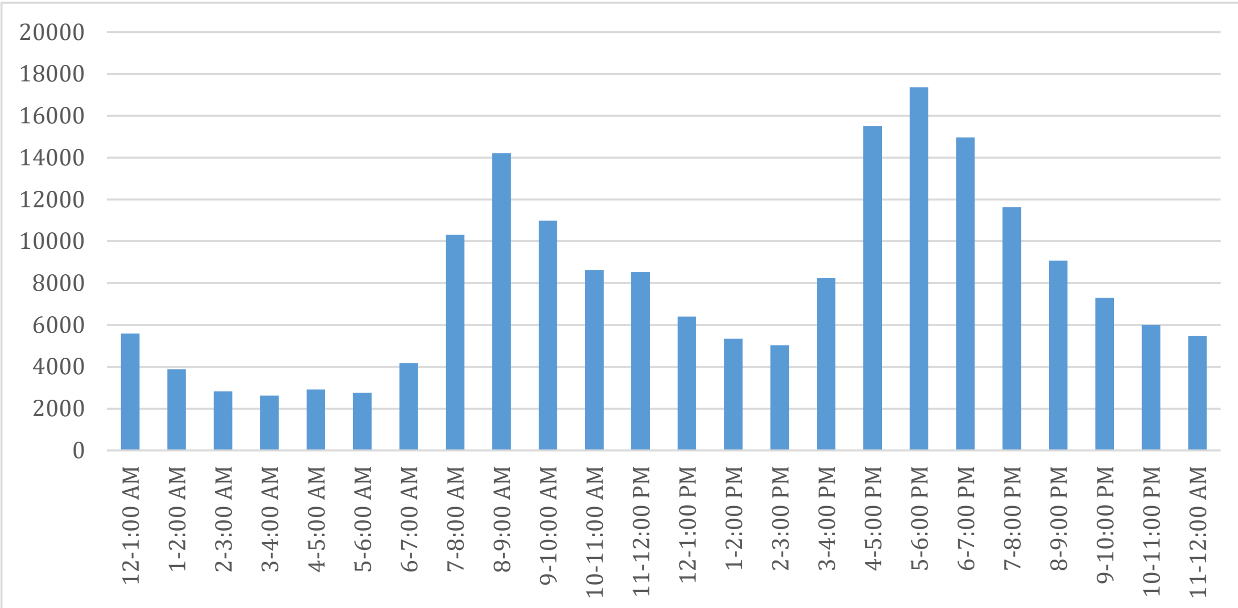


Figure 2.3 illustrates each patrol district's total traffic stops during the study period. Each patrol district had an average of 27,000 traffic stops. The largest number of stops was reported in Districts 2 and 3, with 40 percent of all stops. The smallest number of traffic stops was reported in District 7, with only 7 percent of all traffic stops.

Figure 2. 3: Total Number of Traffic Stops by Patrol District (2019-23)

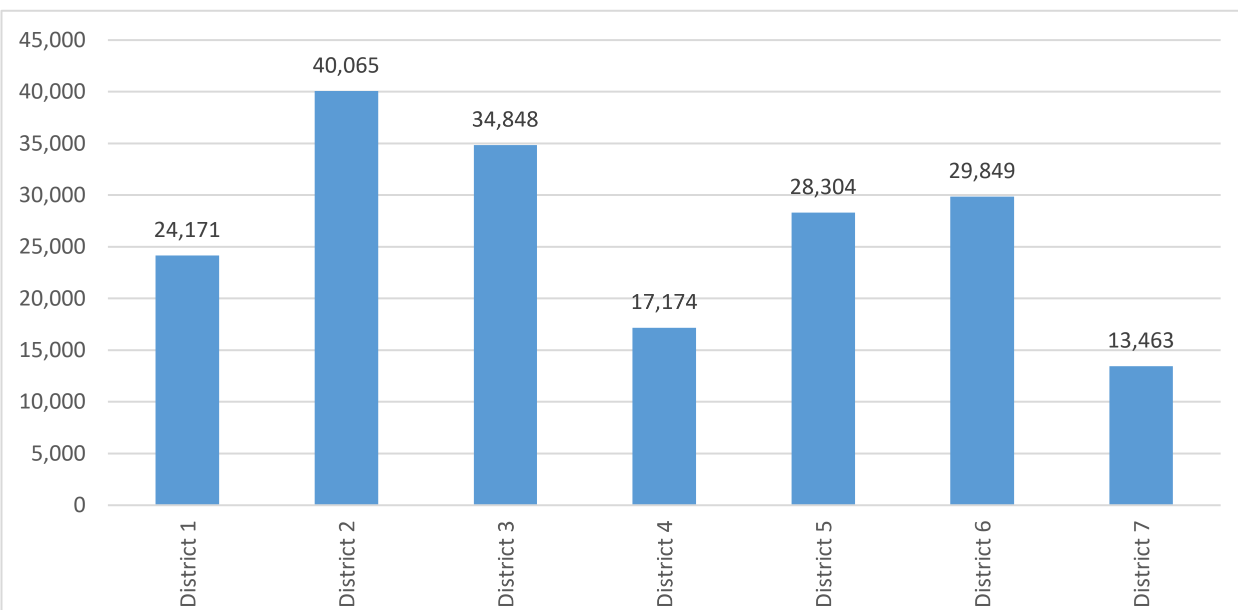


Figure 2.4 displays traffic stops by day of the week for the entire analysis period. This figure shows that traffic stops increase throughout the week and peak on Thursdays. Traffic stops decline substantially on the weekends, with the smallest number occurring on Sundays.

Figure 2. 4: Traffic Stops by Day of Week (2019-23)

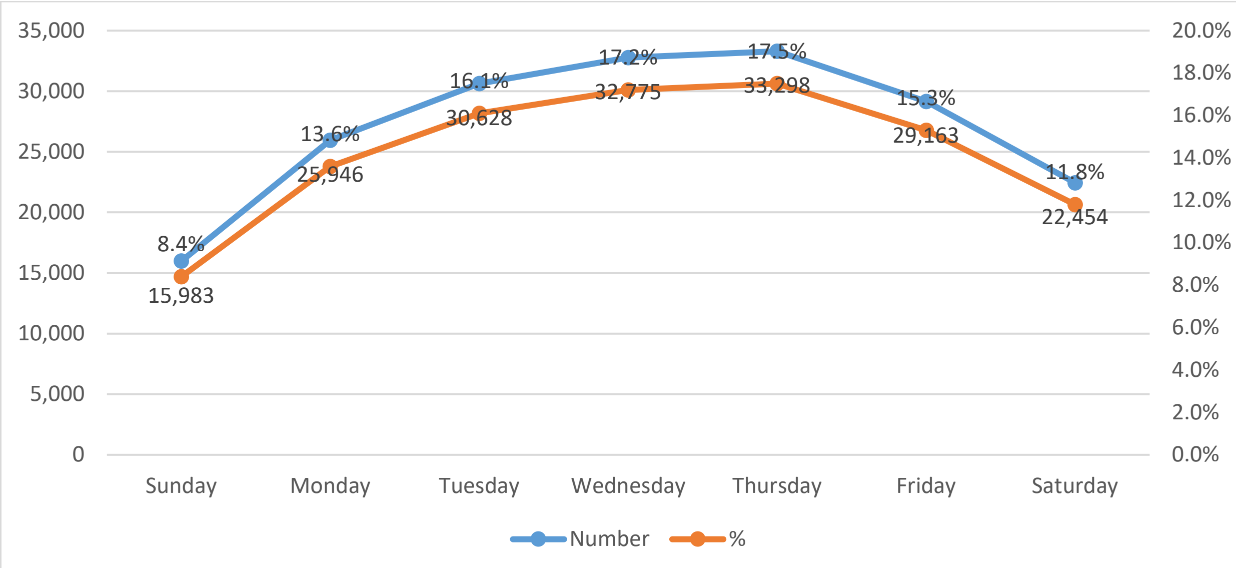


Table 2.1 presents some basic demographic data on persons involved in a traffic stop in the district between July 1, 2019, and June 30, 2023. Officers relied on information gathered from an official government identification card to document stopped individuals' demographic information. Alternatively, if an official government identification card was not presented, officers were instructed to ask for this information if possible.[6] More than two-thirds (68 percent) of individuals stopped were male. Approximately one-third of individuals stopped were under 30 compared to 20 percent over 50. The vast majority of stops were of Black individuals (65 percent), 17 percent were White individuals, 8.5 percent were Hispanic individuals, and 3 percent were all other races. No race or ethnicity was reported for almost 7 percent of all stops.

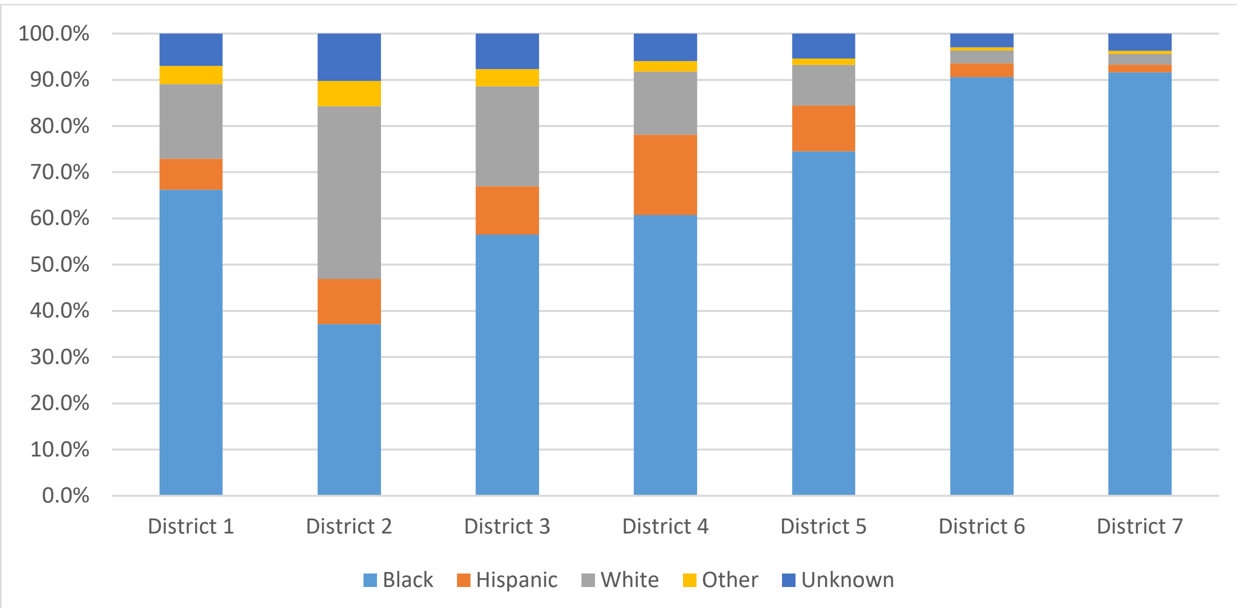
Table 2. 1: Traffic Stop Characteristics

Race and Ethnicity		Gender		Age	
White	17.2%	Male	68.1%	Less than 18	0.5%
Black	64.6%			18 to 20	2.9%
Hispanic	8.5%	Female	30.7%	21 to 30	31.0%
Asian	2.3%			31 to 40	25.8%
Other	0.7%	Unknown	1.2%	41 to 50	16.5%
Not Reported	6.7%			51 to 60	12.3%
				61 +	7.9%
				Unknown	3.1%

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

The racial demographics of those stopped in each patrol district varied. Districts 6 and 7 stopped a greater proportion of Black individuals (91 percent and 92 percent, respectively) than any other patrol district. District 4 stopped the largest percentage of Hispanic individuals (17 percent). The largest percentage of White individuals were stopped in District 2 (37 percent). It should be noted that Districts 6 and 7 are located in the southern portion of the city, while Districts 2 and 4 are in the northern part. Given the city's racial demographics, the racial makeup of stops by patrol districts is unsurprising. For example, a larger share of Districts 6 and 7 residents are Black. The largest share of Hispanic residents live in District 4, and the largest share of White residents live in District 2. However, it is worth pointing out that only about 30 percent of drivers stopped had vehicles registered in DC. Figure 2.5 shows the percentage of stops by race and ethnicity for each patrol district.

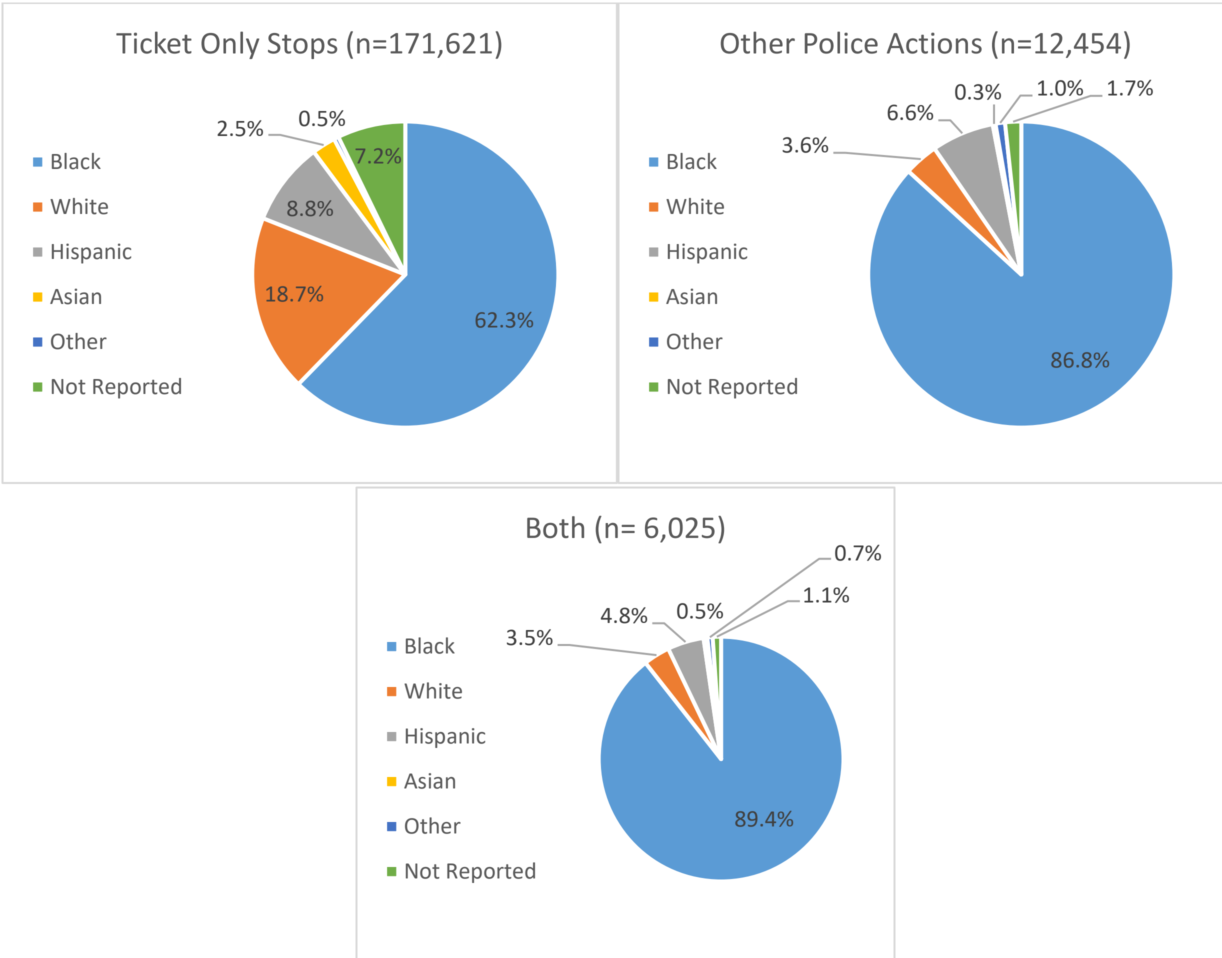
Figure 2. 5: Racial and Ethnic Composition of Stopped Drives by District



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 90 percent resulted in only a ticket, 6.5 percent in other police actions, 3.2 percent in both, and 0.3 percent in harbor activity[7]. Figure 2.6 shows the number of traffic stops that result in a ticket, other police action, or both by race and ethnicity.

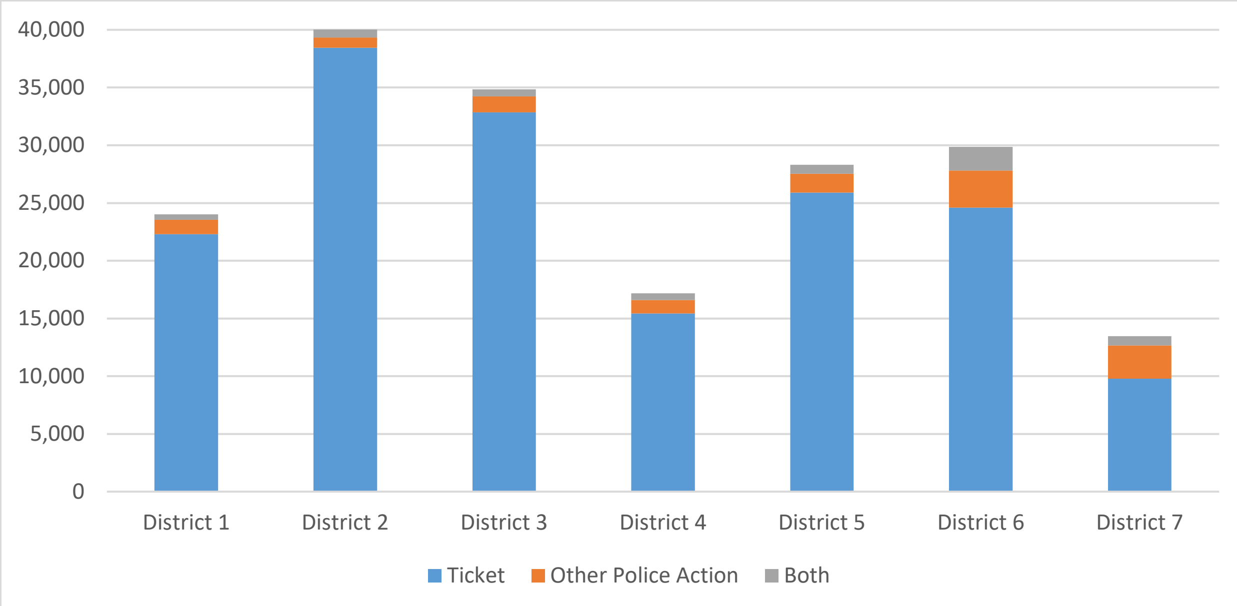
[7] There were 147 records recorded at "Harbor" and were excluded from this analysis.

Figure 2. 6: Traffic Stop Outcome by Type and Race and Ethnicity



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 (96 percent of stops), whereas stops in District 7 resulted in the lowest rate (73 percent). District 6 and 7 had the highest rate of stops that resulted in some other police action and not a ticket. District 6 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 number of traffic stops that result in a ticket, other police action, or both by District.

Figure 2. 7: Traffic Stop Outcome by District (2019-23)



Stops that resulted in only a ticket or only some other police action varied by race and ethnicity across patrol districts. For example, over 90 percent of tickets issued in District 7 were issued to Black individuals, whereas in District 2, only 36 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 disparity was identified. Tables 2.2 and 2.3 show the percentage of traffic stops with a ticket or other police action by race, ethnicity, and patrol district.

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

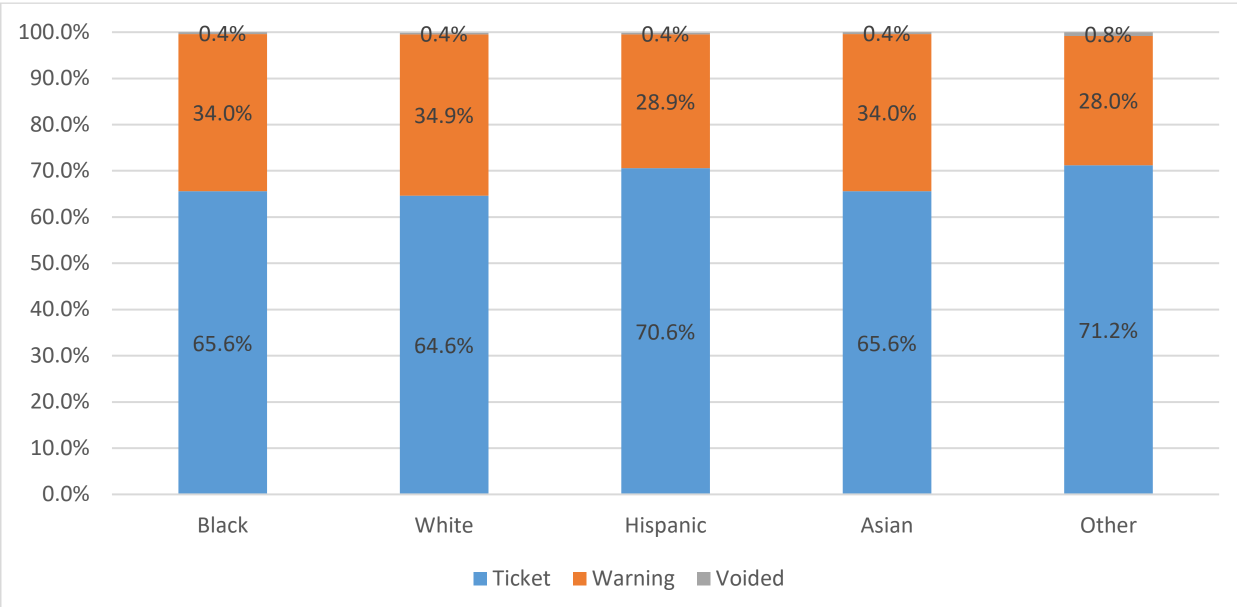
Race/Ethnicity	1D	2D	3D	4D	5D	6D	7D	Citywide
Black	65.0%	35.9%	55.1%	59.3%	73.2%	89.3%	90.4%	62.3%
White	17.1%	38.4%	22.6%	14.7%	9.4%	3.2%	2.6%	18.7%
Hispanic	6.8%	9.6%	10.5%	17.2%	10.3%	3.3%	1.8%	8.8%
Asian	2.9%	4.6%	3.0%	2.0%	1.1%	0.6%	0.7%	2.5%
Other/Unknown	8.2%	11.5%	8.9%	6.8%	6.0%	3.6%	4.5%	7.7%

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	87.4%	60.4%	79.6%	71.3%	86.7%	96.1%	94.6%	86.8%
White	5.3%	13.9%	4.9%	4.8%	3.7%	0.9%	1.6%	3.6%
Hispanic	4.3%	17.7%	11.1%	21.5%	6.3%	1.8%	1.2%	6.6%
Asian	0.7%	1.1%	0.3%	0.2%	0.3%	0.1%	0.1%	0.3%
Other/Unknown	2.2%	6.9%	4.1%	2.3%	3.1%	1.1%	2.6%	2.7%

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 66 percent of stops recorded as tickets were actual tickets, 33 percent resulted in a warning, and 1 percent of tickets were voided. Hispanic individuals received an actual ticket (excluding a warning and a voided ticket) at a higher rate than White or Black individuals (71 percent compared to 65 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.

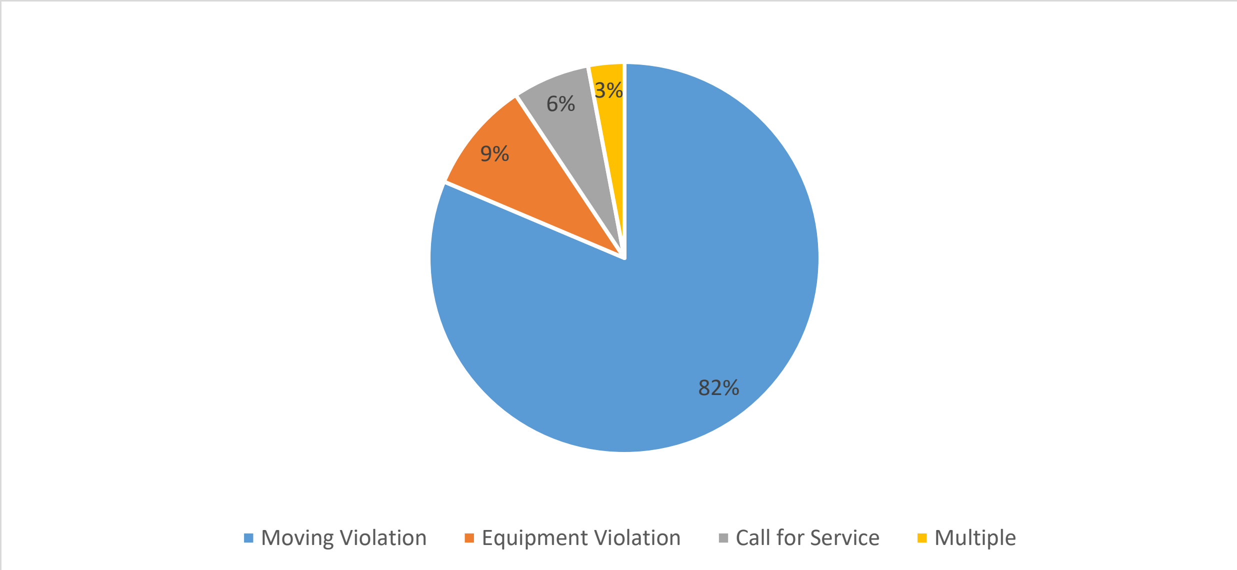
Figure 2. 8: Traffic Stop Outcome for Ticket, Warning, or Voided Ticket by Race and Ethnicity



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.[8] 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 (82 percent). Approximately 9 percent resulted from observing an equipment violation, 6 percent from a call for service, and the remaining 3 percent were a combination of multiple factors. Figure 2.9 shows the reason for the traffic stop that resulted in only a ticket.

[8] 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 District 2 issue tickets for moving violations at a higher rate than other districts. On the other hand, Districts 1 and 7 issue tickets for equipment violations at the highest rate of all patrol districts, which may be due to the fact that they border each other and deal with similar patrol patterns. Interestingly, tickets issued as a result of a call for service appear to be greatest in Districts 4 and 7, which are on opposite sides of the city. 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

Ticket Reason	1D	2D	3D	4D	5D	6D	7D
Moving Violation	76.2%	88.2%	86.4%	77.6%	81.8%	80.5%	68.4%
Equipment Violation	16.5%	4.5%	8.0%	7.6%	9.4%	9.7%	18.5%
Call for Service	4.8%	5.0%	4.1%	12.0%	7.0%	6.5%	10.0%
Multiple	2.5%	2.3%	1.5%	2.8%	1.8%	3.3%	3.1%

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 62 percent resulted in only one violation being cited. However, in 16 percent of stops, two violations were cited; in 12 percent of stops, three violations were cited; and in 10 percent of stops, four or more violations were cited. One stop resulted in 11 violations being cited, the most listed for an individual stop that resulted in a ticket. Of the stops that resulted in a warning, 82 percent resulted in only one violation being cited. However, two violations were cited in 12 percent of stops, and three or more violations were cited in 6 percent of warning stops. Of all the stops that resulted in a ticket (actual or warning), 229,597 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 some 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.

Administrative violations, particularly failure to produce proof of insurance, were the largest violation category, with almost a quarter 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. Of the 52,086 t-code violations for administrative offenses, 14,907 (29 percent) were for failure to display insurance, and 11,663 (22 percent) were for operating an uninsured vehicle. Almost 12 percent of all t-code violations were issued for an insurance violation. Approximately 10 percent of administrative offenses were for failure to exhibit registration, and 7 percent were for failure to exhibit your driver's permit. Again, officers rarely have discretion when issuing a ticket for an administrative offense.

Speeding, traffic light, and other moving violations comprised a significant percentage of tickets issued. Over 14 percent of tickets were issued for speeding, 11 percent for traffic light violations, and 16 percent for some other moving violation. Table 2.5 lists the number of traffic stops made by the t-code violation category.

Table 2. 5: Ticket Code Violation Reported

T-Code Violation Category	Number	%
Administrative (Other)	25,516	11.1%
Administrative (Insurance)	26,570	11.6%
Cell Phone	7,893	3.4%
Equipment	15,742	6.8%
Other Moving	37,343	16.3%
Plate/Tag	11,163	4.9%
Seatbelt	11,339	4.9%
Speed	31,322	13.6%
Stop Sign	22,927	10.0%
Traffic Control Signal	25,969	11.3%
Other	13,753	6.1%

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 rate in District 2, where the rate is more than two times the next closest patrol district. There is more than six times as much speed enforcement in

District 2 compared to District 7. Tickets for equipment violations are highest in District 7, five 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

T-Code Violation Category	1D	2D	3D	4D	5D	6D	7D
Administrative (Other)	10.9%	8.6%	11.3%	8.4%	11.4%	14.7%	14.9%
Administrative (Insurance)	11.2%	9.5%	10.8%	13.4%	13.3%	11.0%	16.1%
Cell Phone	2.7%	4.6%	5.3%	4.1%	2.6%	1.6%	1.2%
Equipment	6.1%	3.3%	7.0%	8.0%	7.0%	6.9%	16.9%
Moving	19.5%	16.2%	17.7%	18.4%	11.8%	18.2%	8.5%
Plate/Tag	4.0%	4.2%	4.3%	3.9%	4.2%	6.2%	10.4%
Seatbelt	3.5%	3.3%	9.4%	3.9%	6.1%	2.8%	3.4%
Speed	11.4%	26.7%	13.1%	6.9%	9.9%	10.2%	4.0%
Stop Sign	9.2%	6.8%	8.1%	13.7%	13.5%	10.6%	12.6%
Traffic Control Signal	16.3%	11.2%	7.1%	10.2%	12.8%	13.9%	6.6%
Other	5.2%	5.7%	5.9%	9.1%	7.4%	3.8%	5.4%

The reasons cited on a ticket also varied by race and ethnicity. Black and Hispanic individuals were 1.7 and 1.5 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

T-Code Violation Category	Black	Hispanic	White	Asian	Other	Not Reported
Administrative (Other)	12.8%	10.2%	6.6%	5.7%	11.8%	0.8%
Administrative (Insurance)	12.7%	12.4%	8.2%	7.6%	12.7%	1.2%
Cell Phone	2.7%	4.5%	5.4%	4.2%	5.2%	4.1%
Equipment	8.2%	5.1%	3.2%	4.8%	9.1%	5.3%
Moving	15.3%	16.7%	18.7%	20.5%	14.2%	17.8%
Plate/Tag	5.6%	3.4%	3.2%	3.0%	5.1%	4.2%
Seatbelt	5.5%	5.5%	3.3%	2.7%	5.5%	3.2%
Speed	11.1%	13.3%	22.0%	19.4%	11.8%	16.5%
Stop Sign	9.6%	8.8%	11.6%	12.4%	8.1%	10.8%
Traffic Control Signal	10.9%	12.3%	11.6%	13.1%	11.0%	13.4%
Other	5.5%	7.9%	6.2%	6.7%	5.4%	22.7%

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.[9] A total of 13 categories can be listed as the reason for the stop that results in some other police actions.[10] Of the 12,455 cases reported as only some other police action and no ticket, most were reported for only one reason (81%). There were 123 cases with five or more reasons listed, with the most being eight reasons, which occurred in two cases. Most of these stops resulted from the officer observing a traffic violation (73 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

Reason for Stop Category	Number	%
Call for Service	1,680	13.5%
Individual's actions	1,875	15.0%
Traffic Violation	9,120	73.2%
Be on the Lookout (BOLO)	616	4.9%
Suspicion of criminal activity	1,006	8.1%
Warrant/Court Order	100	0.8%
Information obtained from LEO source	712	5.7%
Individual's characteristics	706	5.7%
Information obtained from witness or informants	213	1.7%
Prior Knowledge	247	2.0%
Demeanor during field contact	348	2.8%
Observed a weapon	109	0.9%

The reason for a traffic stop resulting in only some other police action also varies by patrol district. As an example, in District 2, almost 14 percent of these stops resulted from a call for service, compared to only 8 percent in District 7. Table 2.9 shows the reason for a traffic stop that resulted in some other police action by patrol district.

Table 2. 9: Reason for Traffic Stops Reported as Resulting in Some Other Police Action by District

Reason for Stop Category	1D	2D	3D	4D	5D	6D	7D
Call for Service	11.2%	13.9%	11.3%	13.3%	11.6%	9.1%	8.1%
Individual's actions	12.5%	7.6%	13.2%	13.5%	12.9%	8.2%	13.2%
Traffic Violation	54.8%	58.4%	55.8%	52.1%	47.7%	65.5%	53.6%
Be on the Lookout (BOLO)	4.4%	4.2%	3.8%	3.1%	5.9%	3.3%	3.0%
Suspicion of criminal activity	6.8%	5.4%	6.6%	6.2%	5.9%	4.4%	7.8%
Warrant/Court Order	0.7%	0.2%	0.2%	0.5%	0.6%	0.5%	0.5%
Information obtained from LEO source	3.1%	4.9%	3.0%	2.7%	5.4%	3.2%	2.8%

[9] 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.

[10] Stops that resulted from a response to a crash were removed from this analysis.

Reason for Stop Category	1D	2D	3D	4D	5D	6D	7D
Individual's characteristics	1.3%	1.1%	2.4%	3.6%	4.1%	2.1%	6.0%
Information obtained from witness or informants	1.3%	2.0%	1.2%	1.2%	1.5%	0.9%	0.7%
Prior Knowledge	1.9%	0.8%	0.7%	1.8%	1.5%	1.3%	1.3%
Demeanor during field contact	1.3%	1.1%	1.5%	1.8%	2.4%	1.3%	2.1%
Observed a weapon	0.6%	0.5%	0.5%	0.4%	0.4%	0.3%	0.8%

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 190,000 traffic stops, approximately 12,500 resulted in an arrest (6 percent). An arrest could result in multiple charges of an individual. The most an individual was charged with was 20 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 (34 percent of all arrests) and driving under the influence of alcohol or drugs (23 percent of all arrests.) District 6 had the most arrests from a traffic stop, with more than 28 percent of all arrests. District 7 had the highest arrest rate per stop, with 16 percent of stops in District 7 resulting in an arrest, which is almost three times the department 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	1,019	8.1%	4.2%
2	1,343	10.7%	3.3%
3	1,413	11.3%	4.0%
4	1,240	9.9%	7.2%
5	1,789	14.3%	6.3%
6	3,543	28.3%	11.9%
7	2,149	17.2%	16.0%

Arrests resulting from a traffic stop varied by race and ethnicity. Black 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. Hispanic individuals were arrested at a lower rate when compared to Black individuals but at a rate 3.5 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	10,690	8.7%
Hispanic	947	5.8%
White	518	1.6%
Other	189	3.4%
Unknown	169	1.5%

III: ANALYSIS OF TRAFFIC STOPS, SOLAR VISIBILITY

The solar visibility analysis relies on seasonal variation in the timing of sunset to test for evidence of racial and ethnic disparities in police stops. The test operates under the key assumption that police officers are marginally better able to observe the race and ethnicity of individuals during daylight relative to darkness (Grogger and Ridgeway 2006; Ridgeway 2009; Horace and Rohlin 2018; Kalinowski et al. 2017, 2019a, 2019b).[11] The test relies on seasonal variation in the timing of sunset as well as the discrete Daylight Savings Time shift to compare stops made at the same time in darkness versus daylight. The advantage of this methodology, relative to population-based benchmarks, is that it does not require any assumptions about the underlying risk-set of individuals on the roadway. Rather, the test assumes that the composition of individuals does not vary in response to changes in visibility.[12] Within a fixed window when the timing of sunset varies throughout the year, the racial composition of stops in darkness is used as a counterfactual for stops in daylight, i.e. when officers can better observe the race of the motorist.

More specifically, the solar visibility test evaluates whether statistically significant disparities exist in the likelihood that a stopped motorist is a minority during daylight relative to darkness. As detailed explicitly in Appendix A.2, Grogger and Ridgeway (2006) illustrate that under certain conditions the odds-ratio of a stopped motorist being a minority in daylight vs. darkness is equivalent to the odds-ratio that a minority motorist is stopped during daylight vs. darkness. In a practical context, these assumptions are that variations in travel and enforcement patterns (abject of discrimination) do not change differentially by race in response to daylight. To ensure that these conditions are met, the estimates condition on time and day of the week. To further control for inherent differences in daylight and darkness, the sample is restricted to the inter-twilight window, a period of time during the day when solar visibility varies throughout the year (i.e. between the earliest eastern sunset and the latest western end to civil twilight). Conveniently, this window of time falls within the evening commute when we might expect the risk-set of individuals to be less susceptible to seasonal variation.

III.A: AGGREGATE ANALYSIS WITH SOLAR VISIBILITY, 2019-23

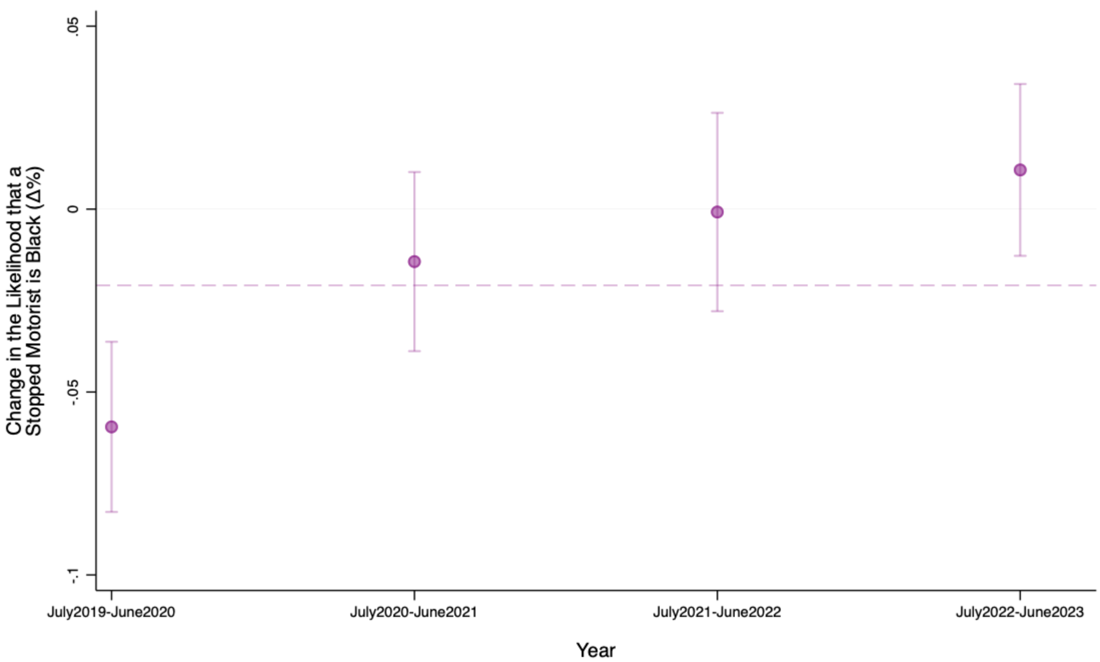
Figures 3.1 to 3.3 present the results of applying the solar visibility test to the aggregate sample of traffic stops made within the inter-twilight sample in D.C. between July 2019 and June 2023. The vertical axis on the figure plots a 95 percent confidence interval around the coefficient estimate of a logistic 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

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

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

periods analyzed, none of the coefficient estimates for Black drivers were positive in magnitude and statistically significant at conventional levels.[13] 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, none of the coefficient estimates for Hispanic drivers were positive in magnitude and statistically significant at conventional levels.[14] 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 of the periods analyzed, none of the coefficient estimates for any minority drivers were positive in magnitude and statistically significant at conventional levels.[15] Coefficient estimates, standard errors, and sample sizes are contained in Table B.1 of Appendix B for Figures 3.1 to 3.3.

Figure 3. 1: Aggregate Solar Visibility Analysis by Year for Black Individuals, All Stops 2019-23



[13] 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 if non-White motorists respond to disparate treatment by driving more safely in response to observation during daylight.
[14] 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 if non-White motorists respond to disparate treatment by driving more safely in response to observation during daylight.
[15] 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 if non-White motorists respond to disparate treatment by driving more safely in response to observation during daylight.

Figure 3. 2: Aggregate Solar Visibility Analysis by Year for Hispanic Individuals, All Stops 2019-23

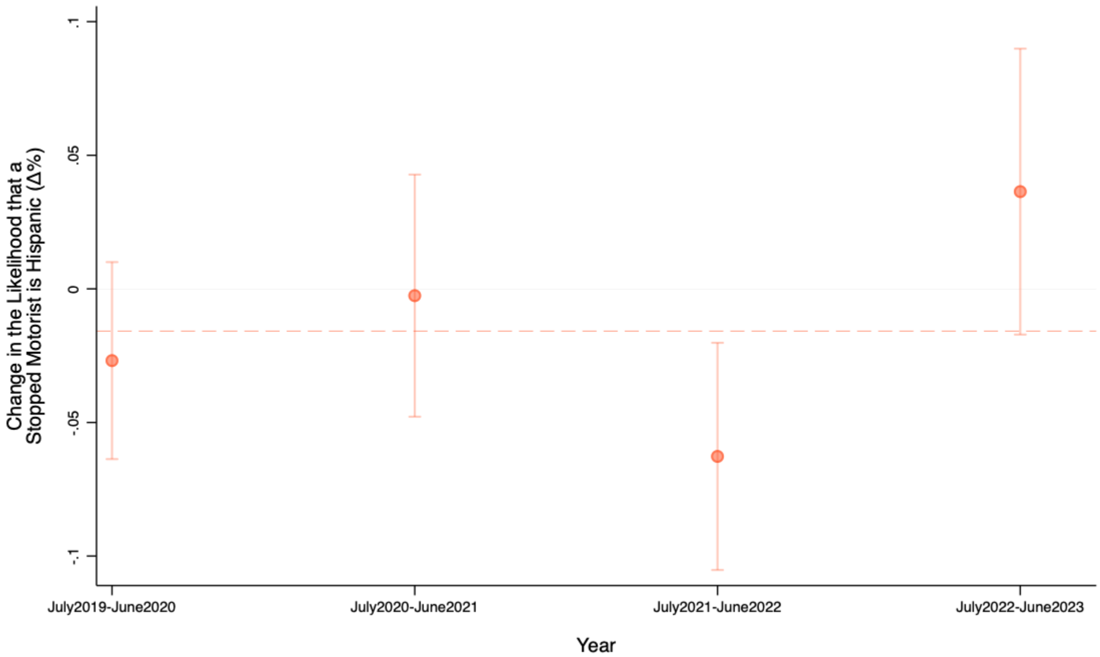
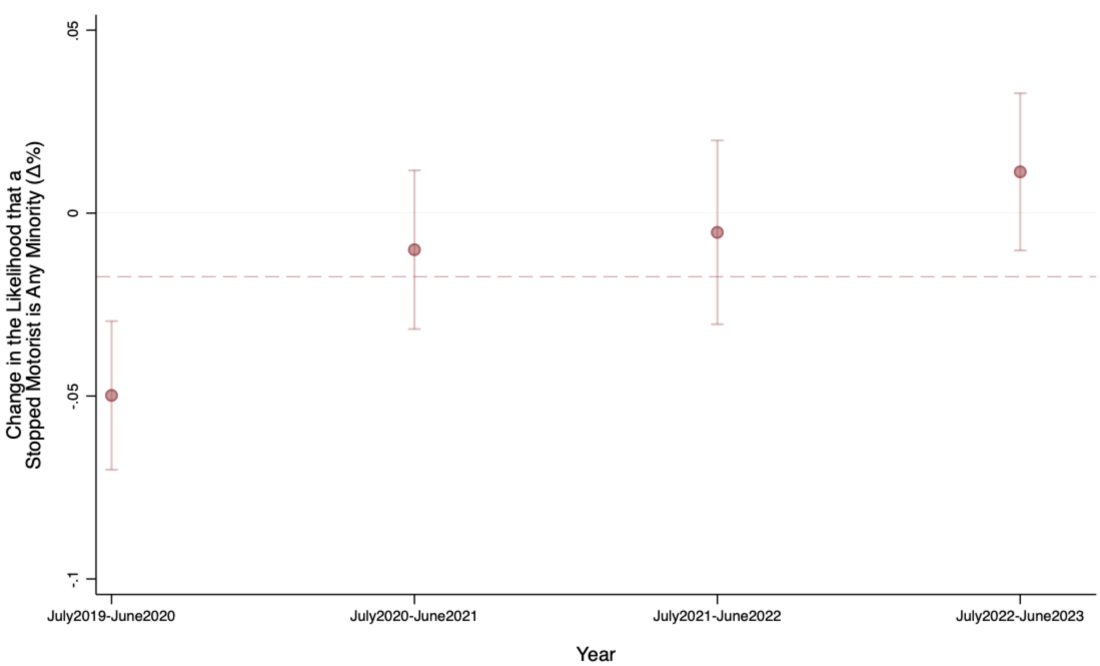
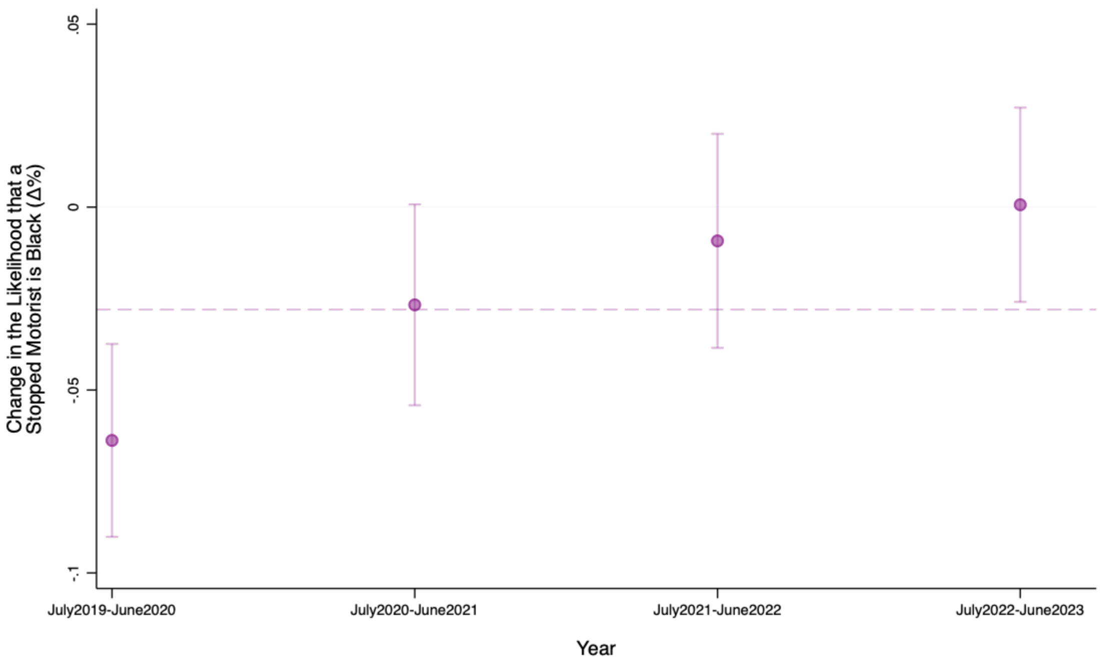


Figure 3. 3: Aggregate Solar Visibility Analysis by Year for Non-White Individuals, All Stops 2019-23



The main estimates in Figures 3.1 to 3.3 are potentially biased by the fact that certain types of equipment and administrative violations are correlated with both visibility and race/ethnicity via socio-economic status, such as lighting, cellphone, and seatbelt violations. Figures 3.4 to 3.6 estimate the solar visibility test on a restricted subsample that excludes stops made for possibly non-moving violations.[16] However, we note that the reason for the stop listed in the stop data is not very detailed, and we are somewhat limited in our ability to impose this sample restriction. The results of this more restrictive subsample of stops are generally consistent with the main estimates, where we find no evidence of a statistically significant positive disparity in any of the years analyzed. Coefficient estimates, standard errors, and sample sizes are contained in Table B.2 of Appendix B for Figures 3.4 to 3.6.

Figure 3. 4: Aggregate Solar Visibility Analysis by Year for Black Individuals, All Moving Violations 2019-23



[16] The subsample excludes equipment-related violations, including offenses related to brakes, mirrors, speedometers, lights, seatbelts, helmets, license plates, windows, windshields, tires, bumpers, and cell phones and other distractions.

Figure 3. 5: Aggregate Solar Visibility Analysis by Year for Hispanic Individuals, All Moving Violations 2019-23

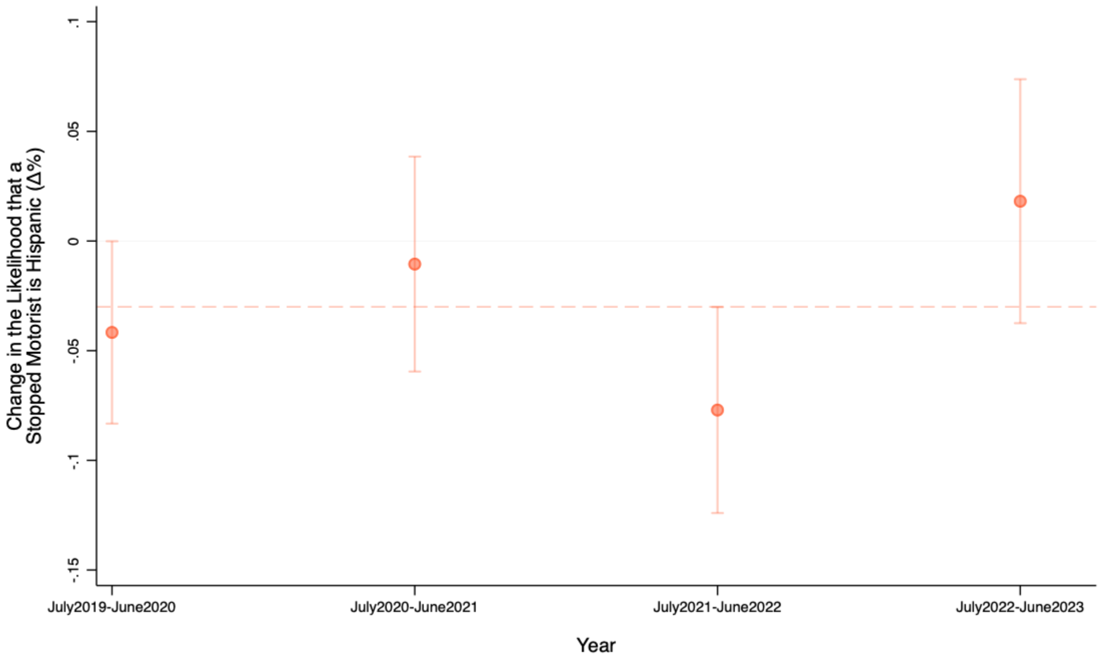
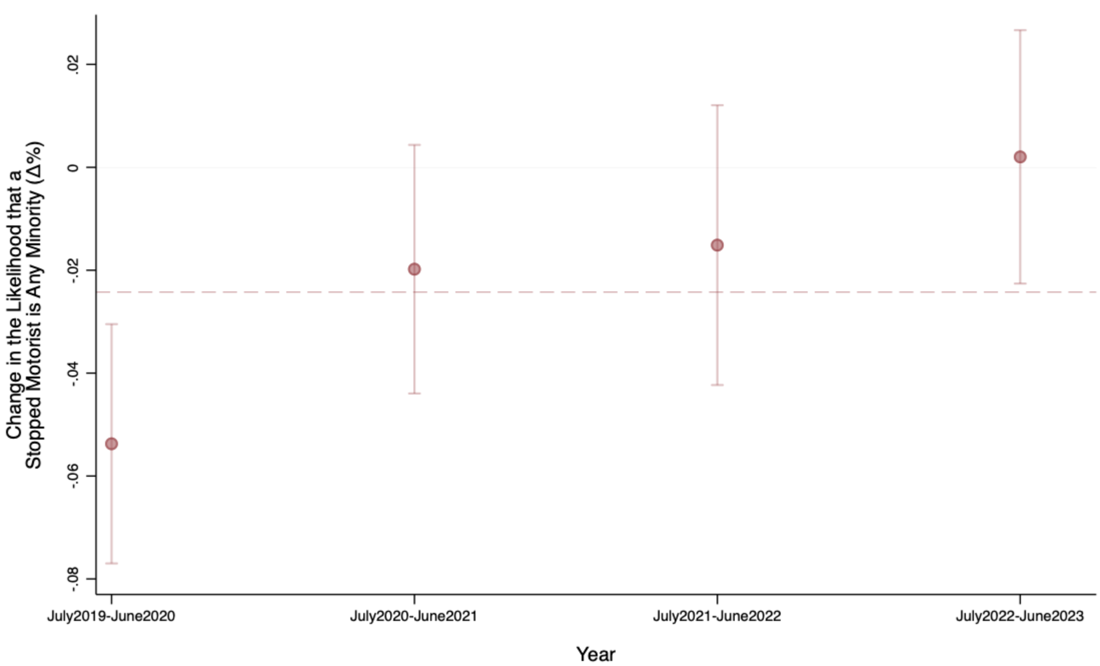


Figure 3. 6: Aggregate Solar Visibility Analysis by Year for Non-White Individuals, All Moving Violations 2019-23



Another potential source of bias to the main estimates contained in Figures 3.1 to 3.3 is a violation of the assumption that the underlying relative risk set of individuals is invariant to changes in visibility. Since we do not have data on the underlying driving population, we cannot perform formal tests of balance in terms of individual attributes across daylight and darkness. To address this potential concern and data limitation, we proceed by assuming a balance failure and controlling for individual attributes (i.e., gender and age) in our primary model. As shown below, the results are very similar to the estimates presented in the main analysis, suggesting that failures of balance are not driving our main results. In particular, we again do not find evidence of a statistically significant positive disparity in any of the years examined. Coefficient estimates, standard errors, and sample sizes are contained in Table B.3 of Appendix B for Figures 3.7 to 3.9.

Figure 3. 7: Robustness Test with Controls of Individual Characteristics by Year for Black Individuals, 2019-23

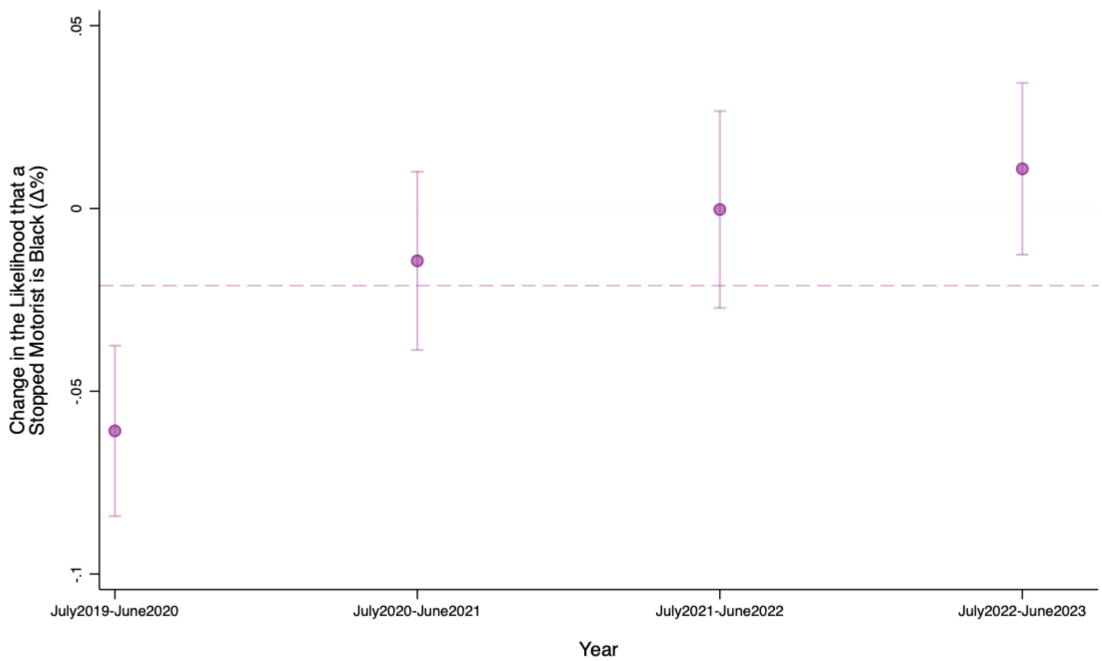


Figure 3. 8: Robustness Test with Controls of Individual Characteristics by Year for Hispanic Individuals, 2019-23

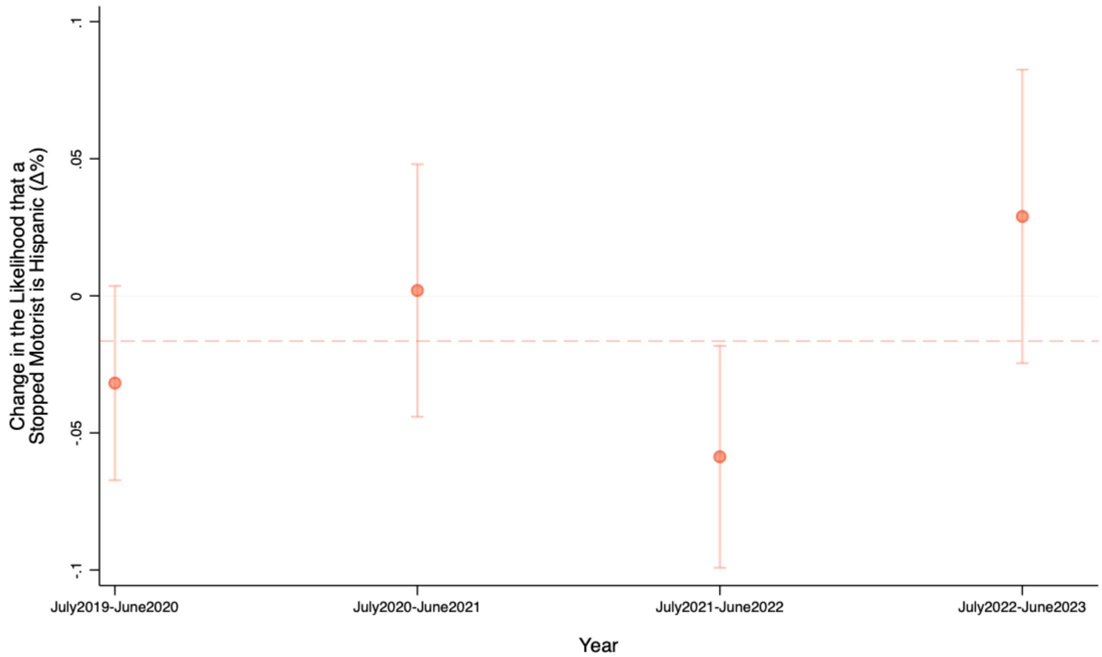
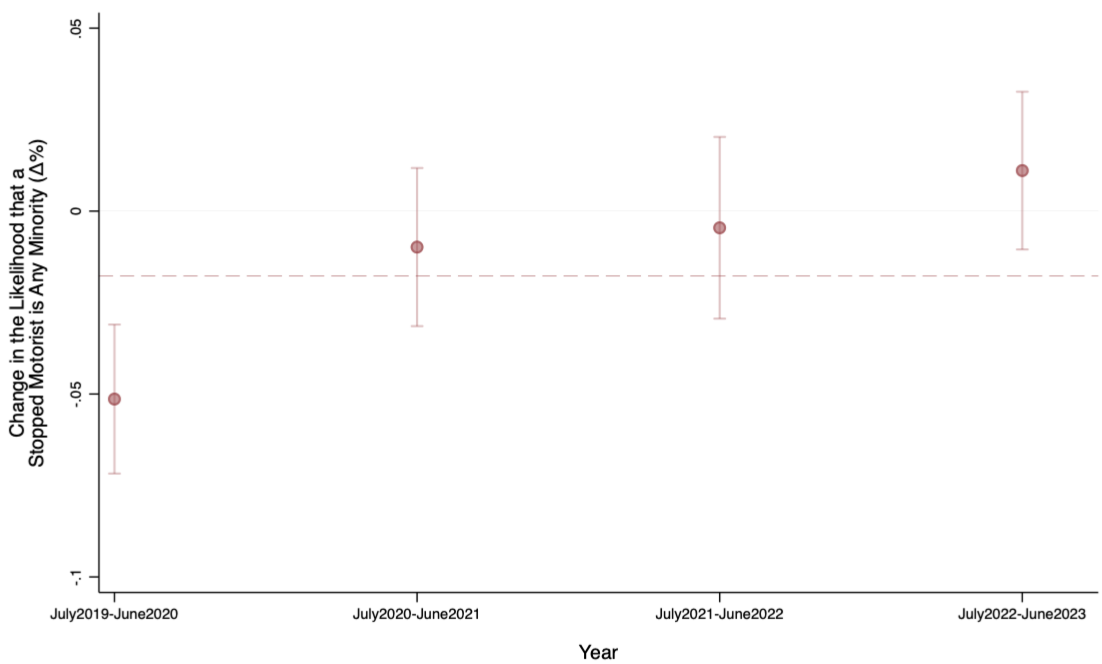


Figure 3. 9: Robustness Test with Controls of Individual Characteristics by Year for Non-White Individuals, 2019-23



A third and final concern about robustness relates to the possibility that the main estimates contained in Figures 3.1 to 3.3 are being driven by seasonal variation in the driving population. This is largely due to the fact that the identifying variation in our main estimates comes from both seasonal changes in the timing of sunset as well as the discrete daylight savings time shift. To address this concern, we isolate a narrow window of time between 21 days before and 21 days after the discrete spring and fall Daylight Savings Time shifts. Rather than an indicator of daylight, we regress race on an indicator of the period with more daylight, i.e., after the spring and before the fall daylight savings time shift. As shown below, the estimates are generally consistent with our main estimates; we find no evidence of a statistically significant positive disparity in any of the periods analyzed. Coefficient estimates, standard errors, and sample sizes are contained in Table B.4 of Appendix B for Figures 3.10 to 3.12.

Figure 3. 10: Robustness Test with Controls for Daylight Savings Time by Year for Black Individuals, 2019-23

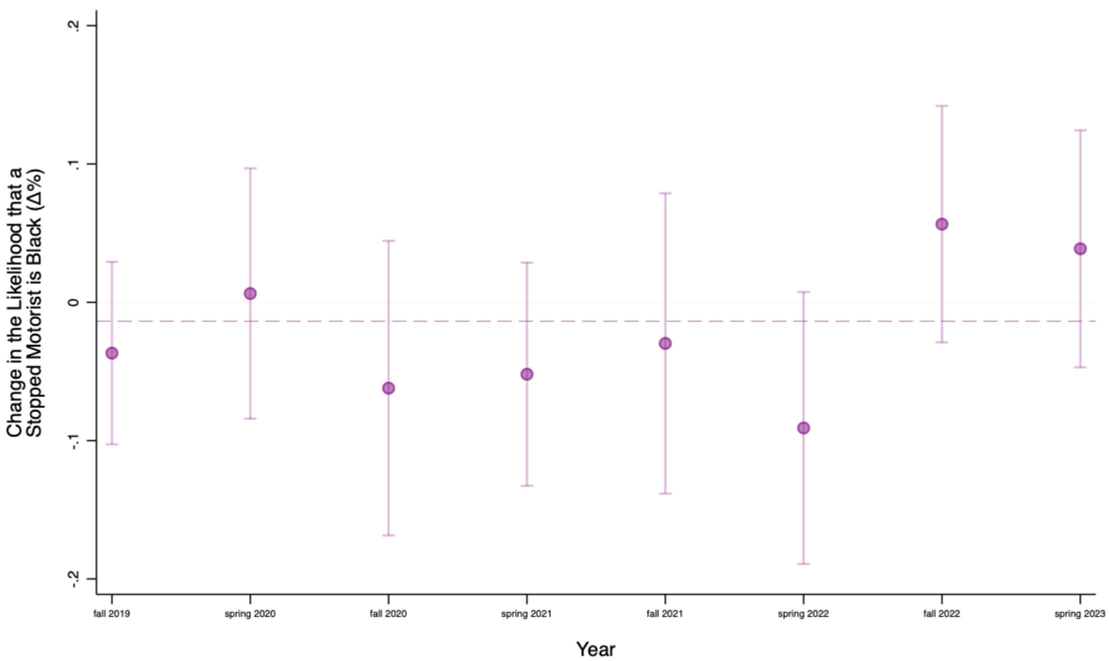


Figure 3. 11: Robustness Test with Controls for Daylight Savings Time by Year for Hispanic Individuals, 2019-23

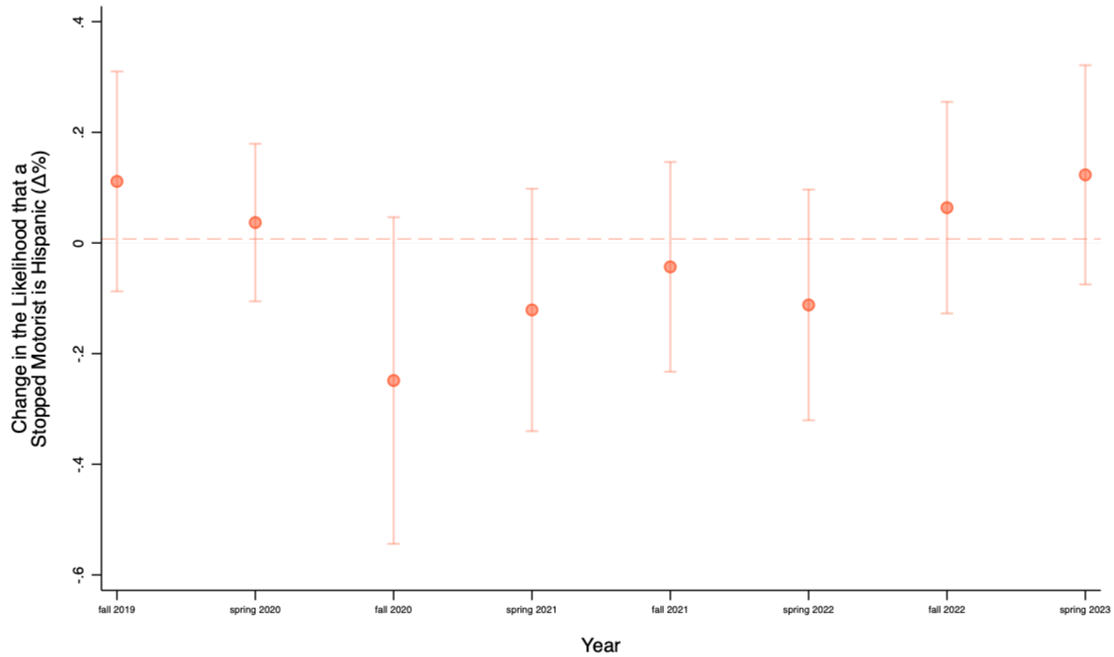
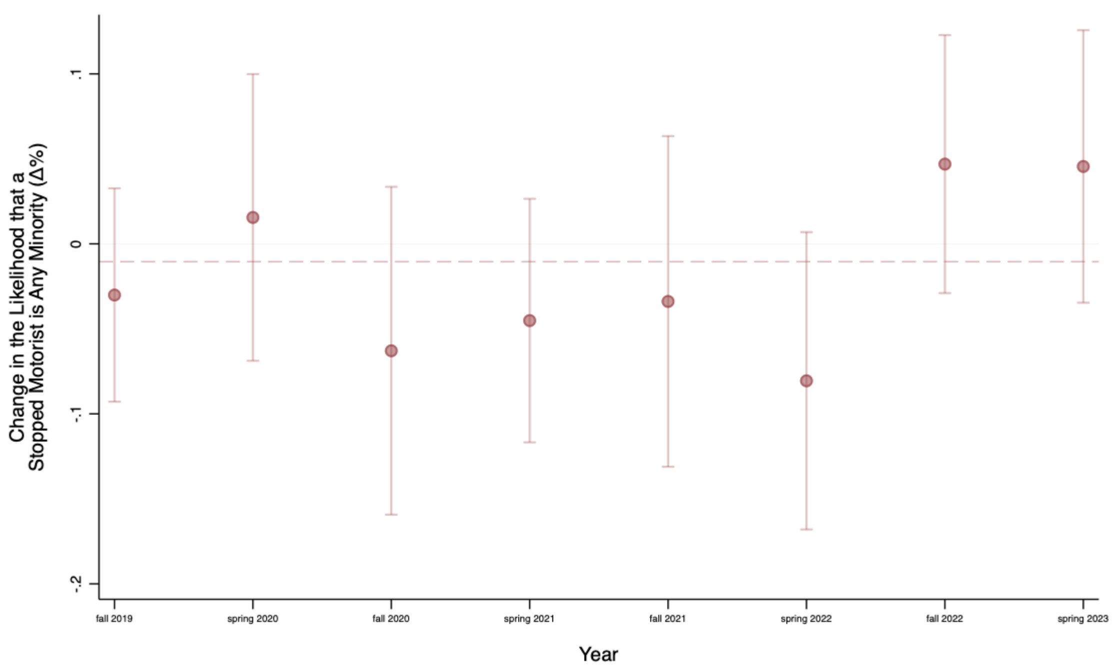


Figure 3. 12: Robustness Test with Controls for Daylight Savings Time by Year for Non-White Individuals, 2019-23



III.B: DISTRICT ANALYSIS WITH SOLAR VISIBILITY TEST, 2019-23

In this section, we graphically present estimates of the solar visibility test (i.e., Equation 4 of Appendix A.2) separately for each district. We provide results for the most recent period between July 2022 and June 2023. We also leverage the total three-year sample from July 2020 to June 2023 and graphically present estimates of the effect of daylight for smaller districts, which may have had an insufficiently small sample to run the test annually.

Figures 3.13 to 3.15 report the results of applying the solar visibility analysis to each of the seven patrol districts from July 2022 through June 2023. Figures 3.13 to 3.15 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 disparities in District 1 (Hispanic: β=23.85pp or 75.09%, $p<0.01$), District 4 (Black: β=8.43pp or 9.92%, $p<0.01$; Any non-White: β=6.56pp or 7.46%, $p<0.01$), District 5 (Black: β=4.49pp or 5.09%, $p<0.01$; Any non-White: β=3.94pp or 4.41%, $p<0.01$), and District 6 (Black: β=1.95pp or 2.03%, $p<0.05$; Any non-White: β=1.91pp or 1.98%, $p<0.05$). In these four districts, the results indicate that racial/ethnic minority drivers are more likely to be stopped in daylight relative to darkness. In other words, non-White drivers are more frequently stopped by police during times of the day when their race or ethnicity is more easily observed before the stop. While these results do not necessarily indicate racial bias, they suggest that these districts engage in enforcement practices that result in disparate treatment, 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 3.13 to 3.15.

Figure 3. 13: Solar Visibility Analysis by District for Black Individuals, July 2022- June 2023

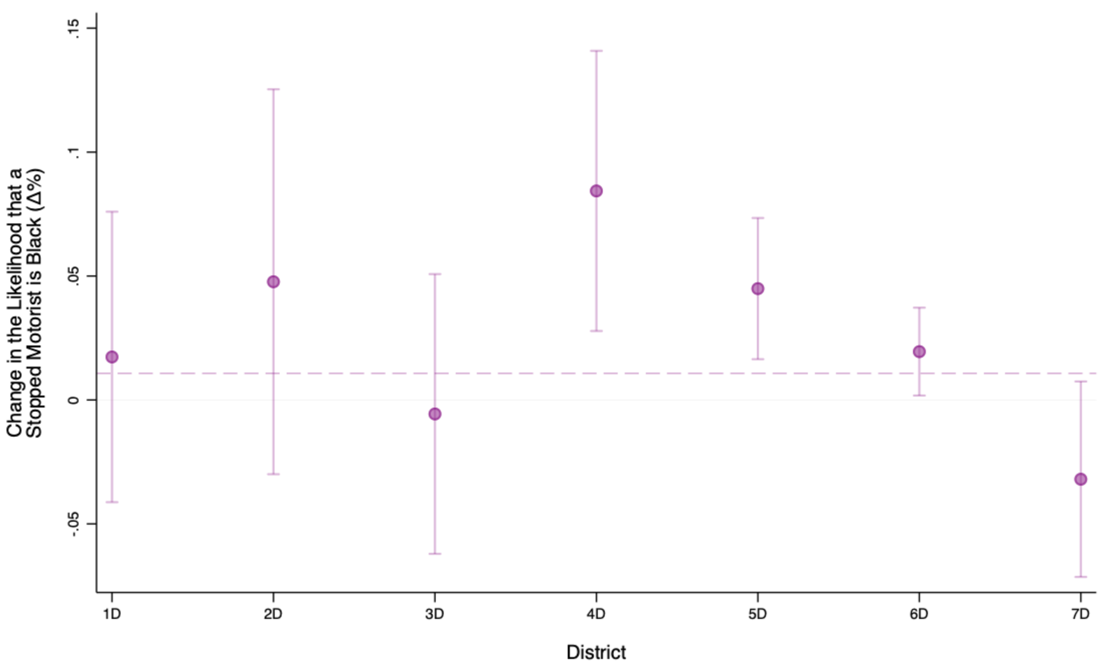


Figure 3. 14: Solar Visibility Analysis by District for Hispanic Individuals, July 2022-June 2023

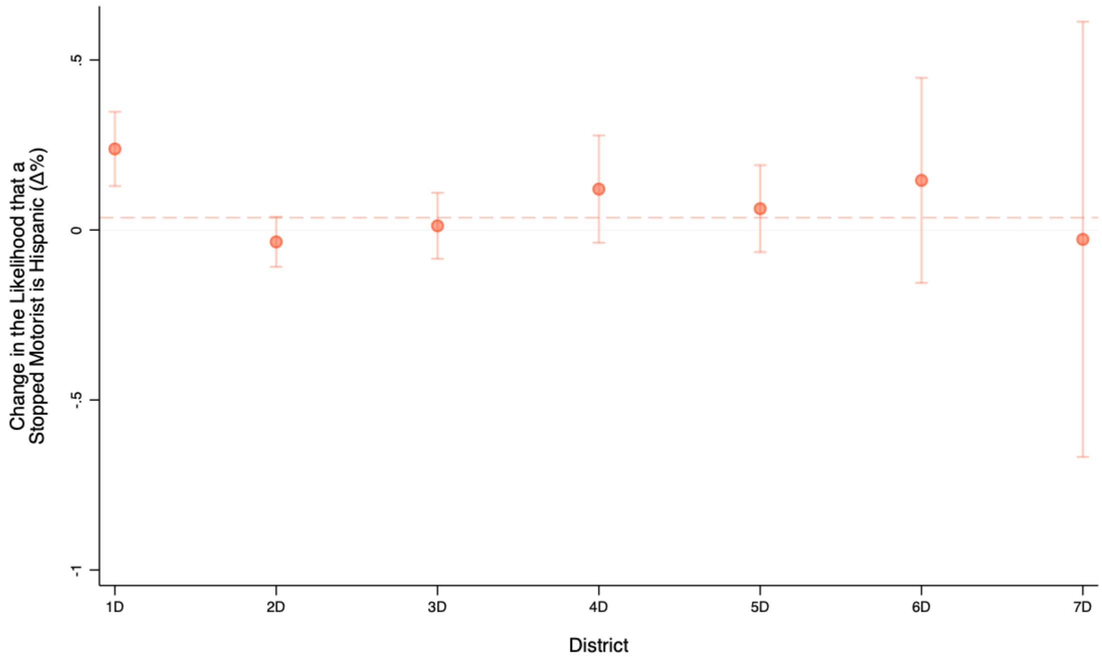
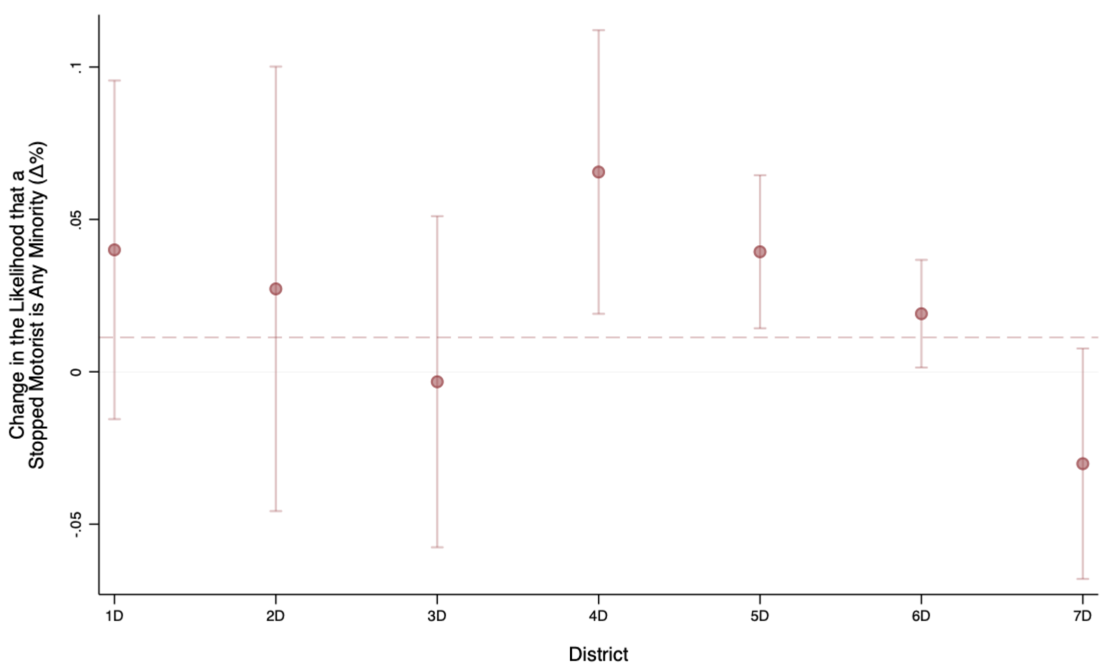


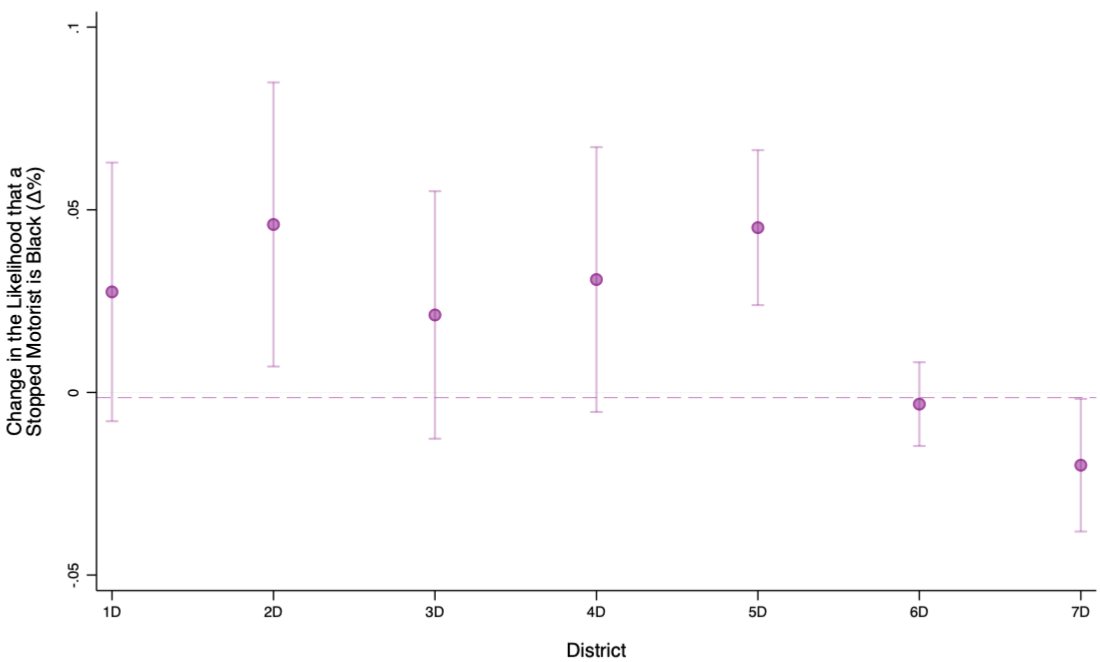
Figure 3. 15: Solar Visibility Analysis by District for Non-White Individuals, July 2022-June 2023



Figures 3.16 to 3.18 report the results of applying the solar visibility analysis to each of the seven patrol districts during the combined three-year period from July 2020 through June 2023. Figures 3.16 to 3.18

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 disparities in District 1 (Hispanic: β=15.28pp or 55.02%, $p<0.01$; Any non-White: β=3.69pp or 4.54%, $p<0.05$), District 2 (Black: β=4.6pp or 8.79%, $p<0.05$), District 4 (Black: β=3.09pp or 3.67%, $p<0.1$), and District 5 (Black: β=4.51pp or 5.03%, $p<0.01$; Hispanic: β=8.82pp or 21.01%, $p<0.1$ Any non-White: β=4.12pp or 4.55%, $p<0.1$).[17] In these four districts, the results indicate that racial/ethnic minority individuals are more likely to be stopped in daylight relative to darkness. In other words, non-White drivers are more frequently stopped by police during times of the day when their race or ethnicity is more easily observed prior to the stop. As discussed with respect to the one-year district results, these results do not necessarily indicate racial bias, but they suggest that these districts engage in enforcement practices that result in disparate treatment. Coefficient estimates, standard errors, and sample sizes are contained in Table B.6 of Appendix B for Figures 3.16 to 3.18.

Figure 3. 16: Solar Visibility Analysis by District for Black Individuals, Three-Year Aggregate



[17] District 2 (Hispanic) and District 7 (Black and Any non-White) had statistically significant negative coefficient estimates. As shown in Kalinowski et al. (2023), this is potentially also a result consistent with disparate treatment.

Figure 3. 17: Solar Visibility Analysis by District for Hispanic Individuals, Three-Year Aggregate

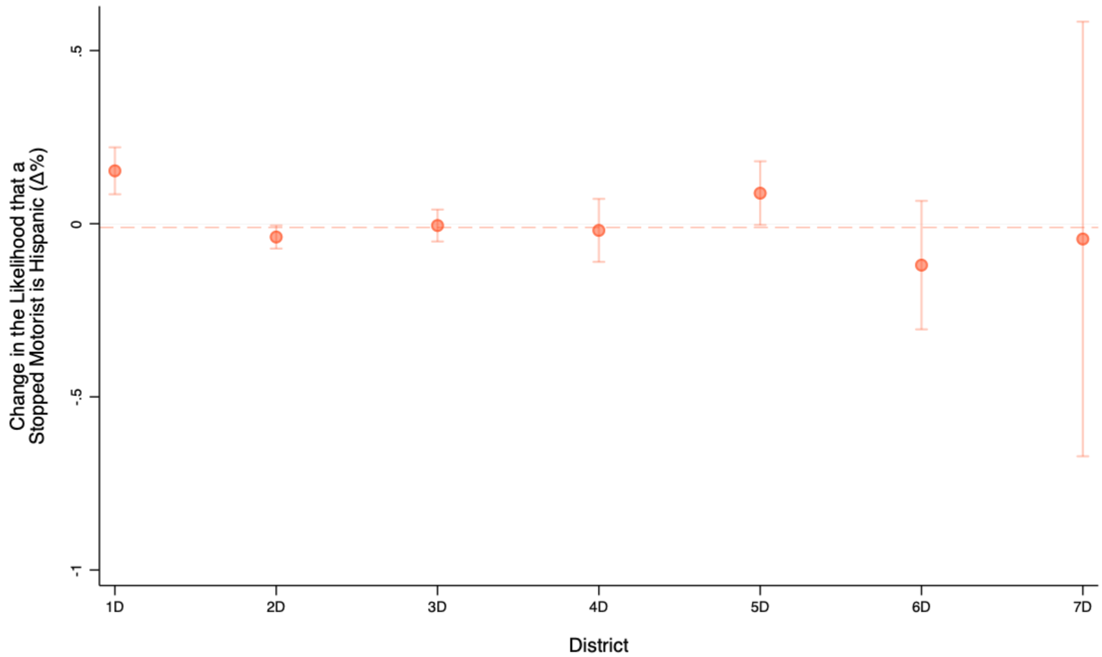
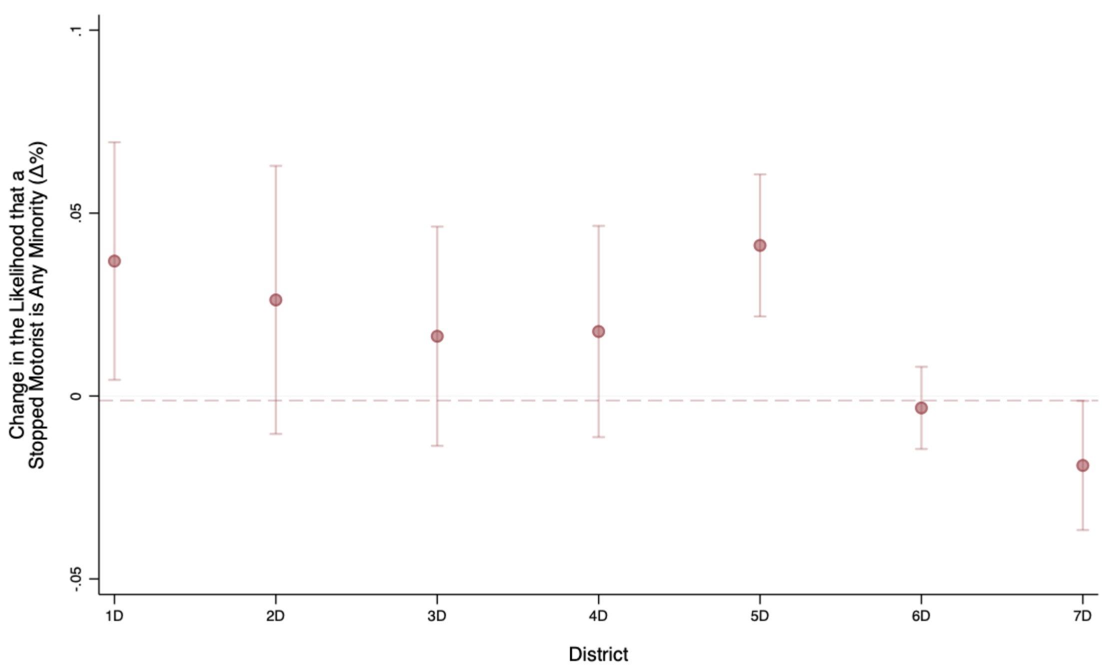


Figure 3. 18: Solar Visibility Analysis by District for Non-White Individuals, Three-Year Aggregate



IV. ANALYSIS OF POST-STOP ENFORCEMENT ACTION

In this section, we test for disparities 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 BY YEAR, 2019-23

Figures 4.1 to 4.3 report results from applying the conditional outcome test focusing on arrests in each of the four years between July 2019 and June 2023. 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=6.12pp or 96.84%, $p<0.01$) following a stop. Similarly, in Figures 4.2 and 4.3, we find that Hispanic (β=3.66pp or 57.85%, $p<0.01$) and any non-White (β=5.6pp or 88.63%, $p<0.01$) individuals were also statistically more likely to be arrested following a stop. As shown below, all of the disparities decrease in each of the years between 2020 and 2023. 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

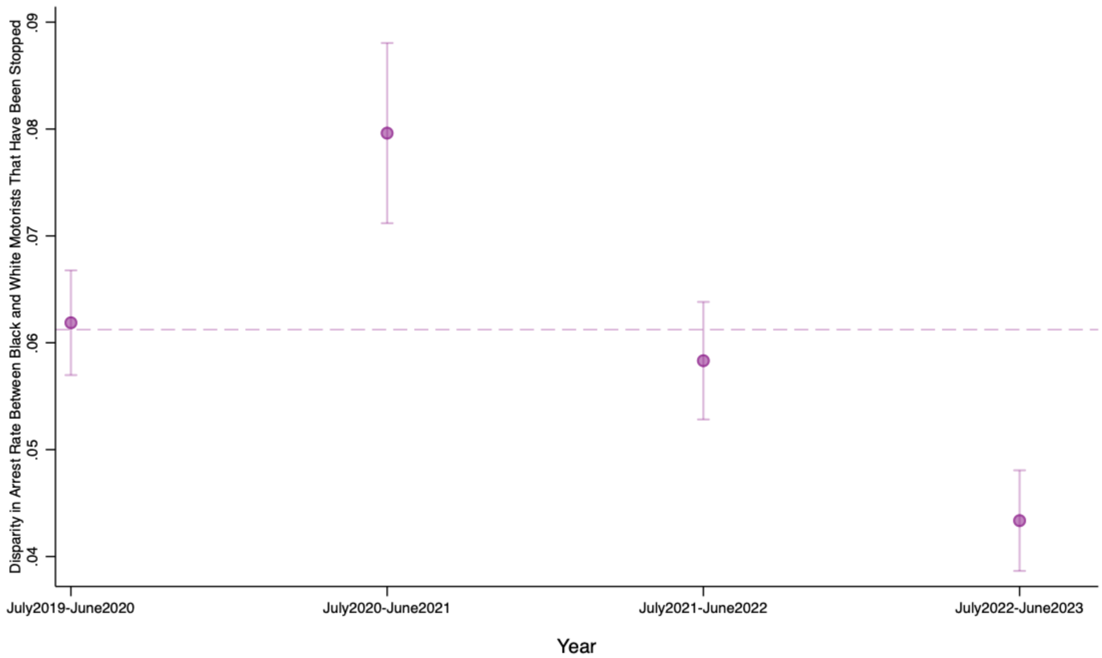


Figure 4. 2: Aggregate Analysis of Decision to Arrest by Year for Hispanic Individuals

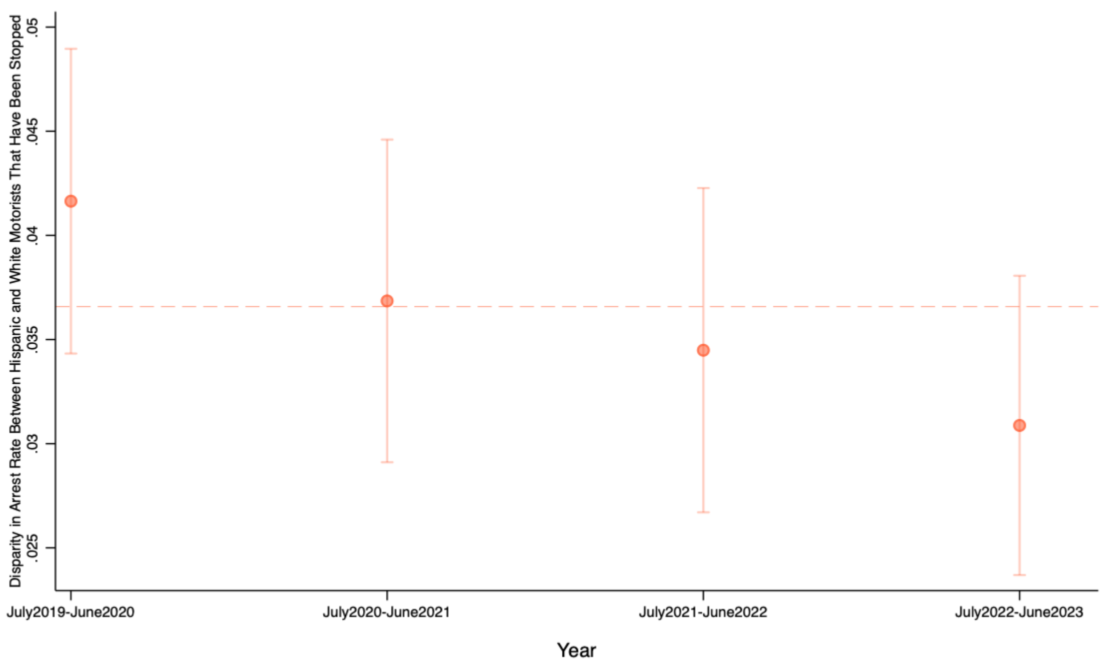
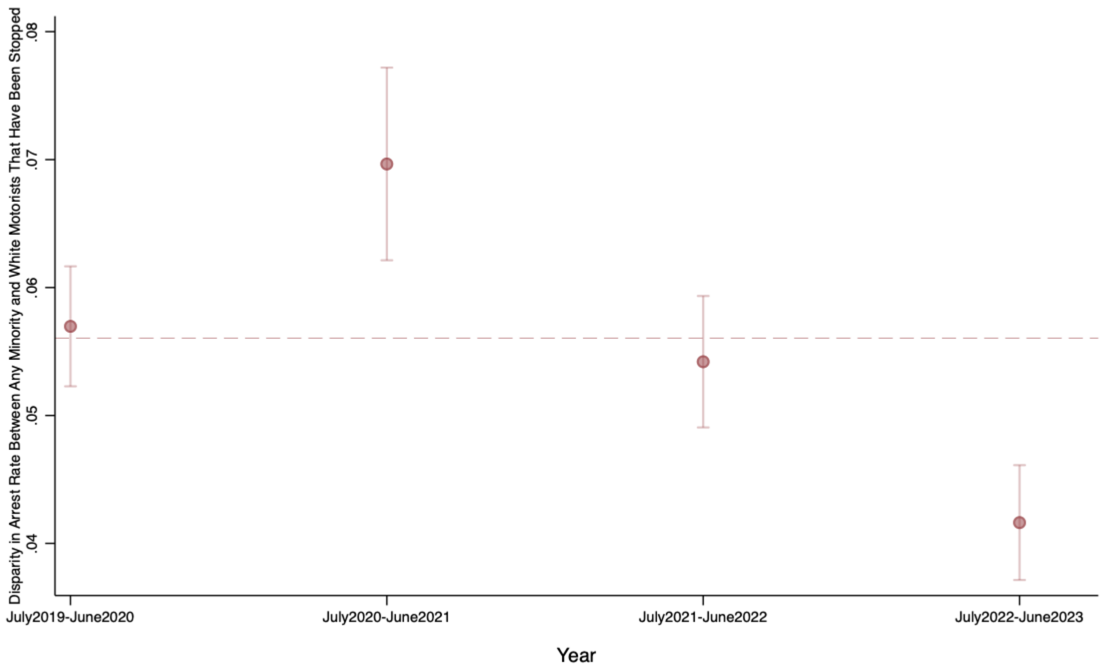


Figure 4. 3: Aggregate Analysis of Decision to Arrest by Year for Non-White Individuals



Figures 4.4 to 4.6 report results from applying the conditional outcome test focusing on the decision to ticket for each of the four years between July 2019 and June 2023. 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. 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 4.4, 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=2.34pp or 3.5%, $p<0.01$) following a stop. In Figure 4.5, we find that Hispanic individuals are more likely to receive a ticket (β=6.89pp or 10.29%, $p<0.01$) in all four years examined. In Figure 4.6, we find that any non-White driver was statistically more likely to receive a ticket (β=2.95pp or 4.37%, $p<0.01$) in all years except 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

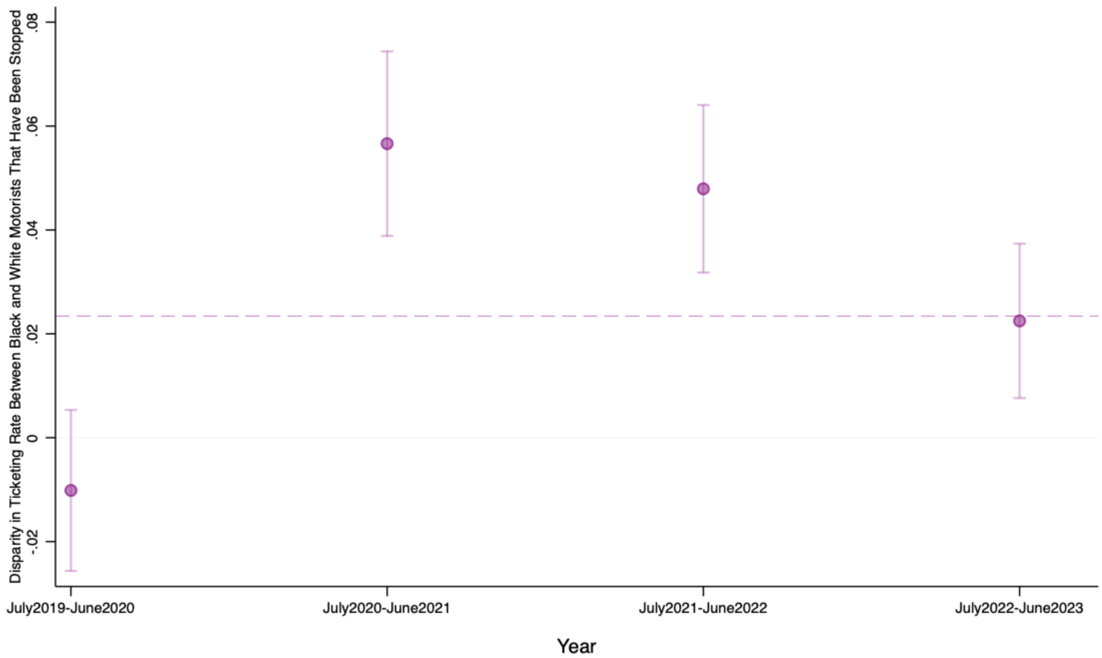


Figure 4. 5: Aggregate Analysis of Decision to Ticket by Year for Hispanic Individuals

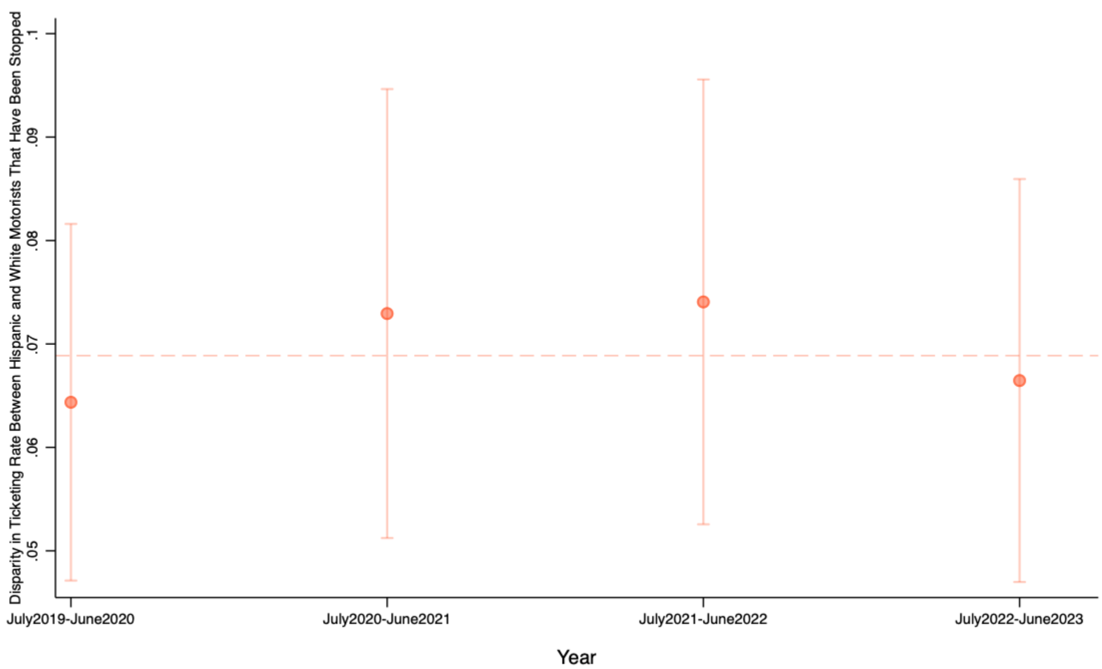
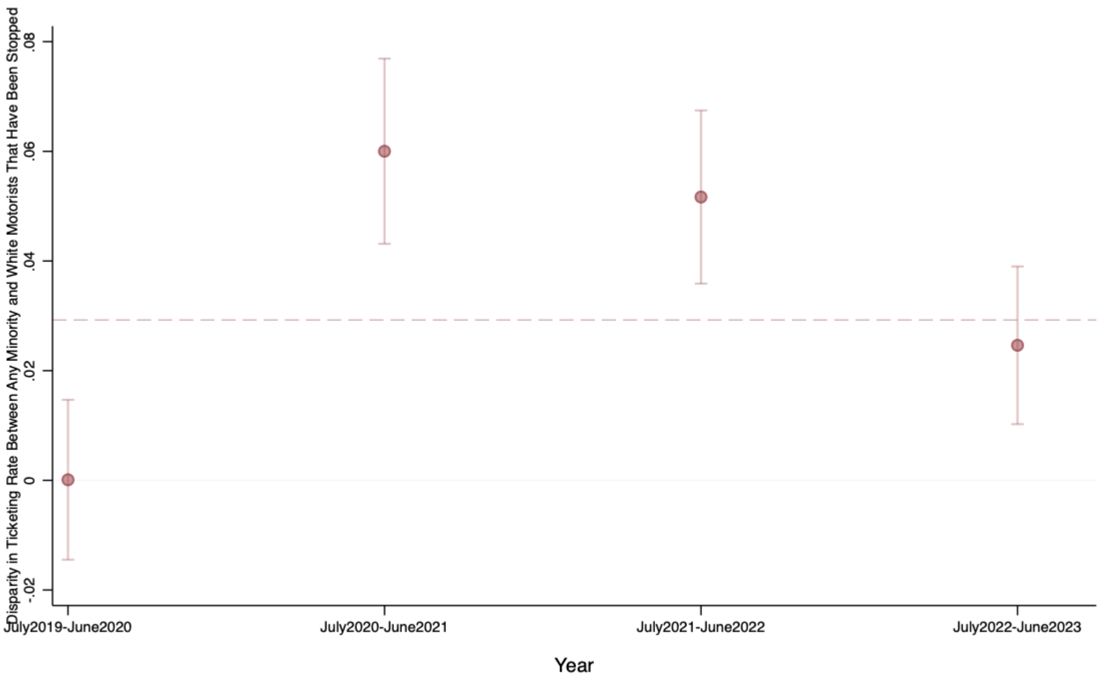


Figure 4. 6: Aggregate Analysis of Decision to Ticket by Year for Non-White Individuals



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 four years between July 2019 and June 2023. 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.[18] 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 only June 2020 to July 2021, we estimate a statistically significant positive difference in stop duration (β=5.21min or 13.63%, $p<0.02$) for Black drivers. In Figure 4.8, we estimate a statistically significant lower stop duration for Hispanic drivers (b=-4.85min or -11.66%, $p<0.01$) across the entirety of the period. In Figure 4.9, we effectively estimate no difference in stop duration for any non-White motorists across the entirety of the period. 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.

[18] 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

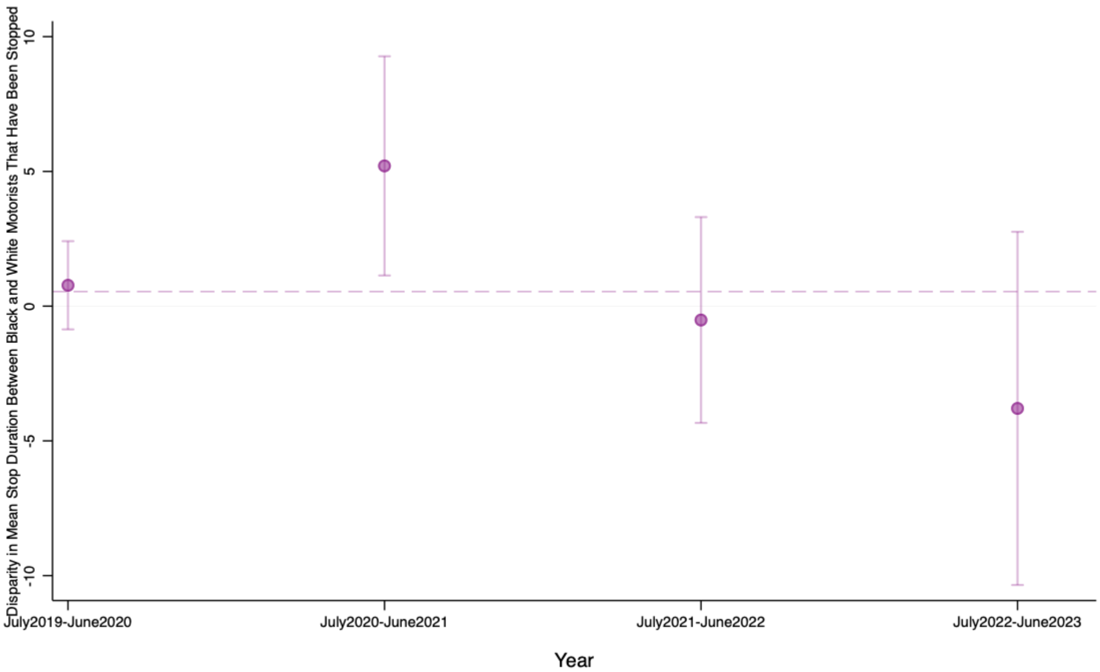


Figure 4. 8: Aggregate Analysis of Stop Duration by Year for Hispanic Individuals

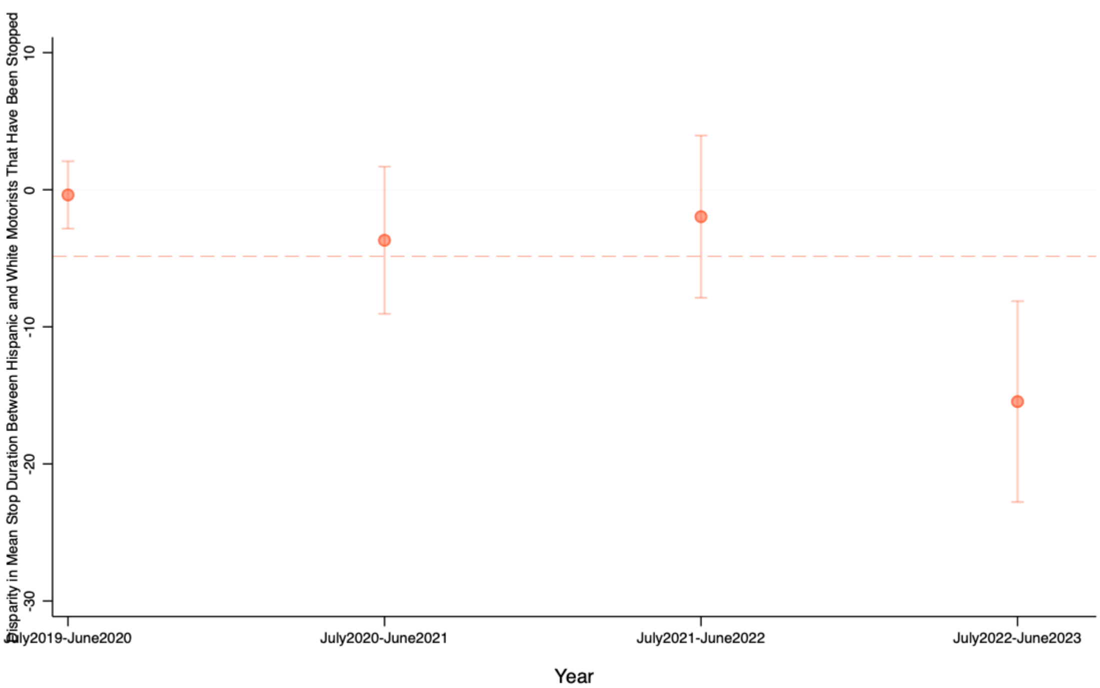
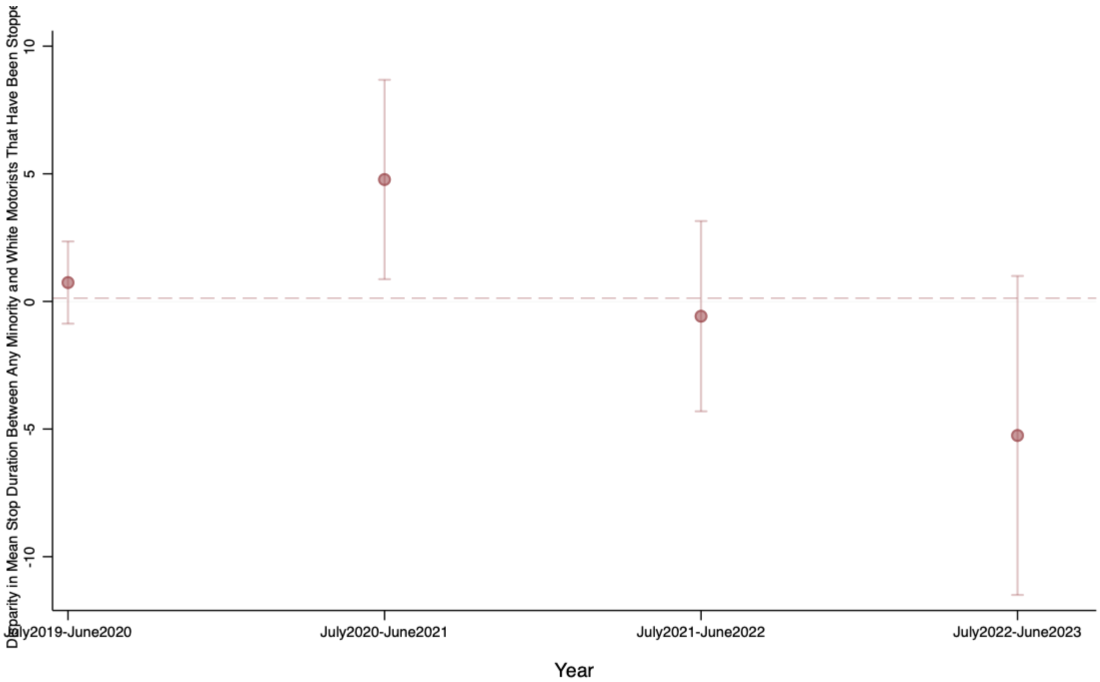


Figure 4. 9: Aggregate Analysis of Stop Duration by Year for Non-White Individuals



IV.B: DISTRICT ANALYSIS OF POST-STOP ENFORCEMENT ACTION BY YEAR, 2020-23

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 2022 through June 2023. 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 disparity for Black and Hispanic motorists in District 7 and Hispanic motorists in District 6. 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 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.

Figure 4. 10: Analysis of Decision to Arrest by District for Black Individuals, July 2022-June 2023

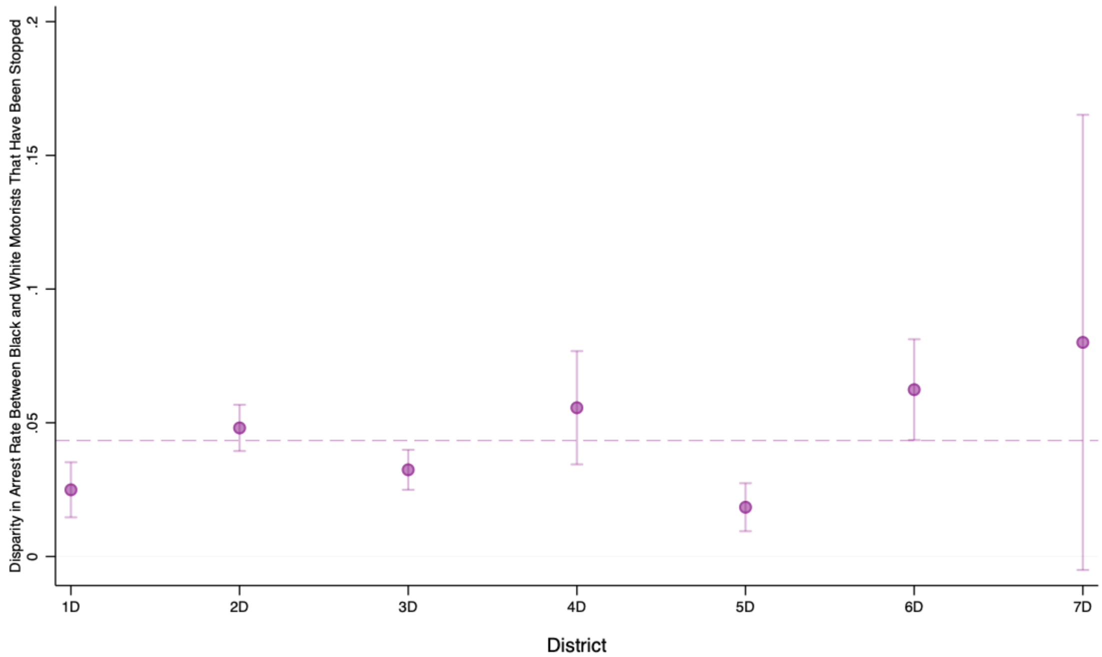


Figure 4. 11: Analysis of Decision to Arrest by District for Hispanic Individuals, July 2022- June 2023

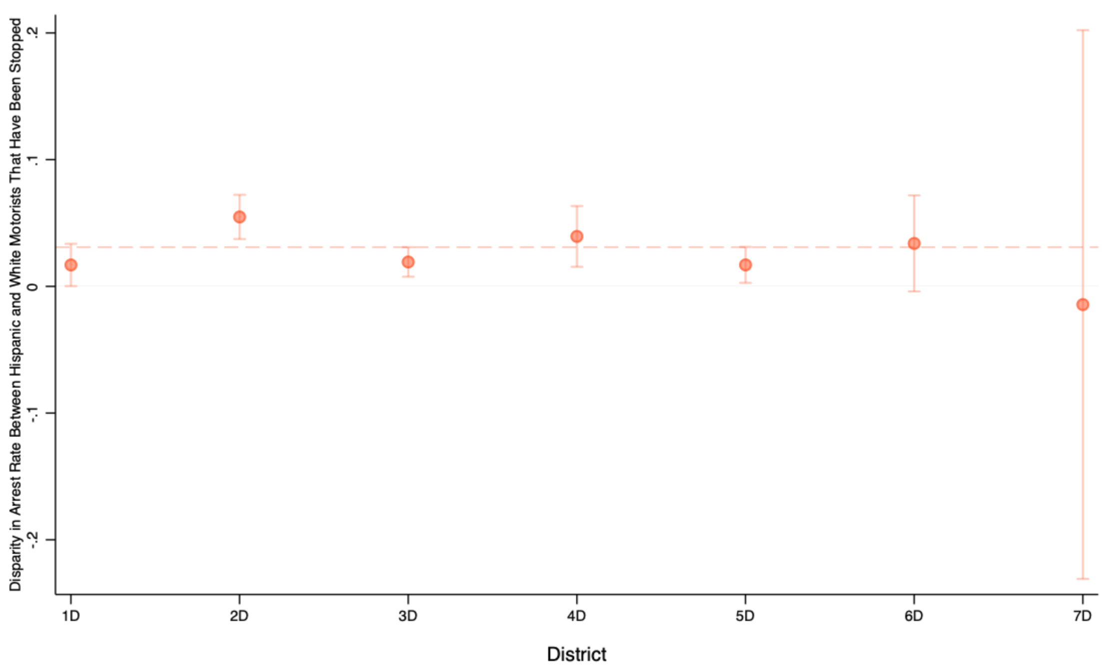
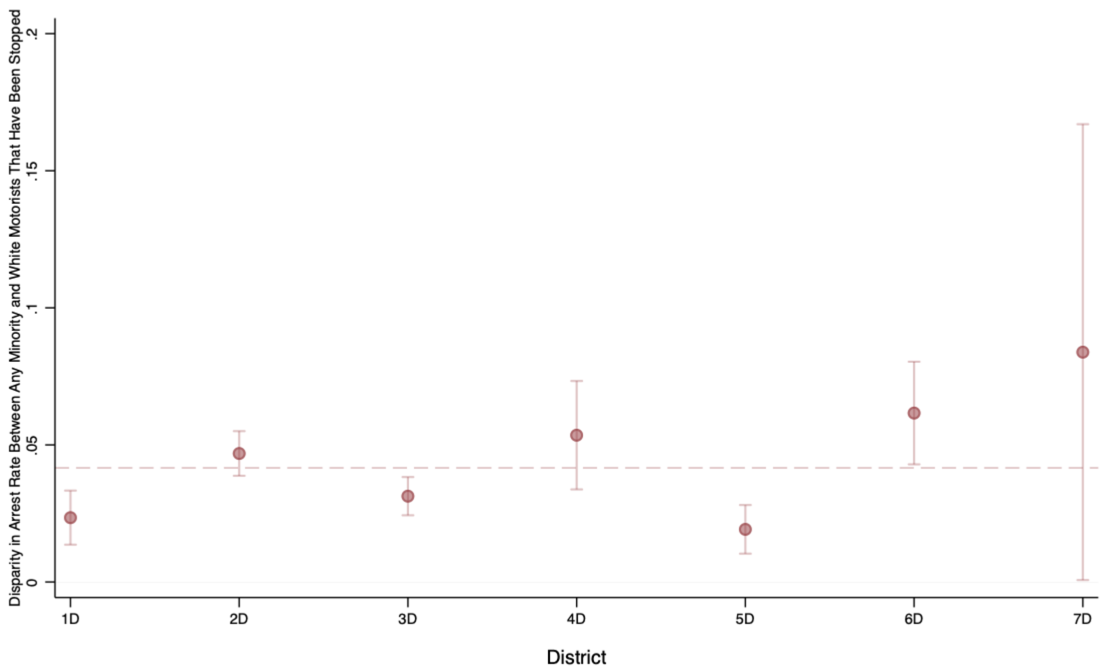


Figure 4. 12: Analysis of Decision to Arrest by District for Non-White Individuals, July 2022- June 2023



Figures 4.13 to 4.15 report the results of applying the conditional outcome test for the decision to arrest in each of the seven patrol districts for the three-year aggregate (July 2020 through June 2023). Figures 4.13 to 4.15 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 disparity for Black or Hispanic motorists in District 7. 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 an arrest. Coefficient estimates, standard errors, and sample sizes are contained in Table C.5 of Appendix C for Figures 4.13 to 4.15.

Figure 4. 13: Analysis of Decision to Arrest by District for Black Individuals, Three-Year Aggregate

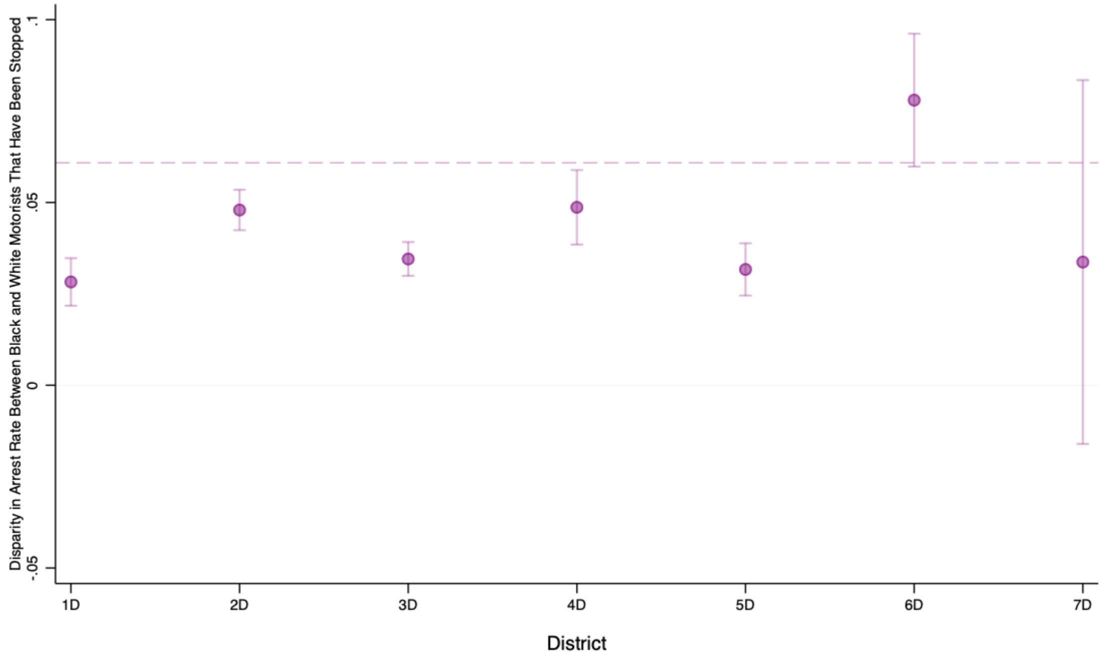


Figure 4. 14: Analysis of Decision to Arrest by District for Hispanic Individuals, Three-Year Aggregate

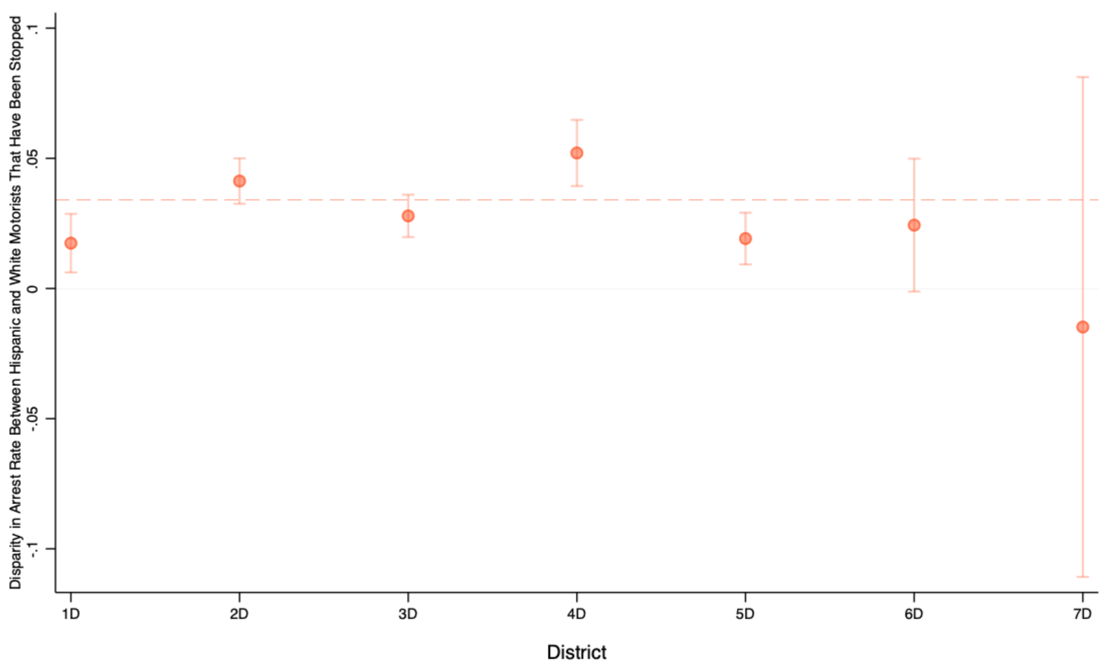
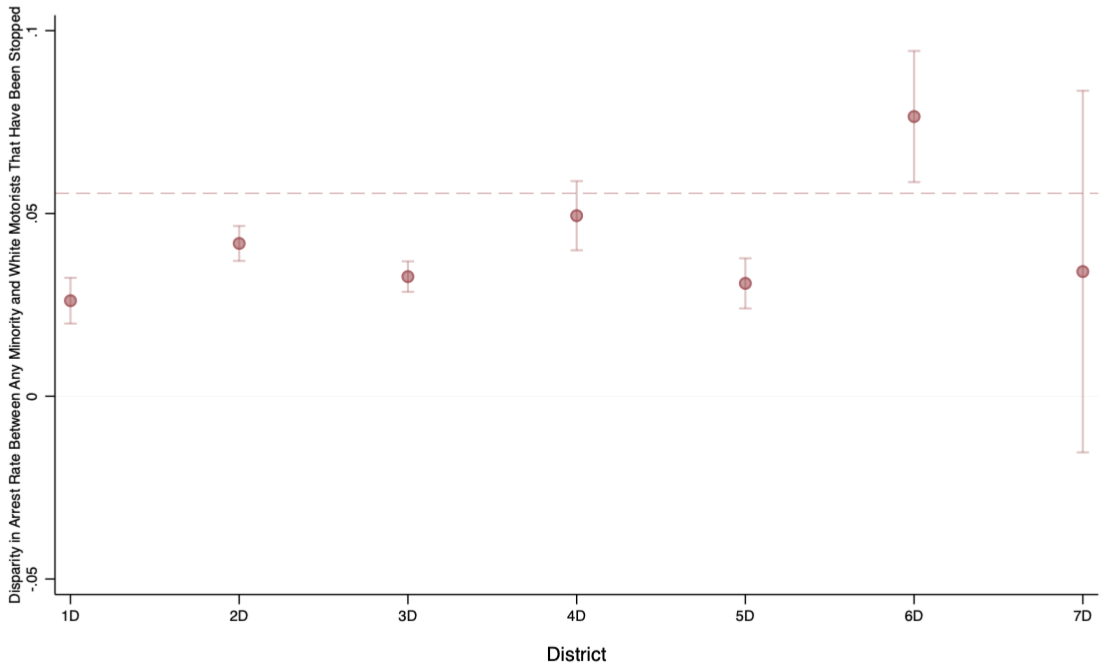


Figure 4. 15: Analysis of Decision to Arrest by District for Non-White Individuals, Three-Year Aggregate



Figures 4.16 to 4.18 report the results of applying the conditional outcome test for the decision to ticket in each of the seven patrol districts from July 2022 through June 2023. 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 disparities in District 1 (Black: β=2.78pp or 3.67%, $p<0.1$; Hispanic: β=7.13pp or 9.42%, $p<0.05$), District 2 (Black: β=4.21pp or 6.54%, $p<0.01$; Hispanic: β=4.02pp or 6.25%, $p<0.1$; Any Non-White: β=4pp or 6.21%, $p<0.01$), District 3 (Hispanic: β=3.45pp or 5.41%, $p<0.1$), District 4 (Black: β=-3.95pp or -6.55%, $p<0.1$), and District 5 (Hispanic: β=11.8pp or 16.38%, $p<0.01$). 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 ticket. Coefficient estimates, standard errors, and sample sizes are contained in Table C.6 of Appendix C for Figures 4.16 to 4.18.

Figure 4. 16: Analysis of Decision to Ticket by District for Black Individuals, July 2022- June 2023

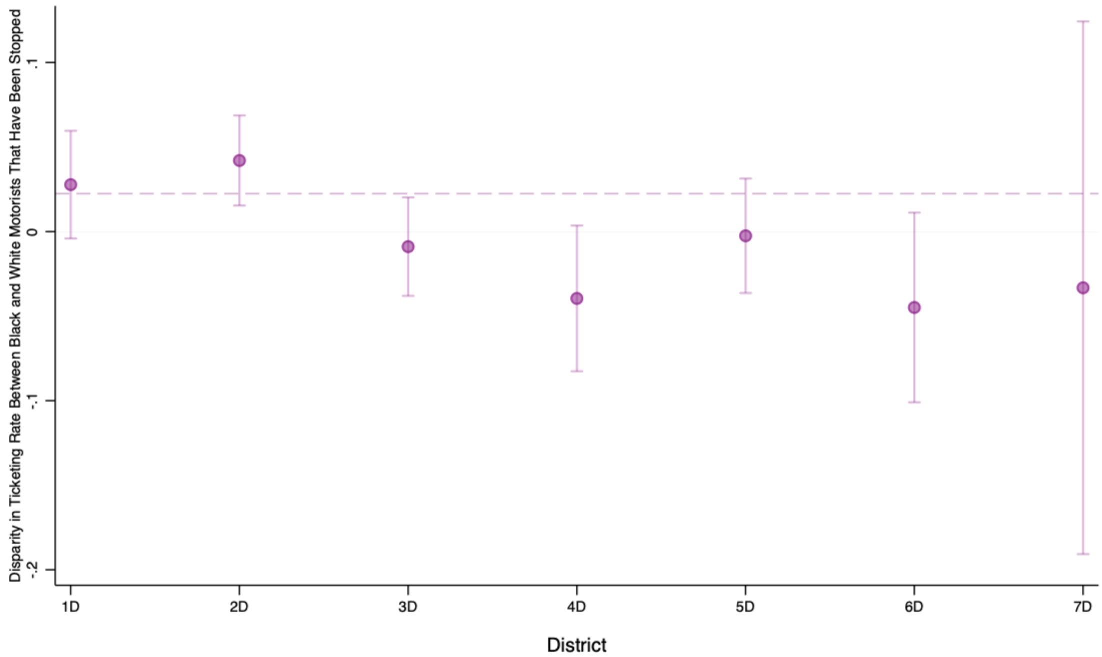


Figure 4. 17: Analysis of Decision to Ticket by District for Hispanic Individuals, July 2022- June 2023

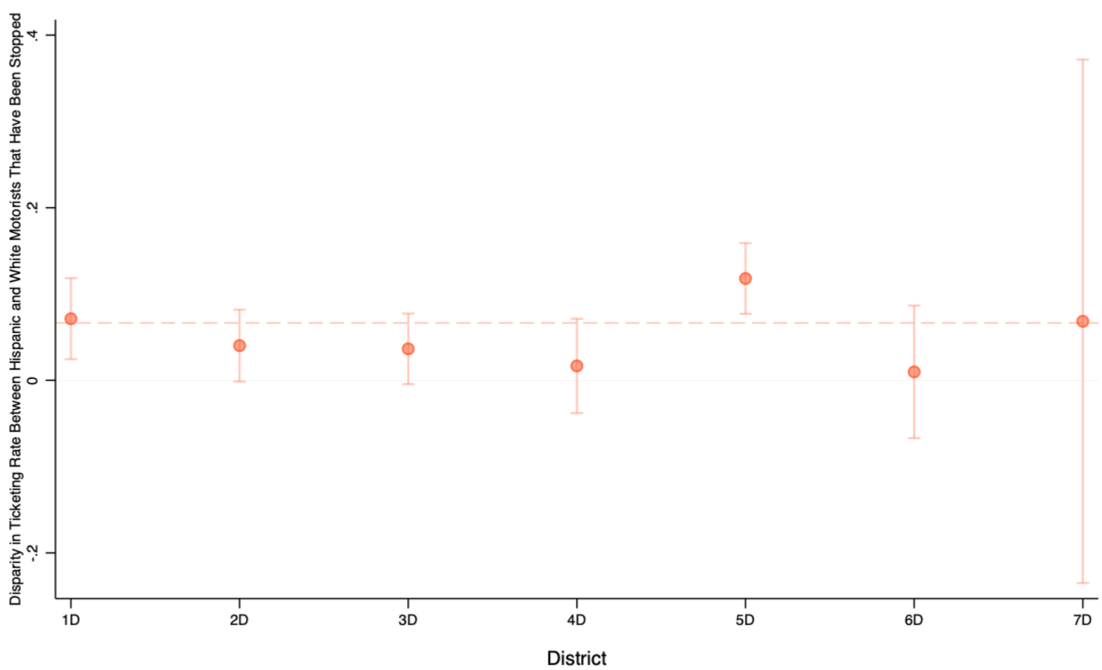
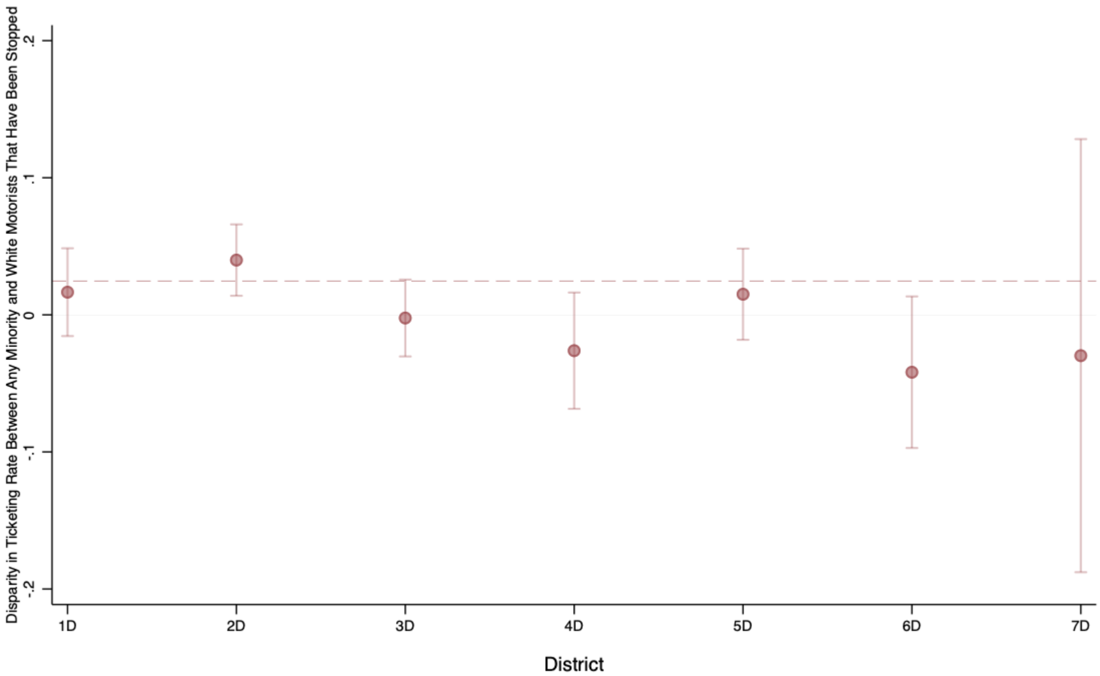


Figure 4. 18: Analysis of Decision to Ticket by District for Non-White Individuals, July 2022- June 2023



Figures 4.19 to 4.21 report the results of applying the conditional outcome test for the decision to ticket in each of the seven patrol districts for the three-year aggregate (July 2020 through June 2023). Figures 4.19 to 4.21 present differences in the likelihood of White drivers receiving a ticket relative to Black, Hispanic, and any non-White drivers during this period. As shown below, we find statistically significant disparities in District 1 (Hispanic: β=7.73pp or 10.2%, p<0.01), District 2 (Black: β=4.14pp or 6.46%, p<0.01; Hispanic: β=6.56pp or 10.25%, p<0.01; Any non-White: β=5.08pp or 7.93%, p<0.01), District 3 (Black: β=2.18pp or 3.26%, p<0.05; Hispanic: β=5.9pp or 8.83%, p<0.01; Any non-White: β=2.88pp or 4.3%, p<0.01), District 4 (Hispanic: β=7.45pp or 12.77%, p<0.01), District 5 (Hispanic: β=8.24pp or 11.97%, p<0.01), District 6 (Black: β=-5.96pp or -8.09%, p<0.01; Any non-White: β=-5.68pp or -7.7%, p<0.01), and District 7 (Black: β=-8.93pp or -15.04%, p<0.1; Any non-White: β=-8.57pp or -15.04%, p<0.05). 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.7 of Appendix C for Figures 4.19 to 4.21.

Figure 4. 19: Analysis of Decision to Ticket by District for Black Individuals, Three-Year Aggregate

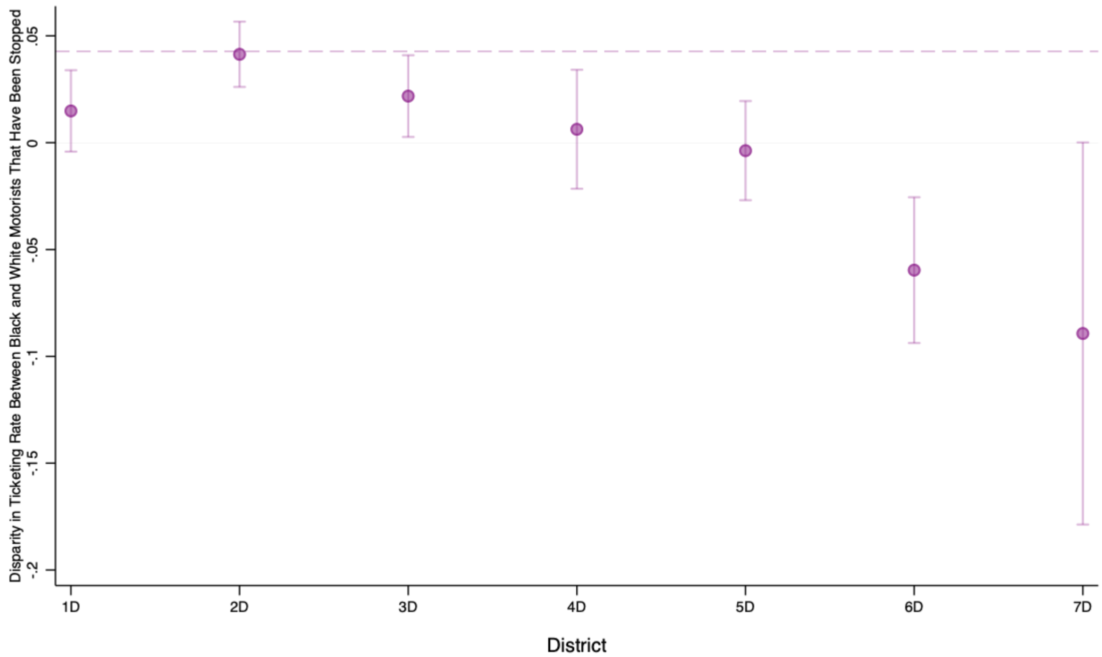


Figure 4. 20: Analysis of Decision to Ticket by District for Hispanic Individuals, Three-Year Aggregate

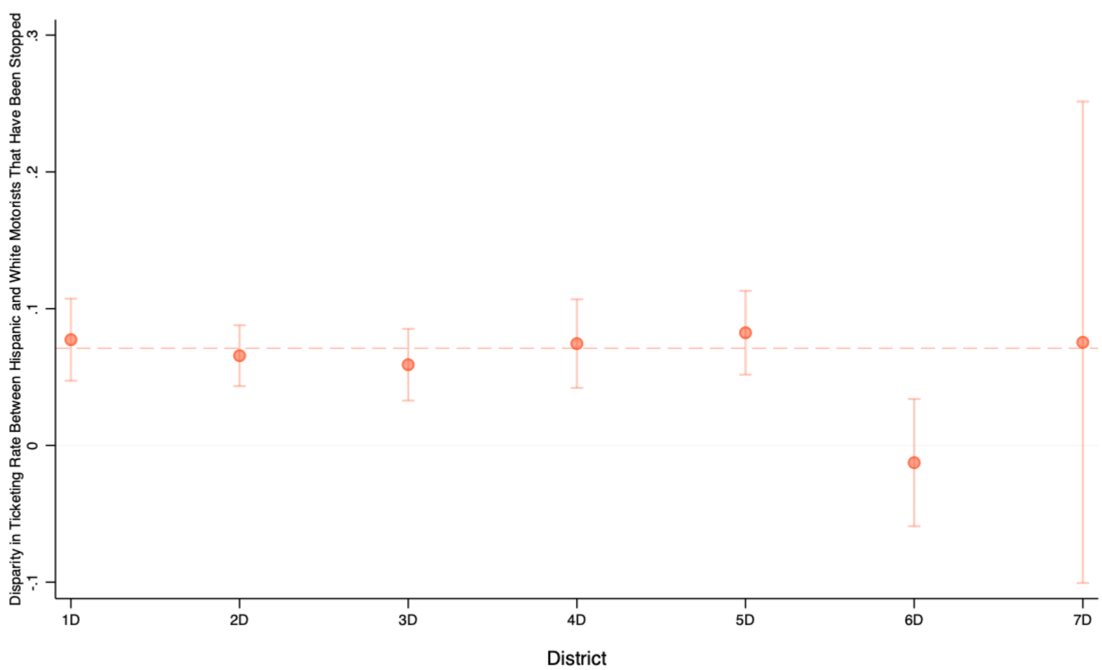
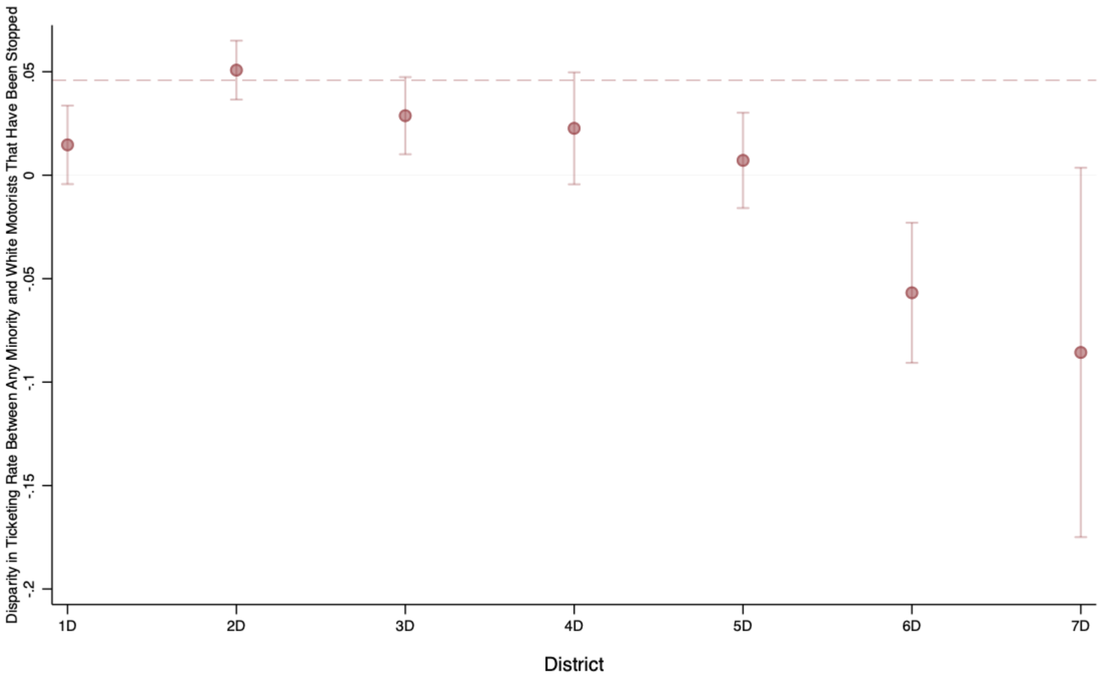


Figure 4. 21: Analysis of Decision to Ticket by District for Non-White Individuals, Three-Year Aggregate



Figures 4.22 to 4.24 report the results of applying the conditional outcome test to stop duration in each of the seven patrol districts from July 2022 through June 2023. Figures 4.22 to 4.24 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 disparities in District 1 (Black: β=-21.84min or -31.29%, p<0.01; Any non-White: β=-20.69min or -29.63%, p<0.01), District 2 (Hispanic: β=-19.96min or -23.93%, p<0.01; Any non-White: β=-10.11min or -12.12%, p<0.1), and District 4 (Hispanic: β=-20.34min or -29.56%, p<0.1). 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.

Figure 4. 22: Analysis of Stop Duration by District for Black Individuals, July 2022-June 2023

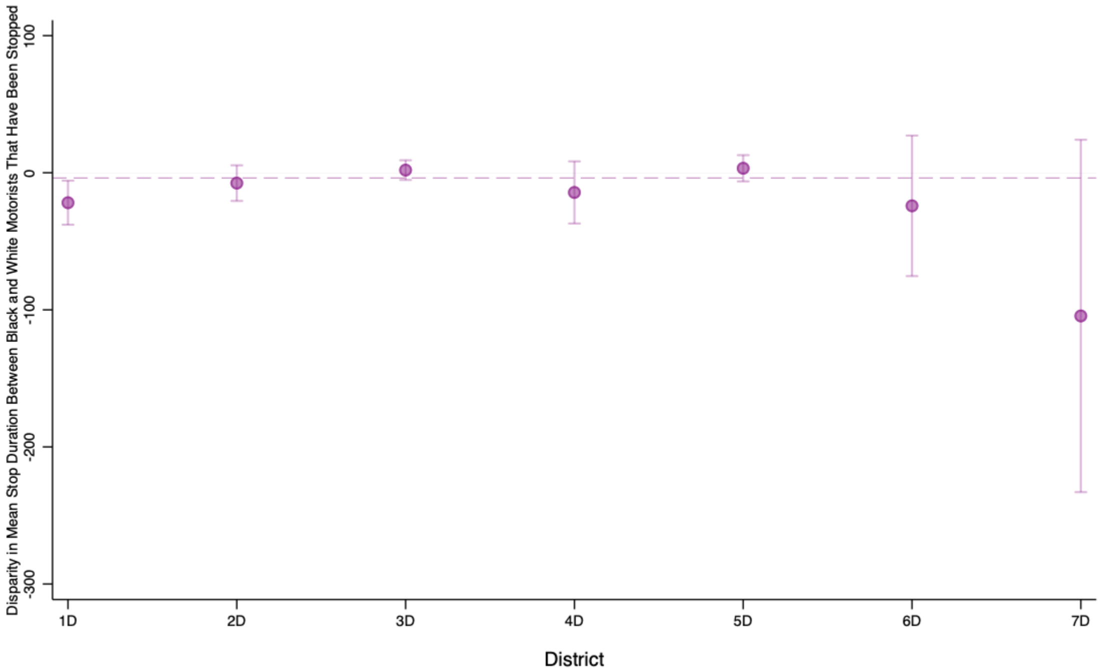


Figure 4. 23: Analysis of Stop Duration by District for Hispanic Individuals, July 2022-June 2023

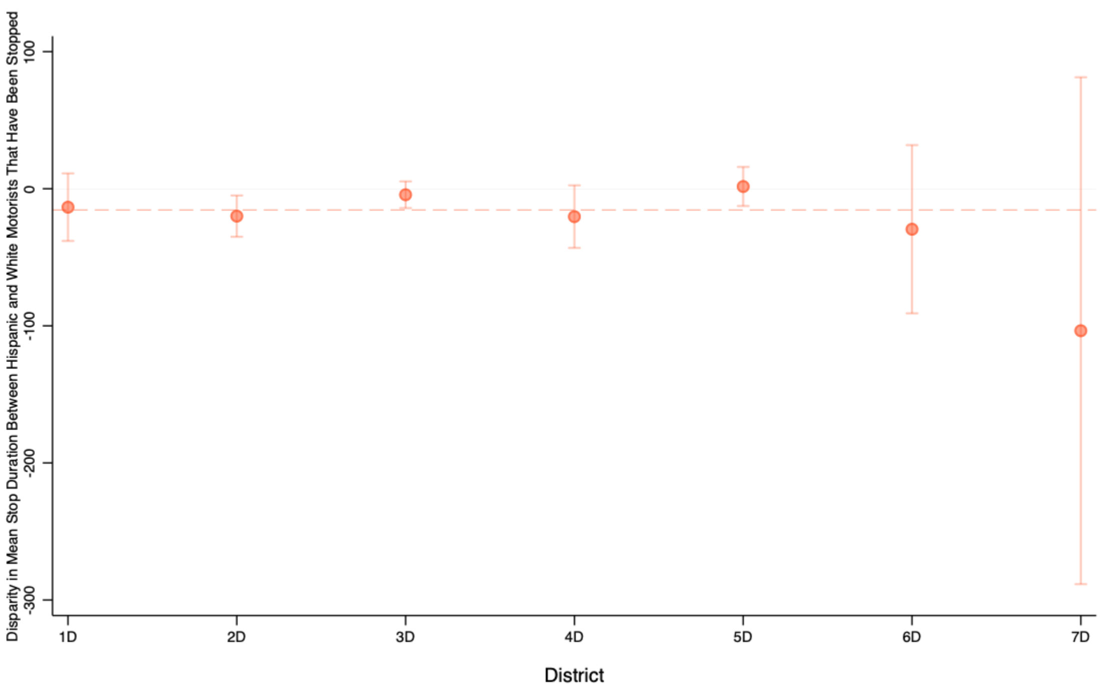
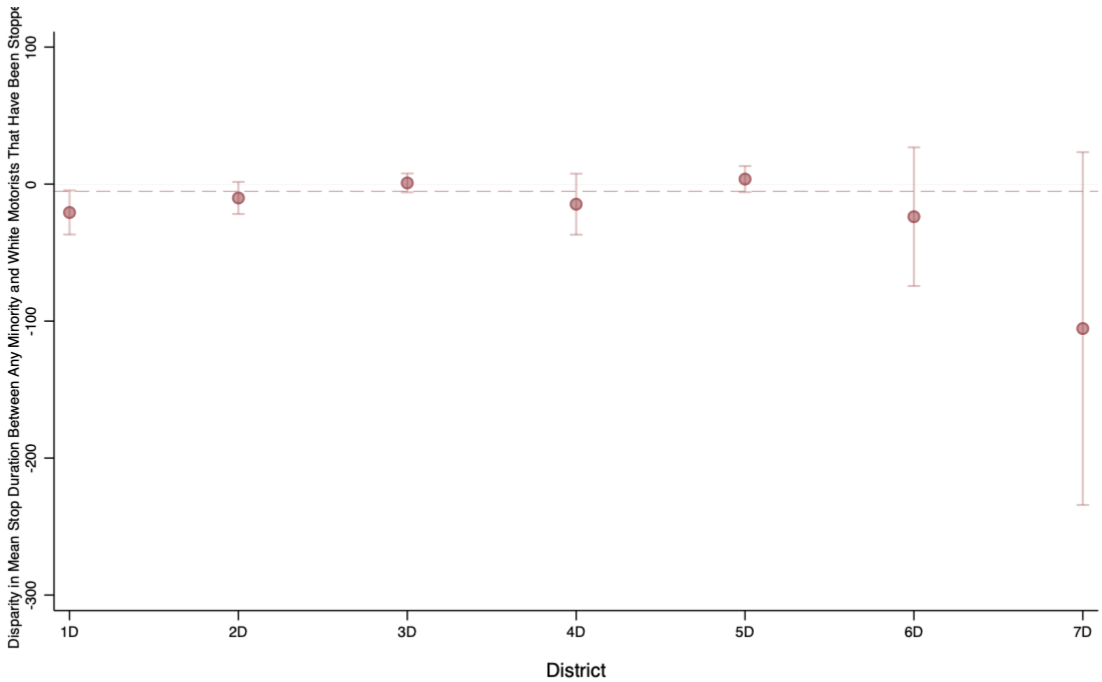


Figure 4. 24: Analysis of Stop Duration by District for Non-White Individuals, July 2022- June 2023



Figures 4.25 to 4.27 report the results of applying the conditional outcome test to stop duration in each of the seven patrol districts for the three-year aggregate period (July 2020 through June 2023). Figures 4.25 to 4.27 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 disparities in District 1 (Black: β=-8.99min or -17.95%, $p<0.05$; Hispanic: β=-11.52min or -23.02%, $p<0.05$; Any non-White: β=-9.25min or -18.47%, $p<0.05$), District 2 (Hispanic: β=-7.82min or -13.02%, $p<0.5$), District 4 (Hispanic: β=-10.33min or -17.07%, $p<0.1$), and District 6 (Black: β=-42.25min or -58.37%, $p<0.01$; Hispanic: β=-36.98min or -51.08%, $p<0.05$; Any non-White: β=-41.98min or -57.99%, $p<0.01$). 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.9 of Appendix C for Figures 4.25 to 4.27.

Figure 4. 25: Analysis of Stop Duration by District for Black Individuals, Three-Year Aggregate

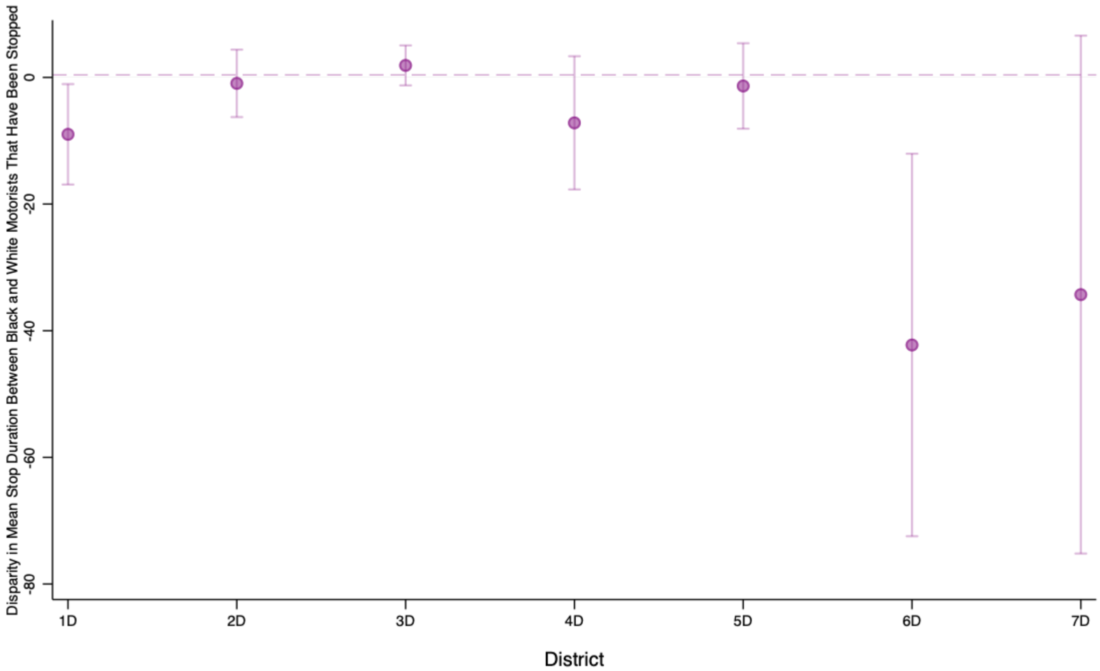


Figure 4. 26: Analysis of Stop Duration by District for Hispanic Individuals, Three-Year Aggregate

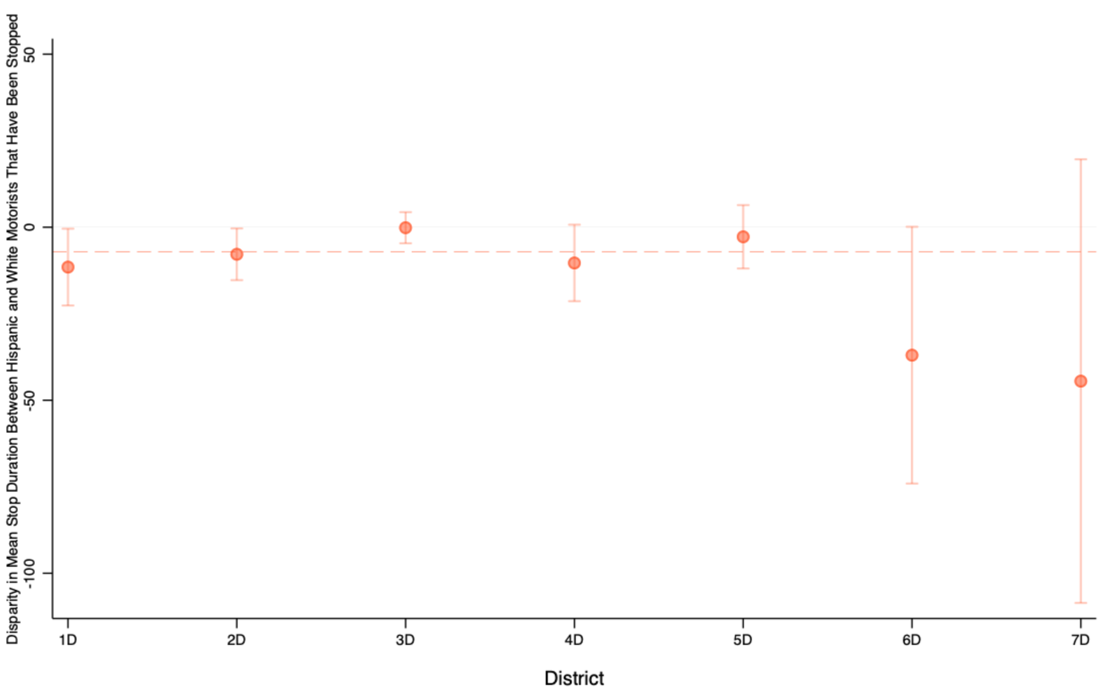
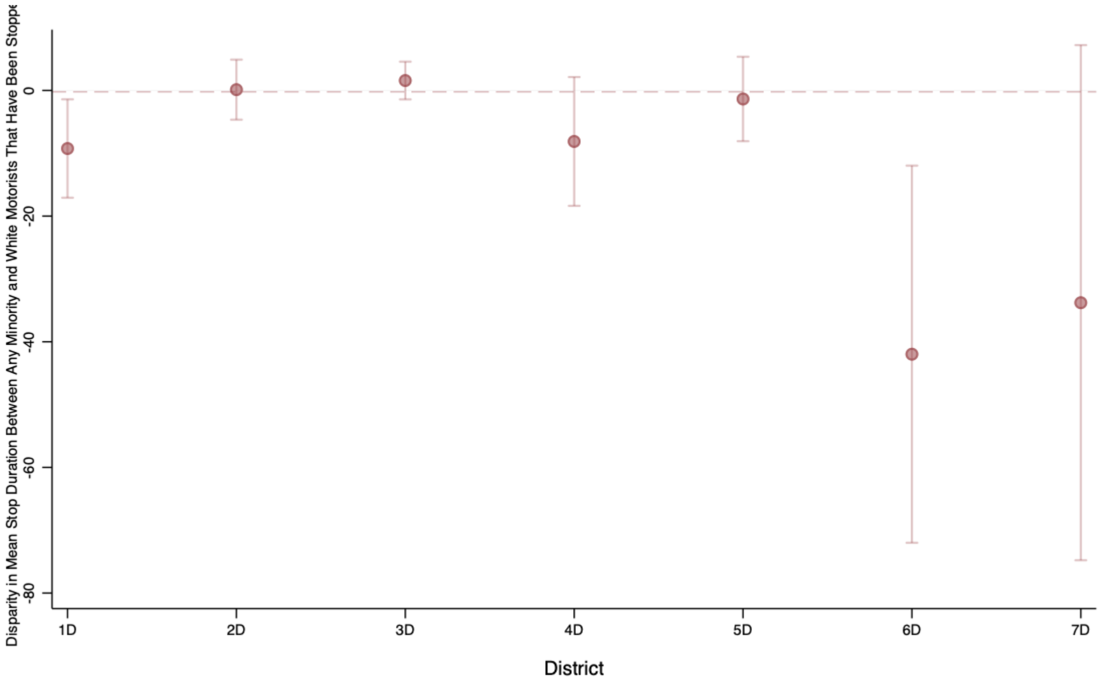


Figure 4. 27: Analysis of Stop Duration by District for Non-White Individuals, Three-Year Aggregate



V. ANALYSIS OF VEHICULAR SEARCHES, KPT HIT-RATE

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. [19]

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 WITH HIT-RATES BY YEAR

Figures 5.1 to 5.3 report results from applying the search hit-rate test to each of the four years between July 2019 through June 2023. 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 defined above. 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. In all periods, we estimate no significant differences in contraband finding rates 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

[19] 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.

Table D.1 of Appendix D for Figures 5.1 to 5.3. We also include estimates using arrest as the outcome variable, rather than contraband finding, in Table D.4 of Appendix D.

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

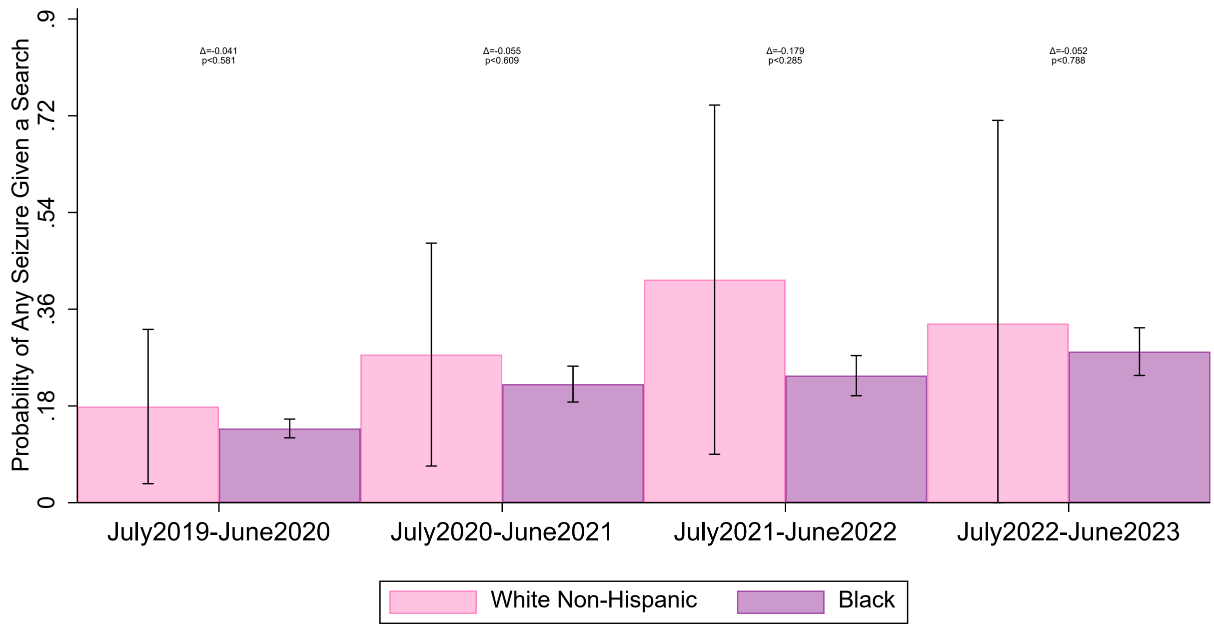


Figure 5. 2: Aggregate Hit-Rate Analysis by Year, Hispanic Individuals

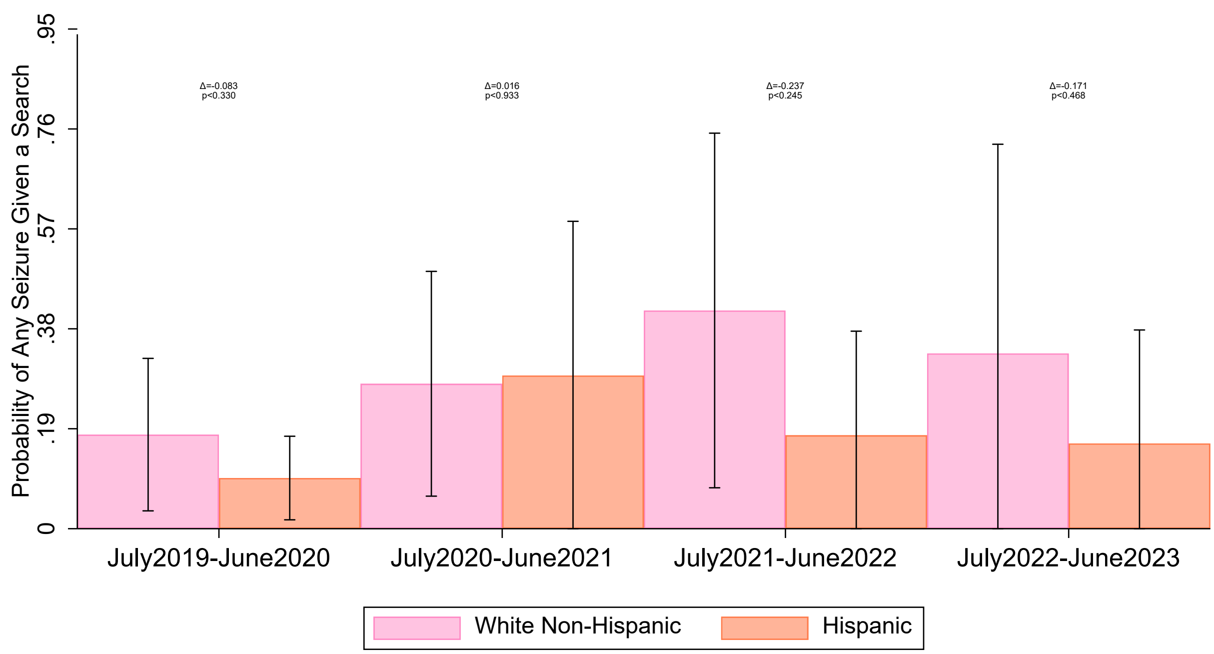
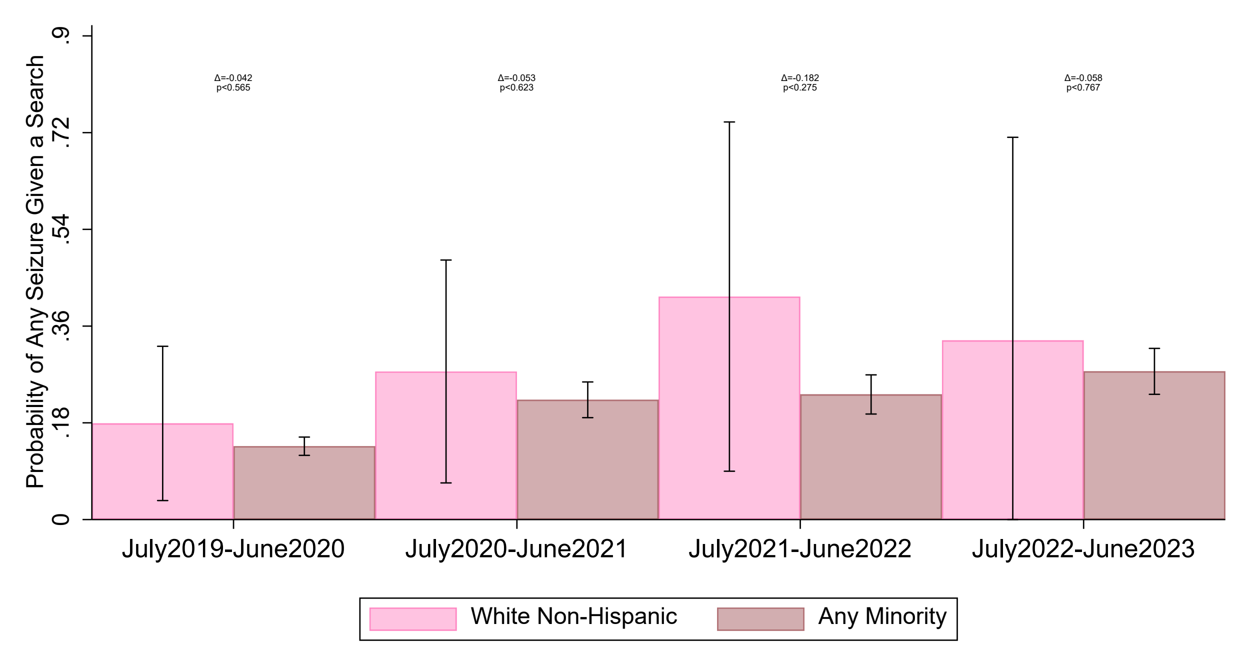


Figure 5. 3: Aggregate Hit-Rate Analysis by Year, Non-White Individuals



V.B: DISTRICT ANALYSIS WITH HIT-RATES BY YEAR

Figures 5.4 to 5.6 report the results of applying the hit-rate analysis to each of the seven patrol districts from July 2022 through June 2023. 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. Coefficient estimates, standard errors, and sample sizes are contained in Table D.2 of Appendix D for Figures 5.4 to 5.6. We also include estimates using arrest as the outcome variable, rather than contraband finding, in Table D.5 of Appendix D.

Figure 5. 4: Aggregate Hit-Rate Analysis by District, July 2022 to June 2023, Black Individuals

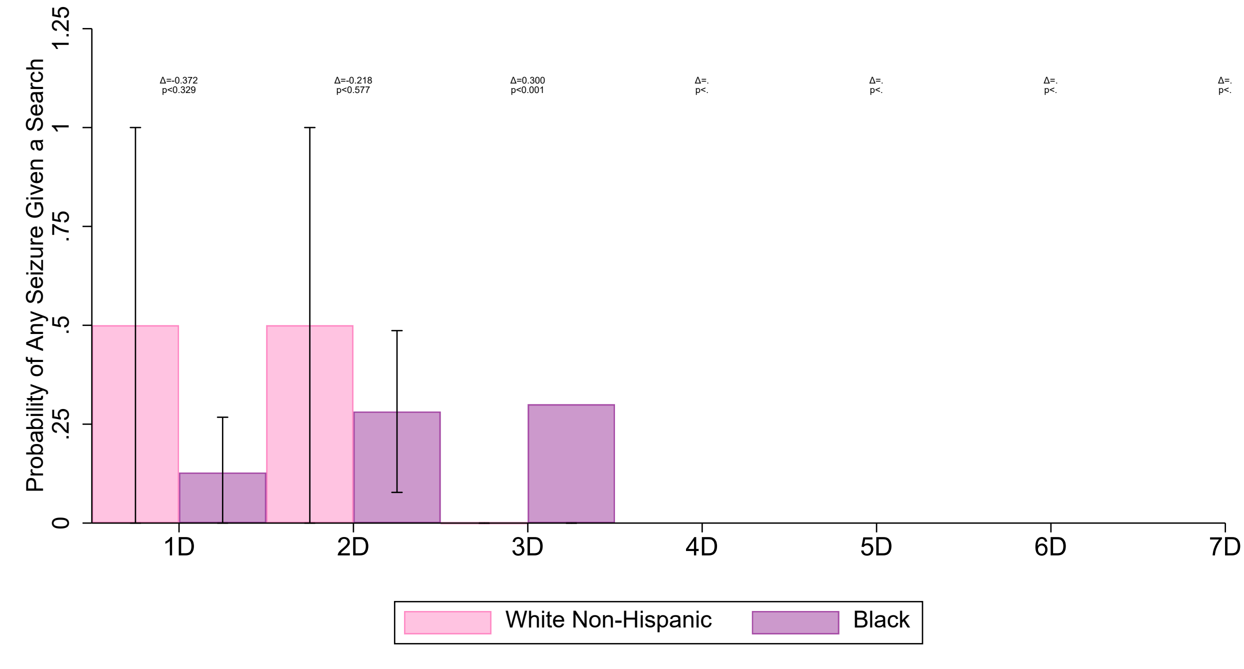


Figure 5. 5: Aggregate Hit-Rate Analysis by District, July 2022 to June 2023, Hispanic Individuals

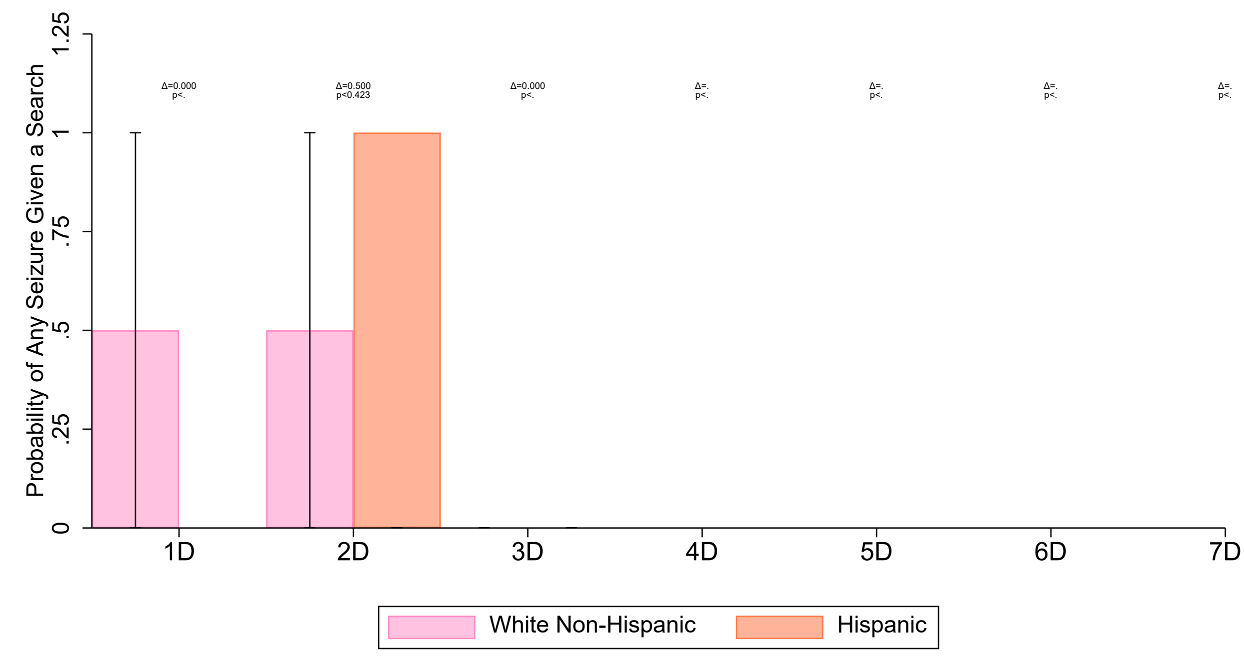
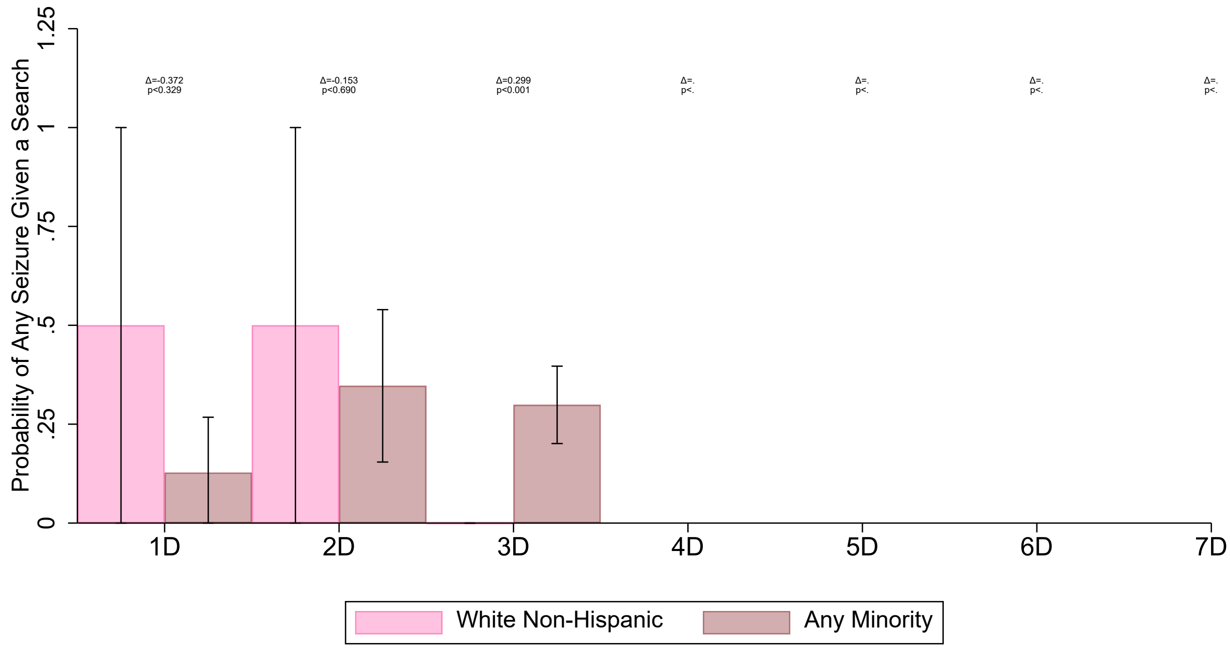


Figure 5. 6: Aggregate Hit-Rate Analysis by District, July 2022 to June 2023, Non-White Individuals



Figures 5.7 to 5.9 report the results of applying the hit-rate analysis to each of the seven patrol districts from July 2020 through June 2023. They present differences in hit rates for White individuals relative to Black, Hispanic, and any non-White individuals during this period. In District 5, there was statistically significant ($p<0.001$) evidence of a disparity of -66pp difference (-194%) between the success rate of searches of White and Black motorists. In District 5, there was also statistically significant ($p<0.022$) evidence of a disparity of -80pp difference (-400%) 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. We also include estimates using arrest as the outcome variable, rather than contraband finding, in Table D.6 of Appendix D.

Figure 5. 7: Aggregate Hit-Rate Analysis by District, July 2020 to June 2023, Black Individuals

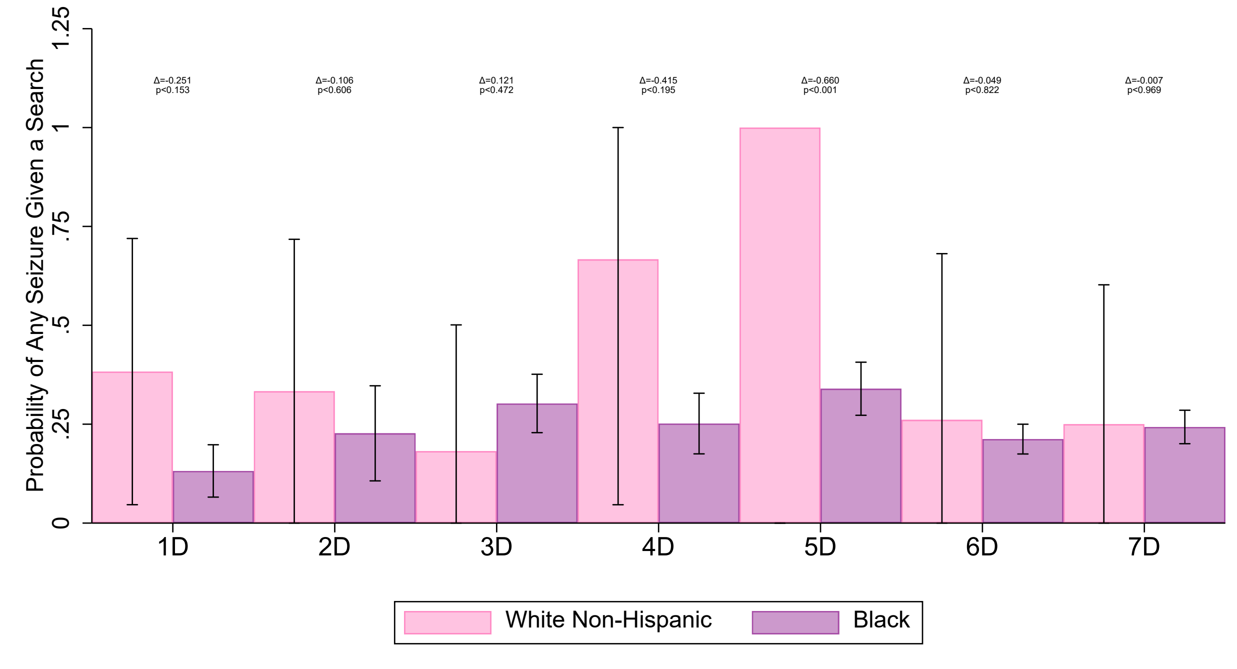


Figure 5. 8: Aggregate Hit-Rate Analysis by District, July 2020 to June 2023, Hispanic Individuals

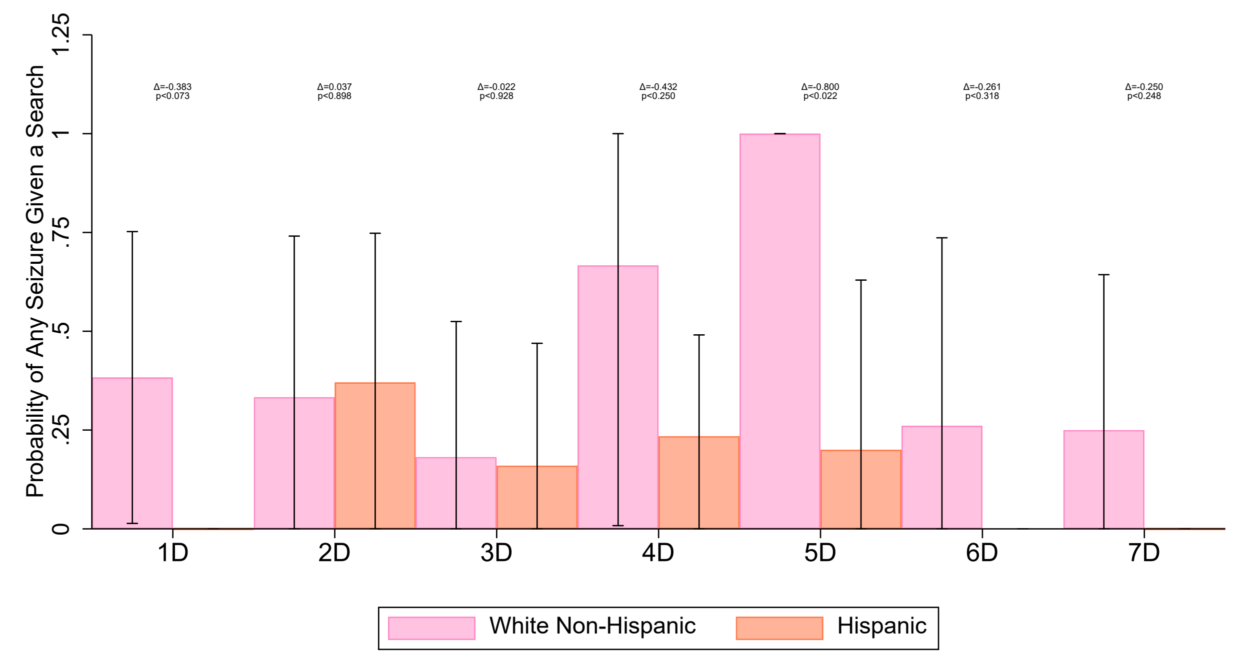
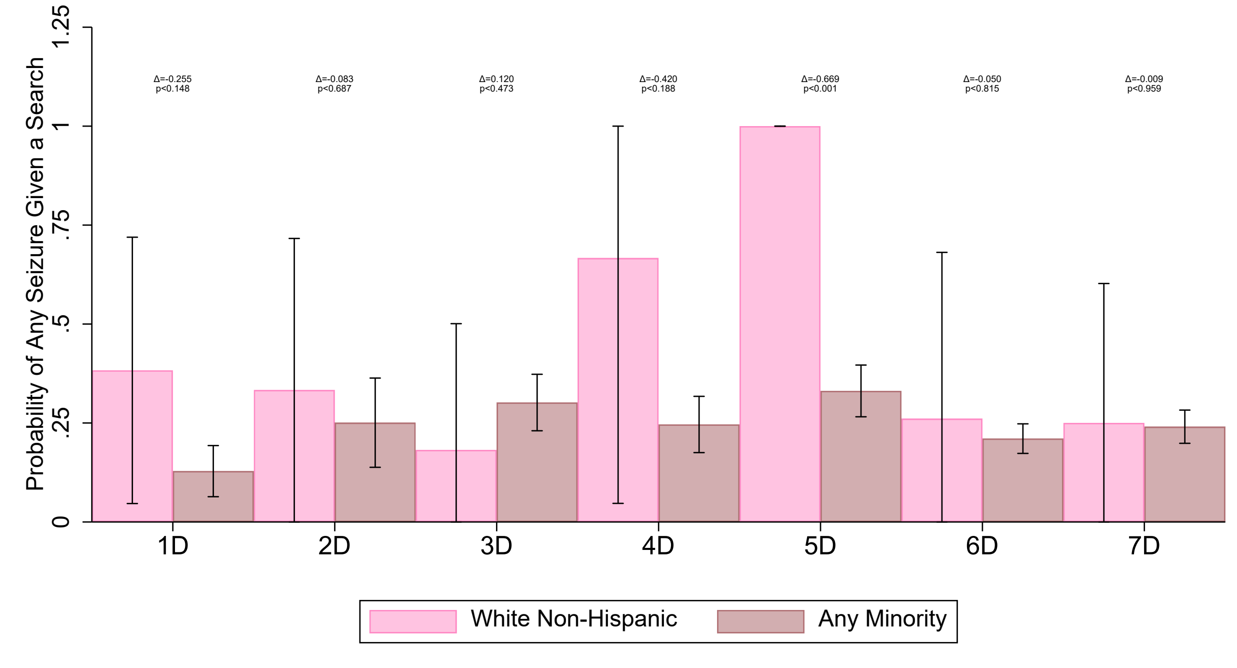


Figure 5. 9: Aggregate Hit-Rate Analysis by District, July 2020 to June 2023, Non-White Individuals



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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) $\frac{P(m|V)P(w|V\prime)}{P(w|V)P(m|V\prime)} = 1$; 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 identifiesK_{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.

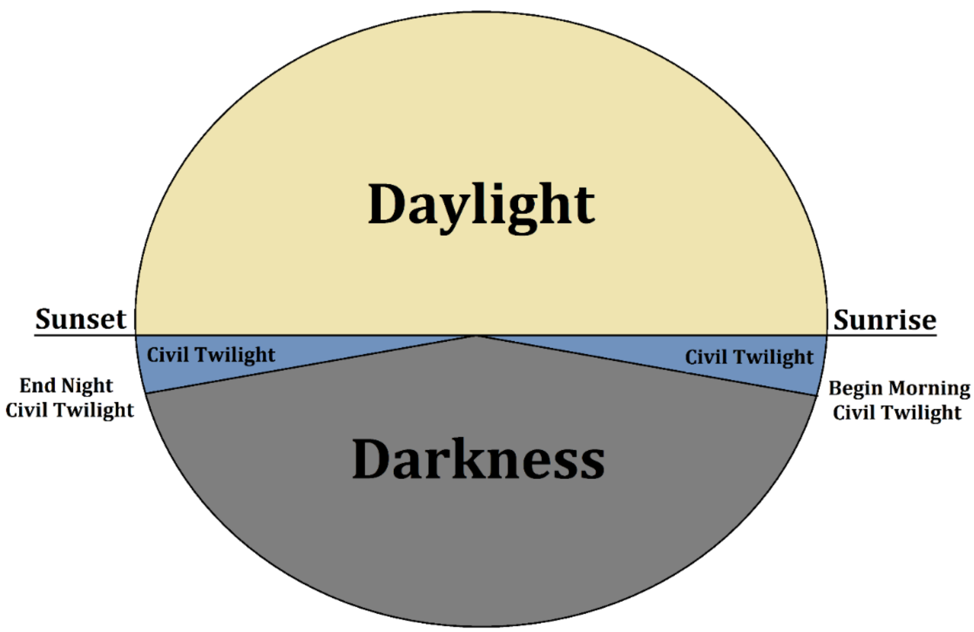
Assuming that the assumptions outlined above hold, Equation 4 can be estimated using a linear probability model

$$1[minority_i] = \beta + \delta 1[daylight_i] + \mu_i \tag{4}$$

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 CONDITIONAL OUTCOME 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 HIT-RATE TEST

The logic of the hit-rate test follows from a simplified game-theoretic exposition. In the absence of disparate treatment, the costs of searching different groups of 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.

$$P(H = 1|m, S) = P(H = 1|S) \; \forall \; r, c \qquad (9)$$

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=
7/2022- 6/2023	Black vs. White	0.0107124	0.0119832	0.3720919	0.8077319	9,351
7/2022- 6/2023	Hispanic vs. White	0.0363964	0.0272949	0.1836756	0.3283192	2,658
7/2022- 6/2023	Any Minority vs. White	0.0112796	0.0109653	0.3044992	0.8293169	10,533
7/2021- 6/2022	Black vs. White	-0.0007927	0.0138359	0.9543496	0.7834329	10,277
7/2021- 6/2022	Hispanic vs. White	-0.0626999	0.0216939	0.0042024	0.2772964	3,076
7/2021- 6/2022	Any Minority vs. White	-0.0052602	0.0128197	0.6818721	0.8074051	11,553
7/2020- 6/2021	Black vs. White	-0.0143449	0.0124898	0.2516913	0.8006873	9,377
7/2020- 6/2021	Hispanic vs. White	-0.0025374	0.0231146	0.9126824	0.3053892	2,700
7/2020- 6/2021	Any Minority vs. White	-0.0100029	0.0110632	0.366657	0.8235443	10,575
7/2019- 6/2020	Black vs. White	-0.0595223	0.0118682	9.21E-07	0.8070221	13,700
7/2019- 6/2020	Hispanic vs. White	-0.0268457	0.0188076	0.1547163	0.2693157	3,655
7/2019- 6/2020	Any Minority vs. White	-0.0498334	0.0103632	2.44E-06	0.826762	15,268
7/2019- 6/2023 (All)	Black vs. White	-0.0208455	0.0064454	0.0012543	0.8001412	42,705
7/2019- 6/2023 (All)	Hispanic vs. White	-0.0158235	0.0113873	0.1649774	0.2925825	12,089
7/2019- 6/2023 (All)	Any Minority vs. White	-0.0173728	0.0057558	0.0025968	0.8219743	47,929

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

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
7/2022- 6/2023	Black vs. White	0.0006477	0.0135481	0.9619008	0.7839971	7,284
7/2022- 6/2023	Hispanic vs. White	0.018146	0.0283756	0.523138	0.3021638	2,235
7/2022- 6/2023	Any Minority vs. White	0.0020289	0.0125621	0.871807	0.8089293	8,229
7/2021- 6/2022	Black vs. White	-0.0092247	0.0149248	0.5370114	0.7714442	8,106
7/2021- 6/2022	Hispanic vs. White	-0.0770708	0.0239604	0.0014821	0.2615765	2,519
7/2021- 6/2022	Any Minority vs. White	-0.0151187	0.0138734	0.2767257	0.7966514	9,107
7/2020- 6/2021	Black vs. White	-0.0267101	0.0140047	0.0575008	0.7896769	6,919
7/2020- 6/2021	Hispanic vs. White	-0.0105136	0.0249965	0.6744443	0.2870855	2,055
7/2020- 6/2021	Any Minority vs. White	-0.019797	0.0123248	0.1093163	0.8134064	7,790
7/2019- 6/2020	Black vs. White	-0.0637723	0.0134542	3.36E-06	0.7823014	9,876
7/2019- 6/2020	Hispanic vs. White	-0.0416773	0.021209	0.050554	0.251845	2,890
7/2019- 6/2020	Any Minority vs. White	-0.053731	0.0118641	8.67E-06	0.8056865	11,066
7/2019- 6/2023 (All)	Black vs. White	-0.0279906	0.0071025	0.0000861	0.7815398	32,185
7/2019- 6/2023 (All)	Hispanic vs. White	-0.0300061	0.0123529	0.0153252	0.2736064	9,699
7/2019- 6/2023 (All)	Any Minority vs. White	-0.0242581	0.0063903	0.0001546	0.8058191	36,192

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

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
7/2022- 6/2023	Black vs. White	0.0108497	0.0119889	0.36623	0.8077319	9,351
7/2022- 6/2023	Hispanic vs. White	0.0289642	0.0273161	0.29008	0.3283192	2,658
7/2022- 6/2023	Any Minority vs. White	0.0110796	0.0109971	0.31454	0.8293169	10,533
7/2021- 6/2022	Black vs. White	-0.0002951	0.0137396	0.98288	0.7834329	10,277
7/2021- 6/2022	Hispanic vs. White	-0.0586729	0.0206564	0.00489	0.2772964	3,076
7/2021- 6/2022	Any Minority vs. White	-0.0045579	0.0126714	0.71933	0.8074051	11,553
7/2020- 6/2021	Black vs. White	-0.0143249	0.0124443	0.25063	0.8006873	9,377
7/2020- 6/2021	Hispanic vs. White	0.001965	0.0234981	0.93343	0.3053892	2,700
7/2020- 6/2021	Any Minority vs. White	-0.009833	0.0110274	0.37329	0.8235443	10,575
7/2019- 6/2020	Black vs. White	-0.0608506	0.0119091	5.84E-07	0.8070221	13,700
7/2019- 6/2020	Hispanic vs. White	-0.0318144	0.0180795	0.07968	0.2693157	3,655
7/2019- 6/2020	Any Minority vs. White	-0.0513758	0.0103921	1.29E-06	0.826762	15,268
7/2019- 6/2023 (All)	Black vs. White	-0.0211066	0.0064649	0.00113	0.8001412	42,705
7/2019- 6/2023 (All)	Hispanic vs. White	-0.0164604	0.0111951	0.1418	0.2925825	12,089
7/2019- 6/2023 (All)	Any Minority vs. White	-0.0177119	0.0057699	0.00219	0.8219743	47,929

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 2023	Black vs. White	0.0386905	0.0437179	0.3770963	0.7961432	1,414
Spring 2023	Hispanic vs. White	0.1231644	0.1010787	0.225275	0.2506329	385
Spring 2023	Any Minority vs. White	0.0455289	0.0408955	0.2667329	0.81442	1,556
Fall 2022	Black vs. White	0.056523	0.0436205	0.1963249	0.7953911	1,412
Fall 2022	Hispanic vs. White	0.0638025	0.0975464	0.5140595	0.3792373	465
Fall 2022	Any Minority vs. White	0.0469229	0.0387129	0.2266854	0.8218845	1,624
Spring 2022	Black vs. White	-0.0908613	0.05016	0.0713089	0.8215613	1,323
Spring 2022	Hispanic vs. White	-0.1120201	0.1063763	0.2944672	0.2878338	324
Spring 2022	Any Minority vs. White	-0.0805513	0.0446213	0.0722478	0.8396794	1,473
Fall 2021	Black vs. White	-0.0297329	0.0554046	0.5920216	0.7642024	1,267
Fall 2021	Hispanic vs. White	-0.0431887	0.0967356	0.6559952	0.3066362	430
Fall 2021	Any Minority vs. White	-0.0338728	0.0496254	0.4955401	0.7941576	1,453
Spring 2021	Black vs. White	-0.0520188	0.0411661	0.207578	0.8316062	1,544
Spring 2021	Hispanic vs. White	-0.1210656	0.1117825	0.2807184	0.3211488	383
Spring 2021	Any Minority vs. White	-0.0451329	0.0365512	0.2180881	0.8503166	1,737
Fall 2020	Black vs. White	-0.0620807	0.0543256	0.2544242	0.7902208	1,260
Fall 2020	Hispanic vs. White	-0.2486329	0.1506037	0.101534	0.3179487	386
Fall 2020	Any Minority vs. White	-0.0628847	0.0492012	0.2025562	0.8152778	1,430
Spring 2020	Black vs. White	0.0063534	0.0461807	0.8906837	0.7643865	1,842
Spring 2020	Hispanic vs. White	0.0368985	0.0726337	0.6122044	0.2465278	574
Spring 2020	Any Minority vs. White	0.0155311	0.0430185	0.7183645	0.7902368	2,067
Fall 2019	Black vs. White	-0.0367522	0.0336601	0.2760557	0.8351477	1,919
Fall 2019	Hispanic vs. White	0.1113207	0.101413	0.2742489	0.2689655	434
Fall 2019	Any Minority vs. White	-0.0300958	0.0320111	0.3481098	0.8495743	2,104
ALL	Black vs. White	-0.0136521	0.0158958	0.3906176	0.8007771	11,981
ALL	Hispanic vs. White	0.0072502	0.0335286	0.8288624	0.2963504	3,382
ALL	Any Minority vs. White	-0.0104398	0.0143552	0.4672337	0.8223892	13,444

Table B.5: Solar Visibility Analysis by District and Race/Ethnicity (July 2022 to June 2023)

District	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	-0.0319742	0.020121	0.119913	0.9763637	466
7D	Hispanic vs. White	-0.0273727	0.3265727	0.934707	0.5	20
7D	Any Minority vs. White	-0.0301631	0.019289	0.1255626	0.9770723	482
6D	Black vs. White	0.0195098	0.0090458	0.0372462	0.9598811	1,191
6D	Hispanic vs. White	0.145957	0.1538103	0.3529586	0.4653465	87
6D	Any Minority vs. White	0.019066	0.0090113	0.0408011	0.9615111	1,243
5D	Black vs. White	0.0449331	0.0145339	0.0035725	0.8820084	2,158
5D	Hispanic vs. White	0.0628046	0.0651997	0.3412024	0.438247	434
5D	Any Minority vs. White	0.0393843	0.0128114	0.0037462	0.8935447	2,382
4D	Black vs. White	0.0843399	0.0288371	0.0055949	0.8497854	844
4D	Hispanic vs. White	0.1203922	0.0805632	0.1431236	0.5820895	306
4D	Any Minority vs. White	0.0655513	0.0237423	0.0085817	0.8784722	1,041
3D	Black vs. White	-0.0056533	0.0287958	0.8453273	0.7228311	1,962
3D	Hispanic vs. White	0.0124912	0.0495169	0.8021979	0.2642424	739
3D	Any Minority vs. White	-0.0032704	0.0277144	0.9066419	0.7580709	2,252
2D	Black vs. White	0.0476973	0.0396201	0.2358973	0.5908762	1,241
2D	Hispanic vs. White	-0.0348849	0.0374192	0.3572398	0.1905444	629
2D	Any Minority vs. White	0.0272175	0.0372094	0.4688645	0.64599	1,433
1D	Black vs. White	0.0173541	0.0298995	0.5648105	0.7963508	1,489
1D	Hispanic vs. White	0.2384494	0.0557452	0.0001278	0.3175542	439
1D	Any Minority vs. White	0.0400233	0.0283456	0.1655027	0.8215575	1,700
ALL	Black vs. White	0.0107124	0.0119832	0.3720919	0.8077319	9,351
ALL	Hispanic vs. White	0.0363964	0.0272949	0.1836756	0.3283192	2,658
ALL	Any Minority vs. White	0.0112796	0.0109653	0.3044992	0.8293169	10,533

Table B.6: Solar Visibility Analysis by District and Race/Ethnicity (July 2020 to June 2023)

District	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	-0.01992	0.009264	0.033496	0.979644	1,740
7D	Hispanic vs. White	-0.04412	0.320182	0.891311	0.411765	56
7D	Any Minority vs. White	-0.01898	0.009008	0.037112	0.980119	1,782
6D	Black vs. White	-0.00319	0.005848	0.585803	0.972233	4,803
6D	Hispanic vs. White	-0.11959	0.094668	0.210213	0.511327	273
6D	Any Minority vs. White	-0.00326	0.005731	0.570987	0.973251	4,988
5D	Black vs. White	0.045115	0.010826	5.74E-05	0.896329	5,567
5D	Hispanic vs. White	0.088234	0.046968	0.062832	0.41991	971
5D	Any Minority vs. White	0.041175	0.009901	0.000059	0.904896	6,060
4D	Black vs. White	0.030907	0.018493	0.097198	0.842449	2,234
4D	Hispanic vs. White	-0.01922	0.046404	0.679553	0.584052	851
4D	Any Minority vs. White	0.017641	0.01473	0.233329	0.874062	2,789
3D	Black vs. White	0.021213	0.017288	0.222132	0.710241	6,096
3D	Hispanic vs. White	-0.0052	0.02351	0.825184	0.277615	2,415
3D	Any Minority vs. White	0.016339	0.015288	0.287248	0.750411	7,060
2D	Black vs. White	0.045978	0.019839	0.02214	0.523286	4,642
2D	Hispanic vs. White	-0.03835	0.017054	0.026383	0.182339	2,710
2D	Any Minority vs. White	0.026272	0.018693	0.1624	0.602165	5,550
1D	Black vs. White	0.027525	0.01806	0.130037	0.788084	3,923
1D	Hispanic vs. White	0.152783	0.034592	2.29E-05	0.277692	1,152
1D	Any Minority vs. White	0.036888	0.016571	0.027816	0.812275	4,432
ALL	Black vs. White	-0.00142	0.007379	0.847674	0.796894	29,005
ALL	Hispanic vs. White	-0.01096	0.014192	0.440065	0.30254	8,434
ALL	Any Minority vs. White	-0.00124	0.006718	0.853634	0.819741	32,661

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=
7/2022- 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
7/2019- 6/2023 (All)	Black vs. White	0.0612318	0.0015438	0	0.0632324	153,543
7/2019- 6/2023 (All)	Hispanic vs. White	0.0365822	0.0019398	0	0.0632324	48,358
7/2019- 6/2023 (All)	Any Minority vs. White	0.0560418	0.0014249	0	0.0632324	175,091

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

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
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	5E-13	0.6594633	16,232
7/2019- 6/2020	Any Minority vs. White	0.0001072	0.007438	0.9885007	0.6594633	59,613
7/2019- 6/2023 (All)	Black vs. White	0.0234044	0.004243	3.66E-08	0.6695058	141,702
7/2019- 6/2023 (All)	Hispanic vs. White	0.0688659	0.0050497	0	0.6695058	46,896
7/2019- 6/2023 (All)	Any Minority vs. White	0.0292534	0.0040498	5.89E-13	0.6695058	162,195

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

Period	Comparison	B=	SE=	P=	Y_Mean=	N=
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
7/2019- 6/2023 (All)	Black vs. White	0.5382429	0.9637355	0.5765321	41.6334	153,543
7/2019- 6/2023 (All)	Hispanic vs. White	-4.854444	1.302752	0.000197	41.6334	48,358
7/2019- 6/2023 (All)	Any Minority vs. White	0.1254146	0.9301816	0.8927536	41.6334	175,091

Table C.4: Stop Disposition Test for Decision to Arrest by Year and Race/Ethnicity (July 2022 to June 2023)

District	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	0.0800525	0.0434286	0.0670995	0.1664859	1,662
7D	Hispanic vs. White	-0.0143735	0.1104747	0.8969565	0.1664859	93
7D	Any Minority vs. White	0.0838443	0.0424172	0.0497676	0.1664859	1,725
6D	Black vs. White	0.0623887	0.0096219	9.68E-10	0.0707677	3,570
6D	Hispanic vs. White	0.033885	0.0193411	0.0831109	0.0707677	309
6D	Any Minority vs. White	0.0616301	0.0095561	1.16E-09	0.0707677	3,748
5D	Black vs. White	0.0184158	0.0045809	0.0000883	0.0386989	6,248
5D	Hispanic vs. White	0.0169429	0.0072348	0.0205395	0.0386989	1,634
5D	Any Minority vs. White	0.0192051	0.0045273	0.0000368	0.0386989	7,268
4D	Black vs. White	0.0556106	0.010808	0.000000742	0.0765969	2,762
4D	Hispanic vs. White	0.0394075	0.0122399	0.0015564	0.0765969	1,111
4D	Any Minority vs. White	0.0535442	0.0100886	0.00000035	0.0765969	3,475
3D	Black vs. White	0.0324122	0.0038139	1.02E-14	0.0349206	6,436
3D	Hispanic vs. White	0.0192517	0.0059564	0.0014957	0.0349206	2,539
3D	Any Minority vs. White	0.0313087	0.0035585	1.67E-15	0.0349206	7,572
2D	Black vs. White	0.0480753	0.0044158	3.58E-21	0.0394997	5,580
2D	Hispanic vs. White	0.0547913	0.0088993	5.57E-09	0.0394997	3,236
2D	Any Minority vs. White	0.0468829	0.0041542	2.59E-22	0.0394997	6,639
1D	Black vs. White	0.0249289	0.0052555	0.00000449	0.0344491	4,794
1D	Hispanic vs. White	0.0168919	0.0085084	0.0488063	0.0344491	1,366
1D	Any Minority vs. White	0.0234738	0.0050318	0.00000629	0.0344491	5,451
ALL	Black vs. White	0.0433567	0.0024024	0	0.04901	31,052
ALL	Hispanic vs. White	0.0308767	0.0036663	1.37E-16	0.04901	10,292
ALL	Any Minority vs. White	0.0416263	0.0022901	0	0.04901	35,878

Table C.5: Stop Disposition Test for Decision to Arrest by Year and Race/Ethnicity (July 2020 to June 2023)

District	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	0.0337029	0.025392	0.1850161	0.1769491	6,065
7D	Hispanic vs. White	-0.014796	0.0489857	0.762959	0.1769491	278
7D	Any Minority vs. White	0.0341055	0.025241	0.1772468	0.1769491	6,225
6D	Black vs. White	0.0779869	0.0092714	4.21E-16	0.1202148	15,965
6D	Hispanic vs. White	0.0243433	0.0130235	0.0624756	0.1202148	1,016
6D	Any Minority vs. White	0.0765126	0.0091504	6.11E-16	0.1202148	16,648
5D	Black vs. White	0.0316861	0.0036469	5.31E-17	0.0522399	16,318
5D	Hispanic vs. White	0.0191868	0.0050722	0.0001762	0.0522399	3,840
5D	Any Minority vs. White	0.0308784	0.0034963	1.76E-17	0.0522399	18,651
4D	Black vs. White	0.0486705	0.0051975	2.56E-19	0.0670446	8,122
4D	Hispanic vs. White	0.0520791	0.0064848	7.33E-15	0.0670446	3,527
4D	Any Minority vs. White	0.049393	0.0048282	1.92E-22	0.0670446	10,340
3D	Black vs. White	0.0345392	0.0023611	0	0.0369382	17,993
3D	Hispanic vs. White	0.0278913	0.0041475	5.04E-11	0.0369382	7,311
3D	Any Minority vs. White	0.0327295	0.0021312	0	0.0369382	21,274
2D	Black vs. White	0.047939	0.0028178	0	0.0372361	19,191
2D	Hispanic vs. White	0.0412808	0.0044562	6.59E-19	0.0372361	11,975
2D	Any Minority vs. White	0.0417988	0.0024363	0	0.0372361	23,203
1D	Black vs. White	0.0282549	0.0033201	2.01E-16	0.0382037	12,390
1D	Hispanic vs. White	0.0174289	0.0057421	0.0025346	0.0382037	3,611
1D	Any Minority vs. White	0.0261419	0.0031918	2.17E-15	0.0382037	14,089
ALL	Black vs. White	0.0608611	0.0019616	0	0.0614056	96,044
ALL	Hispanic vs. White	0.0340473	0.0022316	0	0.0614056	31,565
ALL	Any Minority vs. White	0.0555132	0.0017736	0	0.0614056	110,430

Table C.6: Stop Disposition Test for Decision to Ticket by Year and Race/Ethnicity (July 2022 to June 2023)

District	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	-0.0332209	0.0803717	0.6799068	0.6155392	1,337
7D	Hispanic vs. White	0.0683872	0.1547802	0.6605144	0.6155392	81
7D	Any Minority vs. White	-0.0297857	0.080596	0.7121897	0.6155392	1,387
6D	Black vs. White	-0.0448692	0.0286273	0.118924	0.7247783	3,196
6D	Hispanic vs. White	0.0097991	0.0392014	0.8031752	0.7247783	304
6D	Any Minority vs. White	-0.0418541	0.0281981	0.1396175	0.7247783	3,364
5D	Black vs. White	-0.002463	0.0172655	0.8867394	0.720506	6,030
5D	Hispanic vs. White	0.1179996	0.0209039	8.59E-08	0.720506	1,598
5D	Any Minority vs. White	0.015046	0.0169645	0.376427	0.720506	7,011
4D	Black vs. White	-0.0395171	0.0219882	0.0741108	0.603103	2,597
4D	Hispanic vs. White	0.016661	0.0279325	0.5517079	0.603103	1,049
4D	Any Minority vs. White	-0.0261317	0.0216332	0.2287767	0.603103	3,253
3D	Black vs. White	-0.0088779	0.0148569	0.5509435	0.6745213	6,138
3D	Hispanic vs. White	0.0364579	0.0208892	0.0828892	0.6745213	2,494
3D	Any Minority vs. White	-0.0023078	0.0143012	0.8719954	0.6745213	7,226
2D	Black vs. White	0.0420702	0.013587	0.0023004	0.6436595	5,425
2D	Hispanic vs. White	0.040206	0.0212617	0.0603974	0.6436595	3,177
2D	Any Minority vs. White	0.0399513	0.0132821	0.0030376	0.6436595	6,441
1D	Black vs. White	0.0277745	0.0162493	0.0892591	0.7573208	4,609
1D	Hispanic vs. White	0.0713686	0.0239714	0.0033611	0.7573208	1,339
1D	Any Minority vs. White	0.0165352	0.0163371	0.3129416	0.7573208	5,249
ALL	Black vs. White	0.0224946	0.0075861	0.0030861	0.6857246	29,332
ALL	Hispanic vs. White	0.0664626	0.0099394	3.92E-11	0.6857246	10,046
ALL	Any Minority vs. White	0.0246301	0.0073391	0.0008162	0.6857246	33,931

Table C.7: Stop Disposition Test for Decision to Ticket by Year and Race/Ethnicity (July 2020 to June 2023)

District	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	-0.0892998	0.0456214	0.0508606	0.5938928	4,454
7D	Hispanic vs. White	0.0754219	0.0898298	0.4024819	0.5938928	220
7D	Any Minority vs. White	-0.0856567	0.0455411	0.0605773	0.5938928	4,584
6D	Black vs. White	-0.0596351	0.0174053	0.000662	0.7375817	14,013
6D	Hispanic vs. White	-0.0125806	0.0237405	0.5965266	0.7375817	971
6D	Any Minority vs. White	-0.0568211	0.0172785	0.0010776	0.7375817	14,651
5D	Black vs. White	-0.0037114	0.0118382	0.7540249	0.6882595	15,357
5D	Hispanic vs. White	0.082406	0.0156404	0.000000216	0.6882595	3,734
5D	Any Minority vs. White	0.0071611	0.0117617	0.542907	0.6882595	17,598
4D	Black vs. White	0.0062787	0.0142064	0.6587061	0.5829467	7,554
4D	Hispanic vs. White	0.0744631	0.0165275	0.00000831	0.5829467	3,326
4D	Any Minority vs. White	0.0226541	0.0138043	0.1014032	0.5829467	9,590
3D	Black vs. White	0.0218108	0.0097612	0.0258931	0.6684644	17,183
3D	Hispanic vs. White	0.0590344	0.0133898	0.0000129	0.6684644	7,155
3D	Any Minority vs. White	0.0287638	0.0095119	0.0026222	0.6684644	20,334
2D	Black vs. White	0.0413658	0.0077941	0.000000168	0.6402342	18,612
2D	Hispanic vs. White	0.0656292	0.0113669	1.39E-08	0.6402342	11,739
2D	Any Minority vs. White	0.0507914	0.0072615	8.59E-12	0.6402342	22,475
1D	Black vs. White	0.0148727	0.009719	0.1265821	0.7577563	11,710
1D	Hispanic vs. White	0.0773161	0.0153101	0.000000633	0.7577563	3,507
1D	Any Minority vs. White	0.0146765	0.0096799	0.1301018	0.7577563	13,350
ALL	Black vs. White	0.0427298	0.0048512	1.96E-18	0.6751905	88,883
ALL	Hispanic vs. White	0.0711034	0.0061578	3.58E-30	0.6751905	30,664
ALL	Any Minority vs. White	0.0458742	0.0046877	2.49E-22	0.6751905	102,582

Table C.8: Stop Disposition Test for Stop Duration by Year and Race/Ethnicity (July 2022 to June 2023)

District	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	-104.4509	65.57574	0.113136	94.16757	1,662
7D	Hispanic vs. White	-103.5597	94.32727	0.2770414	94.16757	93
7D	Any Minority vs. White	-105.4404	65.70545	0.110486	94.16757	1,725
6D	Black vs. White	-24.12773	26.15108	0.3575319	102.934	3,570
6D	Hispanic vs. White	-29.52402	31.30838	0.3481471	102.934	309
6D	Any Minority vs. White	-23.7753	25.81826	0.3584459	102.934	3,748
5D	Black vs. White	3.280716	4.878378	0.5022053	43.4172	6,248
5D	Hispanic vs. White	1.64684	7.269719	0.8211029	43.4172	1,634
5D	Any Minority vs. White	3.670907	4.862442	0.4513544	43.4172	7,268
4D	Black vs. White	-14.35247	11.56161	0.2162023	68.82322	2,762
4D	Hispanic vs. White	-20.34328	11.64393	0.0825483	68.82322	1,111
4D	Any Minority vs. White	-14.64233	11.36006	0.199205	68.82322	3,475
3D	Black vs. White	1.942719	3.658878	0.5961517	46.60247	6,436
3D	Hispanic vs. White	-4.366565	4.966692	0.3806444	46.60247	2,539
3D	Any Minority vs. White	0.8938447	3.512609	0.7994475	46.60247	7,572
2D	Black vs. White	-7.556801	6.629656	0.2559916	83.41264	5,580
2D	Hispanic vs. White	-19.96114	7.691428	0.0103147	83.41264	3,236
2D	Any Minority vs. White	-10.10863	5.977371	0.0926735	83.41264	6,639
1D	Black vs. White	-21.84263	8.192158	0.0084233	69.81329	4,794
1D	Hispanic vs. White	-13.44055	12.57663	0.2868082	69.81329	1,366
1D	Any Minority vs. White	-20.68701	8.211441	0.0126985	69.81329	5,451
ALL	Black vs. White	-3.795481	3.34377	0.2565703	70.90073	31,052
ALL	Hispanic vs. White	-15.45202	3.738662	0.000039	70.90073	10,292
ALL	Any Minority vs. White	-5.251963	3.187819	0.0997221	70.90073	35,878

Table C.9: Stop Disposition Test for Stop Duration by Year and Race/Ethnicity (July 2020 to June 2023)

District	Comparison	B=	SE=	P=	Y_Mean=	N=
7D	Black vs. White	-34.30209	20.86253	0.1007668	58.19889	6,065
7D	Hispanic vs. White	-44.47758	32.70709	0.1755423	58.19889	278
7D	Any Minority vs. White	-33.78213	20.91451	0.1068902	58.19889	6,225
6D	Black vs. White	-42.25282	15.41017	0.0063265	72.38669	15,965
6D	Hispanic vs. White	-36.97746	18.93025	0.0516149	72.38669	1,016
6D	Any Minority vs. White	-41.97985	15.31253	0.006333	72.38669	16,648
5D	Black vs. White	-1.353893	3.442619	0.6942854	35.67775	16,318
5D	Hispanic vs. White	-2.76422	4.674531	0.554594	35.67775	3,840
5D	Any Minority vs. White	-1.356547	3.430128	0.6926578	35.67775	18,651
4D	Black vs. White	-7.176237	5.367433	0.1818282	60.49955	8,122
4D	Hispanic vs. White	-10.32667	5.638246	0.0676308	60.49955	3,527
4D	Any Minority vs. White	-8.119129	5.22902	0.1211224	60.49955	10,340
3D	Black vs. White	1.89409	1.609975	0.239963	31.57809	17,993
3D	Hispanic vs. White	-0.1417111	2.29455	0.9507799	31.57809	7,311
3D	Any Minority vs. White	1.575829	1.531634	0.3040426	31.57809	21,274
2D	Black vs. White	-0.9425746	2.715392	0.7286457	60.04898	19,191
2D	Hispanic vs. White	-7.816895	3.810914	0.0407899	60.04898	11,975
2D	Any Minority vs. White	0.1251951	2.438652	0.9590769	60.04898	23,203
1D	Black vs. White	-8.989192	4.047132	0.0267878	50.06717	12,390
1D	Hispanic vs. White	-11.52323	5.661595	0.0423709	50.06717	3,611
1D	Any Minority vs. White	-9.24562	3.994967	0.0210531	50.06717	14,089
ALL	Black vs. White	0.4024356	1.441274	0.7800907	53.33528	96,044
ALL	Hispanic vs. White	-7.097031	1.852122	0.0001299	53.33528	31,565
ALL	Any Minority vs. White	-0.2249914	1.384348	0.8709016	53.33528	110,430

APPENDIX D: SEARCH ANALYSIS DATA TABLES

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

Period	Comparison	Race	Mean=	Upper_Bound=	Lower_Bound=	B_Difference=	P=	N=
7/2019- 6/2020	Black vs. White	White	0.1788321	0.3223656	0.0352986	-0.041	0.581	1,866
7/2019- 6/2020	Black vs. White	Black	0.1380596	0.15548	0.1206392	-0.041	0.581	1,866
7/2020- 6/2021	Black vs. White	White	0.2755102	0.482924	0.0680965	-0.055	0.609	724
7/2020- 6/2021	Black vs. White	Black	0.2206109	0.2540153	0.1872064	-0.055	0.609	724
7/2021- 6/2022	Black vs. White	White	0.4148936	0.7398521	0.0899352	-0.179	0.285	573
7/2021- 6/2022	Black vs. White	Black	0.2363725	0.273699	0.1990459	-0.179	0.285	573
7/2022- 6/2023	Black vs. White	White	0.3333333	0.7113899	0	-0.052	0.788	443
7/2022- 6/2023	Black vs. White	Black	0.2810545	0.3254111	0.2366979	-0.052	0.788	443
7/2019- 6/2020	Hispanic vs. White	White	0.1788321	0.3237908	0.0338734	-0.083	0.33	97
7/2019- 6/2020	Hispanic vs. White	Hispanic	0.0962963	0.1757743	0.0168183	-0.083	0.33	97
7/2020- 6/2021	Hispanic vs. White	White	0.2755102	0.4892144	0.061806	0.016	0.933	33
7/2020- 6/2021	Hispanic vs. White	Hispanic	0.2912621	0.5843821	0	0.016	0.933	33
7/2021- 6/2022	Hispanic vs. White	White	0.4148936	0.7520105	0.0777768	-0.237	0.245	27
7/2021- 6/2022	Hispanic vs. White	Hispanic	0.1775148	0.3755162	0	-0.237	0.245	27
7/2022- 6/2023	Hispanic vs. White	White	0.3333333	0.7309393	0	-0.171	0.468	20
7/2022- 6/2023	Hispanic vs. White	Hispanic	0.1621622	0.3777748	0	-0.171	0.468	20
7/2019- 6/2020	Any Minority vs. White	White	0.1788321	0.3223629	0.0353013	-0.042	0.565	1,934
7/2019- 6/2020	Any Minority vs. White	Any Minority	0.1364093	0.1534272	0.1193914	-0.042	0.565	1,934
7/2020- 6/2021	Any Minority vs. White	White	0.2755102	0.4829185	0.0681019	-0.053	0.623	738
7/2020- 6/2021	Any Minority vs. White	Any Minority	0.2228529	0.2560637	0.1896422	-0.053	0.623	738
7/2021- 6/2022	Any Minority vs. White	White	0.4148936	0.7398329	0.0899543	-0.182	0.275	593
7/2021- 6/2022	Any Minority vs. White	Any Minority	0.2328029	0.2692373	0.1963685	-0.182	0.275	593
7/2022- 6/2023	Any Minority vs. White	White	0.3333333	0.7113407	0	-0.058	0.767	470
7/2022- 6/2023	Any Minority vs. White	Any Minority	0.2757322	0.3184582	0.2330062	-0.058	0.767	470

Table D.2: Hit-Rate Analysis (Contraband) by District and Race/Ethnicity (July 2022 to June 2023)

District	Comparison	Race	Mean=	Upper_Bound=	Lower_Bound=	B_Difference=	P=	N=
1D	Black vs. White	White	0.5	1	0	-0.372	0.329	27
1D	Black vs. White	Black	0.1276596	0.2675497	0	-0.372	0.329	27
2D	Black vs. White	White	0.5	1	0	-0.218	0.577	23
2D	Black vs. White	Black	0.2820513	0.4865668	0.0775358	-0.218	0.577	23
3D	Black vs. White	White	8.49E-15	0	0	0.3	0.001	91
3D	Black vs. White	Black	0.3001133	0	0	0.3	0.001	91
4D	Black vs. White	White						47
4D	Black vs. White	Black						47
5D	Black vs. White	White						54
5D	Black vs. White	Black						54
6D	Black vs. White	White						122
6D	Black vs. White	Black						122
7D	Black vs. White	White						73
7D	Black vs. White	Black						73
1D	Hispanic vs. White	White						2
1D	Hispanic vs. White	Hispanic						2
2D	Hispanic vs. White	White						4
2D	Hispanic vs. White	Hispanic						4
3D	Hispanic vs. White	White						5
3D	Hispanic vs. White	Hispanic						5
4D	Hispanic vs. White	White						7
4D	Hispanic vs. White	Hispanic						7
5D	Hispanic vs. White	White						
5D	Hispanic vs. White	Hispanic						
6D	Hispanic vs. White	White						
6D	Hispanic vs. White	Hispanic						
7D	Hispanic vs. White	White						
7D	Hispanic vs. White	Hispanic						
1D	Any Minority vs. White	White	0.5	1	0	-0.372	0.329	27
1D	Any Minority vs. White	Any Minority	0.1276596	0.2675497	0	-0.372	0.329	27
2D	Any Minority vs. White	White	0.5	1	0	-0.153	0.69	28
2D	Any Minority vs. White	Any Minority	0.3469388	0.5395775	0.1543001	-0.153	0.69	28

Table D.2: Hit-Rate Analysis (Contraband) by District and Race/Ethnicity (July 2022 to June 2023)

District	Comparison	Race	Mean=	Upper_Bound=	Lower_Bound=	B_Difference=	P=	N=
3D	Any Minority vs. White	White	-3.94E-15	0	0	0.299	0.001	98
3D	Any Minority vs. White	Any Minority	0.2988625	0.3967007	0.2010242	0.299	0.001	98
4D	Any Minority vs. White	White						58
4D	Any Minority vs. White	Any Minority						58
5D	Any Minority vs. White	White						56
5D	Any Minority vs. White	Any Minority						56
6D	Any Minority vs. White	White						122
6D	Any Minority vs. White	Any Minority						122
7D	Any Minority vs. White	White						75
7D	Any Minority vs. White	Any Minority						75

Table D.3: Hit-Rate Analysis (Contraband) by District and Race/Ethnicity (July 2020 to June 2023)

District	Comparison	Race	Mean=	Upper_Bound=	Lower_Bound=	B_Difference=	P=	N=
1D	Black vs. White	White	0.3829787	0.719513	0.0464444	-0.251	0.153	133
1D	Black vs. White	Black	0.1317407	0.1979303	0.0655511	-0.251	0.153	133
2D	Black vs. White	White	0.3333333	0.7174572	0	-0.106	0.606	56
2D	Black vs. White	Black	0.2268431	0.3470485	0.1066378	-0.106	0.606	56
3D	Black vs. White	White	0.1818182	0.5010381	0	0.121	0.472	178
3D	Black vs. White	Black	0.3023824	0.3761761	0.2285887	0.121	0.472	178
4D	Black vs. White	White	0.6666667	1	0.0463139	-0.415	0.195	142
4D	Black vs. White	Black	0.2515779	0.3282514	0.1749044	-0.415	0.195	142
5D	Black vs. White	White	1	0	0	-0.66	0.001	216
5D	Black vs. White	Black	0.3396373	0.4067665	0.2725081	-0.66	0.001	216
6D	Black vs. White	White	0.2608696	0.6810994	0	-0.049	0.822	537
6D	Black vs. White	Black	0.2123026	0.249944	0.1746613	-0.049	0.822	537
7D	Black vs. White	White	0.25	0.6023965	0	-0.007	0.969	467
7D	Black vs. White	Black	0.2429433	0.2852282	0.2006584	-0.007	0.969	467
1D	Hispanic vs. White	White	0.3829787	0.7522234	0.0137341	-0.383	0.073	11
1D	Hispanic vs. White	Hispanic	5.55E-17	0	0	-0.383	0.073	11
2D	Hispanic vs. White	White	0.3333333	0.7407582	0	0.037	0.898	14
2D	Hispanic vs. White	Hispanic	0.3703704	0.7479396	0	0.037	0.898	14
3D	Hispanic vs. White	White	0.1818182	0.5246726	0	-0.022	0.928	14
3D	Hispanic vs. White	Hispanic	0.16	0.4695599	0	-0.022	0.928	14
4D	Hispanic vs. White	White	0.6666667	1	0.0081686	-0.432	0.25	16
4D	Hispanic vs. White	Hispanic	0.234375	0.4906409	0	-0.432	0.25	16
5D	Hispanic vs. White	White	1	1	0.9999999	-0.8	0.022	6
5D	Hispanic vs. White	Hispanic	0.2	0.6294145	0	-0.8	0.022	6
6D	Hispanic vs. White	White	0.2608696	0.7364773	0	-0.261	0.318	9
6D	Hispanic vs. White	Hispanic	0	0	0	-0.261	0.318	9
7D	Hispanic vs. White	White	0.25	0.6431468	0	-0.25	0.248	10
7D	Hispanic vs. White	Hispanic	-5.55E-17	0	0	-0.25	0.248	10
1D	Any Minority vs. White	White	0.3829787	0.7194564	0.0465011	-0.255	0.148	136
1D	Any Minority vs. White	Any Minority	0.1283587	0.192974	0.0637434	-0.255	0.148	136
2D	Any Minority vs. White	White	0.3333333	0.7162946	0	-0.083	0.687	67
2D	Any Minority vs. White	Any Minority	0.250774	0.3634808	0.1380672	-0.083	0.687	67

Table D.3: Hit-Rate Analysis (Contraband) by District and Race/Ethnicity (July 2020 to June 2023)

District	Comparison	Race	Mean=	Upper_Bound=	Lower_Bound=	B_Difference=	P=	N=
3D	Any Minority vs. White	White	0.1818182	0.5009326	0	0.12	0.473	189
3D	Any Minority vs. White	Any Minority	0.3017046	0.3730359	0.2303732	0.12	0.473	189
4D	Any Minority vs. White	White	0.6666667	1	0.0468602	-0.42	0.188	162
4D	Any Minority vs. White	Any Minority	0.2462562	0.3173447	0.1751677	-0.42	0.188	162
5D	Any Minority vs. White	White	1	1	0.999999	-0.669	0.001	224
5D	Any Minority vs. White	Any Minority	0.3310101	0.3963751	0.2656452	-0.669	0.001	224
6D	Any Minority vs. White	White	0.2608696	0.6810936	0	-0.05	0.815	541
6D	Any Minority vs. White	Any Minority	0.2105263	0.2478982	0.1731544	-0.05	0.815	541
7D	Any Minority vs. White	White	0.25	0.6023901	0	-0.009	0.959	471
7D	Any Minority vs. White	Any Minority	0.2406213	0.2825721	0.1986705	-0.009	0.959	471

Table D.4: Hit-Rate Analysis (Arrest) 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
7/2019- 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
7/2019- 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

Table D.5: Hit-Rate Analysis (Arrest) by District and Race/Ethnicity (July 2022 to June 2023)

District	Comparison	Race	B=	Upper_Bound=	Lower_Bound=	B_Difference=	P=	N=
1D	Black vs. White	White	0.5	1	0	0.245	0.524	27
1D	Black vs. White	Black	0.7446808	0.9268906	0.5624711	0.245	0.524	27
2D	Black vs. White	White	1	1	1	-0.385	0.003	23
2D	Black vs. White	Black	0.6153846	0.8372027	0.3935666	-0.385	0.003	23
3D	Black vs. White	White	0.5	1	0	-0.014	0.969	91
3D	Black vs. White	Black	0.4858437	0.5961342	0.3755532	-0.014	0.969	91
4D	Black vs. White	White		1				47
4D	Black vs. White	Black						47
5D	Black vs. White	White						54
5D	Black vs. White	Black						54
6D	Black vs. White	White						122
6D	Black vs. White	Black						122
7D	Black vs. White	White						73
7D	Black vs. White	Black						73
1D	Hispanic vs. White	White						2
1D	Hispanic vs. White	Hispanic						2
2D	Hispanic vs. White	White						4
2D	Hispanic vs. White	Hispanic						4
3D	Hispanic vs. White	White	0.5	1	0	0.167	0.791	5
3D	Hispanic vs. White	Hispanic	0.6666667	1	0	0.167	0.791	5
4D	Hispanic vs. White	White						7
4D	Hispanic vs. White	Hispanic						7
5D	Hispanic vs. White	White						
5D	Hispanic vs. White	Hispanic						
6D	Hispanic vs. White	White						
6D	Hispanic vs. White	Hispanic						
7D	Hispanic vs. White	White						
7D	Hispanic vs. White	Hispanic						
1D	Any Minority vs. White	White	0.5	1	0	0.245	0.524	27
1D	Any Minority vs. White	Any Minority	0.7446808	0.9268906	0.5624711	0.245	0.524	27
2D	Any Minority vs. White	White	1	1	1	-0.306	0.003	28
2D	Any Minority vs. White	Any Minority	0.6938776	0.8801987	0.5075564	-0.306	0.003	28

Table D.5: Hit-Rate Analysis (Arrest) by District and Race/Ethnicity (July 2022 to June 2023)

District	Comparison	Race	B=	Upper_Bound=	Lower_Bound=	B_Difference=	P=	N=
3D	Any Minority vs. White	White	0.5	1	0	-0.019	0.958	98
3D	Any Minority vs. White	Any Minority	0.4808687	0.5865535	0.3751839	-0.019	0.958	98
4D	Any Minority vs. White	White						58
4D	Any Minority vs. White	Any Minority						58
5D	Any Minority vs. White	White						56
5D	Any Minority vs. White	Any Minority						56
6D	Any Minority vs. White	White						122
6D	Any Minority vs. White	Any Minority						122
7D	Any Minority vs. White	White						75
7D	Any Minority vs. White	Any Minority						75

Table D.6: Hit-Rate Analysis (Arrest) by District and Race/Ethnicity (July 2020 to June 2023)

District	Comparison	Race	B=	Upper_Bound=	Lower_Bound=	B_Difference=	P=	N=
1D	Black vs. White	White	0.6382979	0.9588037	0.3177921	-0.166	0.333	133
1D	Black vs. White	Black	0.4725101	0.5681645	0.3768556	-0.166	0.333	133
2D	Black vs. White	White	0.5	0.9074249	0.0925751	0.177	0.423	56
2D	Black vs. White	Black	0.6767486	0.8121716	0.5413256	0.177	0.423	56
3D	Black vs. White	White	0.3636364	0.7518748	0	0.058	0.773	178
3D	Black vs. White	Black	0.4221136	0.5011867	0.3430406	0.058	0.773	178
4D	Black vs. White	White	0.6666667	1	0.0463139	-0.232	0.469	142
4D	Black vs. White	Black	0.4347571	0.522557	0.3469572	-0.232	0.469	142
5D	Black vs. White	White	1	1	0.9999995	-0.436	0.001	216
5D	Black vs. White	Black	0.5641548	0.6344441	0.4938655	-0.436	0.001	216
6D	Black vs. White	White	0.5217391	0.9478302	0.0956481	-0.136	0.535	537
6D	Black vs. White	Black	0.3861947	0.4308819	0.3415075	-0.136	0.535	537
7D	Black vs. White	White	0.4	0.8120162	0	-0.011	0.957	467
7D	Black vs. White	Black	0.388661	0.4369886	0.3403335	-0.011	0.957	467
1D	Hispanic vs. White	White	0.6382979	0.9899561	0.2866396	0.028	0.944	11
1D	Hispanic vs. White	Hispanic	0.6666667	1	0	0.028	0.944	11
2D	Hispanic vs. White	White	0.5	0.9321394	0.0678606	0.241	0.399	14
2D	Hispanic vs. White	Hispanic	0.7407407	1	0.4184059	0.241	0.399	14
3D	Hispanic vs. White	White	0.3636364	0.7806193	0	0.276	0.365	14
3D	Hispanic vs. White	Hispanic	0.64	1	0.2445157	0.276	0.365	14
4D	Hispanic vs. White	White	0.6666667	1	0.0081686	0.177	0.617	16
4D	Hispanic vs. White	Hispanic	0.84375	1	0.6768733	0.177	0.617	16
5D	Hispanic vs. White	White	1	1		-0.4	0.21	6
5D	Hispanic vs. White	Hispanic	0.6	1	0.0740768	-0.4	0.21	6
6D	Hispanic vs. White	White	0.5217391	1	0.0394978	-0.122	0.78	9
6D	Hispanic vs. White	Hispanic	0.4	1	0	-0.122	0.78	9
7D	Hispanic vs. White	White	0.4	0.8596607	0	-0.4	0.126	10
7D	Hispanic vs. White	Hispanic	-5.55E-17	1		-0.4	0.126	10
1D	Any Minority vs. White	White	0.6382979	0.9587497	0.317846	-0.157	0.357	136
1D	Any Minority vs. White	Any Minority	0.4809173	0.5753053	0.3865294	-0.157	0.357	136
2D	Any Minority vs. White	White	0.5	0.9061918	0.0938082	0.203	0.351	67
2D	Any Minority vs. White	Any Minority	0.7027864	0.8214877	0.584085	0.203	0.351	67

Table D.6: Hit-Rate Analysis (Arrest) by District and Race/Ethnicity (July 2020 to June 2023)

District	Comparison	Race	B=	Upper_Bound=	Lower_Bound=	B_Difference=	P=	N=
3D	Any Minority vs. White	White	0.3636364	0.7517465	0	0.063	0.755	189
3D	Any Minority vs. White	Any Minority	0.4267046	0.503301	0.3501081	0.063	0.755	189
4D	Any Minority vs. White	White	0.6666667	1	0.0468602	-0.172	0.59	162
4D	Any Minority vs. White	Any Minority	0.4943044	0.5766271	0.4119816	-0.172	0.59	162
5D	Any Minority vs. White	White	1	1		-0.434	0.001	224
5D	Any Minority vs. White	Any Minority	0.5656537	0.6345469	0.4967606	-0.434	0.001	224
6D	Any Minority vs. White	White	0.5217391	0.9478243	0.0956539	-0.134	0.54	541
6D	Any Minority vs. White	Any Minority	0.3877445	0.4322833	0.3432058	-0.134	0.54	541
7D	Any Minority vs. White	White	0.4	0.8120087	0	-0.012	0.954	471
7D	Any Minority vs. White	Any Minority	0.3878136	0.4359112	0.339716	-0.012	0.954	471