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Michigan State Police Traffic Stop External Benchmarking: A Final Report on Racial and Ethnic Disparities

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Table of Contents

List of Tables and Appendices

Tables

<u>Appendices</u>

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Executive Summary

This report presents the results of an external benchmark analysis of Michigan State Police (MSP) traffic stops conducted during 2020. There are five primary sections to this report: Census benchmark, traffic-crash benchmark, veil-of-darkness (VOD) benchmark, post-stop outcome analyses, and Secure Cities Partnership analyses. The goal of these analyses is to understand the extent of racial and ethnic disparities in traffic stop behavior. Below we briefly describe the methodology used for each analysis and summarize the main findings. When reviewing the results, it is imperative to understand the difference between “disparity” and “discrimination.” Disparity is an observed difference in the proportion of traffic stops involving a specific group of people compared to that group’s representation in another source of data. Discrimination, on the other hand, involves a police officer intentionally targeting and stopping racial or ethnic minorities solely because of their group status (i.e., racially profiling people and engaging in biased stop behavior). In this way, discrimination involves intent, whereas observed disparity cannot speak to whether an officer acted with intent. This report and its findings can speak only to the extent of racial/ethnic disparity in MSP traffic stops. The data cannot ascertain whether racially discriminatory practices are occurring within MSP.

Details about the data sources are provided in the body of the report below. However, the primary data—MSP traffic stops—represent all traffic stops conducted by MSP during 2020. MSP troopers are required to report the race of drivers involved in traffic stop reports. MSP policy and training instructs troopers to report the driver’s race based on their perception and they are prohibited from asking drivers to self-report their race or ethnicity.

Census benchmark results:

The first set of benchmark analyses involved comparing the racial/ethnic composition of MSP traffic stops to minority group representation in the population using Census data estimates. This type of benchmark is intuitive and provides a good starting point for examining whether racial/ethnic disparities exist within traffic stop data. However, relying solely on Census data as a benchmark is insufficient and can result in inaccurate conclusions. Census data do not accurately represent the racial/ethnic driving population and, therefore, do not adequately estimate the population at risk to be stopped by the police. We recommend only using Census benchmark results for descriptive purposes. The main Census benchmark findings were as follows:

- Across Michigan and within most of MSP’s districts, African Americans were significantly more likely to be involved in a traffic stop than we would have expected based on their representation in the population. African Americans in District 8 were *less likely* to be stopped than we would have expected based on their representation in the district’s population. African Americans were significantly more likely to be involved in a traffic stop than we would have expected based on their representation in the population in most Michigan counties.
- Hispanic drivers were significantly less likely to be stopped than we would have expected based on their representation in the population across Michigan, most of MSP’s districts, and many Michigan counties.

- Asian drivers were significantly less likely to be stopped than we would have expected based on their representation in the population across Michigan and most of MSP's districts. There was a mixture of counties where Asian drivers were more or less likely to be stopped based on the racial/ethnic composition of the population.

Traffic-crash benchmark results:

Next, we used Michigan traffic crash data as a benchmark against MSP's traffic stop data. Traffic crash data is a useful benchmark because it provides a reasonable estimate of the driving population (and, therefore, accounts for exposure to police supervision), including those that drive in a particular community but who may not live in that location (i.e., the commuter population). Due to data availability at the time analyses started for this report, we were limited to traffic crash data during the first six months of 2021. Accordingly, we benchmarked this against traffic stops that occurred during the first six months of 2020 (to avoid seasonality differences).

We used two types of traffic crash data as benchmarks. First, we compared the racial/ethnic composition of traffic stops and "not-at-fault" crashes. Being involved in a crash that is not one's fault is largely a random process and, therefore, such data provide a good estimate of the driving population—people that drive more frequently are more likely to be involved in "not-at-fault" crashes. Second, we compared the racial/ethnic composition of traffic stops and "at-fault" crashes. This benchmark is useful in racial disparity research because it provides a reasonable estimate of the driving population that engages in risky or illegal driving behavior. If particular groups of people are more likely to be involved in "at-fault" crashes, it is likely because they violate traffic laws more frequently which should expose them to more police intervention. The primary findings from the traffic-crash benchmarks were as follows:

- *"Not-at-fault" traffic crashes benchmark*:
    - African Americans were significantly more likely to be involved in traffic stops than we would have expected based on the racial/ethnic makeup of "not-at-fault" traffic crashes across Michigan and each of MSP's districts. Within a significant portion of Michigan counties, African-American drivers were more likely to be stopped relative to their representation in "not-at-fault" traffic crashes. However, there were many counties where African Americans were represented in traffic stops at a rate equal to what we would have expected based on the racial/ethnic makeup of "not-at-fault" traffic crashes.
    - Across the state and MSP's districts, the results were mixed concerning whether Hispanic drivers were more or less likely to be stopped than we would have expected based on their representation in "not-at-fault" traffic crashes. However, across most Michigan counties, Hispanic drivers were stopped at a rate that we would have expected based on the racial/ethnic composition of "not-at-fault" traffic crashes.
    - Asian drivers were less likely or as likely to be involved in traffic stops compared to their representation in "not-at-fault" traffic crashes.

- *"At-fault" traffic crashes benchmark*:
    - While African-American drivers were *less likely* to be stopped by an MSP trooper across the entire state of Michigan compared to their representation in "at-fault" traffic crashes, they were *more likely* to be stopped in Districts 1, 2, 3, and 5. African-American drivers' representation in traffic stops was equal to their involvement in "at-fault" crashes in Districts 6, 7, and 8. There was similar mixed evidence regarding this benchmark at the county-level of analysis.
    - Hispanic drivers were less likely to be stopped or stopped at an expected rate based on the racial/ethnic makeup of "at-fault" traffic crashes.
    - Asian drivers were less likely to be stopped or stopped at their expected rate relative to the racial/ethnic makeup of "at-fault" traffic crashes across the state, all of Michigan's counties, and all of MSP's districts (except District 5 where they were more likely to be stopped than expected).

It is important to point out the limitations of the traffic-crash benchmark analyses. First, the traffic stop and crash data came from different years and do not cover an entire year. However, we conducted supplemental analyses at the end of this report that addressed part of this problem. Second, and relatedly, the COVID-19 pandemic could have impacted traffic stop behavior and outcomes in 2020 but likely had less of an impact on traffic crashes during 2021. Thus, it is possible that COVID-19 impacted driving and enforcement activities in 2020, but the benchmark data do not contain the same influence on driving patterns related to traffic crashes. Again, however, supplemental analyses suggested this may not be the case because we observed the same racial disparities when using 2020 or 2021 traffic stop data.

Another limitation to the traffic crash benchmark analyses is that the crash data do not perfectly match the locations that MSP troopers may patrol. If troopers are more likely to be deployed in areas with crime or traffic safety problems *and* these areas happen to have more minority residents or drivers, we may expect some level of traffic stop disparity that cannot be explained by the crash benchmark analyses. Crash data from the specific locations that troopers patrol could provide a better benchmark.

Finally, it is important to note that we are missing driver race/ethnicity from about 27% of crashes that occurred in Michigan during the first six months of 2021. This occurred because over 10% of Michigan police agencies did not report driver race/ethnicity on their traffic crash reports. It is possible that different results would emerge if we had complete data for the traffic crash benchmark analyses.

Veil-of-darkness benchmark results:

The third set of benchmark analyses leveraged the "veil-of-darkness" (VOD) methodology. According to the VOD, it is more difficult for police officers to determine the race/ethnicity of a driver prior to making a traffic stop when it is dark outside. If officers are engaging in discriminatory stop behavior, this implies they are using the color of a driver's skin when deciding whether to conduct a stop. If a larger proportion of minority drivers are stopped by the police during daylight than at night, this would be evidence of racial/ethnic disparity. Within the VOD methodology, we restricted the analyses to only those traffic stops that occurred during the intertwilight period (i.e., the earliest end of civil twilight to the latest end of civil twilight). Doing so created a natural experiment that leverages the seasonal variation in daylight to account for differences in travel patterns across groups of people. The primary VOD results were as follows:

- According to the VOD analyses, traffic stops conducted during daylight were 33% more likely to involve an African-American driver. This is concerning because it is, arguably, easier to see driver race during daylight than during darkness.
- Daylight did not predict whether a driver involved in a traffic stop was Hispanic, Asian, or from another racial/ethnic group.

One problem with the VOD methodology is that it assumes there are no seasonal differences in driving patterns across driver race/ethnicity or other significant changes that may impact the nature of traffic stops throughout the year. This likely is an inaccurate assumption. Accordingly, VOD researchers sometimes restrict the analyses to stops that occurred during the intertwilight period *and* the 30 days before and after the switch to daylight savings time (DST). Doing so accounts for any seasonal changes in driving patters or the nature of traffic stops (i.e., it only focuses on a single season). When we conducted this analysis, the VOD findings changed:

- After accounting for potential seasonal variations in the nature of traffic stops or the makeup of drivers on the road, the VOD results demonstrated that the amount of daylight *did not* predict whether a driver involved in a traffic stop was African American. Put simply, accounting for seasonality in stops and driver makeup on the road rendered the connection between daylight and African-American representation in traffic stops as no longer significant. This VOD analysis suggests there is no racial disparity in traffic stops conducted by MSP troopers. At the same time, however, the observation period for this analysis (February 7 through April 6, 2020) was the start of the COVID-19 pandemic in the United States. Travel patterns and enforcement activities changed dramatically starting in March 2020 with Michigan’s stay-at-home orders. This could have accounted for the different results between the main VOD results and those observed in the DST-restricted VOD analysis. It is possible that seasonal variation in the nature of traffic stops and/or the racial composition of drivers on the road may explain why daylight predicts driver race rather than trooper bias. VOD analysis in the coming years will help shed light on this possibility.

Post-stop outcome results:

The post-stop outcome analyses considered whether racial/ethnic disparities existed in the types of outcomes drivers receive after a traffic stop. Specifically, we examined whether driver race/ethnicity predicted the odds of receiving a warning, or being cited, searched, or arrested. The results were as follows:

- African-American drivers were significantly more likely than White drivers to be searched or arrested after traffic stops. There was mixed evidence regarding whether they were less likely to receive a citation than White drivers.

- Hispanic drivers were significantly more likely than White drivers to be searched or arrested after traffic stops.
- Asian drivers were significantly less likely to be searched or arrested compared to White drivers. However, they were significantly more likely to receive a citation than White drivers (and less likely to receive a warning).
- Regarding the reason for the traffic stop, drivers stopped for "hazardous" violations were significantly more likely to receive a citation, but less likely to be searched or arrested.

While we accounted for violent crime rates in the outcome analyses, we did not control for prior criminal history of traffic stop drivers. Doing so could change the results of the post-stop outcome analysis.

Secure Cities Partnership results:

There are 11 cities in Michigan that are part of the Secure Cities Partnership (SCP). Part of the SCP involves MSP providing additional patrol support in these jurisdictions to assist with crime suppression and enforcement. The racial/ethnic composition of these communities is much different than many other areas of Michigan. Therefore, it is possible the SCP location stops could influence the overall disparities observed in other analyses. We re-estimated all the above analyses after restricting our attention to only those stops that occurred in SCP locations and the results were as follows:

- Nearly 77% of all traffic stops in 2020 that occurred in SCP locations by troopers assigned to grant/directed patrol duties involved an African-American driver (compared to about 22% of all MSP traffic stops across the state in 2020).
- African-American drivers were significantly more likely to be stopped in 8-out-of-11 SCP locations than we would have expected based on their representation in the jurisdictions' populations. In three of the SCP locations, the percentage of African-American drivers stopped by MSP troopers was what we would have expected based on their representation in the respective city populations.
- In 7-out-of-11 SCP locations, African Americans were significantly more likely to be stopped by MSP troopers than we would have expected based on their representation in "not-at-fault" traffic crashes. In the remaining locations, African-American drivers were stopped less frequently or as frequently as we would have expected based on their representation in "not-at-fault" traffic crashes.
- African-American drivers were more likely to be stopped in 6-out-of-11 SCP locations than we would have expected based on the racial/ethnic composition of "at-fault" traffic crashes. In the remaining locations, African-American drivers were stopped less frequently or as frequently as we would have expected based on their representation in "at-fault" traffic crashes.
- To check the robustness of the main results of the report, we re-ran the primary analyses after excluding the SCP-related traffic stops. Stops that take place in SCP locations are likely

the result of different patrol/enforcement strategies (when compared to other locations throughout Michigan). The locations themselves also are different in terms of population sociodemographic makeup compared to areas outside of SCP cities. These factors may lead to differences in the racial/ethnic composition of SCP traffic stops compared to those outside of SCP locations. The analyses revealed that many of the substantive findings remained unchanged (i.e., the main findings are not caused solely by SCP location traffic stops). However, the magnitude of racial disparity was smaller across several districts after excluding SCP-related stops. Moreover, the largest difference was observed in District 3. After excluding SCP-related stops from the analysis in District 3, the amount of racial disparity was reduced by nearly 50%.

- The VOD analyses of the traffic stops that took place in SCP locations mirrored the findings from the main VOD results. Stops conducted during daylight were significantly more likely to involve African-American drivers than those that occurred during darkness. However, after accounting for potential seasonal variation in the nature of traffic stops or the makeup of drivers on the road, daylight no longer predicted whether a driver involved in a traffic stop was African American.

- The post-stop outcome analyses for the SCP stops largely reflected those conducted with all the traffic stops. African-American drivers were more likely than White drivers to be searched and arrested, but less likely to receive a citation. Drivers stopped for hazardous violations were more likely to receive a citation and less likely to be searched or arrested in SCP locations.

Conclusion:

- When taken as a whole, the various analyses in this report suggested African-American drivers experienced significant disparities with respect to MSP traffic stops. African-American drivers were significantly more likely to be stopped than we would have expected based on their representation in “not-at-fault” and “at-fault” traffic crashes. They were also more likely to be stopped during daylight compared to during darkness, which suggests racial bias *may* play a role in some troopers’ stop behavior. However, after accounting for potential seasonal variation in driving and enforcement patterns, daylight no longer predicted if a driver was African American. This mixed VOD evidence suggests MSP should examine the nature of traffic stops in more detail to better understand where disparities can be addressed. Moreover, African Americans were more likely to be searched and arrested than White drivers, after accounting for relevant predictors of post-stop outcomes (e.g., reason for stop, violent crime rate). Again, the results should not be interpreted as evidence of the existence of racially discriminatory traffic stop practices at MSP. Rather, based on the findings, we strongly encourage MSP to dedicate additional time to more fully understand the extent to which observed disparities manifest because of discriminatory practices. The internal benchmarking dashboard MSP is currently working on is a step in the right direction. Using the dashboard may uncover specific areas or troopers that have problematic behavior. Or, use of the dashboard may provide important insight into why some disparities exist that are not due to discrimination.

INTRODUCTION

American policing has progressed as a profession over the decades due, in no small part, to reform efforts led by police agencies themselves and the communities they serve. Although policing has come a long way in reducing excessive use of force, protecting civil liberties, and ensuring fair and impartial law enforcement, the profession will always face calls for improvement. Change and reform are constant in policing because the profession is faced with some of the most complex problems in our society, and policing is often saddled with an impossible mandate and unreasonable corresponding expectations. However, if policing is truly a profession, it will constantly aim to better itself and respond to new challenges and public demands.

This situation is exemplified by the current state of affairs in American law enforcement. Policing is at a critical turning point as reformers—citizens, politicians, and police themselves—aim to reimagine policing in our country and improve the quality of justice it dispenses. Key within current reform movements is identifying ways to reduce racial and ethnic disparities in outcomes the police provide to members of the public. Addressing racial/ethnic disparities has proven to be a persistent problem in American policing (Alpert, MacDonald, & Dunham, 2005). The good news is that many police agencies around the country are looking inward to help reduce disparities.

In January of 2021, the Michigan State Police (MSP) began a partnership with researchers from the School of Criminal Justice (SCJ) at Michigan State University (MSU). MSP had the goal of better understanding the extent of, and potential remedy to, racial/ethnic disparities in MSP traffic stop behavior. MSP aimed to create an internal benchmarking dashboard that would allow individual troopers to be compared to one another to identify potentially problematic racial/ethnic disparities in their traffic stop behavior. Moreover, MSP aimed to conduct an external benchmark analysis of MSP traffic stop data to assess whether there is evidence of meaningful racial/ethnic disparities. MSP reached out to Dr. Scott Wolfe and Dr. Ed McGarrell from the SCJ at MSU to assist in both endeavors. From January through May 2021, Drs. Wolfe and McGarrell consulted with MSP as they created the internal benchmark dashboard. Then, MSP commissioned Dr. Wolfe to lead an independent external benchmark analysis of their traffic stop data. The current report provides the results of that analysis. Before discussing the findings, the next section provides a brief overview of what external benchmarking of traffic stop data involves.

Traffic Stop Benchmarking Strategies

Traffic stop data benchmarking involves comparing the racial/ethnic composition of a police agency's traffic stops to the racial/ethnic group representation in other sources of data. The goal of such analyses is to examine the extent of racial/ethnic disparities in traffic stop behavior. Within such discussions, it is vital to understand the difference between *disparity* and *discrimination* (or *racial profiling* or *racial bias*). Racial/ethnic disparity is an observed difference in the proportion of traffic stops involving a specific group of people compared to that group's representation in the population. Discrimination, on the other hand, involves a police officer intentionally treating racial or ethnic minorities differently based on their group status. Discrimination involves intent, whereas observed disparity cannot speak to whether there was intent from the officer. Nearly all available benchmarking strategies can only explore the extent of racial/ethnic disparity in traffic stops. The purpose of examining multiple benchmarks is to determine whether disparities can be explained by legitimate factors and to get closer to understanding whether there is any evidence of discrimination or racial profiling in officers' traffic stop behavior. However, common benchmarking strategies cannot definitively conclude whether officers are discriminatory in their traffic stop behavior. It is important to remember this reality throughout this report.

Census benchmarking

The most commonly used benchmark by the media and laypersons is to compare the proportion of traffic stops of racial/ethnic minorities to group representation in the population using Census data. Such "first generation" racial disparity benchmark comparisons, as Smith and colleagues (2019, p. 2) refer to them, are useful for gaining a basic understanding of the racial/ethnic composition of traffic stops compared to the percentage of minority group members in the overall population. These comparisons and data sources are easy to understand. While useful as a starting point, Census benchmarking is fraught with problems if the intention is to determine whether officers practice discriminatory decision-making during traffic stops. Census benchmarking also is problematic for understanding whether any observed racial/ethnic disparities are meaningful.

The problem is that Census data do not provide an accurate estimate for the population at risk of being stopped by the police (COPS, 2016). Consider the situation where 40% of a police department's traffic stops involve African-American drivers but only 25% of the jurisdiction's population is African American. This *could* be one indicator of potential racial bias (i.e., discrimination) but the disparity could also be explained by legitimate factors. Such a comparison is not meaningful "without an appropriate comparison population against which to evaluate whether the percentage of minorities stopped exceeded what would be expected given minority representation in the population legitimately *available* and *at risk* for being stopped" (Smith et al., 2019, p. 3, italics in original). Relatedly, Census data cannot account for the presence of drivers that do not live in the area under consideration or actual driving behavior (e.g., either normal driving or dangerous driving that increases exposure to being stopped by the police). For this reason, we will start with a Census benchmark in this report, but we will use several other benchmark strategies to address the problems associated with the approach.

Traffic-crash benchmarking

To address the problems associated with Census benchmarking, many researchers use traffic crash data as a benchmark. There are two types of traffic crash data that are used to benchmark against traffic stop data. First, the racial/ethnic composition of drivers involved in not-at-fault crashes is compared to the racial/ethnic composition of drivers from traffic stops (Alpert et al., 2004; COPS, 2016; Smith, Rojek, Tillyer, & Lloyd, 2017; Tillyer et al., 2010). Not-at-fault crashes are a useful benchmark because they represent a random event (i.e., being involved in a traffic crash that is not one's fault) and, therefore, provides a reasonable estimate of the racial/ethnic composition of the driving population. In this way, not-at-fault traffic crash data is a more appropriate benchmark than Census data because it more accurately represents the composition of the driving population that is at risk to be stopped by the police. At the same time, West (2018) found evidence that the assignment of fault during traffic crashes investigations may be biased.

West's analysis revealed that White officers were more lenient on White drivers when assigning fault. However, Smith and colleagues (2019, p. 6) provided an important caveat to this critique:

> "Even if true, though, bias in the assignment of fault would result in lower estimates of the minority driving population based on not-at-fault driver assignment since more minorities would be cited and assigned at-fault status than their actual representation in the driving population. This, in turn, would show a greater disparity between the percentage of minorities stopped and their estimated representation in the driving population than exists in reality. In effect, West's implicit critique of not-at-fault crash data demonstrates that such data may provide a conservative estimate of minority representation in the driving population. Thus, a finding of no disparity between minorities stopped and minority representation among not-at-fault crash victims would yield a high degree of confidence that minorities were not being targeted for stops at rates greater than their estimated representation in the driving population."

Accordingly, not-at-fault crash data is one of the best sources of data to benchmark with traffic stops. A limitation of this approach is that such data do not provide a reasonable estimate of the racial/ethnic composition of drivers that engage in risky driving behavior. One of the primary reasons police officers stop vehicles is because the driver committed some type of infraction. One way to account for this would be to benchmark traffic stop data against arrest data. The problem is that arrest data is partially influenced by officer decision-making and, if racial bias exists, it will impact arrest behavior in the same manner as it would stop activity. To address this problem, researchers have begun using at-fault traffic crash data as a benchmark (Smith et al., 2019). Such data provide a reasonable estimate of the racial/ethnic composition of the driving population that may have a higher propensity for dangerous driving activity. West's (2018) critique discussed above applies to at-fault crash data but, when combined with other benchmarking strategies, helps us gain a deeper understanding of the extent of racial/ethnic disparities in traffic stop behavior.

Another limitation of both the not-at-fault and at-fault crash benchmarking strategies is that they rarely match the specific locations that police officers patrol. Within our analyses below, we will benchmark traffic stop data against crash data at various levels of aggregation (e.g., statewide, MSP districts, Michigan counties). However, because the determination of where troopers will patrol is not a random process, any racial/ethnic disparities observed in the traffic crash benchmark analyses could partially be attributed to patrol deployment strategies. If troopers are more likely to be deployed in areas with crime or traffic safety problems *and* these areas happen to have more minority drivers, we may expect some level of traffic stop disparity that cannot perfectly be explained by the crash benchmark analyses. Accordingly, we must use another benchmark to improve our understanding of observed disparities.

"Veil-of-darkness" benchmarking

One of the most sophisticated benchmarking strategies to date attempts to overcome most of the limitations of other benchmarks (COPS, 2016; Stacey & Bonner, 2021; Taniguchi, 2017). The veil-of-darkness (VOD) analysis is a benchmarking strategy proposed by Grogger and Ridgeway (2006). They made the argument that after dark police officers are less able to know the race/ethnicity of a driver before initiating a traffic stop. Accordingly, if police officers stop more minorities in the daytime—when they can more easily identify the race/ethnicity of a driver prior to initiating a stop—this could be evidence of discriminatory stop behavior (i.e., racial profiling). However, it is not useful to simply compare the racial/ethnic composition of daytime stops to nighttime stops because the racial/ethnic composition of drivers on the road may vary by time of day. As such, the VOD methodology restricts the analysis to traffic stops that occurred during the intertwilight period, which is the time between the earliest end of civil twilight and the latest end of civil twilight. As Taniguchi and colleagues (2017, pp. 424-425) put it: "The VOD methodology takes advantage of a natural experiment that is made possible by seasonal variation in the amount of daylight in a time period known as the intertwilight period…The VOD approach compares the racial distribution of motorists stopped during the intertwilight period when it is daylight with the racial distribution of motorists stopped after dark during the intertwilight period."

For example, it is daylight at 6:30pm during some parts of the year, but it is dark during other parts of the year. The VOD methodology allows researchers to examine whether more racial/ethnic minorities are stopped during daylight compared to dark during the same time of day (which accounts for variation in driving patterns across race/ethnicity and time of day). If more racial/ethnic minority drivers are stopped during daylight than when it is dark, racial bias may exist in the way police officers carry out traffic stops. While the VOD analysis cannot definitively speak to whether discriminatory practices have occurred during traffic stops, it gets the closest to being able to make such conclusions. When combined with the results of other benchmarks, the VOD analysis provides police agencies with useful data about the extent of racial disparity, and potential discrimination, among their officers.

Post-stop outcome analysis

Another popular strategy for investigating racial/ethnic disparities in traffic stops is to examine the outcomes citizens receive *after* the traffic stop is initiated. Policing is highly discretionary, and officers have latitude when deciding the outcomes of traffic stops. While not technically a benchmarking strategy, many researchers examine whether racial/ethnic minority drivers are more likely to receive particular outcomes than their White counterparts after the conclusion of a traffic stop (Alpert et al., 2006; Alpert, Dunham, & Smith, 2007). This is typically referred to as a "post-stop outcome analysis." Researchers use driver race or ethnicity as the primary predictor of various post-stop outcomes. For example, within such an analysis, a researcher could examine the extent to which driver race/ethnicity predicts the likelihood of receiving a warning or citation, or whether the driver is searched or arrested. After conducting the benchmark comparisons described earlier, we will complete a series of post-stop outcome analyses to further examine the extent of racial/ethnic disparities in MSP traffic stops.

TRAFFIC STOP EXTERNAL BENCHMARKING ANALYSES

This report examines Michigan State Police (MSP) troopers' traffic stop decision-making during 2020. We focus on a single year because it was not until July 2019 that MSP troopers were required to identify the driver of the stopped vehicle. We assessed traffic stop behavior in two primary steps. First, we examined whether there were any racial/ethnic disparities in the composition of traffic stops conducted by MSP. Second, we explored the potential actions that troopers can take after the initial decision to stop a vehicle. This is referred to as the "post-stop outcome analysis" and involved the examination of racial/ethnic disparities in issuing a verbal warning or citation and searching or arresting the driver. We used several analytic methods to determine whether there were any racial/ethnic disparities in MSP traffic stop behavior. Again, as discussed above, the analyses only speak to whether disparities exist and cannot determine whether such disparities are the result of discrimination or racial bias. Next, we describe the data and methods used in the analyses.

Traffic Stop Data

Traffic stop data were provided by MSP and reflect all traffic stop reports collected between January 1, 2020 and December 31, 2020.[1] MSP troopers are required to complete daily activity logs while on duty (referred to as "UD-2"). Accordingly, all self-initiated traffic stop incidents are recorded in troopers' daily logs where they collect information about the characteristics of the stop (e.g., date, time, location, and reason for stop), basic demographics of the driver (e.g., race and gender), and any outcomes associated with the stop (e.g., warning, citation, search, or arrest). All traffic stop logs are completed electronically (e.g., using mobile computers in troopers' vehicles).

For our analyses, we focused only on the race/ethnicity of the driver and the stop outcomes experienced by the driver. These analyses do not examine the racial/ethnic composition of passengers in vehicles stopped by MSP troopers or the outcomes they may have received during the stop. It is also important to note that it is possible for multiple vehicles to be stopped in a single traffic stop incident. In such cases, we treated each vehicle as a separate traffic stop.

The initial database provided by MSP contained 306,006 traffic stops. We removed 29 stops conducted by Capitol Security because these are not completed by typical sworn MSP troopers. We excluded 8,175 stops where the race/ethnicity of the driver was unknown. While this is a large number, it represents a small percentage of the overall traffic stops (0.3%). This left us with 297,802 traffic stops for the analyses.

Driver race and ethnicity coding

We will describe the variables used in each of the analyses within their respective sections below. At this point, however, it is necessary to discuss the primary variable of interest in this report—driver race/ethnicity. MSP troopers are required to report the race of the driver in the traffic stop reports. MSP policy and training instructs troopers to report the driver's race based on their perception and they are prohibited from asking drivers to self-report their race. When combined with the fact that Michigan does not include race on its driver's licenses, there is considerable room for error in the reporting of driver race in the MSP traffic stop data. We will turn to this issue again in the "recommendations" section of the report for suggestions on how to overcome this problem.

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[1] MSP worked with their vendor, LexisNexis, to use a query to pull the traffic stop data in July 2021. It is important to understand that a query conducted at a different date could produce a slightly different number of traffic stops due to updates to incidents in the database over time. Such changes would be minimal and would not significantly influence the analyses given the overall large number of traffic stops conducted by troopers in 2020.

Troopers are required to indicate whether a driver's race is "White," "Black/African American," "Hispanic/Latino," "Asian," "American Indian or Alaskan Native," "Native Hawaiian or Other Pacific Islander," or "unknown." Because knowing the race/ethnicity of the driver was key to the analyses, we removed all traffic stops where the driver's race/ethnicity was unknown. For the analyses, we recoded driver race into a series of binary variables: *White* (1 = yes, 0 = no), *Black* (1 = yes, 0 = no), *Hispanic* (1 = yes, 0 = no), *Asian* (1 = yes, 0 = no), and *Other* (1 = yes, 0 = no). The "other" race/ethnicity category combined American Indians, Alaskan Natives, Native Hawaiians, and Other Pacific Islanders. Throughout this report, we refer to these categories as driver "race/ethnicity" because MSP procedures and data reporting practices include Hispanic/Latino in the race categorization (even though it is an ethnicity). While the traffic stop report allows troopers to record driver ethnicity (separately from race), nearly 88% of traffic stops reports were missing information in this data field. Accordingly, we must rely on trooper reporting of race/ethnicity for our analyses.

Basic traffic stop characteristics

Table 1 provides the distribution of traffic stops conducted by MSP troopers in 2020 by driver race/ethnicity. A majority of traffic stops involved a White driver (74.5%). African Americans represented 22.1% of traffic stops in 2020, whereas 2.3% of stops involved a Hispanic driver. Less than 1% of traffic stops involved an Asian driver or a driver from another racial/ethnic category, respectively.

Table 1 also reports driver gender, the MSP District where the traffic stop took place, and the MSP troopers' assignments at the time of the stop. About 67% of traffic stops in 2020 involved a male driver (33% involved a female driver). It is worth noting that 102 traffic stops had missing information in the driver gender data field. The distribution of traffic stops across MSP Districts was as follows: 15.8% in District 1, 18.9% in District 2, 18.2% in District 3, 14.2% in District 5, 9.7% in District 6, 11.7% in District 7, and 11.6% in District 8.[2] Most traffic stops—about 62%—were conducted by troopers assigned to "general" patrol activities. About one-fifth of traffic stops were completed by troopers working under a "grant/directed patrol" assignment. The remaining traffic stops in 2020 were conducted by troopers assigned to the "Field Training" program (6.3%), "Hometown Security Team" duties (6.0%), sergeant's duties (3.8%), or other assignments (2.2%).[3]

Table 2 provides a breakdown of the racial/ethnic composition of traffic stops across MSP districts in 2020. The bulk of traffic stops in all districts involved White drivers. In fact, over 95% of stops in Districts 7 and 8 involved White drivers. District 2 had the largest percentage of African-American drivers—47.9%—involved in traffic stops. African Americans accounted for 31.5% of stopped drivers in District 3, 21% in District 5, 18.1% in District 1, and 11.5% in District 6. Each of the remaining racial/ethnic groups did not account for large shares of traffic stop activity. However, 5.7% of stops in District 5 involved Hispanic drivers. While these numbers help describe

[2] MSP does not have a district named "District 4."

[3] The "other assignment" category includes troopers assigned to the following duties: abandoned vehicle officer, accident investigator, administrative support, canine, court officer, community service trooper, desk assignment trooper, ES team, grant/nonpatrol/mobilization, marine services, traffic safety initiative, training-attend, training-instruct, trooper investigator, or vehicle maintenance officer.

the racial/ethnic composition of MSP traffic stops in 2020, the figures tell us nothing about whether racial/ethnic disparities exist. Such a discussion will be the focus of the benchmark analyses discussed in later sections of this report.

Table 1. 2020 MSP traffic stop data descriptive statistics (N = 297,802)

	Number of Stops	Percentage
Driver Race/Ethnicity		
White (non-Hispanic)	221,714	74.5%
African American (non-Hispanic)	65,909	22.1%
Hispanic	6,909	2.3%
Asian	2,166	0.7%
Other	1,104	0.4%
Driver Gender		
Male	199,173	66.9%
Female	98,527	33.1%
Missing	102	0.03%
MSP District		
1	47,083	15.8%
2	56,235	18.9%
3	54,330	18.2%
5	42,144	14.2%
6	28,898	9.7%
7	34,700	11.7%
8	34,412	11.6%
Trooper Assignment		
General	184,047	61.8%
Grant/directed patrol	59,342	19.9%
Field Training program	18,697	6.3%
Hometown Security Team	17,762	6.0%
Sergeant’s duties	11,450	3.8%
Other assignment	6,504	2.2%

Note: Percentages may not sum to 100 due to rounding.

To conserve space in the main body of this report, we provided a county-level breakdown of the racial/ethnic composition of traffic stops in Appendix A. About two-thirds of all traffic stops in Wayne County during 2020 involved an African-American driver. This partially explains why District 2 (where Wayne is located) had the largest percentage of African Americans involved in traffic stops. And, as we will see below, Wayne has the largest African-American population. Nearly 59%

of Genessee County traffic stops involved African-American drivers and about 53% of stops in Saginaw County involved African-American drivers. Hispanic drivers represented 9% of stops in Van Buren County, 7.7% of stops in Oceana County, 7.1% of stops in Berrien County, and 6.6% of stops in Kent County. We will discuss more counties' racial/ethnic composition of traffic stops in the benchmark analyses below when we compare such numbers to other sources of data.

Table 2. Racial/ethnic composition of traffic stops across MSP districts in 2020

	% White	% African American	% Hispanic	% Asian	% Other
District					
1	78.2%	18.1%	2.4%	1.1%	0.2%
2	49.4%	47.9%	1.7%	0.8%	0.2%
3	66.3%	31.5%	1.8%	0.3%	0.1%
5	71.8%	21.0%	5.7%	1.1%	0.4%
6	84.5%	11.5%	3.2%	0.6%	0.2%
7	96.8%	1.7%	0.9%	0.4%	0.3%
8	95.3%	1.7%	0.6%	0.8%	1.7%

Note: Percentages may not sum to 100 due to rounding. White and African American represent non-Hispanic Whites and African Americans, respectively.

Benchmark Data and Analytic Strategy

We used several sources of data to conduct a series of benchmark analyses. This involved comparing the racial/ethnic composition of traffic stops to the racial/ethnic composition in data that is less influenced by police behavior. This allowed us to answer whether African Americans, Hispanics, Asians, or drivers in other racial/ethnic groups were more likely to be stopped by MSP troopers than White drivers. We used three benchmark analyses to accomplish this goal: Census, traffic crash, and veil-of-darkness. Benchmarks help us determine if there are disparities in the racial/ethnic composition of traffic stops. Our first analysis will use Census data to examine whether there is initial evidence of racial/ethnic disparities in the traffic stops. However, such a comparison is naïve to many potential factors that influence troopers' stop behavior that could account for racial/ethnic disparity. As such, our second benchmark involves comparing the racial/ethnic composition of traffic stops to that of traffic crashes in Michigan. The third benchmark is referred to as the "veil-of-darkness" test. This benchmark strategy attempts to isolate the extent to which racial/ethnic disparities in traffic stops can be attributed to potential bias or discrimination. Next, we discuss the data and analytic strategy used for each benchmark.

Census data benchmark

First, we benchmarked MSP traffic stops against U.S. Census Bureau data using the 2019 American Community Survey (ACS) five-year estimates. These data provide estimates of demographic and socioeconomic characteristics at the county level between the decennial Censuses. We collected race and ethnicity data from the ACS in addition to other contextual information that will be used in the outcome analysis (e.g., percent of the population that lives under the poverty threshold). We used MSP districts and Michigan counties as our units of analysis throughout each of the benchmark analyses. MSP districts follow county boundaries which allowed us to calculate Census characteristics at the district level by aggregating county-level data for the counties contained in the district. See Figure 1 for a map of MSP districts and Michigan counties.

Figure 1. Michigan Counties and Michigan State Police Districts, Posts, and Detachments

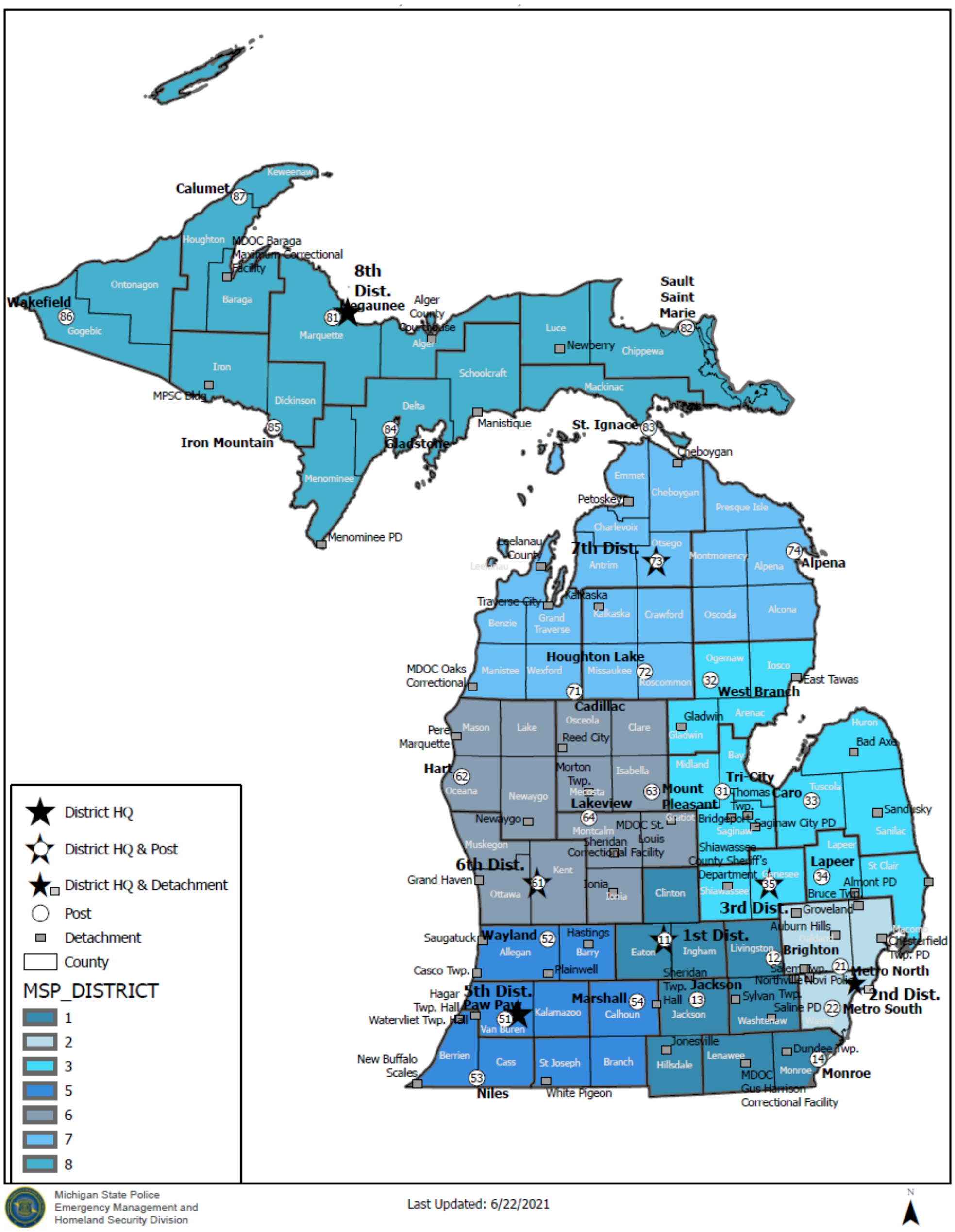

Table 3 provides the state-level and district-level demographic and contextual characteristics. While we use these variables in the benchmark and stop outcome analyses, they are also useful for understanding what Michigan and MSP's districts look like from a sociodemographic standpoint. Michigan's population of 9,965,265 is comprised of 75% White, 13.6% African American, 5.1% Hispanic, 3.1% Asian, and 3.1% from other racial/ethnic groups. As can be seen in the table, these racial/ethnic characteristics varied across the seven MSP districts. In terms of population size, District 2 is the largest with 3,880,809 residents and is the most diverse with 63.4% of citizens identifying as White, 24.4% as African American, 4.6% as Hispanic, 4.8% as Asian, and 2.7% as another race/ethnicity. More than 80% of the population in each of the other districts is comprised of Whites. District 6 has the highest percentage of Hispanic residents (8.2%). District 2 has the highest percentage of Asian residents (4.8%). More than 7% of District 8's population identifies as another racial/ethnic group.

We provided all county-level demographic and contextual characteristics in Appendix B. This table clearly demonstrates the diversity of size and demographic composition across Michigan's counties. For example, the most populated county in the state—Wayne—has over 1.7 million residents, whereas the least populated county—Keweenaw—has only 2,111 residents. Likewise, Wayne County is the most diverse with 38.5% of its population composed of African Americans. In contrast, many other counties in Michigan are composed of more than 90% White residents. Such variation underscores the need to examine racial/ethnic disparities in traffic stops within individual counties.

From a socioeconomic standpoint, over 14% of Michigan residents live in poverty and nearly 6% are unemployed. About 29% of Michigan residents are renters and nearly 28% of households are female-headed. Again, these Census characteristics varied across MSP's seven districts. With respect to poverty, District 7 had the fewest residents living below the poverty line (12.3%), whereas District 3 had the most with 15.6%. The percentage of unemployed residents hovered around the state average with a low of 4.7% in District 6 and a high of 7.1% in District 3. The percentage of residents who are renters varied across the districts with District 7 having the lowest (19.3%) and District 2 having the highest (32.5%). The same pattern was observed with respect to the percentage of female-headed households.

Not surprisingly, a lot of variation in sociodemographic characteristics exists at the county-level. Appendix B shows that about 26% of Isabella County residents live in poverty which is the highest percentage in the state. In contrast, only about 5% of Livingston County residents live in poverty. Unemployment rates are highest in Clare and Oscoda counties where slightly more than 10% of residents are unemployed, respectively. About 4-out-of-10 housing units in Ingham, Washtenaw, and Wayne counties are occupied by renters, respectively. Wayne County has the most female-headed households in the state (35.9%).

Crime data

MSP provided crime data for 2020 which allowed us to construct a violent crime rate for all Michigan counties and MSP districts. It was important to account for the violent crime rate in the stop outcome analyses because racial/ethnic disparities in troopers' behavior may be partially accounted for by crime levels in each area. We calculated the county-level violent crime rate by

Table 3. State and MSP district-level population characteristics

	Total pop.	% White	% African American	% Hispanic	% Asian	% Other	% Poverty	% Unemp.	% Renter	% FHH	Violent crime rate
State of Michigan	9,965,265	75.0%	13.6%	5.1%	3.1%	3.1%	14.4%	5.9%	28.8%	27.7%	482.2
<u>District</u>											
1	1,487,687	80.6%	7.0%	5.0%	4.1%	3.4%	12.9%	4.8%	29.7%	25.9%	377.4
2	3,880,809	63.4%	24.4%	4.6%	4.8%	2.7%	15.1%	6.6%	32.5%	31.1%	623.1
3	1,314,807	82.8%	9.4%	4.2%	0.9%	2.7%	15.6%	7.1%	24.9%	27.0%	433.8
5	959,003	81.3%	7.6%	5.9%	1.6%	3.6%	14.2%	5.2%	27.7%	25.9%	498.5
6	1,560,073	80.4%	6.4%	8.2%	2.0%	3.1%	13.3%	4.7%	26.4%	25.0%	385.6
7	461,023	93.3%	0.7%	2.2%	0.5%	3.2%	12.3%	5.6%	19.3%	22.9%	236.9
8	301,863	87.8%	2.3%	1.6%	0.9%	7.3%	15.4%	6.0%	25.5%	24.5%	220.6

Note: Percentages may not sum to 100 due to rounding. White and African American represent non-Hispanic Whites and African Americans, respectively. Pop.=population; Unemp.=unemployed; FHH=female-headed household. % Unemp. was calculated by dividing the number of unemployed residents by the number of people in the civilian labor force. % Renter was calculated by dividing the number of renter occupied housing units by the number of occupied housing units. % FHH was calculated by dividing the number of female-headed households by the total number of households. Violent crime is the number of violent crimes per 100,000 people.

taking the number of violent crimes (i.e., aggravated assault, murder, rape, and robbery) reported in each county in 2020 and dividing by the total county population size. Then, we multiplied these values by 100,000. To create the district-level violent crime rate, we summed the total number of violent crimes in each county contained in a district, divided by the district's population, and multiplied the values by 100,000. Table 3 provides the violent crime rates for the State of Michigan and each MSP district. The violent crime rate in Michigan in 2020 was 482.2 per 100,000 residents. There were 623.1 violent crimes per 100,000 in District 2 in 2020. This ranks District 2 as the most violent district in MSP's jurisdiction. District 5 had the next highest violent crime rate at 498.5 per 100,000. This was followed by District 3 with 433.8 violent crimes per 100,000, District 6 with 385.6 violent crimes per 100,000, and District 1 with 377.4 violent crimes per 100,000. Districts 7 and 8 had the lowest violent crime rates in the state with 236.9 and 220.6 violent crimes per 100,000, respectively.

Appendix B provides the violent crime rates for each of Michigan's 83 counties. A tremendous amount of variation exists when examining violent crime rates across counties. For example, Wayne County has the highest violent crime rate with 1095.7 violent crimes per 100,000 residents. This statistic demonstrates that Wayne is the most violent county in Michigan, but it also ranks it as one of the most violent places in the United States. Wayne County's violent crime rate is nearly three times greater than the national average (366.7 violent crimes per 100,000 residents in 2019). The other counties in District 2 are Macomb and Oakland and each is much less violent. Macomb's violent crime rate is 286.9 per 100,000, whereas Oakland only experienced 193.7 violent crimes per 100,000 residents in 2020. This underscores how different MSP troopers' experiences may be in counties that are within the same district. As such, examining county-level variation in traffic stop outcomes is important. Some of the safest counties in Michigan during 2020 were Monroe (violent crime rate = 34.1), Dickinson (violent crime rate = 62.9), Montmorency (violent crime rate = 75.6), Clinton (violent crime rate = 91.8), and Houghton (violent crime rate = 94.3). Leelanau County was the safest in Michigan in 2020 with 0 reported violent crimes.

Traffic crash data benchmark

Our second benchmarking method compared traffic crash data to MSP traffic stop data. This strategy was first used in the early 2000s and continues to be a popular method for examining disparities in police traffic stop behavior (Alpert, Smith, & Dunham, 2002; COPS Office, 2016; McLean & Rojek, 2016; Tillyer et al., 2010). Traffic crash data, particularly not-at-fault drivers, is valuable in this context because it provides a reasonable estimate of the racial/ethnic composition of the driving population (Stamatiadis & Deacon, 1997). This overcomes a huge limitation of using Census data as a benchmark for traffic stop data because such data do not accurately capture the population that is at-risk to be stopped by the police. Accordingly, we will compare the racial/ethnic composition of not-at-fault drivers involved in traffic crashes to the racial/ethnic composition of traffic stops.

Information about the racial/ethnic composition of *at-fault* drivers found in traffic crash data can also be used to generate estimates of the population that is more likely to engage in dangerous/illegal driving (Withrow & Williams, 2015). If racial/ethnic disparities exist in traffic stop data, one possibility is that different groups of people may be more likely to violate traffic laws and come to the attention of the police. We will explore this possibility by benchmarking the racial/ethnic composition of at-fault crashes against the racial/ethnic composition of traffic stops conducted by MSP in 2020.

All police agencies in Michigan report traffic crash data to the Traffic Crash Reporting System (TCRS). The TCRS serves as the central repository for all traffic crashes that occurred in Michigan. By law, all police agencies in the state are required to complete and submit to MSP a standard traffic crash report form. This report is called the State of Michigan Traffic Crash Report or, more commonly, the UD-10. Nearly all agencies in Michigan electronically submit their UD-10 reports to MSP, but a small number still submit hard copies.

MSP provided traffic crash data for the first six months of 2021. Race and ethnicity of the driver were not collected on UD-10 reports prior to 2021; thus, we will compare the racial/ethnic composition of not-at-fault and at-fault drivers involved in traffic crashes between January 1, 2021 and June 25, 2021 to the racial/ethnic composition of traffic stops that occurred between January 1, 2020 and June 25, 2020. This strategy is less-than-ideal because it does not afford the ability to analyze an entire year's worth of data for the same year. However, we restricted the traffic stop data to the same time of year that the traffic crash represents, which helps account for seasonal fluctuations in the data. Moving forward, MSP will have the ability to compare traffic stop and crash data contemporaneously.

We restricted our analysis to the 189,543 motor vehicle drivers involved in traffic crashes in Michigan during the observation period. Accordingly, our analysis did not consider data from bicyclists, pedestrians, passengers, or train engineers involved in crashes. But, if a driver of a motor vehicle crashed with a pedestrian, the car driver's information was considered in our analysis.[4] We excluded 38,953 cases that were missing information on the race/ethnicity of the driver and another 12,602 cases that were classified as "unknown" driver race/ethnicity. It is important to note that there were agencies with high numbers of missing information on driver race/ethnicity. Out of the 562 agencies represented in the traffic crash data, 60 did not report driver race/ethnicity on *any* of their UD-10 reports. For another 136 agencies, driver race/ethnicity was missing from at least 25% of their crash reports. As such, we are missing traffic crash data from a non-trivial number of Michigan police agencies. We are also missing driver race/ethnicity for many crashes investigated by other agencies. Taken together, we are missing driver race/ethnicity for about 27% of crashes that occurred in Michigan during the first six months of 2021. This is a significant limitation to the traffic crash benchmark that we will discuss more later.

To determine whether the driver was "not-at-fault" or "at-fault" for the crash, we used the data field called "hazardous action." According to the UD-10 manual (p. 47), "Hazardous action coding reflects whether, in the investigating officer's opinion, a person is "at fault" in any way; i.e., did the person's action(s) contribute to the crash?" We removed 163 cases that were missing information in this data field and another 5,246 that were classified as "unknown."

This left 132,579 drivers across 86,552 unique traffic crashes available for the analysis. The data represent traffic crashes reported by 502 law enforcement agencies in Michigan. We coded

[4] We did this by restricting our analysis to only cases that were classified as "driver" in the "party type" field. This removed 33,622 non-drivers from the analysis.

Table 4. Michigan traffic crash data descriptive statistics (1/1/2021 to 6/25/2021; N = 132,579 drivers)

	Total # Drivers	Driver Race/Ethnicity: White N %	African American N %	Hispanic N %	Asian N %	Other N %	Driver Gender: Male N %	Female N %	Missing N %	Hazardous Action: At-Fault N %	Not-At-Fault N %
State of Michigan	132,579	100,048	27,076	3,580	1,559	316	75,731	56,496	352	59,428	73,151
		75.5%	20.4%	2.7%	1.2%	0.2%	57.1%	42.6%	0.3%	44.8%	55.2%
District											
1	16,571	13,802	2,074	418	248	29	9,588	6,959	24	7,428	9,143
		83.3%	12.5%	2.5%	1.5%	0.2%	57.9%	42.0%	0.1%	44.8%	55.2%
2	52,687	32,767	18,118	911	767	124	29,842	22,667	178	24,847	27,840
		62.2%	34.4%	1.7%	1.5%	0.2%	56.6%	43.0%	0.3%	47.2%	52.8%
3	17,797	14,759	2,680	273	56	29	9,964	7,764	69	7,882	9,915
		82.9%	15.1%	1.5%	0.3%	0.2%	56.0%	43.6%	0.4%	44.3%	55.7%
5	12,644	10,332	1,653	533	110	16	7,396	5,225	23	5,431	7,213
		81.7%	13.1%	4.2%	0.9%	0.1%	58.5%	41.3%	0.2%	43.0%	57.1%
6	23,604	19,354	2,458	1,395	339	58	13,398	10,154	52	10,288	13,316
		82.0%	10.4%	5.9%	1.4%	0.3%	56.8%	43.0%	0.2%	43.6%	56.4%
7	5,553	5,420	53	37	24	19	3,323	2,229	1	2,087	3,466
		97.6%	1.0%	0.7%	0.4%	0.3%	59.8%	40.1%	0.02%	37.6%	62.4%
8	3,723	3,614	40	13	15	41	2,220	1,498	5	1,465	2,258
		97.1%	1.1%	0.4%	0.4%	1.1%	59.6%	40.2%	0.1%	39.4%	60.7%

Note: Percentages may not sum to 100 due to rounding. “Total # drivers” is the total frequency of drivers involved in traffic crashes. White and African American represent non-Hispanic Whites and African Americans, respectively.

driver race/ethnicity in the same manner as the traffic stop data described above. Table 4 presents the demographic characteristics of the drivers involved in traffic crashes in Michigan from 1/1/2021 to 6/25/2021. More than three-quarters of drivers involved in crashes during this period were White and about 20% were African-American. Accordingly, a larger percentage of drivers involved in crashes are African American than would be expected based on their composition in the population (e.g., compare to Table 2). There could be many reasons why this difference exists that the data cannot address. For example, African Americans may be more likely than their counterparts to drive in heavily populated and congested areas compared to White drivers across Michigan. This could increase their exposure to traffic crash risk and disparate outcomes related to traffic stops. Less than 3% of drivers were Hispanic and about 1% were Asian (0.2% were from another racial/ethnic category). Slightly more than 57% of drivers were male, whereas about 43% were female. Lastly, about 45% of drivers were deemed to be “at-fault” for the crash and about 55% were classified as “not-at-fault” by the reporting officer.

To examine the racial/ethnic composition of traffic crashes across MSP’s seven districts, we aggregated the traffic crash data to the district-level of analysis. It is important to emphasize that these traffic crash reports were completed by all police agencies in Michigan and, thus, do not *only* represent those investigated by MSP.[5] The purpose of aggregating to the district level is to provide an understanding of the driving population demographic composition in each district. Table 4 reveals that driver race/ethnicity varies across MSP districts and the pattern does not match what may be expected from demographic differences across the districts (e.g., compared to Table 3). Namely, African Americans were involved in a much higher proportion of traffic crashes than would be expected based on their composition in each districts’ population. More than 34% of drivers involved in crashes in District 2 were African American, whereas only 24.4% of the population in that district is African American. About 15% of crash-involved drivers are African American in District 3, 13.1% in District 5, 12.5% in District 1, 10.4% in District 6, 1.0% in District 7, and 1.1% in District 8. In most cases (apart from Districts 7 and 8), these percentages are about 1.5 times greater than their representation in the district populations.

Table 5 provides the racial/ethnic distribution of at-fault versus not-at-fault traffic crashes. About 72.8% of at-fault drivers were White, whereas nearly 22.7% were African American. However, about 77.6% of not-at-fault drivers were White and 18.6% were African American. At the district level, 34.8% of at-fault and 34.1% of not-at-fault crashes in District 2 involved an African-American driver.

Appendix C provides a breakdown of crash-involved driver race/ethnicity across Michigan’s counties. Consistent with the demographic and traffic stop racial/ethnic compositions discussed earlier, the race/ethnicity of drivers involved in crashes varied across Michigan counties. For example, 51.4% of traffic crashes in Wayne County during the observation period involved an African-American driver. Over 20% of crashes in Genessee, Saginaw, Oakland, and Berrien counties, respectively, involved African-American drivers. Of the crashes in Allegan, Kent, Ottawa,

[5] We considered traffic crashes investigated by all Michigan police agencies because the purpose of the benchmark data is to approximate the racial/ethnic composition of the driving population. Restricting our focus to only crashes investigated by MSP would produce an arbitrary and unrepresentative sample of the driving population.

Table 5. Racial/ethnic composition of at-fault (N = 59,428) vs. not-at-fault (N = 73,151) traffic crashes (1/1/2021 to 6/25/2021)

Hazardous Action	At-Fault					Not-At-Fault				
Driver Race/Ethnicity	White	African American	Hispanic	Asian	Other	White	African American	Hispanic	Asian	Other
	%	%	%	%	%	%	%	%	%	%
State of Michigan	72.8%	22.7%	3.1%	1.2%	0.2%	77.6%	18.6%	2.4%	1.2%	0.2%
District										
1	80.2%	15.4%	2.8%	1.6%	0.1%	85.8%	10.3%	2.3%	1.4%	0.2%
2	61.6%	34.8%	1.9%	1.4%	0.3%	62.7%	34.1%	1.6%	1.5%	0.2%
3	79.3%	18.4%	1.8%	0.3%	0.2%	85.8%	12.5%	1.8%	0.3%	0.2%
5	77.5%	15.4%	5.3%	0.7%	0.2%	84.9%	10.6%	3.4%	1.0%	0.1%
6	78.7%	12.8%	6.7%	1.5%	0.2%	84.5%	8.6%	5.3%	1.4%	0.3%
7	96.7%	1.6%	0.9%	0.6%	0.2%	98.2%	0.6%	0.6%	0.3%	0.4%
8	95.9%	1.9%	0.3%	0.3%	1.5%	97.8%	0.5%	0.4%	0.4%	0.8%

Note: Percentages may not sum to 100 due to rounding. “Total # drivers” is the total frequency of drivers involved in traffic crashes. White and African American represent non-Hispanic Whites and African Americans, respectively.

St. Joseph, Oceana, and Van Buren counties, about 6% involved Hispanic drivers, respectively. Washtenaw County had the highest percentage of crashes involving Asian drivers (2.9%).

Veil-of-darkness benchmark

Our final benchmark analysis involved testing the "veil-of-darkness" (VOD) hypothesis with the 2020 MSP traffic stops. Recall that the VOD analysis examines whether racial/ethnic minorities are more likely to be stopped during daylight. To do so, we restricted our attention to only those traffic stops that occurred during the intertwilight period. This is the period between the earliest end of civil twilight and the latest end of civil twilight. We also omitted stops that occurred during the roughly 30-minute period between sunset and the end of civil twilight (i.e., dusk), because "that period is difficult to classify as either daylight or dark" (Grogger & Ridgeway, 2006, p. 883; see also, Stacey & Bonner, 2021; Taniguchi et al., 2017). Daylight is classified as clock times that fall before sunset. Darkness is defined as clock times falling after the end of civil twilight. This method provides a natural experiment of sorts because some clock times during the intertwilight period are daylight during one time of year but dark during another.

The method required us to calculate sunset and civil twilight times within the intertwilight period for each county in Michigan. Sun times were calculated utilizing the *suncalc* package for RStudio (github.com/datastorm-open/suncalc). The statistical package derives times based on the position of the sun and Earth (www.aa.quae.nl/en/reken/zonpositie.html). We used this information along with the latitude and longitude of the center of each Michigan county to derive county-specific sunset and civil twilight times. Time zones were set as EST, with the exception of four counties (Dickinson, Gogebic, Iron, and Menominee), which were set as CST. Daylight savings time (DST) was calculated as beginning March 8th and ending November 1st. Accordingly, the earliest and latest end of civil twilight times varied by county but ranged from 4:07pm to 10:37pm. Restricting our analysis to this intertwilight period within each county resulted in 68,628 traffic stops included in the VOD analysis.

RESULTS

The results are divided into several sections. First, we compared the racial/ethnic composition of MSP traffic stops in 2020 to the racial/ethnic composition of the population according to the 2019 ACS five-year estimates. Second, we benchmarked the 2020 traffic stop data with the 2021 traffic crash data. This involved separate benchmark analyses for "not-at-fault" and "at-fault" crashes. Each set of analyses was conducted separately for three racial/ethnic groups: African Americans, Hispanics, and Asians. Differences in the coding between datasets for other racial/ethnic groups precluded us from examining them in the benchmark analyses.

The results for the Census and traffic-crash benchmark analyses are presented in tables that feature several pieces of information. For one, we provide the percentage of the respective racial/ethnic group involved in traffic stops and the percentage of that group that is represented in either the population or traffic crashes (depending on the benchmark under consideration). Next, the tables report *z*-statistics, which are tests of whether two population means are different from one another in a statistically meaningful way. For example, a statistically significant *z*-statistic would tell us that the percentage of African-American drivers stopped by MSP is different (either larger or smaller) than the group's representation in the population (or traffic crashes). A *z*-statistic that is not statistically significant indicates that the racial/ethnic group's composition in traffic stops is about what would be expected based on their representation in the population. The tables also provide an odds ratio for each comparison which is useful for interpretation purposes. Odds ratios larger than 1 indicate that members of the racial/ethnic group are more likely to be stopped than would be expected based on their representation in the population (or traffic crashes). An odds ratio smaller than 1 would indicate that the racial/ethnic group is less likely to be stopped by MSP than would be expected based on the group's representation in the population (or traffic crashes).[6] We also color-coded the *z*-statistics and odds ratios in the tables to help with interpreting the results. Red highlighting indicates that the percentage of stops involving a particular racial/ethnic group is higher than would be expected based on their representation in the population or traffic crashes. Green highlighting indicates that the likelihood of members from a particular racial/ethnic group being stopped is lower than would be expected based on their representation in the population or traffic crashes. And, finally, gray highlighting indicates that the percentage of stops involving a particular racial/ethnic group is consistent with what would be expected based on their representation in the population or traffic crashes.

The third section of the results focused on the VOD hypothesis. This stage of the analysis will rely on logistic regression where we predict the odds of a driver being of a particular race/ethnicity based on whether the stopped occurred during daylight or darkness. We provide more information about this analysis below. The final section of the results centered attention on the stop outcome analysis. Here, again, we used logistic regression to predict the odds of a driver receiving particular outcomes after the stop is initiated (e.g., warning, citation, search, or arrest). More details on the analytic strategy are provided below.

Census Benchmark

Table 6 compares the distribution of traffic stops conducted by MSP troopers in 2020 involving an African-American driver to the distribution of African Americans in the population according to Census estimates. Before presenting these results, it is important to underscore that *relying solely on Census data benchmark results to assess the extent of racial disparity in traffic stops is inappropriate, potentially misleading, and entirely insufficient to address whether discrimination or bias exists in MSP trooper traffic stop behavior*. Yet, this exercise is useful to gain an understanding of the distribution of traffic stops across race/ethnicity compared to population composition.

[6] Odds ratios allow us to interpret the odds of drivers being stopped relative to their representation in the population (or traffic crashes). An odds ratio of 1.50, for example, would imply that the odds of a racial/ethnic group member being stopped are 50% greater than we would have expected based on their representation in the population. The 50% comes from the fact that the odds ratio is 50% larger than 1. An odds ratio of 1 would indicate equal odds of being stopped relative to one's group representation in the population. Odds ratios can also be interpreted in a different way. Take, for example, an odds ratio of 3. Here, we could say that a racial/ethnic group is 3 times more likely to be stopped than we would have expected based on their representation in the population (or, equivalently, 200% more likely).

Table 6. Comparison of African-American traffic stops to African-American representation in population

	% of stops involving African-American driver	% of population that is African American	*z*-statistic	Odds ratio
Statewide	22.1%	13.6%	130.51*	1.80
District				
1	18.1%	7.0%	87.59*	2.96
2	47.9%	24.4%	122.44*	2.84
3	31.5%	9.4%	153.29*	4.43
5	21.0%	7.6%	92.89*	3.21
6	11.5%	6.4%	34.55*	1.91
7	1.7%	0.7%	20.18*	2.46
8	1.7%	2.3%	-7.67*	0.71

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. Red highlighting indicates that the percentage of stops involving African-American drivers is higher than would be expected based on their representation in the population. Green highlighting indicates that the percentage of stops involving African-American drivers is lower than would be expected based on their representation in the population. Gray highlighting indicates that the percentage of stops involving African-American drivers is consistent with what would be expected based on their representation in the population.

Across the entire state of Michigan, 22.1% of stops involved African-American drivers, whereas African Americans composed only 13.6% of the population. The difference between these percentages is statistically significant at the 0.05 level of significance (z = 130.51).[7] The result indicates that African-American drivers were about 80% more likely (odds ratio = 1.80) to be stopped by MSP troopers than would be expected based on their estimated representation in the population. A similar pattern of results held for most of MSP's districts. The largest difference was observed in District 3. Within this district, 31.5% of traffic stops involved an African-American driver, whereas only 9.4% of the population was comprised of African Americans. This is a large and statistically significant difference (z = 153.29). African-American drivers are more than four times more likely (odds ratio = 4.43) to be stopped than expected based on their composition in District 3's population. African Americans were about three times more likely to be stopped by District 1, 2, and 5 troopers and about two times more likely to be stopped by District 6 and 7 troopers, respectively, based on their representation in the population. The opposite was true in District 8, where African-American drivers were about 29% *less likely* (odds ratio = 0.71) to be stopped than would be expected based on their representation in the district's population.

Appendix D provides the same comparison at the county level. As the table reveals, most Michigan counties experienced the same pattern of disparity as discussed above. For example,

[7] We indicated statistically significant *z*-statistics in all tables with an asterisk (*). A *z*-statistic that is at the 0.05 level of significance means that we are at least 95% confident that we did not obtain this result by chance.

Wayne County has the most diverse population in the state. Over 38% of the county is African American but, over 66% of traffic stops in the county by MSP troopers involved African-American drivers (*z* = 83.70). According to the odds ratio, African Americans were about three times more likely to be involved in a traffic stop than we would have expected based on their composition in the population (odds ratio = 3.17). It is too tedious to go through every county presented in this table, but a few are worth pointing out. Livingston County, for example, has a very small African-American population (0.6%) but more than 16% of MSP traffic stops in the county involved an African-American driver. This is a large and statistically significant difference (*z* = 74.84). In Genesee County, 19.5% of the population is African American, but they represent 58.5% of traffic stops in the area (*z* = 109.84). About 20% of traffic stops in Monroe County involved an African-American driver but only 2.3% of the population is African American (*z* = 55.33).

It is important to note that an opposite pattern of results was observed in several counties. Over 6% of Luce County's population is African American, whereas the group only represents 1.6% of traffic stops (*z* = -8.23). Thus, African Americans were 77% *less likely* to be stopped in Luce than we would have expected based on their representation in the population (odds ratio = 0.23). One of the big take-away points from Appendix D is that there is a lot of variation in traffic stop disparities across Michigan counties for African Americans when using Census data as a benchmark.

Table 7 provides a comparison of the distribution of 2020 traffic stops involving a Hispanic driver and compares it to the group's representation in the population. Here again, we see disparity in traffic stops but in the opposite direction and magnitude of the African-American disparity observed above. About 5.1% of Michigan's population is Hispanic, but they represent only 2.3% of traffic stops conducted by MSP troopers. This is a large and statistically significant difference (*z* = -66.47) and suggests that Hispanic drivers were about 56% less likely (odds ratio = 0.44) to be pulled over than we would have expected based on their representation in the population. The same pattern of results remained across all MSP districts. Hispanic drivers were 52% less likely in District 1, 63% less likely in District 2, 58% less likely in District 3, 62% less likely in District 6, 62% less likely in District 7, and 67% less likely in District 8 to be pulled over by a trooper than we would have expected based on their population representation. The percentage of stops involving Hispanic drivers was about what we would have expected in District 5 based on the ethnic composition of the population (based on the non-statistically significant *z*-statistic).

Appendix E presents these comparisons for Hispanic drivers across Michigan counties. Throughout most counties, Hispanic drivers were less likely to be pulled over by MSP troopers than expected based on the composition of the population. In only one county did Hispanics face disparity in traffic stops. In Berrien County, 7.1% of stops involved Hispanic drivers, whereas 5.5% of the population is Hispanic. This is a moderate but statistically significant difference (*z* = 7.11). Hispanic drivers are about 31% more likely to be stopped compared to their representation in the county's population (odds ratio = 1.31).

Table 8 presents a comparison of the distribution of Asian drivers involved in traffic stops to the group's representation in the population. Like Hispanic drivers, Asian drivers were significantly less likely to be stopped based on their population composition across the state (*z* = -68.34). About 3.1% of Michigan's population is Asian but less than one-percent of traffic stops involved Asian drivers. This suggests that Asians were about 77% less likely to be stopped than we would have expected based on their population representation (odds ratio = 0.23). A similar pattern of results held across nearly all of MSP's districts. Within District 8, however, Asians were stopped at a rate that matches their representation in the population (z = -1.84).

Table 7. Comparison of Hispanic traffic stops to Hispanic representation in population

	% of stops involving Hispanic driver	% of population that is Hispanic	*z*-statistic	Odds ratio
Statewide	2.3%	5.1%	-66.47*	0.44
<u>**District**</u>				
1	2.4%	5.0%	-24.60*	0.48
2	1.7%	4.6%	-31.01*	0.37
3	1.8%	4.2%	-26.86*	0.42
5	5.7%	5.9%	-1.92	0.96
6	3.2%	8.2%	-29.30*	0.38
7	0.9%	2.2%	-16.53*	0.38
8	0.6%	1.6%	-14.90*	0.33

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. Red highlighting indicates that the percentage of stops involving Hispanic drivers is higher than would be expected based on their representation in the population. Green highlighting indicates that the percentage of stops involving Hispanic drivers is lower than would be expected based on their representation in the population. Gray highlighting indicates that the percentage of stops involving Hispanic drivers is consistent with what would be expected based on their representation in the population.

More variation exists when we examined the Asian benchmark across counties. Appendix F presents these results, and it is clear from the non-statistically significant z-statistics for many counties, Asians were represented in traffic stops in a manner consistent with what we would have expected based on their population representation. However, there are also numerous counties where Asians were less likely to be stopped based on their population composition, and some counties where Asians were stopped at a rate greater than expected based on their population composition.

Census benchmark limitations

Census data benchmarking is a good starting point, but it is problematic because it does not represent the driving population. The benchmark simply compares the racial/ethnic composition of traffic stops to the racial/ethnic composition of the population. It is possible (and highly likely) that the driving population is not necessarily the same as the residential population, especially in areas with interstate highways. This limitation is particularly salient when examining traffic stops conducted by a state police agency with a great deal of presence on interstates. Therefore, we must use other benchmarking strategies to gain a fuller understanding of whether meaningful disparities exist in MSP's traffic stops.

Table 8. Comparison of Asian traffic stops to Asian representation in population

	% of stops involving Asian driver	% of population that is Asian	*z*-statistic	Odds ratio
Statewide	0.7%	3.1%	-68.34*	0.23
<u>District</u>				
1	1.1%	4.1%	-30.63*	0.25
2	0.8%	4.8%	-38.67*	0.17
3	0.3%	0.9%	-14.41*	0.30
5	1.1%	1.6%	-7.26*	0.71
6	0.6%	2.0%	-15.79*	0.30
7	0.4%	0.5%	-3.13*	0.75
8	0.8%	0.9%	-1.84	0.89

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. Red highlighting indicates that the percentage of stops involving Asian drivers is higher than would be expected based on their representation in the population. Green highlighting indicates that the percentage of stops involving Asian drivers is lower than would be expected based on their representation in the population. Gray highlighting indicates that the percentage of stops involving Asian drivers is consistent with what would be expected based on their representation in the population.

Traffic-crash benchmark

Traffic crash data is a commonly used benchmark when examining traffic stop racial disparities because it does a better job estimating the driving population than does Census data. We begin the traffic-crash benchmark analyses by exploring "not-at-fault crashes." Before doing so, we restricted the traffic stop data in our analyses to only those stops that occurred between 1/1/2020 and 6/25/2020. This allowed us to compare the traffic stops to crashes during the same time of year. While we do not have crash data for 2020, this strategy allows us to account for potential seasonal differences in stops and crashes throughout the year. For example, if we compared traffic stops for all of 2020 to the crash data for which we only have the first six months of 2021, differences in stop activity from July through December could confound the benchmark analyses.

"Not-at-fault" traffic crash benchmark results

Table 9 provides a comparison of the percentage of 2020 (January to June) traffic stops that involved an African-American driver to the percentage of 2021 (January to June) traffic crashes that involved an African-American driver that was found to be "not-at-fault" for the crash. During this period, 21.2% of MSP traffic stops involved an African-American driver, whereas 18.6% of "not-at-fault" crashes involved an African-American driver. This difference was statistically significant (*z*-statistic = 13.71), and the odds ratio indicates that African Americans were about 18% more likely to be stopped by MSP than would be expected based on their involvement in "not-at-fault" crashes. This is a meaningful, but moderate, level of racial disparity. A larger amount of disparity was observed across each of MSP's districts. For example, in District 6 African

Americans were about 47% more likely to be stopped compared to their representation as drivers in "not-at-fault" crashes (*z*-statistic = 9.15). This was the least amount of racial disparity out of the seven districts. District 3 had the largest gap where African-American drivers represented 32.1% of traffic stops but only 12.5% of "not-at-fault" crashes (*z*-statistic = 35.29). This translated into African-American drivers being about 233% more likely to be stopped than would be expected based on their representation in "not-at-fault" crashes.

Table 9. Comparison of African-American traffic stops to African-American representation in "not-at-fault" crashes (All crashes)

	% of stops involving African-American driver	% of crashes involving African-American drivers	*z*-statistic	Odds ratio
Statewide	21.2%	18.6%	13.71*	1.18
District				
1	17.3%	10.3%	15.23*	1.83
2	46.1%	34.1%	27.19*	1.65
3	32.1%	12.5%	35.29*	3.33
5	19.3%	10.6%	16.59*	2.02
6	12.1%	8.6%	9.15*	1.47
7	1.4%	0.6%	3.91*	2.51
8	1.5%	0.5%	3.49*	2.83

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving African-American drivers is higher than would be expected based on their representation in not-at-fault crashes. Green highlighting indicates that the percentage of stops involving African-American drivers is lower than would be expected based on their representation in not-at-fault crashes. Gray highlighting indicates that the percentage of stops involving African-American drivers is consistent with what would be expected based on their representation in in not-at-fault crashes.

Appendix G presents a county-level comparison of African-American driver representation in traffic stops and crashes. In 37% of Michigan counties, the composition of African-American drivers in traffic stops was about what we would have expected based on their involvement in "not-at-fault" crashes (as evidenced by the non-statistically significant *z*-statistics). However, in about 39% of counties, African-American drivers were significantly more likely to be stopped than we would have expected based on their representation in "not-at-fault" crashes. For example, African Americans were between 4 and 6 times more likely to be stopped than we would have expected based on group representation in "not-at-fault" crashes in counties such as Branch, Clinton, Genessee, Hillsdale, Ionia, Jackson, Livingston, Midland, Ottawa, St. Joseph, Tuscola, and Van Buren. Although Muskegon County has fewer traffic stops and crashes than more populated counties, it had the largest gap. Here, African-American drivers were almost 23 times more likely to be stopped by an MSP trooper than we would have expected based on their representation in "not-at-fault" crashes (*z*-statistic = 5.35, odds ratio = 22.94). As we mentioned earlier, however, there are many agencies in Michigan that insufficiently reported driver race/ethnicity in traffic crash reports. It is possible (if not likely) that large differences observed in Appendix G are partially caused by this lack of vital traffic crash data.

A different pattern of results emerged when comparing Hispanic drivers' composition in traffic stops and crashes (see Table 10). Statewide, Hispanic drivers were slightly *less likely* to be stopped than we would have expected based on their involvement in "not-at-fault" crashes (*z*-statistic = -2.06, odds ratio = 0.94). In 5-of-the-7 districts, Hispanic representation in traffic stops was either what we would have expected or lower than we would have expected based on their involvement in "not-at-fault" crashes. Only in Districts 2 and 5 were Hispanics more likely to be stopped than we would have expected based on their representation in "not-at-fault" crashes.

Table 10. Comparison of Hispanic traffic stops to Hispanic representation in "not-at-fault" crashes (All crashes)

	% of stops involving Hispanic driver	% of crashes involving Hispanic drivers	*z*-statistic	Odds ratio
Statewide	2.3%	2.4%	-2.06*	0.94
<u>**District**</u>				
1	2.2%	2.3%	-0.38	0.97
2	1.8%	1.6%	2.23*	1.17
3	1.6%	1.3%	1.79	1.21
5	5.4%	3.4%	6.72*	1.62
6	3.3%	5.3%	-7.51*	0.62
7	0.5%	0.5%	-0.11	0.97
8	0.4%	0.4%	0.06	1.02

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving Hispanic drivers is higher than would be expected based on their representation in not-at-fault crashes. Green highlighting indicates that the percentage of stops involving Hispanic drivers is lower than would be expected based on their representation in not-at-fault crashes. Gray highlighting indicates that the percentage of stops involving Hispanic drivers is consistent with what would be expected based on their representation in not-at-fault crashes.

The same results emerged in the county-level comparison presented in Appendix H. Hispanic drivers were more likely to be involved in traffic stops than we would have expected based on their representation in "not-at-fault" crashes in only six counties. In all other counties where comparisons could be calculated, Hispanic driver representation in traffic stops matched the ethnic composition of "not-at-fault" crashes.

Table 11 compares the composition of Asian drivers involved in traffic stops to their representation in "not-at-fault" crashes. Asian drivers are about 40% less likely to be stopped than we would have expected based on their representation in the "not-at-fault" crashes (*z*-statistic =

-10.31, odds ratio = 0.60). Across all of MSP's districts, Asian drivers' odds of being stopped were lower or equal to their representation in the "not-at-fault" crashes. Appendix I presents the county-level comparison and the same results emerged. In nearly all counties, Asian drivers' representation in traffic stops was what we would have expected based on their composition in "not-at-fault" crashes. In only two counties were Asian drivers more likely to be stopped than we would have expected.

Table 11. Comparison of Asian traffic stops to Asian representation in "not-at-fault" crashes (All crashes)

	% of stops involving Asian driver	% of crashes involving Asian driver	*z*-statistic	Odds ratio
Statewide	0.7%	1.2%	-10.31*	0.60
<u>District</u>				
1	1.1%	1.4%	-1.87	0.81
2	0.9%	1.5%	-5.92*	0.59
3	0.3%	0.3%	-0.81	0.83
5	1.1%	1.0%	0.50	1.07
6	0.6%	1.4%	-6.10*	0.42
7	0.3%	0.3%	-0.47	0.85
8	0.5%	0.4%	0.18	1.06

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving Asian drivers is higher than would be expected based on their representation in not-at-fault crashes. Green highlighting indicates that the percentage of stops involving Asian drivers is lower than would be expected based on their representation in not-at-fault crashes. Gray highlighting indicates that the percentage of stops involving Asian drivers is consistent with what would be expected based on their representation in not-at-fault crashes.

Supplemental "not-at-fault" traffic-crash benchmark analysis

We conducted a supplemental traffic crash benchmark analysis to assess the robustness of the results. The analyses discussed above focused on all traffic crashes regardless of the number of vehicles involved. The problem, however, is that the racial disparity research literature is unclear on whether this is the appropriate methodology. Some researchers contend that including all crashes, regardless of the number of vehicles involved, provides a reasonable estimate of the driving population (Williams & Withrow, 2015). Other researchers recommend that traffic crash benchmark analyses be restricted to only those crashes involving two vehicles (Alpert, Smith, & Dunham, 2004). This recommendation is based on research by traffic engineers who have shown that two-vehicle, not-at-fault crashes provide a valid estimate of the driving population (Kirk & Stamatiadis, 2001; Lyles, Stamatiadis, & Lighthizer, 1991; Stamatiadis & Deacon, 1997). The argument is that a driver being involved in a two-vehicle crash for which they are not responsible is more random than being involved in a single-vehicle crash. Deficiencies in driver ability (regardless of whether the driver is deemed at-fault or not) are more likely to be a factor in single-vehicle crashes than two-vehicle crashes according to this view. As such, the randomness of two-vehicle crashes may better approximate the racial/ethnic composition of the driving population than single-vehicle crashes would.

We cannot arbitrate this issue, but we felt it was important to explore whether restricting our attention to only two-vehicle, "not-at-fault" crashes impacted the above results. In doing so, we focused only on comparing African-American drivers' involvement in stops and "not-at-fault" crashes because that is where the most disparity was observed above. After restricting the analysis to only two-vehicle crashes during the observation period, we were left with 47,265 drivers involved in "not-at-fault" crashes. Table 9-*Supplemental* presents the results of this supplemental analysis. About 22.9% of two-vehicle, "not-at-fault" crashes involved an African-American driver. Accordingly, there was a greater percentage of African Americans involved in "not-at-fault" crashes when only examining two-vehicle crashes (compared to all crashes above). This caused the disparity that was originally observed statewide in Table 9 (above) to disappear. Across the entire state, African-American drivers were about 10% less likely to be stopped than we would have expected based on their involvement in two-vehicle, "not-at-fault" crashes (*z*-statistic = -7.94, odds ratio = 0.90).

Table 9-*Supplemental*. Comparison of African-American traffic stops to African-American representation in "not-at-fault" crashes (Only two-vehicle crashes)

	% of stops involving African-American driver	% of crashes involving African-American drivers	*z*-statistic	Odds ratio
Statewide	21.2%	22.9%	-7.94*	0.90
<u>District</u>				
1	17.3%	12.7%	8.11*	1.44
2	46.1%	35.0%	23.64*	1.59
3	32.1%	17.6%	20.74*	2.21
5	19.3%	13.9%	7.83*	1.48
6	12.1%	10.7%	2.96*	1.15
7	1.4%	0.4%	2.87*	3.68
8	1.5%	0.6%	2.14*	2.64

Note: These comparisons are restricted to only two-vehicle crashes. Percentages may not sum to 100 due to rounding. *$p < 0.05$. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving African-American drivers is higher than would be expected based on their representation in not-at-fault crashes. Green highlighting indicates that the percentage of stops involving African-American drivers is lower than would be expected based on their representation in not-at-fault crashes. Gray highlighting indicates that the percentage of stops involving African-American drivers is consistent with what would be expected based on their representation in in not-at-fault crashes.

The racial disparity patterns remained when we examined the comparisons across each of the MSP districts. African-American drivers were more likely to be stopped in each of the districts compared to their involvement in two-vehicle "not-at-fault" crashes. We also re-ran the analyses across each Michigan county and those results are presented in Appendix G-*Supplemental*. The substantive results remained unchanged. All counties that had racial disparity had the same results when examining only two-vehicle, "not-at-fault" crashes. Six counties that originally did not have evidence of racial disparity did so when the analysis examined only two-vehicle, "not-at-fault" crashes. These findings suggest that the bulk of the results observed above remains regardless of whether we consider all "not-at-fault" crashes or only two-vehicle, "not-at-fault" crashes.

"At-fault" traffic crash benchmark results

At this point we turn our attention to benchmarking racial/ethnic composition of traffic stops with "at-fault" crashes. These analyses are useful because racial/ethnic disparities in traffic stop behavior may be partially a function of differences in risky or illegal driving behaviors across racial/ethnic groups. Table 12 presents this comparison for African Americans. Across the entire state, African-American drivers are slightly less likely to be stopped compared to their involvement in "at-fault" crashes (z-statistic = -7.44, odds ratio = 0.91). In Districts 6, 7, and 8, the percentage of African-American drivers stopped by MSP troopers matched what we would have expected based on their representation in "at-fault" crashes. However, in Districts 1, 2, 3, and 5 African-American

Table 12. Comparison of African-American traffic stops to African-American representation in "at-fault" crashes

	% of stops involving African-American driver	% of crashes involving African-American drivers	z-statistic	Odds ratio
Statewide	21.2%	22.7%	-7.44*	0.91
District				
1	17.3%	15.3%	4.02*	1.16
2	46.1%	34.8%	24.86*	1.60
3	32.1%	18.3%	22.63*	2.11
5	19.3%	16.4%	4.75*	1.21
6	12.1%	12.8%	-1.72	0.93
7	1.4%	1.6%	-0.52	0.91
8	1.5%	1.9%	-1.26	0.77

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving African-American drivers is higher than would be expected based on their representation in at-fault crashes. Green highlighting indicates that the percentage of stops involving African-American drivers is lower than would be expected based on their representation in at-fault crashes. Gray highlighting indicates that the percentage of stops involving African-American drivers is consistent with what would be expected based on their representation in at-fault crashes.

drivers were significantly more likely to be stopped than we would have expected based on the benchmark data. For example, an African-American driver's odds of being stopped in District 3 was about two times greater than we would have expected based on the racial composition of "at-fault" crashes in the district (*z*-statistic = 22.63, odds ratio = 2.11). African-American drivers were 60% more likely to be stopped in District 2 than we would have expected based on their involvement in "at-fault" crashes (*z*-statistic = 24.86, odds ratio = 1.60).

The county-level comparison results are presented in Appendix J. On the one hand, this analysis reveals smaller disparities between African-American traffic stops and at-fault crashes than what we saw when we used "not-at-fault" crashes as the benchmark (see Appendix G). This suggests that part of the disparity in traffic stops could be attributed to different driving behavior among African Americans. Or, it is also possible that troopers were more likely to assign fault to African-American drivers than other races/ethnicities. These data cannot speak to which explanation is correct. On the other hand, there are still many counties where African Americans are significantly more likely to be stopped than we would have expected based on their involvement in "at-fault" crashes. Yet, in 49 Michigan counties, African Americans were stopped at a rate that is similar to (or less than) what we would have expected based on their involvement in "at-fault" traffic crashes.

Table 13. Comparison of Hispanic traffic stops to Hispanic representation in "at-fault" crashes

	% of stops involving Hispanic driver	% of crashes involving Hispanic drivers	*z*-statistic	Odds ratio
Statewide	2.3%	3.1%	-10.14*	0.73
District				
1	2.2%	2.8%	-2.63*	0.80
2	1.8%	1.9%	-0.38	0.97
3	1.6%	1.8%	-1.11	0.89
5	5.4%	5.3%	0.51	1.04
6	3.3%	6.7%	-11.49*	0.47
7	0.5%	0.9%	-1.84	0.62
8	0.4%	0.3%	0.13	1.06

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving Hispanic drivers is higher than would be expected based on their representation in at-fault crashes. Green highlighting indicates that the percentage of stops involving Hispanic drivers is lower than would be expected based on their representation in at-fault crashes. Gray highlighting indicates that the percentage of stops involving Hispanic drivers is consistent with what would be expected based on their representation in at-fault crashes.

Table 13 presents the results from the benchmark analysis comparing Hispanic driver composition in traffic stops to their representation in "at-fault" crashes. Hispanics in Michigan were about 27% less likely to be stopped than expected when using "at-fault" crashes as the benchmark (*z*-statistic = -10.14, odds ratio = 0.73). In Districts 2, 3, 5, 7, and 8, Hispanic drivers were stopped at a rate that we would have expected based on the benchmark. And, in Districts 1 and 6, Hispanic drivers were less likely to be stopped than we would have expected based on their involvement in "at-fault" crashes. The same pattern of results emerged in the county-level comparison that is presented in Appendix K. In only one county—Berrien—were Hispanics slightly more likely to be stopped than we would have expected based on the benchmark (*z*-statistic = 2.05, odds ratio = 1.37).

Table 14 compares the percentage of Asian drivers stopped by troopers to their involvement in "at-fault" crashes. Nearly the same results emerged as those in the "not-at-fault" crash benchmark. Across Michigan, Asian drivers were 42% less likely to be stopped than expected based on their involvement in "at-fault" crashes (*z*-statistic = -10.59, odds ratio = 0.58). In all districts except one, Asian drivers' representation in traffic stops was lower or what we would have expected based on their involvement in at-fault crashes. In District 5, Asians were about 60% more likely to be stopped than we would have expected based on the benchmark (*z*-statistic = 2.61, odds ratio = 1.60). It is important to point out, however, that this is based on a relatively low base rate of Asian driver involvement in stops and crashes. When we do this comparison at the county level (see Appendix L), there were zero counties in Michigan for which comparisons could be calculated where Asian drivers were more likely to be stopped than expected.

Table 14. Comparison of Asian traffic stops to Asian representation in "at-fault" crashes

	% of stops involving Asian driver	% of crashes involving Asian driver	*z*-statistic	Odds ratio
Statewide	0.7%	1.2%	-10.59*	0.58
<u>**District**</u>				
1	1.1%	1.6%	-3.10*	0.70
2	0.9%	1.4%	-5.63*	0.60
3	0.3%	0.3%	-1.13	0.76
5	1.1%	0.7%	2.61*	1.60
6	0.6%	1.5%	-6.37*	0.40
7	0.3%	0.6%	-2.60*	0.43
8	0.5%	0.3%	0.70	1.38

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving Asian drivers is higher than would be expected based on their representation in at-fault crashes. Green highlighting indicates that the percentage of stops involving Asian drivers is lower than would be expected based on their representation in at-fault crashes. Gray highlighting indicates that the percentage of stops involving Asian drivers is consistent with what would be expected based on their representation in at-fault crashes.

Traffic crash benchmark limitations

The results from the "not-at-fault" and "at-fault" traffic crash benchmark analyses provide important insight concerning racial/ethnic disparities in MSP's 2020 traffic stops. There are disparities with respect to African-American drivers that warrant closer examination. At the same time, however, there are several limitations with these benchmarks that are worth noting. First, not all Michigan crashes were represented in the crash database. As discussed earlier, many Michigan police agencies did not report driver race/ethnicity on their crash reports. We are missing driver race/ethnicity for about 27% of traffic crashes in the first six months of 2021. Accordingly, a portion of the racial disparities observed in these benchmark analyses may be attributable to missing data rather than problematic behavior on the part of MSP troopers. It is possible that the percentage of African-American drivers involved in "not-at-fault" and "at-fault" crashes would increase if we had complete data. If this were to occur, the amount of disparity currently attached to MSP traffic stop behavior would be reduced (or eliminated). Of course, it is also possible that the opposite could occur. Unfortunately, we are unclear about the true racial makeup of Michigan traffic crashes due to this missing data.

Second, the traffic stop and crash data did not cover an entire year (i.e., each covers about six months). This introduces uncertainty about whether the same conclusions would be reached if we had complete data to work with. The good news is that MSP will be able to conduct such analyses in the future as data becomes available.

Third, and relatedly, the stop and crash data came from different years (i.e., 2020 and 2021, respectively). This is important because 2020 witnessed the beginning of the COVID-19 pandemic and related changes to people's work, travel, and driving patterns, and operational changes in traffic stop behavior (e.g., potentially less stop activity caused by less frequent citizen driving). While people worked from home more often during 2020, this trend may not have applied equally across racial groups. In particular, African Americans may have been on the road traveling to and from work more often than their White counterparts because, as a group, they may have been more likely to work in service-oriented jobs that could not operate remotely. If true, it is possible that a larger proportion of drivers on the road were African American in 2020 compared to normal years. This would necessarily increase African-American drivers' exposure risk to being stopped by the police. When driving patterns return to normal, it is possible the observed disparities will become weaker. Answers to such questions await future inquiry.

The final limitation with the traffic crash benchmarks is that they are imprecise when it comes to matching the locations that troopers patrol. Police officers often are deployed in strategic manners. For example, officers are typically assigned to patrol areas that have recent experience with crime and/or traffic safety problems. If African Americans are more likely to live or work in areas with such concerns, we would have expected traffic stop disparities to a certain degree. Unfortunately, the traffic crash data benchmarks do not resolve this problem because they are aggregated to a level that is larger than assigned patrol locations in many situations. Ideally, we would be able to geographically locate both traffic stop and crash data to create more precise comparisons. However, such data and analytic capabilities are often unavailable.

Veil-of-Darkness Benchmark

The veil-of-darkness (VOD) analysis used logistic regression equations to predict driver race/ethnicity (i.e., the dependent variables) with an indicator of daylight (i.e., the primary independent variable). We also controlled for the day of the week (Sunday was used as the reference category) and the time the traffic stop took place. We created a time bin to represent the clock time of the traffic stop by dividing the intertwilight period into 45-minute intervals. Following the approach used by Taniguchi et al. (2017), we separated the intertwilight period into eight equal temporal groups with the earliest block (from the earliest end of civil twilight to 45-minutes later) coded as one, the second 45-minute block coded as two, and so on. The models also controlled for trooper assignment type (general patrol assignment was used as the reference category) and the county-level violent crime rate where the stop occurred.

Table 15 provides the racial/ethnic composition of traffic stops occurring during the intertwilight period, and the percentage of stops during daylight and darkness across each racial/ethnic category. A majority of traffic stops during the intertwilight period involved a White driver (76.6%). About 20.4% of stops during the intertwilight period involved an African-American driver. The racial composition of drivers during daylight and darkness varied. Among stops that occurred during daylight, 75.2% were White drivers and 21.5% were African-American drivers. However, 77.6% of stops during darkness involved White drivers and 19.4% involved African-American drivers. The percentage of stops involving African-American drivers was slightly smaller during darkness.

Table 15. Veil of Darkness descriptive statistics

	ITP		Daylight ITP		Darkness ITP	
	N	%	*N*	%	*N*	%
<u>Driver Race/Ethnicity</u>						
White (non-Hispanic)	52,542	76.6%	23,197	75.2%	29,345	77.6%
African American (non-Hispanic)	13,967	20.4%	6,621	21.5%	7,346	19.4%
Hispanic	1,335	2.0%	635	2.1%	700	1.9%
Asian	450	0.7%	226	0.7%	224	0.6%
Other	334	0.5%	155	0.5%	179	0.5%
Total	68,628		30,834		37,794	

Note: ITP = Intertwilight period. Percentages may not sum to 100 due to rounding.

Table 16 presents the results from four logistic regression equations that used the daylight variable to predict the race/ethnicity of drivers involved in traffic stops. The first model examined whether daylight predicted whether a driver was African American. The results reveal a statistically significant relationship between driver race and daylight. Daylight traffic stops were 33% more likely to involve African-American drivers than stops conducted during dark (b = .288, p < .01; OR = 1.33). This suggests that African-American drivers were more likely to be stopped during daylight hours when, presumably, it is easier to see a driver's race. Daylight was not associated with the odds of a driver being Hispanic, Asian, or from another race/ethnicity category.

Table 16. Veil of Darkness logistic regressions predicting race/ethnicity of driver (N = 68,628)

	Driver Race/Ethnicity [a]			
Variables	African-American	Hispanic	Asian	Other Race/Ethnicity
	b (SE) OR	*b* (SE) OR	*b* (SE) OR	*b* (SE) OR
Daylight traffic stop (1 = daylight, 0 = darkness)	.288** (.069) 1.33	.118 (.121) 1.13	.189 (.150) 1.21	.091 (.154) 1.10
Day of the week [b]				
Monday	.062 (.065) 1.06	-.158 (.130) 0.85	-.168 (.252) 0.85	-.175 (.277) 0.84
Tuesday	.192* (.090) 1.21	.073 (.122) 1.08	-.259 (.231) 0.77	-.234 (.254) 0.79
Wednesday	.005 (.074) 1.01	-.023 (.105) 0.98	-.276 (.202) 0.76	-.295 (.206) 0.75
Thursday	.055 (.067) 1.06	.021 (.110) 1.02	-.274 (.197) 0.76	.034 (.206) 1.03
Friday	-.030 (.072) 0.97	-.145 (.102) 0.86	-.143 (.173) 0.87	-.037 (.180) 0.96
Saturday	.096 (.062) 1.10	.152 (.101) 1.16	.084 (.166) 1.09	-.100 (.176) 0.90
Time bin [c]	.072* (.030) 1.07	.006 (.030) 1.01	-.005 (.034) 1.00	.045 (.072) 1.05
Trooper assignment [d]				
Grant/directed patrol	.837** (.303) 2.31	-.226 (.195) 0.80	-.124 (.220) 0.88	.058 (.243) 1.06
Field Training program	.090 (.468) 1.09	-.008 (.128) 0.99	-.298 (.258) 0.74	-.629 (.392) 0.53
Hometown Security Team	.169 (.445) 1.18	.564* (.239) 1.76	-.099 (.398) 0.91	.561 (.388) 1.75
Sergeant's duties	.192 (.136) 1.21	.372 (.209) 1.45	.630* (.316) 1.88	--- [e]
Other assignment	-.160 (.216) 0.82	-.540 (.424) 0.58	.333 (.235) 1.40	-.436 (.447) 0.65
County-level violent crime rate	.004** (.001) 1.004	.001* (.0005) 1.001	-.0003 (.0003) 0.995	-.002* (.001) 0.998
Intercept	-3.89** (.502)	-4.46** (.295)	-4.83** (.273)	-4.62** (.344)
Wald χ^2	272.32**	92.91**	24.48*	23.58*
Pseudo R^2	.202	.014	.006	.021

Note: Entries are unstandardized partial regression coefficients (*b*), robust standard errors that adjust for clustering at the county level (SE), and odds ratios (OR).

[a] A separate logistic regression equation was estimated for each driver race/ethnicity category.

[b] Reference category = Sunday.

[c] Time bin is an ordered-categorical variable where the time of traffic stops were classified into eight 45-minute periods. The earliest stops in the intertwilight period were coded 1 and the latest as 8.

[d] Reference category = General patrol assignment.

[e] Omitted due to collinearity.

***p*<0.01; **p*<0.05.

Several other variables were significantly associated with the odds of a driver being African American. Traffic stops conducted on Tuesdays were significantly more likely to involve an African-American driver than those conducted on Sundays (b = .192, p < .05; OR = 1.21). The time bin variable also was positively and significantly associated with driver race (b = .072, p < .05; OR = 1.07). Specifically, stops conducted later in the evening were more likely to involve African-American drivers, net of other factors accounted for in the model. Trooper assignment emerged as a significant predictor of driver race. Traffic stops conducted by troopers assigned to "grant/directed patrol" activities were 131% more likely to involve African-American drivers than stops conducted by troopers assigned to general patrol activities, net of other relevant factors (b = .837, p < .01; OR = 2.31). Lastly, county-level violent crime rate was positively and significantly associated with driver race (b = .004, p < .01; OR = 1.004). The odds of a driver being African-American are expected to increase by 20% for every additional 50 violent crimes per 100,000 residents.

Some researchers have restricted their VOD analyses to the 30-days before and after the switch to daylight savings time (DST) as a sensitivity analysis (Stacey & Bonner, 2021; Taniguchi et al., 2017). According to Taniguchi et al. (2017, p. 439), "The DST switch causes a well-defined difference in daylight at the same time of day and limits the amount of variance that could be caused by seasonal differences in traffic patterns." As a robustness check, we restricted our VOD analysis to only stops that occurred during the 30-days before and after the switch to DST and the intertwilight period. DST started on March 8th in 2020. Therefore, this analysis considers MSP traffic stops that occurred from February 7, 2020 through April 6, 2020. This resulted in 9,050 stops in the restricted VOD analysis. The results from these analyses are presented in Appendix M. Two important results emerged that conflict with the main VOD analyses discussed earlier. First, with the DST restriction, daylight no longer predicted the odds of a driver being African American. Second, the final model in Appendix M demonstrates that traffic stops conducted during daylight (during the 30-days before and after the change to DST) were about 3.5-times more likely to involve a driver from the other race/ethnicity category than stops conducted in the dark (b = 1.314, p < 0.05; OR = 3.72).

These findings provide some caution when interpreting the VOD results. One of the problems with the typical VOD analysis is that it assumes there are no seasonal differences in driving patterns across driver race/ethnicity. As Taniguchi et al. (2017, p. 441) point out, "Certain conditions (i.e., large population changes based on university schedule or large seasonal changes in population) may invalidate this assumption." We tested this assumption by restricting the VOD to the 30-days before and after the switch to DST. The fact that daylight failed to predict whether a driver is African American in this restricted analysis, suggests there could be seasonal differences in the "nature of traffic stops, or in the makeup of drivers on the road, depending on the time of year" (Stacey & Bonner, 2021, p. 66). While it is a valuable technique, the inconsistent findings underscore the importance of not relying solely on the VOD methodology when assessing traffic stop disproportionality.

Veil of darkness benchmark limitations

In addition to the mixed VOD results, there was an important limitation related to the DST-restricted analyses. Specifically, the observation period for these analyses (February 7 through

April 6, 2020) was the start of the COVID-19 pandemic in the United States. Travel patterns and enforcement activities likely changed dramatically starting in March 2020 with Michigan's stay-at-home orders. It is possible that this caused the mixed results to emerge. If COVID-19 had not occurred, travel patterns may have remained the same and daylight could have predicted the odds of being an African-American driver in both sets of VOD analyses. However, it is also possible that the DST-restricted analyses produced valid results. Unfortunately, our data cannot speak to which possibility is correct.

Stop Outcome Analysis

We now turn our attention to the post-stop portion of the analysis, where we explored the different outcomes that stemmed from MSP traffic stops. Our goal here was to examine whether African-American, Hispanic, or Asian drivers disproportionately received sanctions during traffic stops, net of other factors that may influence trooper decision making during post-stop activities. For the stop outcome analysis, we used the same traffic stop, Census, and crime data as described above. However, we used several new variables for this portion of the analysis, each of which is described next.

Stop outcome analysis variables

We coded for whether a warning, citation, search, or arrest occurred during each traffic stop (1 = yes, 0 = no). It is important to note that these categories were not mutually exclusive because multiple outcomes could have occurred during the same traffic stop. For example, during a single traffic stop, a trooper could issue a warning for a broken taillight and citation for speed. During the same encounter, the trooper could have conducted a consent search and arrested the driver based on contraband found during that search. In such an incident, the data would be coded "1" for each of the outcomes.

Searches were grouped into three categories based on the level of discretion available to the trooper—consent, high-discretion, and low-discretion searches. Consent searches were those in which a driver consented to a trooper's request to conduct a search (i.e., either verbal or written consent). High-discretion searches were those carried out without a driver's consent but based on probable cause (or plain view/smell). Low-discretion searches included searches incident to a lawful arrest, vehicle inventories, or warrants. We only considered consent searches and high-discretion searches in the outcome analyses because trooper discretion is limited in the low-discretion searches. As one government report put it: "In situations in which the officer has discretion, a completely unbiased officer decides whom to search based solely on the likelihood of discovering drugs, evidence, or other contraband, while a biased officer may search drivers of a particular racial or ethnic group based on the incorrect assumption that the group as whole may present a higher likelihood of possessing drugs or other contraband" (COPS, 2016, p. 319).

MSP troopers list the reason for the traffic stop when completing their reports. There are hundreds of options that troopers can pick from when listing the reason for the stop. However, there is also an indicator in the traffic stop data for whether the stop was for a "hazardous" violation. Troopers are trained to indicate that the stop was for a "hazardous" reason if the violation was a danger to the individual or the public. Accordingly, we controlled for whether the traffic stop was conducted for a hazardous violation in the stop outcome analyses with a binary variable (1 = hazardous violation, 0 = non-hazardous violation).

As discussed earlier, the structural features of the communities that troopers patrol may impact their post-stop decision-making. Accordingly, we accounted for district- and county-level structural characteristics in their respective analyses. We controlled for the racial and ethnic composition of the district or county in which the traffic stop took place by accounting for the percentage of the area that was African American (*% African American*) and Hispanic (*% Hispanic*). We did not control for the percentage of the population that is White, Asian, or other race/ethnicity in the analyses because doing so would have caused problematic levels of collinearity (i.e., they were inversely correlated with the percentage of the population that is African American and Hispanic).

Research reveals that the degree of concentrated disadvantage in a community is associated with a wide range of negative outcomes such as higher rates of violent victimization (Kubrin & Weitzer, 2003). Concentrated disadvantage also has been shown to predict police officer post-stop behavior (COPS, 2016). Accordingly, we accounted for the level of concentrated disadvantage in the district or county where the traffic stop took place. The variable is a mean scale constructed by summing and averaging values from three structural indicators: the percentage of the population that is unemployed, the percentage that lives below the poverty line, and the percentage of households that are female-headed.[8] These indicators are commonly used to capture concentrated disadvantage (Parker & Reckdenwald, 2008). Principal-axis factoring demonstrated the items loaded on a single factor (District Disadvantage eigenvalue = 1.83; County Disadvantage eigenvalue = 1.92), and Cronbach's alpha revealed the items had adequate internal consistency (District Disadvantage alpha = .70; County Disadvantage alpha = .78). Recall from our earlier discussion that we calculated the violent crime rate which represents the number of violent crimes in 2020 per 100,000 residents at the district- and county-level of analysis, respectively. Prior research has shown that the violent crime rate influences officer post-stop behavior (COPS, 2016). Accordingly, the post-stop outcome analyses account for the violent crime rate of the location the stop took place.

Stop outcome analytic strategy

The stop outcome analyses consisted of two steps. First, the distribution of stop outcomes was examined across driver race/ethnicity. This step allowed us to determine whether driver race/ethnicity was associated with any of the stop outcomes. Second, we estimated a series of multivariate logistic regression equations that examined whether driver race/ethnicity predicted the types of outcomes they receive. Specifically, a separate logistic model was estimated for each of the four stop outcomes. Logistic regression was used in this stage of the analysis because the dependent variables (i.e., the stop outcomes) were binary (i.e., 1 = yes, 0 = no). Each model accounted for the variables described above. This allowed us to determine the extent to which driver race/ethnicity is associated with the odds of receiving each of the stop outcomes, after

[8] We attempted to include the percentage of occupied dwellings that are rented (as opposed to owner-occupied) in the concentrated disadvantage index. However, it did not load with the other structural indicators (i.e., it was poorly associated with them) and had to be removed from the index.

accounting for the reason for the stop (i.e., hazardous vs. non-hazardous), concentrated disadvantage, racial and ethnic composition of the area, and violent crime rate. We conducted two sets of analyses—one that controlled for district characteristics and another that controlled for county characteristics where the traffic stop took place. We also used robust standard errors that adjusted for clustering at the district- of county-level in each set of analyses, respectively.

Stop outcome results

Table 17 provides the distribution of post-stop outcomes across driver race/ethnicity. About the same percentage of White and African-American drivers received a warning (74.0% and 73.1%, respectively) and citation (30.2% and 30.9%, respectively) during traffic stops in 2020. However, 12.0% of African-American drivers were searched during their stops, whereas only 3.5% of White drivers were searched. This difference was statistically significant (z-statistic = 79.88, $p < 0.01$), and suggested that African-American drivers were nearly four-times more likely to be searched during a traffic stop than White drivers (odds ratio = 3.80). Likewise, 13.3% of African-American drivers were arrested but only 4.8% of White drivers were arrested at the conclusion of the traffic stop (z-statistic = 73.08, $p < 0.01$). Thus, African-American drivers were about three-times more likely to be arrested after a traffic stop than White drivers (odds ratio = 3.03). It is also worth noting that Asian drivers were about 116% more likely to receive a citation than White drivers (z-statistic = 17.72, $p < 0.01$; odds ratio = 2.16).

Table 17. Post-stop outcomes by driver race/ethnicity

	Warning	Citation	Search	Arrest
Total	219,486	90,696	16,145	20,2036
	73.7%	30.5%	5.4%	6.8%
Driver race/ethnicity				
White	164,070	66,933	7,676	10,663
	74.0%	30.2%	3.5%	4.8%
African American	48,172	20,344	7,897	8,753
	73.1%	30.9%	12.0%	13.3%
Hispanic	5,037	2,134	472	666
	72.3%	30.9%	6.8%	9.6%
Asian	1,323	1,044	36	43
	61.1%	48.2%	1.7%	2.0%
Other race/ethnicity	884	241	64	111
	80.1%	21.8%	5.8%	10.1%

Note: Entries represent the frequency and percentage of traffic stops that involved the respective outcome. Percentages do not sum to 100% because traffic stops could have more than one outcome. White and African American represent non-Hispanic Whites and African Americans, respectively.

While instructive, these comparisons do not account for the reason for the stop or community characteristics where the stop took place. The logistic regression models presented in Table 18 do so. This table provides the results from logistic regression equations for each of the stop outcomes and that controlled for the district characteristics in which the stop took place. In Model 1, the outcome "warning" was regressed on driver race/ethnicity and the control variables. The results revealed that African-American, Hispanic, and other race/ethnicity drivers were no more likely than White drivers to receive a warning after controlling for the reason for the stop, and district-level characteristics. However, Asian drivers were about 37% less likely (b = -.463, p < 0.01; odds ratio = 0.63) to receive a warning than White drivers, net of control variables. Not surprisingly, the reason for the stop was a significant predictor of whether a driver received a warning (b = -.661, p < 0.01). Drivers stopped for a violation classified as "hazardous" were about 48% less likely to receive a warning than someone stopped for a non-hazardous violation (odds ratio = 0.52).

With respect to district characteristics, several findings emerged from the analysis worth mentioning. The extent of district-level concentrated disadvantage where the stop occurred was a significant predictor of whether the driver was issued a warning (b = .316, p<0.01; odds ratio = 1.37). With each unit increase in the concentrated disadvantage scale, the odds of receiving a warning increased by 37%. The percentage of African Americans that live within a district was also associated with the odds of receiving a warning (b = -.072, p < 0.01; odds ratio = 0.93). For every 5% increase in the percentage of African Americans in a district, the odds of receiving a warning decreased by 35%. The opposite was true for the composition of Hispanic residents in the district of the stop (b = .023, p < 0.01; odds ratio = 1.02). For every 5% increase in the Hispanic population of a district, the odds of receiving a warning increased by about 10%. As the violent crime rate increased in a district, the odds of receiving a warning slightly decreased (b = -.001, p < 0.01; odds ratio = 0.999).

We now turn our attention to Model 2 in Table 18 that presents the results of the equation that predicted the odds of receiving a citation. Here again, African-American and Hispanic drivers were no more likely to receive a citation than White drivers. But, consistent with the previous results, Asian drivers were more about 84% more likely to receive a citation than White drivers (b = .608, p < 0.01; odds ratio = 1.84). Drivers from the other race/ethnicity category were about 19% less likely to receive a citation than White drivers (b = -.210, p < 0.01; odds ratio = 0.81). As expected, drivers stopped for a hazardous violation were about 3.5 times more likely to receive a citation than those stopped for non-hazardous violations (b = 1.243, p < 0.01; odds ratio = 3.47). The district-level characteristics were also associated with the odds of receiving a citation in a manner consistent with what we would have expected based on Model 1. Concentrated disadvantage was negatively associated with the odds of receiving a citation (b = -.436, p < 0.01; odds ratio = 0.65). As the percentage of the African-American population increased in a district, the odds of receiving a citation increased (b = .141, p < 0.01; odds ratio = 1.15). In fact, the odds ratio indicates that for a 5% increase in the African-American population we would have expected the odds of receiving a citation during a traffic stop to increase by 75%. The Hispanic composition (b = -.022, p < 0.01) and violent crime rate (b = -.001, p < 0.01) had a slight negative relationship with the odds of receiving a citation.

Table 18. Logistic regression equations predicting stop outcomes controlling for district characteristics (N = 297, 802)

	Model 1 - Warning	Model 2 -Citation	Model 3 -Search	Model 4 -Arrest
	b (SE) OR	*b* (SE) OR	*b* (SE) OR	*b* (SE) OR
Driver race/ethnicity				
African American	.145 (.132) 1.16	-.285 (.164) 0.75	1.196** (.174) 3.31	.937** (.193) 2.55
Hispanic	.024 (.089) 1.03	-.025 (.114) 0.98	.685** (.137) 1.99	.652** (.119) 1.92
Asian	-.463** (.156) 0.63	.608** (.162) 1.84	-.607** (.215) 0.55	-.933** (.198) 0.39
Other race/ethnicity	.156 (.114) 1.17	-.210** (.052) 0.81	.478 (.376) 1.61	.907** (.327) 2.48
Reason for stop				
Hazardous	-.661** (.055) 0.52	1.243** (.075) 3.47	-.833** (.069) 0.44	-.712** (.088) 0.49
District characteristics				
Concentrated disadvantage	.316** (.025) 1.37	-.436** (.013) 0.65	.686** (.174) 1.99	-.181** (.037) 0.84
% African American	-.072** (.004) 0.93	.141** (.002) 1.15	-.096** (.036) 0.91	.023** (.007) 1.02
% Hispanic	.023** (.006) 1.02	-.022** (.005) 0.98	.153* (.075) 1.17	-.026 (.019) 0.97
Violent crime rate	-.001** (.0003) 0.999	-.001** (.0001) 0.999	-.001 (.003) 0.999	.002** (.001) 1.002
Intercept	-2.363**	3.986**	-12.803**	-.342
McFadden's R^2	.028	.073	.086	.050

Note: Entries are unstandardized regression coefficients (*b*), robust standard errors adjusted for clustering in the seven MSP districts (SE), and odds ratios (OR). African American represents non-Hispanic African Americans. ***p*<0.01; **p*<0.05.

Model 3 provides the results of the logistic model that predicted whether a driver was searched during the traffic stop. African-American drivers were about 231% more likely to be searched after a traffic stop than White drivers (b = 1.196, $p < 0.01$; odds ratio = 3.31). Hispanic drivers were about two times more likely to be searched than White drivers (b = .579, $p < 0.01$; odds ratio = 1.99). Asian drivers were about 45% less likely to be searched than White drivers (b = -.830, $p < 0.01$; odds ratio = 0.55). Interestingly, drivers stopped for hazardous violations were about 56% less likely to be searched than those stopped for non-hazardous violations. This may suggest that pretextual stops—which are mostly non-hazardous—are more likely to result in a search. After all, the purpose of many pretextual stops is to investigate other potentially dangerous criminal activity (e.g., the presence of illegal guns or narcotics). District-level concentrated disadvantage was positively associated with the odds of a search occurring after a traffic stop (b = .686, $p < 0.01$; odds ratio = 1.99). As the African-American population increased in a district, the odds of a driver being searched decreased (b = -.096, $p < 0.01$; odds ratio = 0.91), whereas the Hispanic population was positively related with the odds of a search occurring (b = .153, $p < 0.01$; odds ratio = 1.17).

The final equation in Table 18 (Model 4) examined whether driver race/ethnicity predicted the odds of being arrested after a traffic stop. It is important to underscore that the arrest may or may not have been related to the traffic stop itself (e.g., there may have been an arrest warrant for the driver). From a driver race/ethnicity standpoint, the results are similar to the previous equation. African-American (b = .937, $p < 0.01$; odds ratio = 2.55) and Hispanic (b = .652, $p < 0.01$; odds ratio = 1.92) drivers were 155% and 92% more likely than White drivers to be arrested after a traffic stop, respectively. Asian drivers were 61% less likely to be arrested than White drivers (b = -.933, $p < 0.01$; odds ratio = 0.39). Drivers from the other race/ethnicity category were about 2.5 times more likely than White drivers to be arrested (b = .907, $p < 0.01$; odds ratio = 2.48). Hazardous violations were about 51% less likely to lead to a post-stop arrest (b = -.712, $p < 0.01$; odds ratio = 0.49). Again, this seems to support the idea that non-hazardous violations are typically used as pretextual stops because they are more likely to lead to an arrest. This also suggests that a non-trivial portion of pretextual stops led to found contraband or people with warrants as evidenced by the increased odds of an arrest occurring.

Greater concentrated disadvantage in a district was associated with lower odds of a driver being arrested (b = -.181, $p < 0.01$; odds ratio = 0.84). The percentage of the district population that is African American (b = .023, $p < 0.01$; odds ratio = 1.02) and the district violent crime rate (b = .002, $p < 0.01$; odds ratio = 1.002) were both positively associated with the odds of a driver being arrested.

To summarize some of the key results from Table 18, African-American and Hispanic drivers were more likely to be searched and arrested after a traffic stop compared to White drivers (after controlling for the reason for the stop and the district-level characteristics). However, they were no more or less likely to be issued a warning or citation compared to White drivers. Asian drivers were more likely to be issued a citation, but less likely to be searched or arrested than White drivers. The reason for the stop was important across each model. Drivers stopped for hazardous violations were more likely to be issued a citation but less likely to be given a warning, searched, or arrested. Concentrated disadvantage was also associated with each of the post-stop outcomes. Drivers stopped in districts with greater disadvantage were less likely to be given a citation. This could have occurred for a number of reasons. Perhaps troopers have more problems to deal with in disadvantaged districts and are more likely to be lenient on drivers. Or, it is possible that more pretextual stops occur in disadvantaged districts which decreases the likelihood of issuing a citation. Given that concentrated disadvantage was positively associated with the odds of a search and negatively associated with the odds of an arrest, this possibility is worth pursuing in greater detail with an analysis capable of considering a more fine-grained measurement of the reason for the stop. The racial/ethnic composition of the district was also associated with the post-stop outcomes. Drivers stopped in districts with larger African-American populations were more likely to receive a citation and be arrested, but less likely to be searched or given a warning. Drivers stopped in districts with larger Hispanic populations were less likely to receive a citation but more likely to be searched and given a warning, all else equal. Lastly, the district-level violent crime rate was significantly related to a driver's odds of being arrested (b =.002, $p < 0.01$; odds ratio = 1.002). For every additional 50 violent crimes per 100,000 district residents, the odds of a driver being arrested increase by 10%.

Table 19. Logistic regression equations predicting stop outcomes controlling for county characteristics (N = 297, 802)

	Model 1 - Warning	Model 2 -Citation	Model 3 -Search	Model 4 -Arrest
	b (SE) OR	*b* (SE) OR	*b* (SE) OR	*b* (SE) OR
<u>Driver race/ethnicity</u>				
African American	.119 (.103) 1.13	-.264* (.131) 0.77	1.060** (.097) 2.89	.861** (.133) 2.37
Hispanic	.005 (.074) 1.01	-.048 (.073) 0.95	.663** (.092) 1.94	.659** (.078) 1.93
Asian	-.469** (.096) 0.63	.590** (.104) 1.80	-.680** (.207) 0.51	-.927** (.186) 0.40
Other race/ethnicity	.292* (.148) 1.34	-.387* (.158) 0.68	.409 (.247) 1.51	.833** (.146) 2.30
<u>Reason for stop</u>				
Hazardous	-.657** (.038) 0.52	1.235** (.053) 3.44	-.836** (.056) 0.43	-.685** (.057) 0.50
<u>County characteristics</u>				
Concentrated disadvantage	.095** (.032) 1.10	-.142** (.050) 0.87	.188* (.089) 1.21	-.058* (.028) 0.94
% African American	-.050** (.011) 0.95	.086** (.017) 1.09	-.013 (.018) 0.99	.013* (.005) 1.01
% Hispanic	-.019 (.024) 0.98	.024 (.034) 1.02	.020 (.053) 1.02	-.024 (.020) 0.98
Violent crime rate	.001 (.0004) 1.001	-.001 (.001) 0.999	-.001 (.001) 0.999	.001* (.0003) 1.001
Intercept	.393	-.063	-5.297**	-1.841**
McFadden's R^2	.023	.063	.081	.051

Note: Entries are unstandardized regression coefficients (*b*), robust standard errors adjusted for clustering in the 83 Michigan counties (SE), and odds ratios (OR). African American represents non-Hispanic African Americans. ***p*<0.01; **p*<0.05.

Table 19 presents results from the same post-stop outcome logistic models discussed above, but this time we controlled for county-level characteristics. While there were slight differences in the size of some of the effects, the results are virtually identical to those presented in Table 18 that controlled for district-level characteristics. From a driver race/ethnicity standpoint, only one finding differed. In Model 2, after controlling for county-level characteristics, we see that African-American drivers were about 23% less likely than White drivers to receive a citation ($b = -.264$, $p < 0.05$; odds ratio = 0.77).

Post-stop outcome analyses limitations

We were able to account for the reason for the search and aggregate-level violent crime rates (along with other important variables) in the search and arrest post-stop outcome analyses. However, it would be helpful to consider the prior criminal history of a driver when conducted these analyses. Trooper search and arrest behavior may be partially influenced by a driver's criminal history which could explain some of the disparity.

Secure Cities Partnership Analyses

In the final section of this report, we will examine the racial/ethnic composition of traffic stops conducted by MSP troopers in 2020 under the Secure Cities Partnership (SCP). The SCP involves cooperation with several local police departments around Michigan where MSP provides patrol support to assist with violent crime problems. During 2020, there were 11 SCP locations: Benton Harbor, Detroit, Flint, Hamtramck, Harper Woods, Highland Park, Inkster, Lansing, Muskegon Heights, Pontiac, and Saginaw. Given the demographic differences of these communities compared to the larger counties from which they are situated, it was important to consider the extent to which stops in these cities influenced any racial/ethnic disparities observed in earlier analyses.

To do so, we selected the traffic stops that occurred only in the SCP locations and were conducted by troopers assigned to grant/directed patrol duties. This allowed us to focus on only those traffic stops that occurred in an SCP location and were related to SCP activities (rather than including stops that happened to occur in one of the cities but were not part of SCP activities). Table 20 provides the descriptive statistics for the SCP traffic stops that occurred in 2020. The table clearly shows that the racial/ethnic composition of SCP traffic stops was drastically different from all other traffic stops. Whereas about 22% of all MSP traffic stops across Michigan in 2020 involved an African-American driver, nearly 77% of SCP-related traffic stops involved an African-American driver. Only 20.5% of SCP traffic stops involved a White driver. This is at least partially expected given that many of the SCP locations have higher percentages of African-American residents than the larger counties they are part of. A majority of SCP stops occurred in two cities—Flint (38.8%) and Saginaw (23.1%).

SCP census benchmark

We conducted several benchmark analyses that focused on the SCP locations. While doing so, we only conducted comparisons with African-American drivers because they were the group most involved in SCP-related traffic stops (less than 3% of SCP stops involved Hispanic, Asian, or other race/ethnicity drivers). Table 21 provides the results from a benchmark comparison of the

Table 20. Descriptive statistics for the 2020 MSP traffic stops that occurred in the Secure Cities Partnership locations (N = 19,206)

	Number of Stops	Percentage
<u>Driver Race/Ethnicity</u>		
White (non-Hispanic)	3,942	20.5%
African American (non-Hispanic)	14,767	76.9%
Hispanic	451	2.4%
Asian	35	0.2%
Other	11	0.1%
<u>Driver Gender</u>		
Male	13,967	72.7%
Female	5,234	27.3%
Missing	5	0.03%
<u>MSP Secure Cities Partnership Location</u>		
Benton Harbor	1,184	6.2%
Detroit	2,548	13.3%
Flint	7,450	38.8%
Hamtramck	9	0.05%
Harper Woods	7	0.04%
Highland Park	135	0.7%
Inkster	1,223	6.4%
Lansing	721	3.8%
Muskegon Heights	1,420	7.4%
Pontiac	82	0.4%
Saginaw	4,427	23.1%

Note: Percentages may not sum to 100 due to rounding.

percentage of SCP traffic stops involving an African-American driver to the percentage of the population that is African American in each SCP location. The table reveals that, indeed, a larger percentage of the population in the SCP locations is African American compared to the counties, districts, and statewide results described earlier. However, a significant amount of disparity existed in the SCP locations. African-Americans were about 78% more likely to be stopped by MSP troopers across all SCP cities compared to what we would have expected based on their representation in the population. This finding holds true in eight of the SCP cities. The percentage of African-American drivers stopped by MSP troopers in Harper Woods, Highland Park, and Pontiac was what we would have expected based on their representation in the respective city populations. It is important to note, however, that there were relatively few SCP-related stops in these locations.

Table 21. Comparison of African-American traffic stops in SCP locations to African-American representation in SCP population locations (N = 19,206)

	% of stops involving African-American drivers	% of population that is African American	*z*-statistic	Odds ratio
All SCP Locations	77.9%	65.2%	33.40*	1.78
<u>SCP Locations</u>				
Benton Harbor	92.3%	83.6%	7.62*	2.36
Detroit	79.8%	78.0%	2.20*	1.12
Flint	75.1%	53.2%	35.44*	2.65
Hamtramck	44.4%	11.5%	2.71*	6.16
Harper Woods	42.9%	59.8%	0.90	0.50
Highland Park	87.4%	91.4%	1.64	0.65
Inkster	86.9%	73.3%	10.27*	2.42
Lansing	61.0%	22.2%	22.18*	5.48
Muskegon Heights	79.5%	75.4%	3.41*	1.27
Pontiac	48.8%	50.2%	0.26	0.94
Saginaw	73.4%	42.7%	37.19*	3.71

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. Red highlighting indicates that the percentage of stops involving African-American drivers is higher than would be expected based on their representation in the population. Green highlighting indicates that the percentage of stops involving African-American drivers is lower than would be expected based on their representation in the population. Gray highlighting indicates that the percentage of stops involving African-American drivers is consistent with what would be expected based on their representation in the population.

SCP traffic-crash benchmark

Next, we benchmarked the percentage of African-American drivers involved in traffic stops to the racial composition of not-at-fault traffic crashes. In the same manner as above, we restricted the traffic stop data in this analysis to only those SCP-related stops that occurred between 1/1/2020 and 6/25/2020 to match the available traffic crash data from 2021. Also, we restricted the traffic crash data to only those crashes that occurred in the 11 SCP cities. Table 22 provides the results from this benchmark. Among SCP-related traffic stops during the observation period, African-American drivers were 82% more likely to be stopped than we would have expected based on their representation in "not-at-fault" traffic crashes. This pattern held for seven of the SCP locations. African-American drivers were more likely to be stopped in SCP locations by troopers assigned to directed patrol/grant activities than we would have expected based on their representation in not-at-fault crashes in Benton Harbor (odds ratio = 3.39), Detroit (odds ratio =

1.40), Flint (odds ratio = 2.91), Highland Park (odds ratio = 3.41), Inkster (odds ratio = 2.25), Lansing (odds ratio = 5.67), and Saginaw (odds ratio = 3.05).[9]

Table 22. Comparison of African-American traffic stops in SCP locations to African-American representation in "not-at-fault" crashes in SCP locations (Stops N = 6,687)

	% of stops involving African-American drivers	% of crashes involving African-American drivers	*z*-statistic	Odds ratio
All SCP Locations	74.9%	62.1%	17.45*	1.82
SCP Locations				
Benton Harbor	91.6%	76.2%	2.48*	3.39
Detroit	78.2%	72.0%	3.28*	1.40
Flint	74.8%	50.4%	13.63*	2.91
Hamtramck	0.0%	25.0%	---	---
Harper Woods	0.0%	53.4%	---	---
Highland Park	88.5%	69.2%	2.50*	3.41
Inkster	81.8%	66.7%	3.18*	2.25
Lansing	64.0%	23.9%	9.72*	5.67
Muskegon Heights	78.3%	0.0%	---	---
Pontiac	28.6%	41.8%	-0.69	0.56
Saginaw	70.5%	43.9%	10.67*	3.05

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Crash data is for Muskegon rather than Muskegon Heights because the latter does not exist in the traffic crash database. Red highlighting indicates that the percentage of stops involving African-American drivers is higher than would be expected based on their representation in not-at-fault crashes. Green highlighting indicates that the percentage of stops involving African-American drivers is lower than would be expected based on their representation in not-at-fault crashes. Gray highlighting indicates that the percentage of stops involving African-American drivers is consistent with what would be expected based on their representation in in not-at-fault crashes.

Table 23 provides the results of the benchmark comparison of the percentage of African-American drivers involved in SCP stops to the percentage of African-American drivers involved in "at-fault" crashes. African-American drivers were 76% more likely to be stopped than we would have expected based on their representation in "at-fault" crashes. This pattern held true in Benton Harbor (odds ratio = 4.22), Detroit (odds ratio = 1.25), Flint (odds ratio = 2.63), Inkster (odds ratio = 2.68), Lansing (odds ratio = 4.41), and Saginaw (odds ratio = 2.48).

The crash benchmark analyses provide important insight concerning traffic stop racial disparity within the SCP locations. However, in the same manner as discussed earlier, the benchmarks are

[9] Similar to the main analyses reported above, we reran the "not-at-fault" traffic crash benchmark with the SCP locations after restricting the analysis to only those crashes that involved two vehicles. The findings remained unchanged and, therefore, were not sensitive to the types of crashes included in the benchmark analysis.

imperfect because they do not account for the specific locations that troopers are deployed within each of the cities. Rather, the crash data represent the racial composition of “not-at-fault” and “at-fault” crashes that occurred throughout an entire city. This may artificially deflate the percentage of African-American drivers represented in the crash data. It would be more ideal to benchmark the racial composition of traffic stops in SCP locations to the racial composition of traffic crashes that occurred in the specific patrol areas that troopers are assigned in those cities.

Table 23. Comparison of African-American traffic stops in SCP locations to African-American representation in “at-fault” crashes in SCP locations (Stops N = 6,687)

	% of stops involving African-American drivers	% of crashes involving African-American drivers	*z*-statistic	Odds ratio
All SCP Locations	74.9%	62.9%	15.78*	1.76
SCP Locations				
Benton Harbor	91.6%	72.0%	2.85*	4.22
Detroit	78.2%	74.2%	2.14*	1.25
Flint	74.8%	52.9%	12.46*	2.63
Hamtramck	0.0%	36.3%	---	---
Harper Woods	0.0%	55.1%	---	---
Highland Park	88.5%	83.5%	0.79	1.51
Inkster	81.8%	62.7%	3.55*	2.68
Lansing	64.0%	28.7%	8.34*	4.41
Muskegon Heights	78.3%	0.0%	---	---
Pontiac	28.6%	41.6%	-0.69	0.56
Saginaw	70.5%	49.0%	8.80*	2.48

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Crash data is for Muskegon rather than Muskegon Heights because the latter does not exist in the traffic crash database. Red highlighting indicates that the percentage of stops involving African-American drivers is higher than would be expected based on their representation in at-fault crashes. Green highlighting indicates that the percentage of stops involving African-American drivers is lower than would be expected based on their representation in at-fault crashes. Gray highlighting indicates that the percentage of stops involving African-American drivers is consistent with what would be expected based on their representation in in at-fault crashes.

Supplemental benchmark analysis without SCP location traffic stops[1]

To further test the robustness of the main findings described throughout the report, we excluded the SCP-related traffic stops from the analyses and reran several of the benchmarks from earlier in the report. This removed 19,206 stops and left us with 278,596 stops for re-analysis. First, we reran the benchmark from Table 6 that compared the percentage of traffic stops involving African-American drivers to the percentage of African Americans in the population. While the percentage of African-American drivers involved in traffic stops changed slightly, in most Districts this change was relatively small, and the substantive findings remained. African-American drivers were significantly more likely to be stopped across Michigan and within Districts 1, 2, 3, 5, 6, and 7 than we would have expected based on their representation in the respective populations (a table of these findings is not provided in the report but is available upon request of the lead author). Within District 8, African-American drivers were stopped at a lower rate than we would have expected based on their representation in the population.

While much of the substantive findings remained the same after excluding SCP location stops, there were two important issues to note. First, the magnitude of racial disparity was smaller across most districts after excluding SCP-related stops. Second, the largest difference was observed in District 3. The results from Table 6 showed that 31.5% of stops in District 3 involved an African-American driver but only 9.4% of the population was African American. After excluding the SCP stops, the data revealed that only 19.5% of stops involved an African-American driver in District 3. This suggests that a large portion of the stops contributing to the overall racial disparity were accounted for by SCP stops in this district. It is important to note that there may be legitimate reasons why some of this disparity exists (e.g., the time and location of SCP-related patrol activities in District 3). Nonetheless, the amount of racial disparity in District 3 is cut by nearly 50% if the SCP stops are removed from the analysis.

Next, we reran the traffic-crash benchmark analyses presented in Table 9 ("not-at-fault" crash comparison). As with the main analyses, this supplemental analysis was restricted to stops that occurred between 1/1/2020 and 6/25/2020. Again, some of the substantive findings remained unchanged but several important differences were observed. After excluding SCP stops, the percentage of stops across Michigan that involved an African-American driver dropped to 18%. Accordingly, African-American drivers were stopped at a lower rate than we would have expected based on their involvement in not-at-fault crashes.

Importantly, however, there were still disparities observed across several districts. African-American drivers were more likely to be stopped in Districts 1, 2, 3, 5, 7, and 8 than we would have expected based on their representation in not-at-fault crashes. For some of the districts, the amount of racial disparity was less than that observed in Table 9. Again, however, the largest reduction was observed in District 3. After excluding SCP, the amount of racial disparity in District 3 dropped by nearly 50%. It is also worth noting that there was no racial disparity observed in District 6 after excluding SCP stops according to this benchmark. In fact, African-American drivers were stopped less often than we would have expected in District 6 based on their involvement in not-at-fault crashes.

Lastly, we compared the percentage of African-American drivers involved in traffic stops (after excluding SCP-related stops) to the group's representation in "at-fault" traffic crashes. Nearly the same findings presented in Table 12 emerged in this analysis across each of MSP's districts—African-American drivers were significantly more likely to be stopped than we would have expected based on their composition in "at-fault" crashes in Districts 1, 2, 3, and 5. However, African Americans were stopped at a rate we would have expected (or less than we would have expected) based on their representation in "at-fault" crashes in Districts 6, 7, and 8, and when examining the entire state. Similar to the other supplemental benchmark analyses, we also observed a large reduction in racial disparity in District 3 after excluding SCP stops when using the at-fault crash benchmark.

SCP veil-of-darkness analysis

We conducted the same VOD analysis as described earlier using only those traffic stops that occurred in the SCP locations (we did not account for trooper assignment because all troopers were assigned to grant/directed patrol). Given that daylight only predicted the odds of being an African-American driver in the main VOD analysis, we only estimated models predicting whether

Table 24. Veil of Darkness logistic regressions predicting whether a driver is African American in SCP locations

Variables	African-American Driver [a]	
	Model 1	Model 2
	b (SE) OR	*b* (SE) OR
Daylight traffic stop (1 = daylight, 0 = darkness)	.544** (.193) 1.72	-.322 (.207) 0.72
Day of the week [b]		
Monday	-.083 (.147) 0.92	-.218 (.070) 0.80
Tuesday	.094 (.145) 1.10	-.028 (.240) 0.97
Wednesday	.171** (.046) 1.19	-.180 (.209) 0.84
Thursday	.095 (.088) 1.10	-.764** (.124) 0.47
Friday	.201 (.156) 1.22	-.446** (.108) 0.64
Saturday	.096 (.105) 1.10	-.366 (.212) 0.69
Time bin [c]	.133** (.041) 1.14	-.019 (.047) 0.98
County-level violent crime rate	.001* (.0004) 1.001	-.001** (.0002) 0.999
Intercept	-.374 (.378)	1.792** (.308)
Pseudo R^2	.014	.011
N	5,789	807

Note: Entries are unstandardized partial regression coefficients (*b*), robust standard errors that adjust for clustering at the county level (SE), and odds ratios (OR).
[a] Each logistic model used "African-American driver" as the dependent variable. Model 1 is the main VOD analysis and Model 2 is the VOD analysis with the restriction to 30-days before and after the change to DST.
[b] Reference category = Sunday.
[c] Time bin is an ordered-categorical variable where the time of traffic stops were classified into eight 45-minute periods. The earliest stops in the intertwilight period were coded 1 and the latest as 8.
***p*<0.01; **p*<0.05.

the driver was African American in these SCP-specific analysis. Table 24 presents the findings from this analysis. Model 1 is the logistic regression equation estimated using the traditional VOD analysis (i.e., without any restrictions). We see in this model that daylight traffic stops in SCP locations were 72% more likely to involve an African-American driver than nighttime stops (b = .544, p < .01; odds ratio = 1.72). Again, this evidence suggests that African Americans were significantly more likely to be stopped during the day when it was, presumably, easier for troopers to see the race of the driver. Model 2 in Table 24 presents the results from the VOD analysis restricted to those stops that occurred in the 30-days before and after the switch to DST. Similar to the results discussed earlier, daylight no longer predicted the odds of the driver being African American while using this restriction. It appears there may be seasonal variation in the nature of stops and/or the racial composition of drivers on the road. Again, this finding provides caution when interpreting the main VOD results (Model 1). It is possible that seasonal variation in the nature of traffic stops and/or the racial composition of drivers on the road may explain why daylight predicts driver race rather than trooper bias.

SCP stop outcome analyses

Finally, we conducted the stop outcome analyses for only the 19,206 traffic stops that occurred in the SCP locations (see Table 25). Like above, Model 1 estimated the effect of driver race/ethnicity on the odds of the driver receiving a warning, net of stop-level and county-level characteristics. Several different findings emerged in this analysis. Most importantly, we see that African-American drivers were significantly more likely to receive a warning than their White counterparts (b = .329, p < .05, odds ratio = 1.39). Like the main analysis above, being stopped for a hazardous violation decreased the odds of receiving a warning by about 39%, net of statistical controls.

With respect to Model 2 in Table 25 (citation), African-American drivers were about 40% less likely to receive a citation compared to White drivers (b = -.506, p < .01; odds ratio = 0.60) in SCP locations. Drivers stopped for a hazardous violation were over four-times more likely to receive a citation compared to those stopped for non-hazardous reasons (b = 1.443, p < .01, odds ratio = 4.23).

The results from Model 3 in Table 25 (search) show that African-American drivers were no more likely than Whites to be searched. This finding differs from the main analyses presented in Tables 18 and 19. Drivers stopped for a hazardous violation were about 28% less likely to be searched than those stopped for other reasons (b = -.331, p < .01, odds ratio = 0.72). Lastly, in Model 4 of Table 25, African-American drivers were no more likely than White drivers to be arrested after the traffic stop in the SCP locations. Again, this finding differs from those presented in Tables 18 and 19.

Table 25. Logistic regression equations predicting stop outcomes controlling for county characteristics in SCP locations (N = 19,206)

	Model 1 - Warning	Model 2 -Citation	Model 3 -Search	Model 4 -Arrest
	b (SE) OR	*b* (SE) OR	*b* (SE) OR	*b* (SE) OR
<u>Driver race/ethnicity</u>				
African American	.329* (.157) 1.39	-.506** (.150) 0.60	.132 (.076) 1.14	.143 (.343) 1.15
Hispanic	.325 (.018474) 1.38	-.246 (.259) 0.78	.140 (.100) 1.15	.157 (.147) 1.17
Asian	-.061 (.155) 0.94	.359** (.104078 1.43	.351 (.652) 1.42	---[a]
Other race/ethnicity	-.787 (.465) 0.46	.718 (.615) 2.05	-.782 (1.037) 0.46	---[a]
<u>Reason for stop</u>				
Hazardous	-.484* (.193) 0.62	1.443** (.058) 4.23	-.331** (.071) 0.72	-.130* (.061) 0.88
<u>County characteristics</u>				
Concentrated disadvantage	.213 (.186) 1.24	-.328 (.354) 0.72	1.215** (.167) 3.37	-.168 (.099) 0.85
% African American	-.038 (.081) 0.96	.145 (.157) 1.16	.064* (.030) 1.07	.017 (.045) 1.02
% Hispanic	.277* (.128) 1.32	-.308 (.257) 0.74	.889** (.141) 2.43	-.175* (.076) 0.84
Violent crime rate	-.003 (.003) 0.997	.002 (.006) 1.002	-.014** (.002) 0.99	.003* (.002) 1.003
Intercept	-.439	.144	-21.203**	-.587**
McFadden's R^2	.081	.258	.047	.034

Note: Entries are unstandardized regression coefficients (*b*), robust standard errors adjusted for clustering in the 8 Michigan counties that SCP stops took place in (SE), and odds ratios (OR). African American represents non-Hispanic African Americans.

[a] Variable was omitted from the analysis due to multicollinearity. This reduced the analytic sample to 19,160 traffic stops.

***p*<0.01; **p*<0.05.

Recommendations

The final section of the report provides recommendations to MSP regarding traffic stop data tracking and reporting procedures. These recommendations are based on the research team's work with MSP and the agency's traffic stop data over the past nine months. The recommendations are in no particular order, but we attempted to group them into similar categories.

Driver Race and Ethnicity

Driver race and ethnicity are two of the most important data fields in a traffic stop database for external benchmarking analyses. Without accurate and complete information on driver race and ethnicity, benchmarking strategies are either flawed or impossible to complete. Within MSP's traffic stop reporting, driver race and ethnicity are based on troopers' judgements. MSP prohibits troopers from asking drivers to self-report their race or ethnicity. Moreover, similar to most states, Michigan driver's licenses do not list driver race or ethnicity. This creates a situation where there is room for error and inaccurate reporting. This is problematic in its own right but becomes especially challenging for benchmark analyses. Next, we discuss several issues we encountered with respect to the reporting of driver race and ethnicity within the 2020 traffic stop data.

The "race" field in the traffic stop data contains seven possibilities: American Indian or Alaskan Native (I), Asian (A), Black or African American (B), Hispanic or Latino (H), Native Hawaiian or Other Pacific Islander (P), White (W), and Unknown (U). The eDaily data dictionary does not clearly provide a code book for these categories. Rather, only letter designations are provided in the dictionary and within the data. Some of the letters are intuitive, but the research team had to communicate with MSP to verify what the letters represented.

- *RECOMMENDATION 1*: Clarify the coding of race in the data dictionary and database. This will help external entities avoid mistakes when using the data.

Relatedly, the "race" field contains both racial and ethnic categories. This is problematic for at least two reasons. First, race and ethnicity are distinct classifications. People who identify as Hispanic ethnicity also will have a racial identity (e.g., White or Black). Second, this type of coding limits the racial and ethnic data in MSP traffic stops from being readily compared to other sources of data. Take for example Census data that tracks the percentage of the population that is "non-Hispanic White" and "non-Hispanic Black." Census numbers like this are not directly comparable to the racial/ethnic composition of MSP traffic stops because race and ethnicity are combined into a single category. There is an "ethnicity" data field in the traffic stop database, but troopers are not required to enter an ethnicity and as expected, the field has a tremendous amount of missing data (i.e., most troopers do not complete the field).

- *RECOMMENDATION 2*: Race and ethnicity should be coded separately so the traffic stop data is more comparable to external data sources (e.g., Census estimates). Given that it is difficult for a trooper to accurately report someone's race *and* ethnicity simultaneously, this recommendation may be difficult to act upon. Without having drivers self-report their race and ethnicity, or having such information on a driver's license, coding race and ethnicity may prove difficult.

- *RECOMMENDATION 3*: At the very least, troopers need to be trained on the difference between race and ethnicity and why it is important to gather such information in an accurate manner.
- *RECOMMENDATION 4*: An ideal situation would be for Michigan driver's licenses to list a person's race and ethnicity. This would remove the burden from troopers, ensure accurate reporting of critical information, and allow for more precise benchmarking (and other analyses) in the future. The research team encourages MSP leadership to communicate the importance of this issue to appropriate officials in the State of Michigan. Yet, we also recognize that most states do not provide race or ethnicity on their driver's licenses (Withrow & Williams, 2015).

Data Reporting Practices

There were several data reporting practices that could be addressed to improve the overall quality of data collected by MSP. For starters, the current MSP traffic stop database provides a data field for the "address of stop." The problem, however, is that the information contained in this field cannot be used for most analytic purposes. Most incidents simply list a general location—for example, "US-23" or WB I-94"—under "address of stop." This information lacks precision regarding where the actual stop took place. A researcher could use this data in combination with information about the county where the stop occurred, but it is still limited. With the current reporting practice, it is impossible to determine the exact location of a traffic stop. Such information can be valuable for racial and ethnic disparity analyses.

- *RECOMMENDATION 5*: The latitude and longitude data should be collected and automatically populated in electronic applications utilized by troopers. This could be done by using GPS location technology in troopers' patrol cars in conjunction with the mobile data computers.

We have several recommendations concerning the reporting of searches and other outcomes that occur during traffic stops.

- *RECOMMENDATION 6*: Troopers should be required to document when a search is conducted (regardless of whether contraband is found). Current software allows troopers to provide additional information about searches, but it is not required to do so. Searches must be documented and accountability mechanisms for failure to do so must be in place. Failure to properly track searches harms transparency with the community.

Relatedly, the outcome of a search should be tracked within the MSP traffic stop database. Currently, there is not a field that indicates whether contraband was discovered as part of the search. Researchers and analysts would need to read the traffic stop narratives to determine whether contraband was found. This information could be used in racial and ethnic disparity analyses by allowing for the calculation of "hit rates" (i.e., the proportion of searches that result in found contraband). Analyses have revealed that significant disparities in hit rates are found even in situations where benchmarking disparities are not observed (COPS, 2016).

- *RECOMMENDATION 7*: MSP should track the outcomes of searches during traffic stops. The following categories could be included:
    - Seizure resulting from search? (Yes / No)
    - Type of contraband/evidence seized (for example, MSP may wish to track if weapons, drugs or other contraband were seized).

Similarly, the reason for an arrest should be tracked. The current data indicates whether an arrest occurred but does not specify the reason for the arrest.

- *RECOMMENDATION 8*: The primary basis for arrests should be tracked in the traffic stop database. The following categories could be used:
    - Warrant
    - On-view probable cause
    - Pre-existing probable cause
    - Other (specify)

Currently, there are four post-stop outcomes that are tracked in the traffic stop database: warning (yes/no), citation (yes/no), search (yes/no), and arrest (yes/no).

- *RECOMMENDATION 9*: In addition to the recommended changes above, we suggest MSP increase the number of disposition/outcome categories. Specifically, we recommend including the following disposition/outcome categories:
    - No action taken (Yes/No)
    - Verbal warning (Yes/No)
    - Written warning (Yes/No)
    - Criminal citation (Yes/No)
    - Traffic citation (Yes/No)
    - Total number of citations issued to the driver
    - Primary citation number (for cross-reference purposes)
    - Vehicle impounded (Yes/No)
    - Search (Yes/No; see above recommendations)
    - Arrest (Yes/No; see above recommendations)

Data Documentation

We encountered several data documentation issues that are worth noting. Accounting for a trooper's assignment (e.g., general patrol vs. directed patrol activities) is useful in benchmarking and post-stop outcome analyses. MSP traffic stop data provide a field entitled "Assignment Type" that includes several possibilities for trooper assignment. The eDaily data dictionary provides descriptions of the assignments but they are largely unhelpful. For example, the following description is provided for the assignment type "Hometown Security Team": "Hometown Security Team is an assignment used by the Hometown Security Team members." For the assignment type "Sergeant's Duties" the following description is provided: "Sergeant's Duties is an assignment used by uniform sergeants." Such definitions are self-evident but do not provide enough detail about what the assignment entails. The purpose of a data dictionary is to provide lay people (especially external entities that may be inspecting the data) with a firm understanding of what specific codes mean. Providing better descriptions in the data dictionary will help prevent frequent questions from external entities and ensure MSP employees correctly understand the coding.

- *RECOMMENDATION 10*: Ensure data dictionaries provide sufficient detail so users understand the coding of specific data fields.

Accounting for the reason for a traffic stop is important within benchmark and post-stop outcome analyses. The MSP traffic stop data provide a lengthy list of reasons why a trooper could have initiated a traffic stop. However, there are several hundred reasons in this list which makes recoding difficult and introduces the possibility of inconsistent analytic procedures as people conduct benchmark analyses (and other analyses) over time. We used the data field "hazardous" to account for the reason for the stop in this report. This was done because the field allowed for a rough comparison of whether the stop was for a violation that endangered others or for a non-dangerous (e.g., non-moving) violation. This is useful in some respects, but it is insufficient for many of the questions benchmark researchers may have. For example, having defective equipment would be classified as a "hazardous" violation in the MSP coding scheme. This may be true in some situations (e.g., a broken windshield); however, in other situations, other agencies or researchers may classify these offenses differently. For example, a broken taillight could be more accurately described as a non-moving violation.

Having a data field that is more detailed than "hazardous," but more concise than "reasons for the stop," would help in several ways. First, it would allow for more fine-grained analyses. This is especially important in benchmarking because the purpose of such methodologies is to determine if racial or ethnic disparities can be accounted for by legitimate factors. It is possible that accounting for more reasons for stops would help explain some of the observed disparities. Second, a new data field of this type would improve consistency in the analyses conducted by MSP employees or external entities. If people must solely rely on the lengthy "reason for stop" data field, they will inevitably recode the data to create categories. This may introduce inconsistencies in coding and analysis between researchers.

- *RECOMMENDATION 11*: MSP should develop a new data field in the traffic stop database that provides more detail than the "hazardous" designation but condenses the "reason for stop" data field. This could either be done with the addition of a new dropdown menu for troopers to complete, or automatically coded by the system after the trooper enters the actual reason for the stop. The following categories could be used in this new "type of stop" data field (these are only suggestions for MSP to consider):
    - Moving violations
    - Penal Code violations
    - Mechanical or nonmoving violations
    - Driving Under the Influence (DUI) investigations
    - Traffic crashes
    - Criminal alerts and wanted persons (including Be on the Lookout/All Points Bulletins/warrants)

  This would allow analysts to account for the type of traffic stop that was conducted and differentiate between moving and non-moving violations, or low-discretion and high-discretion stops. If researchers wished to use the original "reason for stop" data field, they could still do so.

Some benchmark and post-stop outcome analyses account for the characteristics of the police officer who conducted the traffic stop (COPS, 2016). This allows researchers to control for differences across officers that may influence stop behavior (e.g., years of service, officer race or ethnicity, rank). This information is available in a database separate from the MSP traffic stop data but was not part of the data requested by the research team. Accordingly, we have the following recommendation:

- *RECOMMENDATION 12*: Make the trooper characteristics database available for future traffic stop analyses. MSP should ensure the trooper data can be merged easily with the traffic stop database (i.e., both databases need a trooper identification number). Trooper race, ethnicity, age, gender, years of service, and rank (and other information as deemed appropriate) should be included in the database.

The MSP traffic stop database includes a data field specifying the MSP district in which the stop took place. In our analysis, there were 1,404 stops where "HQ" was listed as the district. Further analysis revealed that all these stops were classified as "marine services" under the "assignment type" data field. While it is important to know that such stops were conducted by a marine unit, it is also valuable to understand what district the stop took place in.

- *RECOMMENDATION 13*: Rather, than listing such stops as taking place in "HQ," the actual district of the stop should be recorded for marine services stops.

The database contains fields for the "district" and "county" of the traffic stop. Given that MSP district boundaries follow Michigan county lines, these fields should overlap (i.e., the listed district should include the county for which the stop is listed). However, our analyses revealed that there were a meaningful number of stops that were coded as occurring in a county that is not contained in the listed district. For example, there were some stops that were listed as occurring in Washtenaw County and District 2. The problem is that Washtenaw County is in District 1. Upon further examination (and discussion with MSP employees), it appears this issue arises for "border stops"—traffic stops that were conducted in a county that borders a different district. Sticking with the Washtenaw County example, we see that most stops attributed to the county and listed as District 1 (the correct district for Washtenaw County) were listed as Brighton Post for the "worksite." Brighton Post oversees Washtenaw County and is in District 1. The Washtenaw County stops coded as occurring in Washtenaw County and District 2 had Metro South Post listed as the worksite. This suggests that a Metro South Post trooper from District 2 conducted a traffic stop in Washtenaw County (which borders District 2). Accordingly, the county designation in the traffic stop database is correct if a researcher or analyst is interested in accounting for where the stop physically took place. But, the district designation only represents the trooper's assigned area. We used the county designation to determine the location of stop in the current report. This allowed us to match the location of the stop with the location's characteristics (e.g., racial and ethnic composition of the population). This is an important issue for anyone who uses the traffic stop data to understand. If an analyst were to use the listed district as the location of the stop, there would be many stops incorrectly attributed to those locations.

- *RECOMMENDATION 14*: This issue needs to be clearly described in the data dictionary and other documentation related to the traffic stop data. Specifically, the data dictionary should indicate that the “county” field is the county where the stop took place and “district” corresponds with a trooper’s assigned area. This will help ensure accurate use of the data.

Accurate county, post, and district maps are necessary for benchmarking and post-stop outcome analyses. Such methodologies require the collection and aggregation of external data and having access to accurate boundary maps is essential during this process. Having publicly available, accurate boundary maps will help avoid errors when external (or internal) entities analyze MSP traffic stop data.

- *RECOMMENDATION 15*: MSP should ensure accurate county, post, and district maps are posted publicly and made available to anyone that analyzes the traffic stop data.

Addressing Disparities in the Future

Meaningful racial disparities were observed in the 2020 MSP traffic stop data. While the results discussed in this report cannot speak to whether troopers are engaging in or agency policies are causing discriminatory stop behavior, we encourage MSP to continue efforts to understand the roots of the disparity and address it where possible. This should be part of routine practices within MSP. To continue this effort, there are two primary recommendations we have for MSP to help address observed racial disparities in traffic stops moving forward:

- *RECOMMENDATION 16*: MSP has developed, and pilot tested, an internal benchmarking data dashboard. The agency plans to formally introduce the dashboard in the near future. We encourage them to do so after carefully planning the intended outcomes of the dashboard, clearly documenting procedures to be followed, and providing necessary training to those who will use the dashboard. Moreover, we recommend MSP engages in a robust evaluation of the dashboard to assess the extent to which it produces desirable outcomes (including its potential impact on traffic stop disparities). Securing external funding and partnering with a university-based research team is a viable strategy to accomplish this goal. Doing such an evaluation will not only help MSP continue addressing disparities in the future, but it will also help establish a model approach for other police agencies aiming to impact their own disparities.

- *RECOMMENDATION 17*: MSP should conduct robust disparity analyses like those in this report on regular intervals moving forward. This will help MSP track overall trends across the agency and address issues when they arise. Again, partnering with a university-based research team could help with this endeavor by providing research expertise. In addition to the analyses used in this report, we recommend MSP work with a university research team to address important disparity-based research questions. For example, it would be useful to match criminal history data with drivers of traffic stops to examine whether prior criminal involvement accounts for some of the disparity observed in the post-stop outcome analyses. Additionally, there are other sophisticated research designs that researchers could use to dive deeper into the traffic stop disparity observed in this report.

Multilevel modeling, testing different operationalization strategies within the VOD methodology, examining the predictors of at-fault traffic crash designations, and exploring the connection between reason for stop and the various outcomes would all assist MSP in more fully understanding various aspects of racial/ethnic disparities in their stop activity.

Addendum for Traffic Crash Benchmark

Analyses for this report began in May 2021. Accordingly, we could not examine racial disparities in the 2021 traffic stop data. In particular, we were limited in the traffic crash benchmark analyses to comparing 2020 stop data to 2021 crash data (for the first six months of each year). Traffic stop data for the first six months of 2021 became available as we concluded the analyses for this report in September 2021. Accordingly, we conducted supplemental analyses that benchmarked the 2021 stop data against the 2021 "not-at-fault" and "at-fault" crash data. This was done because it allowed us to compare the data more appropriately from the same year (see above limitations). Moreover, these analyses allowed us to determine whether travel pattern or enforcement changes during 2020 due to COVID could have impacted the disparities we observed, or if the same trend is observed in 2021. MSP will likely continue disparity analyses using complete years of data moving forward, but this set of analyses will help foreshadow those results.

Addendum Table 1. Comparison of African-American traffic stops to African-American representation in "not-at-fault" crashes (All crashes; 2021 stop and crash data)

	% of stops involving African-American driver	% of crashes involving African-American drivers	*z*-statistic	Odds ratio
Statewide	20.9%	18.6%	12.22*	1.15
District				
1	18.9%	10.3%	17.98*	2.03
2	45.8%	34.1%	24.32*	1.63
3	32.1%	12.5%	36.42*	3.32
5	22.8%	10.6%	21.53*	2.50
6	12.6%	8.6%	10.97*	1.55
7	1.7%	0.6%	4.77*	3.02
8	1.4%	0.5%	3.31*	2.68

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. This analysis is compares traffic stops that occurred between 1/1/2021 and 6/25/2021 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving African-American drivers is higher than would be expected based on their representation in not-at-fault crashes. Green highlighting indicates that the percentage of stops involving African-American drivers is lower than would be expected based on their representation in not-at-fault crashes. Gray highlighting indicates that the percentage of stops involving African-American drivers is consistent with what would be expected based on their representation in in not-at-fault crashes.

These analyses are restricted to stops and crashes that occurred between 1/1/2021 and 6/25/2021. We only focus on the African-American benchmark analyses because this is where the most disparity was observed in the main report. Addendum Table 1 provides a comparison of African-American traffic stops to African-American representation in "not-at-fault" crashes. The results were virtually identical to those presented above (see Table 9). Across the entire state and within each of MSP's districts, African-American drivers were more likely to be stopped than their involvement in "not-at-fault" traffic crashes. Like earlier, we also conducted this benchmark after restricting the crash data to only crashes involving two vehicles. The results remained the same. Addendum Table 2 presents the results from the benchmark comparing the percentage of traffic stops involving African-American drivers to their involvement in "at-fault" crashes.

Essentially, the same results were observed in this analysis as those presented above (see Table 12). Taken together, it appears that the same patterns of racial disparity in the traffic crash benchmark analyses are observed regardless of whether we use the 2020 or 2021 traffic stop data. This suggests that changes in travel patterns or enforcement activities caused by COVID in 2020 likely did not impact the disparities we observed in the main analyses above.

Addendum Table 2. Comparison of African-American traffic stops to African-American representation in "at-fault" crashes (2021 stop and crash data)

	% of stops involving African-American driver	% of crashes involving African-American drivers	*z*-statistic	Odds ratio
Statewide	20.9%	22.7%	-9.05*	0.90
<u>**District**</u>				
1	18.9%	15.3%	6.88*	1.29
2	45.8%	34.8%	22.28*	1.58
3	32.1%	18.3%	23.39*	2.10
5	22.8%	16.4%	9.91*	1.50
6	12.6%	12.8%	-0.47	0.98
7	1.7%	1.6%	0.47	1.09
8	1.4%	1.9%	-1.52	0.73

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. This analysis is compares traffic stops that occurred between 1/1/2021 and 6/25/2021 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving African-American drivers is higher than would be expected based on their representation in at-fault crashes. Green highlighting indicates that the percentage of stops involving African-American drivers is lower than would be expected based on their representation in at-fault crashes. Gray highlighting indicates that the percentage of stops involving African-American drivers is consistent with what would be expected based on their representation in at-fault crashes.

Appendices

Appendix A. Race/ethnicity of drivers involved in traffic stops across Michigan counties in 2020

County	Total # of stops	% White	% African American	% Hispanic	% Asian	% Other
Alcona	733	98.4	1.1	0.6	0.0	0.0
Alger	1,207	95.2	1.6	1.2	1.4	0.6
Allegan	5,420	81.2	11.9	5.8	0.8	0.2
Alpena	4,368	98.7	0.9	0.3	0.1	0.0
Antrim	1,165	97.9	1.1	0.3	0.5	0.1
Arenac	170	97.7	1.2	1.2	0.0	0.0
Baraga	2,382	89.9	1.6	0.3	1.5	6.7
Barry	1,815	94.4	3.3	2.0	0.4	0.0
Bay	3,451	88.4	9.6	1.6	0.3	0.1
Benzie	1,386	98.0	0.9	0.7	0.1	0.3
Berrien	11,680	57.1	34.1	7.1	1.4	0.4
Branch	4,843	85.1	8.6	5.1	0.7	0.5
Calhoun	5,343	71.8	22.4	4.0	1.4	0.4
Cass	1,680	84.9	11.1	3.4	0.4	0.3
Charlevoix	1,123	96.9	1.5	0.5	0.4	0.6
Cheboygan	1,636	95.1	2.8	0.8	0.9	0.4
Chippewa	3,244	93.3	1.2	0.0	0.6	4.9
Clare	1,469	98.0	1.6	0.3	0.1	0.1
Clinton	3,087	81.1	14.8	2.5	1.5	0.1
Crawford	2,995	95.6	2.6	1.1	0.5	0.2
Delta	3,099	94.5	1.9	0.6	1.0	2.1
Dickinson	3,300	97.4	1.4	0.6	0.3	0.3
Eaton	5,574	79.9	15.6	3.2	1.1	0.2
Emmet	1,703	95.6	1.6	0.8	0.5	1.5
Genesee	17,087	40.2	58.5	1.0	0.1	0.1
Gladwin	137	97.1	1.5	1.5	0.0	0.0
Gogebic	3,114	95.3	1.5	0.7	1.4	1.2
Grand Traverse	2,021	96.4	1.9	1.0	0.2	0.4
Gratiot	280	89.6	5.7	3.9	0.7	0.0
Hillsdale	3,137	96.7	2.2	0.9	0.2	0.1
Houghton	1,790	97.7	0.9	0.1	0.7	0.6
Huron	730	95.3	3.0	1.6	0.0	0.0
Ingham	7,634	71.9	23.0	3.4	1.4	0.3
Ionia	2,291	84.9	11.1	2.8	1.1	0.1
Iosco	1,732	97.6	1.6	0.6	0.3	0.0
Iron	2,421	96.3	1.2	0.8	0.6	1.0
Isabella	1,336	90.2	6.3	2.0	0.2	1.4
Jackson	7,177	75.7	21.3	2.1	0.7	0.2
Kalamazoo	4,219	66.4	28.9	3.5	1.0	0.1
Kalkaska	1,429	96.4	2.0	1.1	0.5	0.1
Kent	5,868	75.8	16.2	6.6	1.3	0.2
Keweenaw	63	95.2	0.0	0.0	4.8	0.0
Lake	244	86.9	10.7	2.1	0.4	0.0
Lapeer	5,205	91.5	5.7	2.3	0.5	0.0
Leelanau	350	92.9	1.4	3.4	0.3	2.0
Lenawee	3,825	92.8	4.4	2.6	0.2	0.0
Livingston	5,826	80.4	16.2	1.9	1.4	0.2
Luce	2,203	97.1	1.6	0.0	0.3	1.0
Mackinac	3,349	95.8	2.5	0.5	0.4	0.8
Macomb	10,089	67.8	30.2	1.3	0.6	0.1
Manistee	1,342	97.4	1.0	1.4	0.1	0.2
Marquette	4,230	95.7	2.2	0.6	0.9	0.7
Mason	792	92.2	3.8	3.8	0.1	0.1
Mecosta	809	93.6	3.7	2.0	0.5	0.3
Menominee	1,718	94.2	2.1	1.5	0.8	1.4
Midland	1,748	89.0	8.4	1.7	0.4	0.5
Missaukee	1,710	97.3	1.1	1.1	0.4	0.2
Monroe	4,203	78.2	19.9	1.4	0.4	0.1
Montcalm	2,935	95.2	2.9	1.8	0.1	0.0
Montmorency	686	98.7	0.9	0.2	0.3	0.0
Muskegon	5,101	66.6	30.7	2.3	0.3	0.1

Newaygo	2,757	95.8	2.3	1.8	0.0	0.1
Oakland	22,160	61.4	35.7	1.5	1.1	0.2
Oceana	1,532	89.8	2.2	7.7	0.3	0.0
Ogemaw	1,186	97.4	1.8	0.8	0.1	0.0
Ontonagon	566	95.8	1.1	0.9	0.9	1.4
Osceola	3,023	95.0	2.8	0.9	1.2	0.3
Oscoda	467	98.3	0.6	1.1	0.0	0.0
Otsego	3,134	96.5	2.0	0.9	0.4	0.2
Ottawa	461	77.9	15.8	5.2	0.7	0.4
Presque Isle	861	98.8	0.6	0.6	0.0	0.0
Roscommon	2,488	94.6	3.7	0.8	0.6	0.2
Saginaw	10,553	42.9	52.6	4.2	0.3	0.0
Sanilac	1,774	97.8	1.3	0.8	0.0	0.1
Schoolcraft	1,726	96.1	1.2	0.7	1.4	0.5
Shiawassee	3,242	91.4	7.1	1.1	0.5	0.0
St. Clair	4,974	90.1	7.5	1.0	0.4	0.0
St. Joseph	1,959	88.0	7.5	4.1	0.4	0.0
Tuscola	2,341	94.5	4.4	0.9	0.2	0.0
Van Buren	5,185	69.1	19.2	9.0	1.8	1.0
Washtenaw	6,620	66.4	28.7	2.8	1.8	0.3
Wayne	23,986	30.6	66.5	2.2	0.7	0.1
Wexford	5,103	96.7	1.7	1.1	0.4	0.1

Note: Percentages may not sum to 100 due to rounding. White and African American represent non-Hispanic Whites and African Americans, respectively.

Appendix B. Michigan county-level characteristics

County	Total pop.	% White	% African American	% Hispanic	% Asian	% Other	% Poverty	% Unemp.	% Renter	% FHH	Violent crime rate
Alcona	10,353	95.8	0.4	1.5	0.2	2.1	17.0	7.6	11.2	21.8	193.2
Alger	9,151	83.6	7.7	1.6	0.1	7.0	11.2	5.2	16.0	21.0	273.2
Allegan	116,143	88.4	1.2	7.3	0.7	2.3	10.4	2.8	17.4	20.0	202.3
Alpena	28,520	95.7	0.6	1.4	0.6	1.7	14.3	6.0	22.1	26.0	298.0
Antrim	23,206	94.7	0.4	2.3	0.3	2.2	11.0	3.8	12.9	19.5	219.8
Arenac	15,070	94.6	0.4	2.0	0.4	2.6	17.1	7.1	16.2	22.4	358.3
Baraga	8,421	72.6	9.3	1.6	0.4	16.1	14.8	6.1	19.7	25.3	201.9
Barry	60,540	94.1	0.5	3.0	0.6	1.8	7.7	4.6	16.5	19.2	186.7
Bay	104,104	90.1	1.7	5.3	0.6	2.4	15.8	6.4	23.2	27.2	367.9
Benzie	17,615	93.8	0.2	2.5	0.4	3.1	9.5	4.5	10.3	21.6	238.4
Berrien	154,133	74.9	14.5	5.5	1.9	3.2	16.1	5.9	29.3	28.9	657.2
Branch	43,513	90.4	2.3	4.8	0.8	1.7	15.8	4.2	25.8	23.1	301.1
Calhoun	134,212	77.5	10.4	5.2	2.4	4.5	16.4	6.2	30.1	28.7	663.9
Cass	51,523	86.1	5.2	3.9	0.8	4.0	12.1	6.3	20.0	21.8	149.4
Charlevoix	26,188	93.7	0.4	2.0	0.5	3.3	10.1	4.0	19.1	23.5	229.1
Cheboygan	25,418	92.1	0.8	1.4	0.4	5.3	14.9	7.5	17.6	22.0	200.6
Chippewa	37,629	69.6	5.9	1.9	1.0	21.6	18.4	8.7	32.6	26.3	305.6
Clare	30,651	94.8	0.6	2.0	0.1	2.4	22.7	10.1	17.1	23.9	293.6
Clinton	78,389	89.9	1.8	4.5	1.5	2.3	8.8	3.5	20.0	22.0	91.8
Crawford	13,892	94.5	0.7	2.0	0.9	1.8	16.3	6.5	18.8	20.4	395.9
Delta	36,026	92.9	0.3	1.4	0.4	5.0	12.9	5.1	22.6	23.0	235.9
Dickinson	25,439	94.9	0.6	1.6	0.7	2.2	11.7	4.6	22.6	25.9	62.9
Eaton	109,456	82.8	6.6	5.4	2.3	2.9	10.1	4.7	27.7	25.6	275.9
Emmet	33,104	91.2	0.7	1.7	0.6	5.9	9.1	4.9	27.2	25.6	154.1
Genesee	407,875	72.4	19.5	3.4	1.0	3.6	18.9	9.3	30.0	31.4	576.9
Gladwin	25,279	95.8	0.3	1.7	0.5	1.7	16.9	5.9	15.1	21.8	288.8
Gogebic	15,061	90.1	3.9	1.5	0.5	4.0	17.0	5.4	22.5	25.8	192.6
Grand Traverse	92,181	92.6	0.9	2.9	0.6	3.1	9.6	4.3	23.7	25.1	274.5
Gratiot	40,916	86.0	5.5	6.1	0.4	2.0	16.7	5.4	25.7	27.7	244.4
Hillsdale	45,757	94.7	0.7	2.3	0.4	2.0	16.2	4.3	23.5	22.1	399.9
Houghton	36,070	92.1	0.7	1.6	2.8	2.8	20.2	5.3	33.1	24.3	94.3
Huron	31,349	95.2	0.5	2.4	0.6	1.3	13.0	4.6	19.1	24.1	159.5
Ingham	290,587	69.6	11.1	7.8	6.7	4.7	19.6	6.4	41.5	31.3	748.1
Ionia	64,300	88.3	4.5	4.8	0.4	2.0	11.8	4.5	23.4	21.2	265.9
Iosco	25,197	93.8	0.7	2.3	0.8	2.5	15.2	7.2	20.1	23.5	388.9
Iron	11,152	94.4	0.5	2.1	0.6	2.4	13.1	5.4	19.2	28.0	206.2
Isabella	70,688	85.4	2.6	4.0	1.8	6.3	26.0	6.5	37.9	29.4	213.6
Jackson	158,636	84.6	7.7	3.5	0.8	3.3	13.8	5.7	26.5	27.1	529.5
Kalamazoo	262,745	77.4	10.6	4.9	2.4	4.7	14.9	5.5	36.0	29.0	675.6
Kalkaska	17,585	94.1	0.8	2.0	0.5	2.5	16.7	7.4	17.4	20.9	432.2
Kent	648,121	73.7	9.2	10.6	3.0	3.5	11.7	4.4	30.2	26.4	487.1
Keweenaw	2,111	96.8	0.9	0.8	0.2	1.3	10.6	7.8	12.0	20.2	142.1

Lake	11,852	85.0	7.9	2.6	0.2	4.3	21.0	8.9	15.8	21.6	708.7
Lapeer	88,038	91.8	1.3	4.7	0.6	1.7	10.1	5.6	16.1	19.3	146.5
Leelanau	21,652	90.0	0.4	4.4	0.6	4.6	6.1	4.5	11.7	20.7	0.0
Lenawee	98,381	86.7	2.3	8.0	0.3	2.8	11.4	4.8	22.5	23.8	269.4
Livingston	189,754	94.3	0.6	2.4	0.9	1.7	5.2	3.7	14.6	19.0	106.5
Luce	6,338	77.7	6.5	3.5	0.5	11.8	17.0	6.4	20.5	21.9	315.6
Mackinac	10,780	73.1	3.2	1.8	0.7	21.2	16.4	9.8	28.1	22.1	194.8
Macomb	870,325	79.0	11.6	2.6	4.0	2.7	10.6	5.4	26.7	28.3	286.9
Manistee	24,457	89.0	2.8	3.2	0.3	4.7	11.5	6.2	16.6	24.0	253.5
Marquette	66,686	92.1	1.7	1.5	0.9	3.8	15.6	5.6	29.2	24.7	310.4
Mason	28,954	91.5	0.9	4.6	0.6	2.5	15.0	4.4	23.1	24.5	321.2
Mecosta	43,251	91.2	2.9	2.3	0.8	2.7	21.2	6.3	26.7	27.0	332.9
Menominee	23,074	92.9	0.3	1.8	0.4	4.6	12.8	4.5	22.3	23.3	147.4
Midland	83,355	91.5	1.3	2.7	2.3	2.1	10.4	5.2	23.4	23.4	146.4
Missaukee	15,028	94.0	0.6	2.9	0.2	2.3	14.2	6.4	19.9	18.5	199.6
Monroe	149,727	91.3	2.3	3.6	0.6	2.2	11.1	4.8	20.3	23.8	34.1
Montcalm	63,413	91.8	2.1	3.5	0.4	2.3	14.4	3.8	21.9	22.0	331.2
Montmorency	9,265	95.9	0.2	1.3	0.2	2.4	16.6	8.0	15.9	21.2	75.6
Muskegon	173,297	76.4	13.5	5.7	0.5	3.9	15.5	6.4	25.3	28.2	418.4
Newaygo	48,366	90.5	1.1	5.8	0.4	2.2	16.6	5.0	16.1	19.9	330.8
Oakland	1,253,185	72.0	13.5	4.1	7.4	2.9	8.2	4.4	29.0	26.5	193.7
Oceana	26,416	81.7	1.1	14.9	0.2	2.1	15.0	5.9	17.4	20.9	477.0
Ogemaw	20,898	94.6	0.3	2.1	0.7	2.2	17.1	8.1	18.6	22.9	253.6
Ontonagon	5,877	94.9	0.5	1.5	0.4	2.7	13.7	6.9	11.8	21.4	272.2
Osceola	23,290	94.5	1.1	1.9	0.3	2.2	17.9	6.9	19.3	23.3	300.6
Oscoda	8,248	95.5	0.5	1.6	0.1	2.2	16.2	10.3	14.7	21.0	315.2
Otsego	24,490	94.5	0.5	1.7	0.6	2.7	13.7	5.6	21.1	20.3	273.6
Ottawa	286,558	83.8	1.4	9.8	2.6	2.3	8.5	3.3	22.3	21.4	256.5
Presque Isle	12,714	95.5	0.6	1.4	0.6	1.9	13.1	7.2	11.2	20.2	212.4
Roscommon	23,851	94.9	0.2	1.9	0.3	2.8	16.7	9.4	18.0	24.3	163.5
Saginaw	191,821	69.4	18.2	8.5	1.2	2.7	18.0	6.9	28.7	31.7	788.8
Sanilac	41,295	94.0	0.5	3.7	0.3	1.5	15.1	6.0	21.28	22.4	210.7
Schoolcraft	8,048	85.7	0.4	1.1	0.4	12.4	16.7	7.9	16.3	24.5	260.9
Shiawassee	68,340	94.1	0.7	2.9	0.3	2.0	10.3	4.6	24.4	22.5	289.7
St. Clair	159,247	91.1	2.2	3.4	0.6	2.7	12.7	6.4	22.7	24.0	280.1
St. Joseph	60,836	86.5	2.2	7.9	0.5	2.9	14.8	4.4	25.4	23.8	463.5
Tuscola	52,939	93.3	0.9	3.4	0.3	2.0	14.2	5.4	17.6	22.1	272.0
Van Buren	75,358	81.2	3.2	11.5	0.7	3.4	14.9	5.7	23.0	23.2	350.3
Washtenaw	367,000	70.1	11.8	4.7	9.1	4.3	14.0	4.0	38.9	27.6	415.5
Wayne	1,757,299	49.5	38.5	5.9	3.3	2.6	22.3	9.2	38.0	35.9	1095.7
Wexford	33,256	94.5	0.5	2.0	0.5	2.5	14.2	6.2	23.2	22.1	270.6

Note: Percentages may not sum to 100 due to rounding. White and African American represent non-Hispanic Whites and African Americans, respectively. Pop.=population; Unemp.=unemployed; FHH=female-headed household. % Unemp. was calculated by dividing the number of unemployed residents by the number of people in the civilian labor force. % Renter was calculated by dividing the number of renter occupied housing units by the number of occupied housing units. % FHH was calculated by dividing the number of female-headed households by the total number of households. Violent crime is the number of violent crimes per 100,000 people.

Appendix C. Traffic crash-involved driver race/ethnicity across Michigan counties in 2020

County	Total # of crashes	% White	% African American	% Hispanic	% Asian	% Other
Alcona	171	98.8	1.2	0.0	0.0	0.0
Alger	84	97.6	2.4	0.0	0.0	0.0
Allegan	1,928	88.0	5.4	5.9	0.5	0.2
Alpena	251	98.8	1.2	0.0	0.0	0.0
Antrim	268	98.5	0.0	0.8	0.4	0.4
Arenac	28	92.9	3.6	3.6	0.0	0.0
Baraga	100	96.0	1.0	0.0	1.0	2.0
Barry	290	93.5	2.8	3.5	0.3	0.0
Bay	1,559	93.7	4.9	1.0	0.2	0.3
Benzie	198	98.5	0.0	1.0	0.0	0.5
Berrien	2,262	74.7	20.3	3.9	1.0	0.1
Branch	286	94.4	2.8	2.8	0.0	0.0
Calhoun	458	84.7	11.6	2.2	1.1	0.4
Cass	681	88.8	7.8	2.5	0.7	0.2
Charlevoix	69	97.1	0.0	0.0	1.5	1.5
Cheboygan	100	97.0	2.0	1.0	0.0	0.0
Chippewa	284	92.3	1.4	0.0	0.7	5.6
Clare	354	98.9	0.3	0.6	0.3	0.0
Clinton	351	92.0	4.8	1.7	1.1	0.3
Crawford	231	97.0	1.3	0.4	1.3	0.0
Delta	442	98.4	0.7	0.2	0.0	0.7
Dickinson	444	98.9	0.5	0.5	0.2	0.0
Eaton	1,516	86.8	9.6	2.1	1.4	0.1
Emmet	106	96.2	1.9	0.0	0.9	0.9
Genesee	6,127	71.8	26.7	1.0	0.4	0.1
Gladwin	298	98.0	1.3	0.7	0.0	0.0
Gogebic	92	95.7	1.1	0.0	1.1	2.2
Grand Traverse	1,363	97.4	1.2	0.6	0.6	0.3
Gratiot	752	94.6	3.6	1.5	0.3	0.1
Hillsdale	871	97.8	0.7	1.3	0.1	0.1
Houghton	508	97.8	0.6	0.4	0.8	0.4
Huron	451	98.7	0.4	0.7	0.0	0.2
Ingham	4,557	75.6	18.1	4.0	2.2	0.1
Ionia	894	92.5	4.3	2.8	0.5	0.0
Iosco	275	98.9	1.1	0.0	0.0	0.0
Iron	203	98.0	0.5	0.0	0.0	1.5
Isabella	782	93.6	2.7	1.3	0.1	2.3
Jackson	2,114	92.2	6.6	0.8	0.2	0.2
Kalamazoo	4,697	77.4	18.4	3.0	1.2	0.1
Kalkaska	271	97.1	1.5	0.4	0.7	0.4
Kent	13,064	74.5	16.1	7.4	1.8	0.2
Keweenaw	22	100.0	0.0	0.0	0.0	0.0
Lake	12	91.7	8.3	0.0	0.0	0.0
Lapeer	1,009	96.7	1.4	1.5	0.3	0.1
Leelanau	239	94.6	1.3	1.3	0.8	2.1
Lenawee	948	93.5	3.8	2.3	0.2	0.2
Livingston	343	92.4	4.7	2.6	0.3	0.0
Luce	51	96.1	2.0	0.0	0.0	2.0
Mackinac	244	96.3	2.1	0.0	0.0	1.6
Macomb	12,648	79.7	18.1	0.9	1.2	0.1
Manistee	336	96.1	1.2	1.2	0.3	1.2
Marquette	784	96.7	1.7	0.5	0.6	0.5
Mason	536	96.6	1.7	1.5	0.2	0.0
Mecosta	674	96.0	2.7	0.9	0.2	0.3
Menominee	186	97.3	1.1	1.1	0.0	0.5
Midland	1,242	95.7	2.7	0.9	0.3	0.3
Missaukee	223	98.2	0.0	1.4	0.5	0.0
Monroe	2,116	88.5	9.1	1.8	0.4	0.1
Montcalm	717	96.5	1.8	1.3	0.1	0.3
Montmorency	105	98.1	0.0	1.9	0.0	0.0
Muskegon	258	94.6	4.3	1.2	0.0	0.0

Newaygo	215	93.0	3.7	2.8	0.0	0.5
Oakland	15,781	74.2	21.4	1.7	2.4	0.3
Oceana	387	92.0	1.3	6.5	0.0	0.3
Ogemaw	338	98.5	0.9	0.3	0.3	0.0
Ontonagon	127	94.5	1.6	1.6	0.8	1.6
Osceola	381	96.1	2.6	0.8	0.5	0.0
Oscoda	105	99.1	1.0	0.0	0.0	0.0
Otsego	423	98.1	1.2	0.5	0.2	0.0
Ottawa	4,578	86.6	4.4	7.0	1.9	0.2
Presque Isle	172	100.0	0.0	0.0	0.0	0.0
Roscommon	344	99.1	0.3	0.6	0.0	0.0
Saginaw	3,169	69.9	25.0	4.4	0.5	0.3
Sanilac	114	97.4	1.8	0.9	0.0	0.0
Schoolcraft	152	99.3	0.0	0.0	0.0	0.7
Shiawassee	1,032	95.3	3.5	0.7	0.5	0.1
St. Clair	1,570	95.1	4.0	0.6	0.2	0.1
St. Joseph	980	89.3	3.3	6.9	0.5	0.0
Tuscola	585	96.6	2.4	1.0	0.0	0.0
Van Buren	1,062	85.1	6.7	7.4	0.7	0.1
Washtenaw	3,755	75.7	18.5	2.6	2.9	0.3
Wayne	24,258	45.2	51.4	2.2	1.0	0.2
Wexford	578	97.1	1.2	1.0	0.5	0.2

Note: Percentages may not sum to 100 due to rounding. White and African American represent non-Hispanic Whites and African Americans, respectively.

Appendix D. County-level comparison of African-American traffic stops to African-American representation in population

County	% of stops involving African-American driver	% of population that is African American	z-statistic	Odds ratio
Alcona	1.1	0.4	2.63*	2.78
Alger	1.6	7.7	-7.02*	0.19
Allegan	11.9	1.2	48.06*	10.89
Alpena	0.9	0.6	2.82*	1.64
Antrim	1.1	0.4	3.23*	2.61
Arenac	1.2	0.4	1.46	2.88
Baraga	1.6	9.3	-10.97*	0.16
Barry	3.3	0.5	13.10*	6.61
Bay	9.6	1.7	29.29*	6.25
Benzie	0.9	0.2	4.62*	4.80
Berrien	34.1	14.5	53.55*	3.05
Branch	8.5	2.3	22.76*	3.97
Calhoun	22.4	10.4	26.92*	2.50
Cass	11.1	5.2	10.34*	2.29
Charlevoix	1.5	0.4	4.90*	3.61
Cheboygan	2.8	0.8	7.61*	3.57
Chippewa	1.2	5.9	-10.15*	0.19
Clare	1.6	0.6	4.21*	2.55
Clinton	14.8	1.8	39.21*	9.45
Crawford	2.6	0.7	8.42*	3.58
Delta	1.9	0.3	10.78*	5.66
Dickinson	1.4	0.6	5.01*	2.31
Eaton	15.6	6.6	24.84*	2.63
Emmet	1.6	0.7	3.81*	2.18
Genesee	58.5	19.5	109.84*	5.81
Gladwin	1.5	0.3	2.28*	5.19
Gogebic	1.4	3.9	-6.46*	0.36
Grand Traverse	1.9	0.9	4.91*	2.26
Gratiot	5.7	5.5	0.18	1.05
Hillsdale	2.2	0.7	9.02*	3.34
Houghton	0.9	0.7	0.76	1.22
Huron	3.0	0.5	8.06*	6.46
Ingham	23.0	11.1	31.42*	2.40
Ionia	11.1	4.5	14.02*	2.63
Iosco	1.6	0.7	3.69*	2.15
Iron	1.2	0.5	3.68*	2.28
Isabella	6.3	2.6	7.86*	2.47
Jackson	21.3	7.7	38.84*	3.25
Kalamazoo	28.9	10.6	35.67*	3.43
Kalkaska	2.0	0.8	4.18*	2.39
Kent	16.2	9.2	18.07*	1.91
Keweenaw	0.0	0.9	---	---
Lake	10.7	7.9	1.55	1.38
Lapeer	5.7	1.3	23.26*	4.75
Leelanau	1.4	0.4	2.60*	3.32
Lenawee	4.4	2.3	8.42*	1.99
Livingston	16.2	0.6	74.84*	32.80
Luce	1.6	6.5	-8.23*	0.23
Mackinac	2.5	3.2	-2.13*	0.77
Macomb	30.2	11.6	54.12*	3.28
Manistee	1.0	2.8	-3.85*	0.34
Marquette	2.2	1.7	2.64*	1.33
Mason	3.8	0.9	7.47*	4.33
Mecosta	3.7	2.9	1.26	1.27
Menominee	2.1	0.3	9.30*	6.74
Midland	8.4	1.3	21.00*	6.80
Missaukee	1.1	0.6	2.23*	1.79
Monroe	19.9	2.3	55.33*	10.35
Montcalm	2.9	2.1	3.10*	1.42
Montmorency	0.9	0.2	2.83*	3.71
Muskegon	30.7	13.5	33.51*	2.84

Newaygo	2.3	1.1	5.53*	2.09
Oakland	35.7	13.5	89.02*	3.56
Oceana	2.2	1.1	4.09*	2.12
Ogemaw	1.8	0.3	6.80*	5.52
Ontonagon	1.1	0.5	1.71	2.16
Osceola	2.7	1.1	7.27*	2.53
Oscoda	0.6	0.5	0.43	1.29
Otsego	2.0	0.5	8.94*	4.03
Ottawa	15.8	1.4	19.95*	13.00
Presque Isle	0.6	0.6	0.00	1.00
Roscommon	3.7	0.2	16.39*	24.06
Saginaw	52.6	18.2	78.67*	4.97
Sanilac	1.3	0.5	4.03*	2.43
Schoolcraft	1.2	0.4	3.66*	2.74
Shiawassee	7.1	0.7	29.01*	11.05
St. Clair	7.5	2.2	22.90*	3.64
St. Joseph	7.5	2.2	14.17*	3.58
Tuscola	4.4	0.9	14.20*	4.83
Van Buren	19.2	3.2	48.32*	7.23
Washtenaw	28.7	11.8	39.92*	3.02
Wayne	66.5	38.5	83.70*	3.17
Wexford	1.7	0.5	9.31*	3.39

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. Red highlighting indicates that the percentage of stops involving African-American drivers is higher than would be expected based on their representation in the population. Green highlighting indicates that the percentage of stops involving African-American drivers is lower than would be expected based on their representation in the population. Gray highlighting indicates that the percentage of stops involving African-American drivers is consistent with what would be expected based on their representation in the population. Dashed lines ("---") are used when calculations are note possible (e.g., dividing by zero).

Appendix E. County-level comparison of Hispanic traffic stops to Hispanic representation in population

County	% of stops involving Hispanic driver	% of population that is Hispanic	z-statistic	Odds ratio
Alcona	0.5	1.5	-2.01*	0.36
Alger	1.2	1.6	-0.88	0.79
Allegan	5.8	7.3	-4.34*	0.77
Alpena	0.3	1.4	-5.59*	0.18
Antrim	0.3	2.3	-3.86*	0.14
Arenac	1.2	2.0	-0.77	0.58
Baraga	0.3	1.6	-4.38*	0.18
Barry	2.0	3.0	-2.39*	0.67
Bay	1.6	5.3	-9.06*	0.29
Benzie	0.7	2.5	-3.93*	0.28
Berrien	7.1	5.5	7.11*	1.31
Branch	5.1	4.8	0.99	1.07
Calhoun	4.0	5.2	-4.09*	0.75
Cass	3.4	3.9	-1.03	0.87
Charlevoix	0.5	2.0	-3.24*	0.26
Cheboygan	0.8	1.4	-2.12*	0.55
Chippewa	0.0	1.9	---	---
Clare	0.3	2.0	-4.02*	0.13
Clinton	2.5	4.5	-5.30*	0.54
Crawford	1.1	2.0	-3.17*	0.56
Delta	0.5	1.4	-3.73*	0.40
Dickinson	0.6	1.6	-4.30*	0.36
Eaton	3.2	5.4	-7.07*	0.58
Emmet	0.8	1.7	-2.79*	0.46
Genesee	1.0	3.4	-16.13*	0.29
Gladwin	1.5	1.7	-0.21	0.86
Gogebic	0.7	1.5	-3.13*	0.50
Grand Traverse	1.0	2.9	-4.69*	0.36
Gratiot	3.9	6.1	-1.50	0.63
Hillsdale	0.9	2.3	-5.04*	0.38
Houghton	0.1	1.6	-3.81*	0.07
Huron	1.6	2.4	-1.32	0.68
Ingham	3.4	7.8	-13.83*	0.41
Ionia	2.8	4.8	-4.24*	0.58
Iosco	0.6	2.3	-4.32*	0.25
Iron	0.8	2.1	-4.04*	0.39
Isabella	1.9	4.0	-3.67*	0.48
Jackson	2.1	3.5	-6.39*	0.59
Kalamazoo	3.5	4.9	-4.17*	0.70
Kalkaska	1.1	2.0	-2.32*	0.55
Kent	6.6	10.6	-9.73*	0.60
Keweenaw	0.0	0.8	---	---
Lake	2.0	2.6	-0.54	0.78
Lapeer	2.3	4.7	-7.92*	0.47
Leelanau	3.4	4.4	-0.85	0.78
Lenawee	2.6	8.0	-11.53*	0.31
Livingston	1.9	2.4	-2.69*	0.77
Luce	0.0	3.5	---	---
Mackinac	0.5	1.8	-4.87*	0.30
Macomb	1.3	2.6	-7.93*	0.50
Manistee	1.4	3.2	-3.50*	0.44
Marquette	0.6	1.5	-4.71*	0.38
Mason	3.8	4.6	-1.04	0.82
Mecosta	2.0	2.3	-0.59	0.86
Menominee	1.5	1.8	-0.91	0.83
Midland	1.7	2.7	-2.59*	0.62
Missaukee	1.1	2.9	-4.16*	0.38
Monroe	1.4	3.6	-7.34*	0.38
Montcalm	1.8	3.5	-4.76*	0.52
Montmorency	0.1	1.3	-2.20*	0.11
Muskegon	2.3	5.7	-9.87*	0.40

Newaygo	1.8	5.8	-8.35*	0.30
Oakland	1.5	4.1	-18.86*	0.35
Oceana	7.7	14.9	-7.60*	0.48
Ogemaw	0.8	2.1	-3.12*	0.35
Ontonagon	0.9	1.5	-1.18	0.58
Osceola	0.9	1.9	-4.09*	0.44
Oscoda	1.1	1.6	-0.94	0.65
Otsego	0.9	1.7	-3.41*	0.51
Ottawa	5.2	9.8	-3.26*	0.50
Presque Isle	0.6	1.4	-1.94	0.41
Roscommon	0.8	1.9	-3.62*	0.44
Saginaw	4.2	8.5	-15.11*	0.48
Sanilac	0.8	3.7	-5.83*	0.21
Schoolcraft	0.7	1.1	-1.52	0.63
Shiawassee	1.1	2.9	-5.96*	0.36
St. Clair	1.0	3.4	-8.65*	0.29
St. Joseph	4.1	7.9	-6.11*	0.49
Tuscola	0.9	3.4	-6.10*	0.27
Van Buren	9.0	11.5	-5.59*	0.76
Washtenaw	2.8	4.7	-7.32*	0.58
Wayne	2.2	5.9	-23.59*	0.35
Wexford	1.1	2.0	-4.22*	0.55

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. Red highlighting indicates that the percentage of stops involving Hispanic drivers is higher than would be expected based on their representation in the population. Green highlighting indicates that the percentage of stops involving Hispanic drivers is lower than would be expected based on their representation in the population. Gray highlighting indicates that the percentage of stops involving Hispanic drivers is consistent with what would be expected based on their representation in the population. Dashed lines ("---") are used when calculations are note possible (e.g., dividing by zero).

Appendix F. County-level comparison of Asian traffic stops to Asian representation in population

County	% of stops involving Asian driver	% of population that is Asian	z-statistic	Odds ratio
Alcona	0.0	0.2	---	---
Alger	1.4	0.1	6.24*	10.04
Allegan	0.8	0.7	1.37	1.23
Alpena	0.1	0.6	-3.78*	0.11
Antrim	0.5	0.3	1.01	1.54
Arenac	0.0	0.4	---	---
Baraga	1.5	0.4	5.38*	3.68
Barry	0.4	0.6	-1.17	0.64
Bay	0.3	0.6	-2.19*	0.50
Benzie	0.1	0.4	-1.53	0.33
Berrien	1.4	1.9	-4.05*	0.72
Branch	0.7	0.8	-0.47	0.92
Calhoun	1.4	2.4	-4.51*	0.59
Cass	0.4	0.8	-2.08*	0.42
Charlevoix	0.4	0.5	-0.22	0.90
Cheboygan	0.9	0.4	2.77*	2.15
Chippewa	0.6	1.0	-2.40*	0.56
Clare	0.1	0.1	-0.54	0.58
Clinton	1.5	1.5	0.16	1.02
Crawford	0.5	0.9	-2.09*	0.57
Delta	1.0	0.4	4.04*	2.25
Dickinson	0.3	0.7	-2.36*	0.46
Eaton	1.1	2.3	-5.71*	0.48
Emmet	0.5	0.6	-0.20	0.94
Genesee	0.1	1.0	-9.74*	0.14
Gladwin	0.0	0.5	---	---
Gogebic	1.4	0.5	5.02*	2.59
Grand Traverse	0.2	0.6	-1.91	0.42
Gratiot	0.7	0.4	0.66	1.60
Hillsdale	0.2	0.4	-2.00*	0.40
Houghton	0.7	2.8	-4.94*	0.24
Huron	0.0	0.6	0.00	0.00
Ingham	1.4	6.7	-16.68*	0.19
Ionia	1.1	0.4	4.66*	2.67
Iosco	0.3	0.8	-2.13*	0.38
Iron	0.6	0.6	-0.03	0.99
Isabella	0.2	1.8	-3.58*	0.13
Jackson	0.7	0.8	-0.98	0.87
Kalamazoo	1.0	2.4	-5.65*	0.42
Kalkaska	0.5	0.5	-0.25	0.91
Kent	1.3	3.0	-7.51*	0.41
Keweenaw	4.8	0.2	4.22*	26.34
Lake	0.4	0.2	0.65	1.95
Lapeer	0.5	0.6	-0.38	0.93
Leelanau	0.3	0.6	-0.77	0.46
Lenawee	0.2	0.3	-0.82	0.76
Livingston	1.4	0.9	4.13*	1.59
Luce	0.3	0.5	-1.39	0.54
Mackinac	0.4	0.7	-1.51	0.65
Macomb	0.6	4.0	-15.00*	0.15
Manistee	0.1	0.3	-1.48	0.22
Marquette	0.9	0.9	-0.58	0.90
Mason	0.1	0.6	-1.52	0.22
Mecosta	0.5	0.8	-0.96	0.62
Menominee	0.8	0.4	2.10*	1.86
Midland	0.4	2.3	-4.66*	0.17
Missaukee	0.4	0.2	1.33	1.82
Monroe	0.4	0.6	-1.45	0.70
Montcalm	0.1	0.4	-2.32*	0.19
Montmorency	0.3	0.2	0.87	1.93
Muskegon	0.3	0.5	-2.40*	0.54

Newaygo	0.0	0.4	-2.36*	0.09
Oakland	1.1	7.4	-30.67*	0.14
Oceana	0.3	0.2	0.37	1.21
Ogemaw	0.1	0.7	-2.04*	0.13
Ontonagon	0.9	0.4	1.50	2.09
Osceola	1.2	0.3	6.85*	4.25
Oscoda	0.0	0.1	---	---
Otsego	0.4	0.6	-1.08	0.73
Ottawa	0.7	2.6	-2.45*	0.24
Presque Isle	0.0	0.6	0.00	0.00
Roscommon	0.6	0.3	2.58*	2.09
Saginaw	0.3	1.2	-7.83*	0.24
Sanilac	0.0	0.3	---	---
Schoolcraft	1.4	0.4	5.03*	3.93
Shiawassee	0.5	0.3	1.71	1.58
St. Clair	0.4	0.6	-1.68	0.70
St. Joseph	0.4	0.5	-0.57	0.81
Tuscola	0.2	0.3	-1.25	0.53
Van Buren	1.8	0.7	8.89*	2.72
Washtenaw	1.8	9.1	-18.33*	0.18
Wayne	0.7	3.3	-20.66*	0.19
Wexford	0.4	0.5	-0.62	0.87

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. Red highlighting indicates that the percentage of stops involving Asian drivers is higher than would be expected based on their representation in the population. Green highlighting indicates that the percentage of stops involving Asian drivers is lower than would be expected based on their representation in the population. Gray highlighting indicates that the percentage of stops involving Asian drivers is consistent with what would be expected based on their representation in the population. Dashed lines ("---") are used when calculations are note possible (e.g., dividing by zero).

Appendix G. County-level comparison of African-American traffic stops to African-American representation in "not-at-fault" crashes (All crashes)

County	% of stops involving African-American driver	% of crashes involving African American drivers	z-statistic	Odds ratio
Alcona	1.4	0.8	0.52	1.80
Alger	2.2	2.2	-0.01	0.99
Allegan	10.9	3.3	6.98*	3.65
Alpena	0.7	1.3	-0.74	0.57
Antrim	0.9	0.0	---	---
Arenac	1.2	5.3	-1.05	0.22
Baraga	1.1	1.3	-0.15	0.85
Barry	3.4	3.6	-0.10	0.96
Bay	10.5	4.3	4.87*	2.64
Benzie	0.8	0.0	---	---
Berrien	30.6	18.4	8.58*	1.95
Branch	7.9	1.9	2.92*	4.44
Calhoun	21.1	6.4	5.63*	3.90
Cass	11.4	6.7	2.56*	1.79
Charlevoix	0.4	0.0	---	---
Cheboygan	2.5	1.4	0.58	1.84
Chippewa	1.1	0.0	---	---
Clare	2.3	0.4	1.59	5.30
Clinton	13.7	3.5	3.78*	4.43
Crawford	2.1	1.8	0.31	1.21
Delta	1.9	0.0	---	---
Dickinson	1.4	0.0	---	---
Eaton	16.6	8.7	5.39*	2.07
Emmet	1.7	1.6	0.05	1.06
Genesee	58.8	24.1	30.97*	4.51
Gladwin	2.2	1.0	0.79	2.21
Gogebic	1.5	0.0	---	---
Grand Traverse	1.2	0.7	1.00	1.77
Gratiot	5.9	2.5	2.13*	2.44
Hillsdale	1.9	0.3	2.41*	5.85
Houghton	0.7	0.8	-0.09	0.93
Huron	4.0	0.0	---	---
Ingham	21.7	15.2	6.06*	1.55
Ionia	10.9	2.7	5.00*	4.46
Iosco	1.4	1.1	0.27	1.23
Iron	1.0	0.6	0.51	1.70
Isabella	5.4	2.2	2.66*	2.50
Jackson	20.2	5.1	11.34*	4.73
Kalamazoo	28.6	15.5	9.79*	2.18
Kalkaska	1.4	0.0	---	---
Kent	15.6	14.2	1.69	1.12
Keweenaw	0.0	0.0	---	---
Lake	7.3	0.0	---	---
Lapeer	6.8	0.8	4.85*	9.26
Leelanau	0.7	1.3	-0.47	0.56
Lenawee	4.4	2.6	1.82	1.72
Livingston	15.2	3.2	4.06*	5.49
Luce	1.6	0.0	---	---
Mackinac	2.3	0.6	1.35	3.97
Macomb	30.5	16.1	17.89*	2.30
Manistee	0.7	1.2	-0.70	0.60
Marquette	1.8	1.0	1.24	1.95
Mason	2.9	1.0	1.85	2.97
Mecosta	2.7	2.1	0.60	1.30
Menominee	1.5	1.2	0.23	1.27
Midland	9.3	2.3	5.39*	4.39
Missaukee	0.8	0.0	---	---
Monroe	20.4	8.2	8.31*	2.86
Montcalm	2.4	1.7	0.83	1.43
Montmorency	0.7	0.0	---	---

Muskegon	33.3	2.1	5.35*	22.94
Newaygo	2.7	2.8	-0.08	0.96
Oakland	35.4	19.9	21.95*	2.21
Oceana	2.0	0.4	1.67	5.65
Ogemaw	2.4	0.0	---	---
Ontonagon	0.4	1.1	-0.62	0.41
Osceola	3.4	1.9	1.17	1.76
Oscoda	0.6	0.0	---	---
Otsego	1.4	0.8	0.72	1.72
Ottawa	15.3	2.9	6.89*	6.03
Presque Isle	0.8	0.0	---	---
Roscommon	3.8	0.0	---	---
Saginaw	53.9	21.8	21.01*	4.21
Sanilac	1.5	1.4	0.08	1.09
Schoolcraft	0.8	0.0	---	---
Shiawassee	6.3	2.6	3.40*	2.50
St. Clair	5.8	2.7	3.34*	2.17
St. Joseph	8.1	1.6	4.75*	5.39
Tuscola	5.4	1.4	2.95*	4.12
Van Buren	18.2	3.8	8.05*	5.68
Washtenaw	28.1	15.9	9.62*	2.07
Wayne	63.4	51.5	17.59*	1.63
Wexford	1.6	0.0	---	---

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving African-American drivers is higher than would be expected based on their representation in not-at-fault crashes. Green highlighting indicates that the percentage of stops involving African-American drivers is lower than would be expected based on their representation in not-at-fault crashes. Gray highlighting indicates that the percentage of stops involving African-American drivers is consistent with what would be expected based on their representation in not-at-fault crashes. Dashed lines (“---“) are used when calculations are note possible (e.g., dividing by zero).

Appendix G-*Supplemental*. County-level comparison of African-American traffic stops to African-American representation in "not-at-fault" crashes (Only two-vehicle crashes)

County	% of stops involving African-American driver	% of crashes involving African American drivers	z-statistic	Odds ratio
Alcona	1.4	0.0	---	---
Alger	2.2	0.0	---	---
Allegan	10.9	4.1	4.29	2.85
Alpena	0.7	2.2	-1.05	0.33
Antrim	0.9	0.0	---	---
Arenac	1.2	0.0	---	---
Baraga	1.1	0.0	---	---
Barry	3.4	5.3	-0.85	0.63
Bay	10.5	4.8	3.64	2.32
Benzie	0.8	0.0	---	---
Berrien	30.6	22.3	4.63	1.54
Branch	7.9	10.5	-0.42	0.73
Calhoun	21.1	6.7	3.32	3.71
Cass	11.4	5.9	2.01	2.06
Charlevoix	0.4	0.0	---	---
Cheboygan	2.5	0.0	---	---
Chippewa	1.1	0.0	---	---
Clare	2.3	0.0	---	---
Clinton	13.7	3.2	2.65	4.82
Crawford	2.1	0.0	---	---
Delta	1.9	0.0	---	---
Dickinson	1.4	0.0	---	---
Eaton	16.6	11.1	2.97	1.59
Emmet	1.7	0.0	---	---
Genesee	58.8	26.8	25.68	3.90
Gladwin	2.2	0.0	---	---
Gogebic	1.5	0.0	---	---
Grand Traverse	1.2	0.2	1.65	5.76
Gratiot	5.9	4.2	0.68	1.42
Hillsdale	1.9	0.6	1.08	3.00
Houghton	0.7	0.6	0.11	1.13
Huron	4.0	0.0	---	---
Ingham	21.7	17.3	3.60	1.33
Ionia	10.9	2.0	3.82	5.85
Iosco	1.4	2.0	-0.32	0.71
Iron	1.0	4.8	-1.45	0.21
Isabella	5.4	5.3	0.08	1.03
Jackson	20.2	7.1	6.96	3.29
Kalamazoo	28.6	17.7	7.31	1.86
Kalkaska	1.4	0.0	---	---
Kent	15.6	15.2	0.41	1.03
Keweenaw	0.0	0.0	---	---
Lake	7.3	0.0	---	---
Lapeer	6.8	0.9	2.90	7.99
Leelanau	0.7	0.0	---	---
Lenawee	4.4	3.3	0.92	1.35
Livingston	15.2	3.5	3.09	4.87
Luce	1.6	0.0	---	---
Mackinac	2.3	0.0	---	---
Macomb	30.5	16.6	16.07	2.21
Manistee	0.7	2.8	-1.59	0.26
Marquette	1.8	0.9	1.06	2.17
Mason	2.9	1.9	0.55	1.53
Mecosta	2.7	4.3	-1.01	0.62
Menominee	1.5	1.9	-0.19	0.82
Midland	9.3	3.4	3.21	2.89
Missaukee	0.8	0.0	---	---
Monroe	20.4	7.7	7.37	3.08
Montcalm	2.4	2.2	0.15	1.09
Montmorency	0.7	0.0	---	---

Muskegon	33.3	4.5	3.96	10.47
Newaygo	2.7	0.0	---	---
Oakland	35.4	20.7	19.06	2.10
Oceana	2.0	2.0	0.01	1.01
Ogemaw	2.4	0.0	---	---
Ontonagon	0.4	0.0	---	---
Osceola	3.4	2.7	0.28	1.23
Oscoda	0.6	0.0	---	---
Otsego	1.4	0.8	0.48	1.64
Ottawa	15.3	2.7	6.69	6.40
Presque Isle	0.8	0.0	---	---
Roscommon	3.8	0.0	---	---
Saginaw	53.9	25.8	16.03	3.37
Sanilac	1.5	0.0	---	---
Schoolcraft	0.8	0.0	---	---
Shiawassee	6.3	2.5	2.24	2.61
St. Clair	5.8	3.6	1.82	1.63
St. Joseph	8.1	2.2	3.16	3.87
Tuscola	5.4	1.0	1.74	5.86
Van Buren	18.2	1.7	4.99	12.61
Washtenaw	28.1	17.6	7.28	1.83
Wayne	63.4	51.8	16.52	1.61
Wexford	1.6	0.0	---	---

Note: Percentages may not sum to 100 due to rounding. **p* < 0.05. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving African-American drivers is higher than would be expected based on their representation in not-at-fault crashes. Green highlighting indicates that the percentage of stops involving African-American drivers is lower than would be expected based on their representation in not-at-fault crashes. Gray highlighting indicates that the percentage of stops involving African-American drivers is consistent with what would be expected based on their representation in not-at-fault crashes. Dashed lines ("---") are used when calculations are note possible (e.g., dividing by zero).

Appendix H. County-level comparison of Hispanic traffic stops to Hispanic representation in "not-at-fault" crashes (All crashes)

County	% of stops involving Hispanic driver	% of crashes involving Hispanic driver	z-statistic	Odds ratio
Alcona	0.7	0.0	---	---
Alger	0.4	0.0	---	---
Allegan	5.9	4.8	1.28	1.24
Alpena	0.2	0.0	---	---
Antrim	0.0	0.5	---	---
Arenac	1.2	5.3	-1.05	0.22
Baraga	0.2	0.0	---	---
Barry	1.7	3.0	-1.09	0.57
Bay	2.0	1.0	1.81	2.13
Benzie	0.3	0.9	-0.81	0.37
Berrien	6.8	3.0	4.96*	2.36
Branch	4.8	2.4	1.57	2.07
Calhoun	3.2	1.7	1.42	1.93
Cass	3.8	2.2	1.40	1.71
Charlevoix	0.2	0.0	---	---
Cheboygan	0.5	0.0	---	---
Chippewa	0.0	0.0	---	---
Clare	0.2	0.9	-1.10	0.26
Clinton	1.7	0.0	---	---
Crawford	0.7	0.6	0.21	1.25
Delta	0.3	0.4	-0.12	0.88
Dickinson	0.4	0.7	-0.76	0.53
Eaton	3.0	1.5	2.20*	1.97
Emmet	0.8	0.0	---	---
Genesee	0.9	0.9	0.19	1.04
Gladwin	1.1	1.0	0.07	1.09
Gogebic	0.6	0.0	---	---
Grand Traverse	0.5	0.5	-0.25	0.83
Gratiot	4.3	0.6	2.99*	7.70
Hillsdale	0.7	1.1	-0.91	0.64
Houghton	0.0	0.4	---	---
Huron	1.0	0.6	0.45	1.57
Ingham	3.4	4.3	-1.83	0.77
Ionia	3.0	1.9	1.29	1.64
Iosco	0.6	0.0	---	---
Iron	0.5	0.0	---	---
Isabella	1.7	0.9	1.09	1.83
Jackson	1.9	0.6	2.93*	3.06
Kalamazoo	4.0	2.7	2.31*	1.52
Kalkaska	0.0	0.6	---	---
Kent	6.9	6.8	0.18	1.02
Keweenaw	0.0	0.0	---	---
Lake	2.4	0.0	---	---
Lapeer	1.7	1.3	0.71	1.33
Leelanau	2.2	0.7	1.06	3.44
Lenawee	2.0	2.1	-0.10	0.97
Livingston	2.0	1.6	0.44	1.30
Luce	0.0	0.0	---	---
Mackinac	0.4	0.0	---	---
Macomb	1.1	0.8	1.82	1.44
Manistee	0.7	1.2	-0.70	0.60
Marquette	0.4	0.7	-0.90	0.53
Mason	3.7	1.5	1.88	2.53
Mecosta	1.6	0.5	1.62	3.62
Menominee	1.0	0.0	---	---
Midland	0.6	0.7	-0.08	0.95
Missaukee	0.8	1.2	-0.55	0.64
Monroe	1.4	1.4	0.02	1.01
Montcalm	1.4	0.7	1.03	1.92
Montmorency	0.3	0.0	---	---
Muskegon	2.3	1.4	0.69	1.65

Newaygo	1.8	3.5	-1.29	0.52
Oakland	1.5	1.4	0.61	1.08
Oceana	8.4	4.7	1.94	1.84
Ogemaw	0.2	0.0	---	---
Ontonagon	0.0	1.1	---	---
Osceola	0.8	0.8	-0.01	0.99
Oscoda	0.6	0.0	---	---
Otsego	0.5	0.8	-0.67	0.57
Ottawa	5.6	7.0	-0.66	0.78
Presque Isle	0.8	0.0	---	---
Roscommon	0.7	0.5	0.32	1.41
Saginaw	4.2	4.1	0.28	1.04
Sanilac	0.8	0.0	---	---
Schoolcraft	0.8	0.0	---	---
Shiawassee	1.2	0.6	1.25	2.01
St. Clair	1.1	0.3	1.91	3.28
St. Joseph	3.9	5.2	-1.24	0.73
Tuscola	0.3	1.1	-1.59	0.25
Van Buren	9.3	5.5	2.97*	1.76
Washtenaw	2.6	2.4	0.47	1.09
Wayne	2.5	2.1	2.07	1.21
Wexford	0.7	0.6	0.15	1.12

Note: Percentages may not sum to 100 due to rounding. **p* < 0.05. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving Hispanic drivers is higher than would be expected based on their representation in not-at-fault crashes. Green highlighting indicates that the percentage of stops involving Hispanic drivers is lower than would be expected based on their representation in not-at-fault crashes. Gray highlighting indicates that the percentage of stops involving Hispanic drivers is consistent with what would be expected based on their representation in not-at-fault crashes. Dashed lines ("---") are used when calculations are note possible (e.g., dividing by zero).

Appendix I. County-level comparison of Asian traffic stops to Asian representation in "not-at-fault" crashes (All crashes)

County	% of stops involving Asian driver	% of crashes involving Asian driver	z-statistic	Odds ratio
Alcona	0.0	0.0	---	---
Alger	1.4	0.0	---	---
Allegan	0.7	0.4	1.00	1.76
Alpena	0.2	0.0	---	---
Antrim	0.2	0.0	---	---
Arenac	0.0	0.0	---	---
Baraga	0.9	0.0	---	---
Barry	0.1	0.0	---	---
Bay	0.4	0.1	1.00	3.07
Benzie	0.3	0.0	---	---
Berrien	1.5	1.3	0.58	1.17
Branch	0.7	0.0	---	---
Calhoun	1.3	1.4	-0.12	0.94
Cass	0.4	0.7	-0.92	0.47
Charlevoix	0.2	2.3	-1.67	0.09
Cheboygan	0.7	0.0	---	---
Chippewa	0.3	1.2	-1.54	0.27
Clare	0.0	0.4	---	---
Clinton	1.5	1.0	0.54	1.50
Crawford	0.3	1.2	-1.48	0.28
Delta	0.5	0.0	---	---
Dickinson	0.5	0.3	0.37	1.49
Eaton	1.4	1.2	0.55	1.22
Emmet	0.3	0.0	---	---
Genesee	0.2	0.3	-1.52	0.53
Gladwin	0.0	0.0	---	---
Gogebic	0.2	1.9	-1.85	0.12
Grand Traverse	0.5	0.5	-0.25	0.83
Gratiot	0.0	0.4	---	---
Hillsdale	0.1	0.0	---	---
Houghton	0.0	0.8	---	---
Huron	0.0	0.0	---	---
Ingham	1.5	2.2	-1.93	0.67
Ionia	0.8	0.2	1.29	3.92
Iosco	0.3	0.0	---	---
Iron	0.1	0.0	---	---
Isabella	0.5	0.2	0.87	2.73
Jackson	0.9	0.2	2.37*	5.73
Kalamazoo	1.2	1.5	-0.71	0.81
Kalkaska	0.2	0.6	-1.01	0.24
Kent	1.3	1.9	-1.73	0.70
Keweenaw	0.0	0.0	---	---
Lake	0.8	0.0	---	---
Lapeer	0.7	0.2	1.46	4.56
Leelanau	0.0	0.7	---	---
Lenawee	0.1	0.2	-0.78	0.33
Livingston	1.3	0.5	0.93	2.58
Luce	0.2	0.0	---	---
Mackinac	0.6	0.0	---	---
Macomb	0.7	1.2	-2.80*	0.55
Manistee	0.0	0.0	---	---
Marquette	0.5	0.7	-0.51	0.71
Mason	0.3	0.3	0.04	1.06
Mecosta	0.4	0.2	0.48	1.79
Menominee	0.7	0.0	---	---
Midland	0.3	0.3	-0.05	0.95
Missaukee	0.3	0.0	---	---
Monroe	0.6	0.5	0.42	1.26
Montcalm	0.0	0.2	---	---
Montmorency	0.7	0.0	---	---
Muskegon	0.3	0.0	---	---

Newaygo	0.1	0.0	---	---
Oakland	1.1	2.4	-5.88*	0.47
Oceana	0.3	0.0	---	---
Ogemaw	0.2	0.5	-0.67	0.39
Ontonagon	0.4	1.1	-0.62	0.41
Osceola	1.4	0.8	0.83	1.87
Oscoda	0.0	0.0	---	---
Otsego	0.0	0.0	---	---
Ottawa	0.7	1.7	-0.90	0.40
Presque Isle	0.0	0.0	---	---
Roscommon	0.8	0.0	---	---
Saginaw	0.1	0.6	-2.62*	0.24
Sanilac	0.0	0.0	---	---
Schoolcraft	0.6	0.0	---	---
Shiawassee	0.4	0.5	-0.33	0.78
St. Clair	0.4	0.1	1.04	3.09
St. Joseph	0.1	0.7	-1.82	0.13
Tuscola	0.0	0.0	---	---
Van Buren	1.9	0.6	2.09*	3.01
Washtenaw	2.0	2.7	-1.53	0.74
Wayne	0.8	1.0	-2.14*	0.73
Wexford	0.2	0.6	-1.14	0.39

Note: Percentages may not sum to 100 due to rounding. **p* < 0.05. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving Asian drivers is higher than would be expected based on their representation in not-at-fault crashes. Green highlighting indicates that the percentage of stops involving Asian drivers is lower than would be expected based on their representation in not-at-fault crashes. Gray highlighting indicates that the percentage of stops involving Asian drivers is consistent with what would be expected based on their representation in not-at-fault crashes. Dashed lines ("---") are used when calculations are note possible (e.g., dividing by zero).

Appendix J. County-level comparison of African-American traffic stops to African-American representation in "at-fault" crashes

County	% of stops involving African-American driver	% of crashes involving African American drivers	z-statistic	Odds ratio
Alcona	1.4	2.5	-0.55	0.54
Alger	2.2	2.6	-0.19	0.82
Allegan	10.9	8.1	2.33*	1.40
Alpena	0.7	1.0	-0.34	0.70
Antrim	0.9	0.0	---	---
Arenac	1.2	0.0	---	---
Baraga	1.1	0.0	---	---
Barry	3.4	1.6	1.03	2.13
Bay	10.5	5.6	3.66*	2.00
Benzie	0.8	0.0	---	---
Berrien	30.6	22.7	5.05*	1.51
Branch	7.9	5.3	0.81	1.52
Calhoun	21.1	21.0	0.03	1.01
Cass	11.4	9.3	0.99	1.26
Charlevoix	0.4	0.0	---	---
Cheboygan	2.5	3.7	-0.38	0.66
Chippewa	1.1	3.5	-2.06*	0.31
Clare	2.3	0.0	---	---
Clinton	13.7	6.7	2.34*	2.21
Crawford	2.1	0.0	---	---
Delta	1.9	1.9	0.02	1.01
Dickinson	1.4	1.3	0.12	1.09
Eaton	16.6	10.7	3.63*	1.65
Emmet	1.7	2.3	-0.32	0.72
Genesee	58.8	29.5	25.82*	3.41
Gladwin	2.2	2.0	0.09	1.09
Gogebic	1.5	2.6	-0.54	0.57
Grand Traverse	1.2	1.7	-0.79	0.69
Gratiot	5.9	6.0	-0.02	0.99
Hillsdale	1.9	1.6	0.35	1.21
Houghton	0.7	0.4	0.52	1.79
Huron	4.0	1.5	1.27	2.76
Ingham	21.7	21.6	0.06	1.00
Ionia	10.9	6.1	2.74*	1.88
Iosco	1.4	1.0	0.33	1.41
Iron	1.0	0.0	---	---
Isabella	5.4	3.6	1.08	1.52
Jackson	20.2	8.9	7.29*	2.57
Kalamazoo	28.6	22.0	4.47*	1.42
Kalkaska	1.4	3.5	-1.56	0.39
Kent	15.6	18.2	-2.79*	0.83
Keweenaw	0.0	0.0	---	---
Lake	7.3	25.0	-1.20	0.23
Lapeer	6.8	2.4	3.05*	2.92
Leelanau	0.7	1.1	-0.30	0.65
Lenawee	4.4	5.3	-0.74	0.83
Livingston	15.2	6.5	2.83*	2.56
Luce	1.6	4.5	-1.01	0.34
Mackinac	2.3	5.6	-1.69	0.39
Macomb	30.5	20.1	12.45*	1.75
Manistee	0.7	1.1	-0.35	0.68
Marquette	1.8	2.5	-0.76	0.75
Mason	2.9	3.6	-0.42	0.79
Mecosta	2.7	3.8	-0.80	0.70
Menominee	1.5	1.0	0.44	1.57
Midland	9.3	3.4	3.84*	2.88
Missaukee	0.8	0.0	---	---
Monroe	20.4	9.9	7.04*	2.32
Montcalm	2.4	2.0	0.36	1.18
Montmorency	0.7	0.0	---	---
Muskegon	33.3	6.8	5.19*	6.79

Newaygo	2.7	5.6	-1.43	0.46
Oakland	35.4	23.0	16.92*	1.83
Oceana	2.0	3.5	-0.99	0.56
Ogemaw	2.4	2.3	0.06	1.04
Ontonagon	0.4	3.1	-1.40	0.14
Osceola	3.4	4.1	-0.41	0.82
Oscoda	0.6	3.3	-1.18	0.18
Otsego	1.4	1.7	-0.34	0.80
Ottawa	15.3	6.0	4.17*	2.82
Presque Isle	0.8	0.0	---	---
Roscommon	3.8	0.7	1.63	5.27
Saginaw	53.9	28.6	16.17*	2.93
Sanilac	1.5	2.3	-0.40	0.65
Schoolcraft	0.8	0.0	---	---
Shiawassee	6.3	4.9	1.03	1.31
St. Clair	5.8	5.6	0.15	1.03
St. Joseph	8.1	5.5	1.75	1.53
Tuscola	5.4	4.1	0.73	1.32
Van Buren	18.2	11.1	3.50*	1.78
Washtenaw	28.1	21.3	5.08*	1.44
Wayne	63.4	51.1	17.49*	1.66
Wexford	1.6	2.8	-1.48	0.54

Note: Percentages may not sum to 100 due to rounding. **p* < 0.05. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving African-American drivers is higher than would be expected based on their representation in at-fault crashes. Green highlighting indicates that the percentage of stops involving African-American drivers is lower than would be expected based on their representation in at-fault crashes. Gray highlighting indicates that the percentage of stops involving African-American drivers is consistent with what would be expected based on their representation in at-fault crashes. Dashed lines ("---") are used when calculations are note possible (e.g., dividing by zero).

Appendix K. County-level comparison of Hispanic traffic stops to Hispanic representation in "at-fault" crashes

County	% of stops involving Hispanic driver	% of crashes involving Hispanic driver	z-statistic	Odds ratio
Alcona	0.7	0.0	---	---
Alger	0.4	0.0	---	---
Allegan	5.9	7.1	-1.23	0.82
Alpena	0.2	0.0	---	---
Antrim	0.0	1.4	---	---
Arenac	1.2	0.0	---	---
Baraga	0.2	0.0	---	---
Barry	1.7	4.1	-1.72	0.41
Bay	2.0	1.1	1.55	1.91
Benzie	0.3	1.2	-1.11	0.26
Berrien	6.8	5.0	2.05*	1.37
Branch	4.8	4.0	0.31	1.21
Calhoun	3.2	3.1	0.09	1.04
Cass	3.8	2.9	0.71	1.33
Charlevoix	0.2	0.0	---	---
Cheboygan	0.5	3.7	-1.64	0.13
Chippewa	0.0	0.0	---	---
Clare	0.2	0.0	---	---
Clinton	1.7	4.0	-1.83	0.42
Crawford	0.7	0.0	---	---
Delta	0.3	0.0	---	---
Dickinson	0.4	0.0	---	---
Eaton	3.0	2.8	0.19	1.05
Emmet	0.8	0.0	---	---
Genesee	0.9	1.2	-1.47	0.73
Gladwin	1.1	0.0	---	---
Gogebic	0.6	0.0	---	---
Grand Traverse	0.5	0.6	-0.44	0.71
Gratiot	4.3	3.4	0.48	1.28
Hillsdale	0.7	1.6	-1.29	0.47
Houghton	0.0	0.4	---	---
Huron	1.0	0.7	0.24	1.35
Ingham	3.4	3.6	-0.51	0.92
Ionia	3.0	3.9	-0.88	0.76
Iosco	0.6	0.0	---	---
Iron	0.5	0.0	---	---
Isabella	1.7	2.0	-0.33	0.83
Jackson	1.9	1.1	1.65	1.82
Kalamazoo	4.0	3.4	0.95	1.19
Kalkaska	0.0	0.0	---	---
Kent	6.9	8.1	-1.78	0.84
Keweenaw	0.0	0.0	---	---
Lake	2.4	0.0	---	---
Lapeer	1.7	1.9	-0.33	0.87
Leelanau	2.2	2.3	-0.02	0.98
Lenawee	2.0	2.6	-0.81	0.75
Livingston	2.0	3.9	-1.52	0.51
Luce	0.0	0.0	---	---
Mackinac	0.4	0.0	---	---
Macomb	1.1	0.9	0.91	1.19
Manistee	0.7	1.1	-0.35	0.68
Marquette	0.4	0.3	0.31	1.40
Mason	3.7	1.5	1.25	2.60
Mecosta	1.6	1.7	-0.03	0.98
Menominee	1.0	1.9	-0.88	0.50
Midland	0.6	1.2	-1.07	0.52
Missaukee	0.8	1.7	-0.70	0.47
Monroe	1.4	2.3	-1.70	0.61
Montcalm	1.4	2.0	-0.81	0.67
Montmorency	0.3	8.0	-2.63*	0.04
Muskegon	2.3	0.9	1.00	2.75

Newaygo	1.8	1.4	0.26	1.31
Oakland	1.5	2.0	-2.14*	0.77
Oceana	8.4	10.6	-0.77	0.77
Ogemaw	0.2	0.8	-1.01	0.24
Ontonagon	0.0	3.1	---	---
Osceola	0.8	0.8	-0.06	0.94
Oscoda	0.6	0.0	---	---
Otsego	0.5	0.0	---	---
Ottawa	5.6	6.9	-0.62	0.79
Presque Isle	0.8	0.0	---	---
Roscommon	0.7	0.7	-0.08	0.92
Saginaw	4.2	4.7	-0.66	0.91
Sanilac	0.8	2.3	-1.02	0.32
Schoolcraft	0.8	0.0	---	---
Shiawassee	1.2	0.8	0.75	1.60
St. Clair	1.1	0.9	0.56	1.30
St. Joseph	3.9	9.3	-4.03*	0.39
Tuscola	0.3	0.9	-1.20	0.30
Van Buren	9.3	10.4	-0.72	0.88
Washtenaw	2.6	2.9	-0.53	0.91
Wayne	2.5	2.4	0.57	1.05
Wexford	0.7	1.6	-1.58	0.41

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving Hispanic drivers is higher than would be expected based on their representation in at-fault crashes. Green highlighting indicates that the percentage of stops involving Hispanic drivers is lower than would be expected based on their representation in at-fault crashes. Gray highlighting indicates that the percentage of stops involving Hispanic drivers is consistent with what would be expected based on their representation in at-fault crashes. Dashed lines (“---“) are used when calculations are note possible (e.g., dividing by zero).

Appendix L. County-level comparison of Asian traffic stops to Asian representation in "at-fault" crashes

County	% of stops involving Asian driver	% of crashes involving Asian driver	z-statistic	Odds ratio
Alcona	0.0	0.0	---	---
Alger	1.4	0.0	---	---
Allegan	0.7	0.7	-0.15	0.93
Alpena	0.2	0.0	---	---
Antrim	0.2	1.4	-1.32	0.15
Arenac	0.0	0.0	---	---
Baraga	0.9	4.5	-1.55	0.19
Barry	0.1	0.8	-1.44	0.13
Bay	0.4	0.3	0.37	1.38
Benzie	0.3	0.0	---	---
Berrien	1.5	0.7	1.89	2.11
Branch	0.7	0.0	---	---
Calhoun	1.3	0.6	0.71	2.07
Cass	0.4	0.7	-0.77	0.49
Charlevoix	0.2	0.0	---	---
Cheboygan	0.7	0.0	---	---
Chippewa	0.3	0.0	---	---
Clare	0.0	0.0	---	---
Clinton	1.5	1.3	0.13	1.10
Crawford	0.3	1.7	-1.46	0.19
Delta	0.5	0.0	---	---
Dickinson	0.5	0.0	---	---
Eaton	1.4	1.6	-0.37	0.88
Emmet	0.3	2.3	-1.73	0.12
Genesee	0.2	0.4	-1.68	0.50
Gladwin	0.0	0.0	---	---
Gogebic	0.2	0.0	---	---
Grand Traverse	0.5	0.6	-0.44	0.71
Gratiot	0.0	0.0	---	---
Hillsdale	0.1	0.4	-1.24	0.17
Houghton	0.0	0.8	---	---
Huron	0.0	0.0	---	---
Ingham	1.5	2.2	-1.78	0.68
Ionia	0.8	0.7	0.13	1.09
Iosco	0.3	0.0	---	---
Iron	0.1	0.0	---	---
Isabella	0.5	0.0	---	---
Jackson	0.9	0.2	1.83	3.85
Kalamazoo	1.2	0.8	1.29	1.57
Kalkaska	0.2	0.9	-1.23	0.17
Kent	1.3	1.8	-1.28	0.77
Keweenaw	0.0	0.0	---	---
Lake	0.8	0.0	---	---
Lapeer	0.7	0.5	0.35	1.31
Leelanau	0.0	1.1	---	---
Lenawee	0.1	0.2	-0.95	0.26
Livingston	1.3	0.0	---	---
Luce	0.2	0.0	---	---
Mackinac	0.6	0.0	---	---
Macomb	0.7	1.2	-2.64*	0.57
Manistee	0.0	1.1	---	---
Marquette	0.5	0.5	-0.09	0.93
Mason	0.3	0.0	---	---
Mecosta	0.4	0.0	---	---
Menominee	0.7	0.0	---	---
Midland	0.3	0.4	-0.46	0.63
Missaukee	0.3	1.7	-1.52	0.15
Monroe	0.6	0.4	0.73	1.54
Montcalm	0.0	0.0	---	---
Montmorency	0.7	0.0	---	---
Muskegon	0.3	0.0	---	---

Newaygo	0.1	0.0	---	---
Oakland	1.1	2.4	-5.91*	0.47
Oceana	0.3	0.0	---	---
Ogemaw	0.2	0.0	---	---
Ontonagon	0.4	0.0	---	---
Osceola	1.4	0.0	---	---
Oscoda	0.0	0.0	---	---
Otsego	0.0	0.6	---	---
Ottawa	0.7	2.1	-1.09	0.33
Presque Isle	0.0	0.0	---	---
Roscommon	0.8	0.0	---	---
Saginaw	0.1	0.3	-1.33	0.43
Sanilac	0.0	0.0	---	---
Schoolcraft	0.6	0.0	---	---
Shiawassee	0.4	0.5	-0.42	0.70
St. Clair	0.4	0.3	0.25	1.23
St. Joseph	0.1	0.2	-0.65	0.40
Tuscola	0.0	0.0	---	---
Van Buren	1.9	0.7	1.63	2.66
Washtenaw	2.0	3.0	-2.07*	0.67
Wayne	0.8	0.9	-1.42	0.80
Wexford	0.2	0.4	-0.49	0.59

Note: Percentages may not sum to 100 due to rounding. *$p < 0.05$. This analysis is compares traffic stops that occurred between 1/1/2020 and 6/25/2020 and traffic crashes that occurred between 1/1/2021 and 6/25/2021. Red highlighting indicates that the percentage of stops involving Asian drivers is higher than would be expected based on their representation in at-fault crashes. Green highlighting indicates that the percentage of stops involving Asian drivers is lower than would be expected based on their representation in at-fault crashes. Gray highlighting indicates that the percentage of stops involving Asian drivers is consistent with what would be expected based on their representation in at-fault crashes. Dashed lines (“---“) are used when calculations are note possible (e.g., dividing by zero).

Appendix M. Veil of Darkness logistic regressions predicting race/ethnicity of driver – 30-days before/after day-light savings restriction

	Driver Race/Ethnicity [a]			
Variables	African-American	Hispanic	Asian	Other Race/Ethnicity
	b (SE)	*b* (SE)	*b* (SE)	*b* (SE)
Daylight traffic stop (1 = daylight, 0 = darkness)	.301 (.259)	.342 (.234)	.283 (.448)	1.314* (.617)
Day of the week [b]				
Monday	-.106 (.118)	-.022 (.283)	-.047 (.424)	.442 (.568)
Tuesday	-.121 (.115)	.181 (.335)	-.071 (.453)	.207 (.630)
Wednesday	-.081 (.198)	.529 (.390)	-.497 (.629)	-.507 (.612)
Thursday	-.054 (.151)	.876 (.366)	-.496 (.498)	.348 (.723)
Friday	-.128 (.084)	.255 (.265)	-.396 (.351)	-.317 (.559)
Saturday	-.064 (.121)	.646** (.224)	-.422 (.363)	-.187 (.507)
Time bin [c]	.076 (.049)	-.042 (.079)	.059 (.109)	.151 (.151)
Trooper assignment [d]				
Grant/directed patrol	1.135** (.358)	-.201 (.526)	-.095 (.375)	.293 (.598)
Field Training program	-.138 (.465)	.021 (.336)	-.531 (.733)	.388 (.576)
Hometown Security Team	-1.285 (.721)	.415 (.671)	--- [e]	-.210 (1.177)
Sergeant's duties	.119 (.178)	.298 (.340)	1.331** (.492)	--- [e]
Other assignment	-.888 (.331)	-1.515 (.911)	.470 (.618)	--- [e]
County-level violent crime rate	.004** (.001)	.002** (.0004)	.001 (.0004)	-.003** (.001)
Intercept	-4.01** (.687)	-5.23** (.392)	-5.45** (.785)	-5.58** (1.115)
Wald χ^2	241.70**	179.72**	29.20**	50.04**
Pseudo R^2	.219	.053	.018	.051
N	9,683	9,683	9,479	9,087

Note: Entries are unstandardized partial regression coefficients (*b*), and robust standard errors that adjust for clustering at the county level (SE).

[a] A separate logistic regression equation was estimated for each driver race/ethnicity category.

[b] Reference category = Sunday.

[c] Time bin is an ordered-categorical variable where the time of traffic stops were classified into eight 45-minute periods. The earliest stops in the intertwilight period were coded 1 and the latest as 8.

[d] Reference category = General patrol assignment.

[e] Omitted due to collinearity.

**p<0.01; *p<0.05.

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[1] Correction: The original version of this report that the Michigan State Police made public in January 2022 featured a calculation error that has since been corrected. The error concerned the supplemental analyses reported on pp. 58-60 in the section entitled "*Supplemental benchmark analysis without SCP location traffic stops*." Specifically, the description of these supplemental results was based on an incorrect number of traffic stops that occurred across the jurisdiction. We corrected the numbers and redid the supplemental analyses. Many of the substantive findings remained the same but several differences emerged. Accordingly, we revised the text in this section to correctly report the findings. Additionally, this resulted in us changing some of the description of results in the "Executive Summary" (pp. 12-13). This version of the report reflects the correct calculations and reported results for these supplemental analyses.