Trends in Racial Disparities in Traffic Stops: Vermont State Police, 2010-19

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EXECUTIVE SUMMARY

This study of Vermont State Police traffic stops forms part of a statewide study of Vermont traffic stop data for 2010-2019. In each study of individual law enforcement agencies, we examine the data for racial disparities in several areas: racial share of stops, tickets vs. warnings, reasons for stops, arrest rates, search rates, and contraband "hit" rates. We also examine trends to determine whether racial disparities change over time. Finally, we comment on the completeness of the data collected by the Vermont State Police (VSP).

Our main findings on Vermont State Police from 2010-19, during this period of time, are:

- The Black share of drivers stopped exceed their shares of the estimated driving population by 36%, using U.S. Census population estimates. But, using DMV accident data as a benchmark, Black drivers were not found to be overstopped. Hispanic drivers, too, were found not to be overstopped.
- Black, Asian, and Hispanic drivers are significantly more likely to be issued a ticket than white drivers.
- The arrest rates of Black and Hispanic drivers were higher than the arrest rate of white drivers by 75% and 42%, respectively.
- Black drivers were 3.91 times as likely to be searched subsequent to a stop than white drivers. Hispanic drivers were more than 3 times more likely to be searched than white drivers during this same 10-year period. Native American drivers were 2.83 times more likely to be searched, compared to white drivers.
- Black, Hispanic, and Native American drivers were less likely to be found with contraband than white drivers despite their higher search rates.

Regarding trends in racial disparities:

- The share of stopped drivers identified as Black, Asian, and Hispanic has risen over time, a phenomenon that cannot be explained by demographic changes in Vermont.
- Over time, racial disparities in post-stop outcomes have varied. In 2018, the Black arrest rate exceeded the white rate by about 20% but by 2019, that rose to 60%. Similarly, while Hispanic drivers were arrested at a lower rate than white drivers in 2018, their 2019 arrest rate was 59% higher than the white rate.
- The data also indicate variation in search rate disparities over time, with a jump in racial disparities in 2019. The Hispanic search rate in 2019 was 8.5 times greater than the white search rate, and the Black rate was 4.5 times higher than the white rate in that year, although search rates of all racial groups have fallen over time. The productivity of searches overall seems to have increased.
- With regard to all types of contraband, the hit rate disparity has been declining especially for Black compared to white drivers. The arrest-worthy hit rate disparity between Black and white drivers is still noteworthy.

In terms of data quality, we find:

- Vermont State Police have been exemplary in their attention to the quality of the data with virtually no missing data on race in 2019. Stop reason is the variable with the most missing information. In 2019, 0.4% of stops failed to record reason.

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I. Introduction

In 2013, the Vermont legislature enacted a bill requiring all law enforcement agencies to: 1) adopt a fair and impartial policing policy, and 2) collect race data on traffic stops beginning in September 2014 and to make those data publicly available.[1] Two of the authors of this study conducted the first statewide analysis of racial disparities in traffic policing using that data (Seguino and Brooks 2017). That report covered 29 law enforcement agencies with data for 2015 for most agencies for which data was available.

In the 2017 study, we reported results for all agencies for which we had data, but due to small sample sizes for a number of agencies, we were only able to make statistical inferences on racial disparities for the state as a whole and for the larger cities and towns. With several additional years of data and thus larger sample sizes, it is possible to provide statistical analysis for a larger number of agencies. It is also possible for us to evaluate trends over time. This report, which will form a component of a statewide report, analyzes data for Vermont State Police (VSP) for 2010-2019. VSP collected data on more than half a million traffic stops during this period of time, having begun data collection before it was mandated by the legislature.

Our study aims to identify whether there are racial disparities in traffic stops and outcomes of the stop in Vermont law enforcement agencies. Our focus is primarily on actions that require trooper discretion on whom to stop, arrest, and search. For this reason, we exclude analysis of arrests based on a warrant, and externally generated stops. That said, trooper behavior is influenced by agency leadership and culture, the extent of implicit bias and other trainings related to race, as well as policies that shape trooper decisions.[2]

The law requires that the following traffic stop data be collected and made available to the public: race, age, and gender of driver; reason for stop; type of search, if any; evidence found during the search, if any; and the outcome of the stop. In Vermont, driver's licenses do not include race/ethnicity of the driver. The race of driver indicated in incident reports on traffic stops is based on trooper perception. In analyzing each agency's data, we identify racial shares of stops as compared to racial shares of the driving population, and racial disparities, if any, in reasons for a stop, arrest rates, search rates, and contraband "hit" rates.[3]

In the next section, we provide an overview of the data and identify methodological issues of relevance to our analysis and report on the quality of Vermont State Police's traffic stop data. We report descriptive data on key indicators in Section III of this report, and we

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[1] The bill is 20 V.S.A. § 2366.

[2] For example, some agencies have a policy that a stopped driver found to be driving with a suspended license is automatically given a citation. Thus, not all officer or trooper decisions are the result of discretion. To some extent, the results reflect the role of leadership, training, agency culture, and policies.

[3] Additional data would have been helpful to include in our analysis, but this would require a change to the legislation that has not yet been forthcoming. For example, the type of contraband found, the duration of the stop, and trooper-level data, would improve the ability to assess the degree, if any, of racial disparities in traffic policing.

discuss results of the hit rate test as well. In Section IV, we assess trends over time in racial disparities. In Section V, we conduct a logit analysis to determine the probability of a search and of finding contraband, based on a variety of factors (such as age, gender, and reason for the stop) in addition to the race of the driver. This analysis helps us to control for the context of the stop thereby better isolating the role of race of driver in a search or finding of contraband. Section VI concludes and, in the appendix, we provide supplemental data and information on missing data.[4]

It should be noted that not all racial disparities are due to racially biased policing (or racial profiling). Racial profiling is defined as the use by law enforcement officials of race or ethnicity as a basis of criminal suspicion. The U.S. Department of Justice, in a 2003 memorandum that specifically banned racial profiling in federal law enforcement, stated, "In making routine or spontaneous law enforcement decisions, such as ordinary traffic stops, federal law enforcement troopers may not use race or ethnicity to any degree, except that troopers may rely on race and ethnicity if a specific suspect description exists" (U.S. Department of Justice 2003).

There may, however, be legitimate reasons for racial disparities in traffic policing. For example, motorists of some racial/ethnic groups may have worse driving behavior than other groups. Age of driver is inversely related to risky driving behavior (Ivers, *et al* 2009). If the driving population of some racial has a larger proportion of younger drivers compared to other racial groups, for example, racial disparities may be expected. Race may also correlate with traffic stop disparities for reasons outside the control of law enforcement. For example, U.S. minorities have higher poverty rates than white Americans. This may result in a larger share of minorities driving with a suspended license due to the accumulation of unpaid parking or traffic citations. Racial disparities in this case are not necessarily due to bias of troopers but rather are a function of systemic racism in which people of color face worse economic outcomes than those who identify as white.

In the absence of explicit evidence of criminal behavior, racial profiling or racial bias in policing may stem from implicit bias – the reliance on unconsciously held racial stereotypes such as the association of skin tone with criminality, especially as regards young males of color. Good people hold such biases. Indeed, no one who has grown up in U.S. culture is immune from the widespread portrayal of these negative stereotypes. For the purposes of our study, we conduct two analyses to help distinguish between racial disparities and racial bias in traffic policing. First, we use the hit rate test, examining racial differences in the percentage of searches that yield contraband (Section III). Second, we conduct a multivariate (logit) analysis to control for other factors that contribute to the decision to a search of a vehicle allowing us to estimate the net effect of race itself controlling for these other factors. If race continues to be statistically significant after controlling for these other factors, there is more reason for concern. We conduct a similar analysis of the probability of contraband being found in a search (Section V).

[4] Full details on the methodology used in this study are available at: https://www.uvm.edu/sites/default/files/Department-of-Economics/faculty/Data_Quality_and_Methodology_for_Traffic_Stop_Data_Analysis.pdf

A note on language used in this report is warranted. Race is not a biological category but rather, is a socially constructed concept. Moreover, language about race is fluid, and reflects political changes over time. For example, Hispanic has become less politically acceptable and is now widely replaced by Latinx (a gender neutral form of Latina/o). We retain the use of Hispanic in this report only because this is terminology used in police traffic stop data reports. Second, in just the last year, the term BIPOC (Black, Indigenous, and other People of Color) has come to replace people of color or minorities. We determined the term is still too new to be widely familiar and thus retain older terminology for these conceptual categories. And finally, the capitalization of black and white groups is contested, with some arguing for black to be capitalized but not white and more recently, some argue all racial groups should be capitalized. We capitalize black but not white, as proposed by the *Columbia Journal Review*.[5] We made these decisions, not because we believe our approach is "right" but rather to note how fluid and rapidly changing race language can be, and to underscore that we are aware of the complexities of race language in the U.S.

II. Data Overview, Methodology, and Data Quality

The data in Table 1 provide an overview of the traffic stop data generated by the Vermont State (VSP) from 2010-19. As can be seen, a total of 500,829 stops were made.[6] The percentage of stops in which a citation was issued is 38.2%.

Table 1. Overview of the Data, 2010-19

	Observations	**Rates**
Total Stops		
incl. EGS	500,829	
excl. EGS	491,241	
2010	22,623	
2011	45,502	
2012	49,947	
2013	54,214	
2014	51,397	
2015	42,623	
2016	49,209	
2017	62,593	
2018	56,525	
2019	56,608	
Citations	187,525	38.2%
Arrests	5,898	1.2%
Searches	4,402	0.9%
Contraband	3,510	0.7%
Contraband as % of Searches	3,510	79.7%

Note: EGS is externally generated stops. All rates, annual totals, and outcome data exclude EGS. Rates are as a percentage of total stops, including those where race of driver is unknown.

[5] To see the reasoning for this rule, see https://www.cjr.org/analysis/capital-b-black-styleguide.php.

[6] VSP began collecting data on passengers searched in 2019. In all, there were 14 rows of data on passengers. We omit these from our analysis because there are so few such incidents, with the sample too small to yield reliable results.

Our focus is primarily on policing decisions based on trooper discretion although it is impossible to entirely disentangle the role of agency culture and leadership from individual trooper decisions. In order to restrict our attention to discretionary decisions and actions, in the following analysis we exclude stops that are externally generated. Externally generated stops are those that rely on external information to initiate a stop. A trooper may be directed to stop a vehicle, for instance, in response to a be-on-the-lookout (BOLO) alert. In this case, the stop is not initiated by the trooper. In the case of Vermont State Police, 1.9% (or 9,588) of all stops were externally generated. These exclusions reduce our sample size to 491,241 traffic stops. The percentage of these stops that resulted in an arrest for violation[7] was 1.2%, while 0.9% of stopped vehicles were searched. And contraband was found in 0.7% of all stops. The contraband hit rate as a percentage of searches was 79.7%.

A challenging problem in the data, not only for Vermont State Police but other agencies as well, is that more than one row in the raw data appeared to refer to the same stop in a number of cases. This typically occurs if there is more than one outcome to a stop. For example, the trooper may issue the driver a citation as well as a warning. This scenario would result in 2 lines of data—one for each outcome—and would lead to over-counting of stops, absent efforts to identify stops with multiple outcomes. We therefore developed a method for detecting and reconciling multiple row stops by matching age, race, gender, and date of stop. We retained all information in the multiple rows with regards to tabulating the outcomes of stops while counting each stop only once.

A summary of the raw data for all racial/ethnic groups is provided in Appendix Table A.1 and Tables A.3a-3c detail information on missing data. Here, we note that in the event there is missing data (sometimes marked as "unknown") those stops are dropped. For example, the race of the driver was omitted in 4,883 stops or in 1.0% of all stops. Since drivers identified as Black are only 2.3% of all drivers stopped by the VSP, the number of drivers without a race recorded is roughly half that of the drivers identified as Black. If those drivers with unknown race are more likely to be people of color then that can impact the analysis. In more than 90% of the stops in which race was not recorded, police were able to complete all other information about the stop leaving only race unrecorded. It is noteworthy, however, that there has been a dramatic reduction in the amount of missing data, so that by 2017, missing data was virtually eliminated. Improvement in data quality continues with only 1 stop out of over 56,000 missing race information in 2019. There is modest backsliding with regard to stop reason which is missing in 0.4% of stops in 2019. Appendix A.4 provides a list of all variables in this report with information on how they are measured.

III. Descriptive Data Analysis of Traffic Stops

A. Racial Shares of Traffic Stops

A straightforward method for identifying racial disparities in traffic stops is to compare the racial shares of traffic stops with estimates of the racial share of the driving population. We use that method here. In theory, we would expect that each racial group's share of stops is

[7] We exclude arrests for warrant since we are focusing on trooper discretion. In the case of Vermont State Police, however, there were no arrests on warrant over this time period.

roughly equal to their share of the driving population, absent any known systematic differences in driving behavior by race/ethnicity. One of the challenges is how to measure racial shares of the driving population, known as the "benchmarking problem." In other words, against what benchmark do we measure the racial shares of the drivers stopped to determine whether racial groups are overstopped or understopped?

Actual measurements of racial shares of Vermont's driving population would be costly to obtain, requiring observers to record the race of drivers at various times of day and locations. This labor-intensive method would likely yield inaccurate results because not all locations, times of day, or times of year could be captured without enormous expense. Further, the racial accuracy of traffic observations is likely to be limited in poor lighting conditions.

Two alternative benchmarks, therefore, are typically used to estimate racial disparities in traffic stops. One relies on the U.S. Census Bureau's estimate of racial shares of the population 15 years and older, using the American Community Survey (ACS) 5-year average for 2013-17. This benchmark is not without its faults. Not everyone over 15 drives a vehicle and not everyone drives with the same degree of frequency. For example, on average, whites drive more than Blacks and Hispanics, a phenomenon related to income and wealth inequality by race (Tal and Handy 2005).[8] Thus, there may be reason to question whether the racial composition of the population in an area is the same as the racial composition of drivers on the road. That said, this benchmark could be enlightening, especially when coupled with alternative benchmarks.

The second benchmark we use is the racial composition of drivers involved in accidents in Vermont. Troopers collect data on the race of drivers in accidents, and these data are reported to the Department of Motor Vehicles (DMV). This approach has emerged as an alternative method to determine an appropriate benchmark against which to compare racial shares of stops. This measure, too, has some weaknesses. It may overestimate Black and Hispanic shares of drivers due to racial dynamics in the U.S. Take, for example, the case of two white drivers involved in a minor traffic accident. These drivers may be more likely to exchange insurance information and go on their way without calling the police than if one of the drivers is white and the other a person of color. In the latter case, white drivers may be more likely to involve the police due to potential implicit bias.

Alpert, *et al* (2004) recommend using only racial shares of not-at-fault drivers under the theoretical assumption that not-at-fault drivers represent a random sample of the driving population. In contrast, at-fault drivers may not comprise a random sample. For example, younger drivers are typically found to be lower quality drivers. Thus, age may be correlated with at-fault accidents, and the age composition of drivers may differ by race. We use all data from the DMV (including at fault drivers), however, in order to maximize sample sizes, given the unreliability of estimates that result from the low number of observations for

[8] Baumgartner, *et al* (2018) report, for example, that 83% of whites own a car, compared to 53% of Blacks, and 49% of Hispanics. Whites also drive approximately 20% more miles per year than Blacks and Hispanics. In Vermont, we find similar racial differences with 19.3% of Blacks using public transportation or walking to work, compared to 6.9% of whites, according to ACS 2013-17 estimates.

minority racial groups in Vermont.[9]

Data on racial shares of stopped drivers and the driving population are shown in Table 2. The share of stops relative to the share of population based on U.S. Census data is calculated only for Blacks, Asians, Native Americans, and whites. This is because the U.S. Census Bureau categorizes Hispanic as an ethnicity rather than race—and, thus, Hispanics may be white or non-white. In contrast, in numerous law enforcement agencies, troopers collecting data on traffic stops in Vermont do not distinguish between white and non-white Hispanics, and simply categorize Hispanics as a separate group. (Other agencies collect data on both race and ethnicity of the driver, but with ethnicity often left blank). The DMV accident data use the same racial/ethnic categories as Vermont law enforcement agencies for traffic stops, and so we can calculate the Hispanic share of drivers using that metric.

White drivers policed by VSP comprised 94.8% of all stopped drivers from 2010 through 2019, with Blacks 2.3%, Asians 1.7%, Hispanics 1.2%, and Native Americans 0.1% of all drivers stopped. Inclusion of externally generated stops does not change these percentages. The Black share of stopped drivers is higher than their share of the driving population, using ACS data. However, the Black share of the driving population is roughly equal to their share of the driving population. For Hispanic drivers, we do not have ACS estimates, but we do have accident data that allow us to estimate their share of the driving population, estimated to be equal to their share of stopped drivers. Asian and Native American drivers are stopped at a rate that is well below their driving population share, whether using the ACS or DMV data.

The Disparity Index (DI) is used as a way to compare racial shares of stops and driving population across groups (Table 2 and Figure 1). The DI is simply the ratio of the racial share of stopped drivers divided by the racial share of the driving population. A DI that is greater than 1 indicates a group is overstopped relative to what would be expected, given its share of the driving population and a ratio of less than 1 indicates a group is understopped. For Blacks in Vermont State Police during this time period, that ratio ranges from 1.04 (2.3%/2.2%) using the DMV data to 1.36 (2.3%/1.7%) using ACS data. Using DMV data, the DI for Hispanic drivers was 0.97, indicating their stop shares were roughly equal to their driving share of the population. Whether we use the ACS or DMV data, white drivers are stopped at a rate proportionate to their driving population share, while Asian drivers are understopped as compared to what would be expected, given their driving population shares (the Asian DI ranges from 0.77 to 0.81).

[9] The original study that uses accident data to measure racial shares of the driving population (Albert, *et al* 2004) was based on accidents in a location with a much larger population. We use it as a plausible second benchmark, albeit one that is potentially noisy.

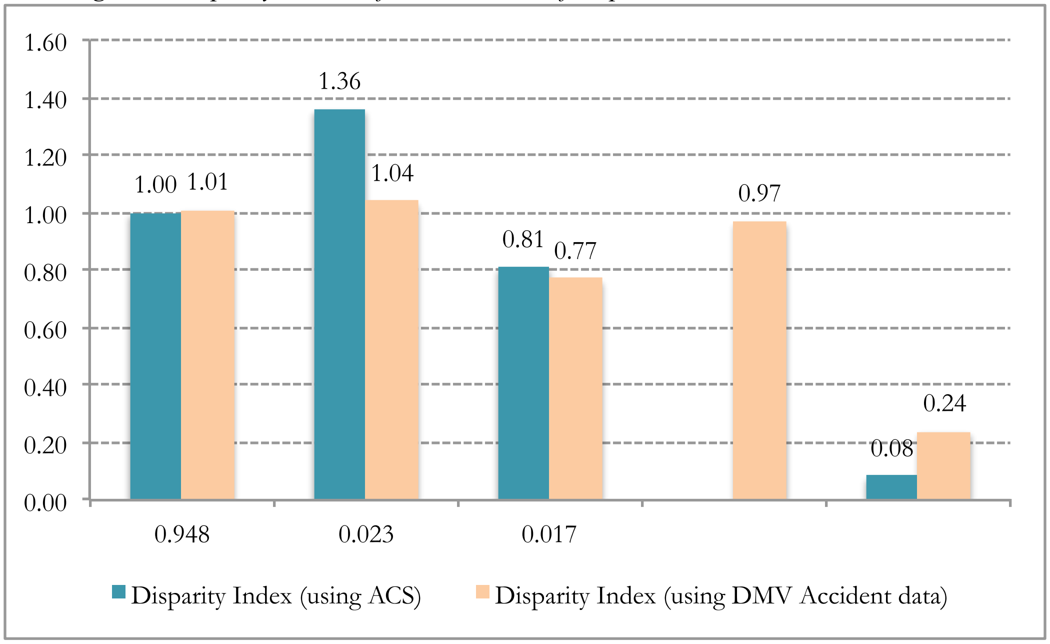
Table 2. Racial Shares of Stops, Reasons for Stops, and Post-Stop Outcomes

	White	Black	Asian	Hispanic	Native American
Racial Shares of Stops					
Including externally generated stops	94.8%	2.3%	1.7%	1.2%	0.1%
Excluding externally generated stops	94.8%	2.3%	1.7%	1.2%	0.1%
Driver Percentage (ACS)	96.2%	1.7%	2.1%		1.2%
Driver Percentage (DMV Accident data)	94.1%	2.2%	2.2%	1.2%	0.4%
Disparity Index (using ACS)	1.00	1.36	0.81		0.08
Disparity Index (using DMV Accident data)	1.01	1.04	0.77	0.97	0.24
Stop Reason as % of All Stops					
Safety Stops	75.5%	79.7%	89.1%	82.8%	81.6%
Moving Violation	75.3%	79.4%	88.8%	82.5%	81.6%
Suspicion of DWI	0.3%	0.3%	0.3%	0.3%	
Investigatory/Pretextual Stops	21.9%	17.2%	9.7%	14.9%	15.0%
Investigatory Stops	1.3%	1.2%	0.5%	0.8%	0.4%
Vehicle Equipment	20.6%	16.1%	9.2%	14.0%	14.6%
Externally Generated Stops	1.9%	2.5%	1.0%	2.0%	3.0%
Multiple Reasons	0.3%	0.2%	0.1%	0.1%	0.2%
Unknown Reason	0.4%	0.4%	0.2%	0.2%	0.2%
Outcome Rates as a % of All Stops					
Warning Rate	61.6%	55.1%	49.2%	52.5%	51.8%
Ticket Rate	37.7%	43.0%	49.9%	45.7%	47.6%
Arrest for Violation Rate	1.2%	2.1%	0.8%	1.7%	1.3%
Arrest for Warrant Rate	0.0%	0.1%	0%	0.1%	0%
No Action Rate	0.3%	0.4%	0.2%	0.4%	0%
Search Rates					
Search rate (excl. searches on warrant)	0.8%	3.0%	0.5%	2.7%	2.2%
Search rate (incl. searches on warrant)	0.8%	3.3%	0.5%	2.8%	2.4%
Hit rates (as a % of PC, RS & Warrant Searches)					
Hit rates (incl. all outcomes)	81.3%	72.0%	76.2%	67.3%	54.6%
Hit rates (excl. warnings as outcomes)	66.8%	52.9%	66.7%	45.5%	54.6%
Hit rates (outcome = arrest)	25.6%	19.7%	28.6%	15.4%	27.3%

Note: ACS refers to the American Community Survey. NA is "not applicable." U.S. Census Bureau data record Hispanics as an ethnicity, not race. Hispanics may be white or non-white. In contrast, Vermont law enforcement agencies treat the category of Hispanics as a mutually exclusive racial category. We therefore use only on DMV accident data for estimates of Hispanic share of the driving population. Outcome rates may not sum to 100% because more than one outcome per stop is possible.

For comparison, at the national level, Pierson, *et al* (2020), using data on almost 100 million traffic stops, find that Black drivers were roughly 50% more likely to be stopped than white drivers in stops conducted by municipal police departments. The authors use the local population as a benchmark, and thus their results are most comparable to our ACS stop disparity estimates. As can be seen, the Black racial share of stopped drivers using ACS data is lower than their estimated share at the national level.

Figure 1. Disparity Indices of Racial Shares of Stops: Vermont State Police, 2010-19



A final note on racial disparities in stops is necessary. The racial share of stops is one of the most contested metrics of racial disparities in traffic policing because of the limitations of the two available measure of the driving population (U.S. Census data and accident data). While the U.S. Census data may underestimate the minority shares of the driving population, given that it measures residents and not drivers, the accident data may overestimate minority shares of the population, given the possibility that not all accidents involve police reports. Most critical to our analysis, however, is post-stop outcomes. Once drivers have been stopped, we know the precise number of drivers of each racial group on which to base calculations of the frequency of post-stop outcomes. Therefore, while racial disparities in stops are noteworthy and should be taken into consideration, it is advisable to rely more heavily on post-stop outcomes to assess racial disparities in policing. We turn to that topic in the next section.

B. Reasons for Stops

Troopers record one of five possible reasons for a traffic stop: moving violation (such as exceeding the speed limit), suspicion of driving while under the influence (DWI), investigatory stop, vehicle equipment (such as obscured license plate), and externally generated stops. Investigatory stops are those in which troopers stop a vehicle to investigate further whether a crime has been committed or not. The law requires that the trooper have reasonable suspicion to conduct such as stop, based on specific and articulable facts. (As noted above, externally generated stops are not trooper-initiated, but instead result from information from a person other than the trooper making the stop). Table 2 shows the distribution of reasons for stops by race. By far the most common reason motorists in Vermont are pulled over by the Vermont State Police is for moving violations (such as speeding), regardless of race of the driver. The second most common reason is vehicle equipment (such as a faulty taillight). Other reasons for stops are far less common.

Following Baumgartner, *et al* (2018), we categorize stops into two groups: *safety stops* and *investigatory/pretextual stops*. Safety stops have a clear purpose of promoting public safety. These include stops due to moving violation or suspicion of DWI. Pretextual stops (whose reasons are investigatory or vehicle equipment), legal under U.S. law, involve an officer stopping a driver for a traffic violation, minor or otherwise, to allow the trooper to then investigate a separate and unrelated, suspected criminal offense. Pretextual stops are also more likely to be cases where racial disparities emerge. This is because investigatory/pretextual stops, often based on hunches or suspicion, may be influenced by racial stereotypes or generalizations about people's behavior, based on their group identity. Negative stereotypes about Blacks and Hispanics in the U.S. are extensive, as evidenced by the results of the Implicit Association Test (Banaji and Greenwald 2013). That negative racial stereotypes in U.S. culture are widespread is documented by social psychologist Jennifer Eberhardt (2019). Her research using social psychology experiments is designed to detect anti-Black bias, which is frequently unconscious or implicit.

If negative stereotypes were operative in Vermont (and there is no reason to think they would not be), we would expect Black and Hispanic drivers to have higher shares of investigatory/pretextual stops as compared to white and Asian drivers. We do not find this pattern. White drivers are more likely to experience a vehicle equipment stop than Black drivers, and white drivers experience investigatory stops as the same rate as Black drivers. Asian and Hispanic drivers experience these stops at lower rates than white drivers.

C. Post-Stop Outcomes

Post-stop outcomes are of particular interest in analyses of racial disparities in traffic stops. That is because, regardless of a law enforcement agent's ability to discern the race of the driver before a stop, she or he has had an opportunity to form a perception of the driver's race once the vehicle has been stopped. This section explores what happens after a stop. Specifically, we ask whether drivers of different racial groups experience systematically different outcomes.

Possible outcomes of a stop are no action taken, warning, citation, arrest, and search. Unlike in the case of stops where we only have estimates of the baseline driving population, in analyzing racial disparities in post-stop outcomes, we know with certainty the number of drivers who have been stopped by race, and therefore can assess racial differences in post-stop outcomes with greater precision than stops.

Table 2 reports Vermont State Police post-stop outcomes by race. In order to make comparisons across racial groups, it is useful to compare outcomes experienced by minority drivers as compared to those of white drivers. Table 3 reports those ratios, whereby the percentage of stopped Black, Asian, and Hispanic drivers experiencing each outcome is divided by the white percentage (for example, the Black search rate divided by the white search rate). A ratio that is greater than one indicates the minority group is more likely to experience a particular outcome than white drivers, and a ratio of less than one indicates the minority group is less likely to experience a particular outcome.

Table 3. A Comparison of Post-Stop Outcomes: Ratio of Minority/White Rates, 2010-19

	Black/white	Asian/white	Hispanic/white	Native American/white
Warning Rate	0.89	0.80	0.85	0.84
Ticket Rate	1.14	1.32	1.21	1.26
Arrest for Violation Rate	1.75	0.66	1.42	1.10
Search rate	3.91	0.61	3.45	2.83

Note: Arrests rates are for violations, and thus exclude arrests on warrant. Search types reported are probable cause or reasonable suspicion; searches on warrant are excluded. Externally generated stops are also excluded.

Black drivers are about 11% less likely to be given a warning than white drivers, and 14% more likely to be issued a citation. Both differences are statistically significant (z=13.92 and z=11.39, respectively). Asian, Hispanic, and Native American drivers are also less likely than white drivers to receive a warning and these differences are also statistically significant. They too are more likely to receive a citation than white drivers, again both statistically significant (z=22.70, z= 12.49, and z=4.37, respectively).

Black drivers are 75% more likely to be arrested by Vermont State Police than white drivers (z=8.54), and Hispanic drivers are about 42% more likely to be arrested subsequent to a stop than white drivers (z=3.47). Native American drivers are 10% more likely to be arrested than white drivers, but this difference is not statistically significant. In contrast, Asian drivers are less likely to be arrested than white drivers (z=3.26).

Search rate data used for Table 3 exclude searches based on a warrant.[10] Black drivers are searched at a rate that is more than 3.91 times greater than that of white drivers, a difference that is statistically significant (z=24.94). Specifically, while 0.8% of white drivers were searched during this period of time, 3.0% of Black drivers were searched. Hispanic drivers were 3.45 times more likely to be searched than white drivers (z=15.91), while Asian drivers were about 40% less likely to be searched than white drivers (z=3.05). And finally, Native American drivers were 2.75 times more likely to be searched than white drivers, a difference that is statistically significant (z=3.38).

The results presented here with regard to higher arrest and search rates of Black drivers as compared to white drivers is consistent with those found in a number of national, state, and local studies. For example, Pierson, *et al* (2020) report national-level data on nearly 100 million US traffic stops, finding that Black drivers are searched at more than twice the rate of white drivers.[11] In a study of 20 million car stops in North Carolina from 2002-2016,

[10] Searches resulting from a warrant could reasonably be described as discretionary because they are the result of a driver refusing to consent to a search. In those cases, the trooper impounds the vehicle and seeks a warrant from a judge. However, in order to be conservative in our approach to defining trooper discretion, we exclude searches on warrant because a judge also participates in the decision to conduct a search.

[11] Pierson, *et al* (2020) do not report racial differences in arrest rates.

Baumgartner, *et al* (2018) also find evidence of higher arrest and search rates of Black drivers. The ratio of Black to white search rates in North Carolina was roughly 2 to 1, similar to Pierson, *et al*'s (2020) results. The Black/white search rate disparity in Vermont State Police, however, is almost double the national-level and North Carolina disparities.

Why might we observe racial differences in search rates? Search rate disparities may be justified if some groups (in this case, Blacks) are more likely to be carrying contraband than white drivers. Police may search vehicles, for example, in an attempt to interdict drugs (a reason that numerous troopers have given, in conversation with the authors of this study) and as a result, they may target Blacks and Hispanics on the basis of racial stereotypes about drug users and couriers are. Implicit bias based on faulty stereotypes may also play a role. For example, evidence shows that Black and white Americans sell and use drugs at similar rates (U.S. Department of Health and Human Services 2012, 2013).

Whether or not there is racial bias (implicit or explicit) in search racial disparities is a question that can be assessed by examining the productivity of searches, that is, the percentage of searches that result in contraband being found, often called the "hit" rate. Contraband in Vermont ranges from underage cigarette possession to stolen goods, to illegal drugs.[12] Absent racial bias (as compared to racial disparities), we would expect that troopers should find contraband on searched minorities at the same rate as on searched white drivers. If searches of minorities turn up contraband at lower rates than searches of white drivers, the hit rate test is consistent with the argument that troopers base their searches of minority drivers on less evidence than they require as a basis for initiating searches of white drivers. Put another way, minority hit rates that are lower than white hit rates are an indication that police may be oversearching minorities (or under-searching white drivers) and that racial bias has influenced the trooper's decision on whom to search.

Vermont law enforcement agencies are only required to report on whether or not contraband is found and are not required to report the type of contraband. As a way to get at racial differences in the severity of contraband found, we differentiate contraband by type in our analysis, and we group hits by the severity of the outcome as follows: a) hit rates for all outcomes (warning, ticket, arrest), b) hit rates in which contraband leads to a ticket(s) and/or an arrest, and c) the arrest-worthy contraband hit rate.

In conducting the hit rate test, we focus on white, Black, and Hispanic drivers. We find that the productivity of searches of Black drivers is lower than that of white drivers for all three hit rates (Table 2). In searches that result in any outcome, the hit rate for white drivers is 81.3% compared to 72.0% for Black drivers. This difference is statistically significant (z=4.24). Similarly, the difference between the lower Black hit rate as compared to the white hit rate for outcomes that lead at least to a ticket and/or arrest is also statistically significant (z=5.31). Finally, of particular interest, given racial stereotypes on drug trafficking, the white arrest-worthy hit rate is 25.6% compared to 19.7% for Black drivers, and this difference is also statistically significant (z=2.47). A similar pattern emerges with regard to differences in Hispanic and white hit rates. The proportion of Hispanic drivers found with contraband is lower than the white proportion for all three types of hit rates and each of these is

[12] Note that firearms for those 21 and over are not necessarily contraband in Vermont, but for those under 21, firearms would be considered contraband.

statistically significant (z=4.35, z=5.50, and z=2.88, respectively). All three Asian hit rates are lower than white hit rates as well, but the differences are not statistically significant. These results suggest VSP has a lower bar of evidence for initiating searches of Black and Hispanic drivers as compared to white drivers. Although the low number of searches of Native American drivers makes statistical inferences unreliable, we note that the contraband hit rate was lower for Native American drivers than white drivers for all outcomes of a search and searches that result in a ticket and/or arrest.

IV. Trends Over Time

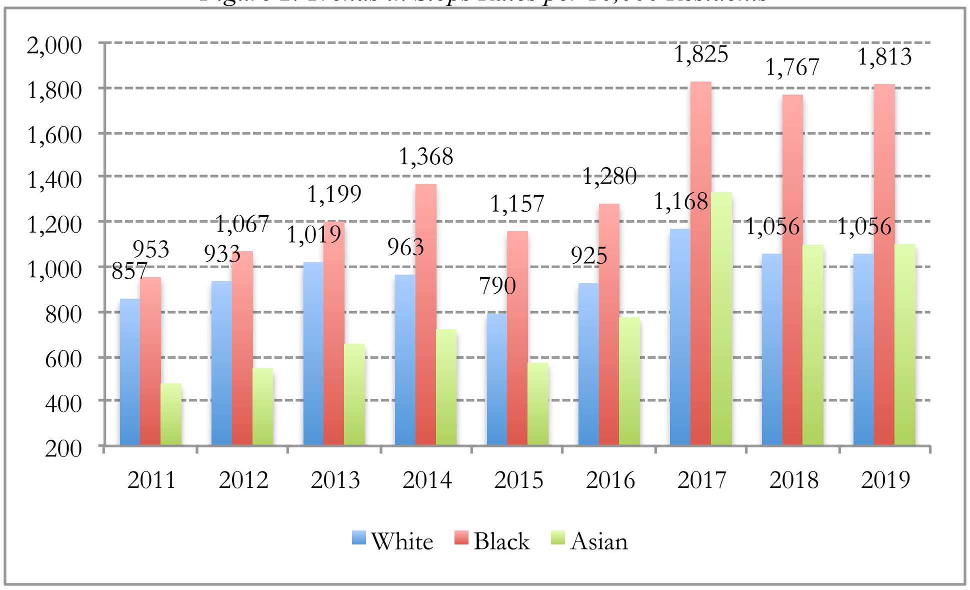
The adoption of fair and impartial policing policies and the availability of traffic stop data may incentivize agencies to review their policies and to conduct trainings on race, policing, and implicit bias. It is therefore useful to explore trends in racial disparities over time to track the effect of such training and exposure to statewide discussions on racial disparities in policing.

First, we examine trends in the number of stops per year in total and by race (for raw data, see Appendix Table A.2b). From 2011 (our first year of complete data) to 2019, the total number of stops increased by 24.4%. The percentage increase in the number of white drivers stopped is very close to that (23.2%), not surprisingly, since the white share of the population is largest. In contrast, stops of Black drivers increased 90.4% over this same time period, and for Asians, the increase was 129.8%. Stops of Hispanic drivers increased 146.2%, the largest increase of all racial/ethnic groups.

For 2019, we estimate that white drivers were stopped at a rate of 1,056 per (white) 10,000 Vermont residents[13] compared to 857 in 2011 (Figure 2). For Black drivers, the rate in 2011 was 953 per 10,000 rising to 1,813 in 2019. Until 2017, the Asian stop rate per 10,000 residents was lower than the white stop rate. But from 2017 to 2019, the Asian stop rate has modestly exceeded the white stop rate.

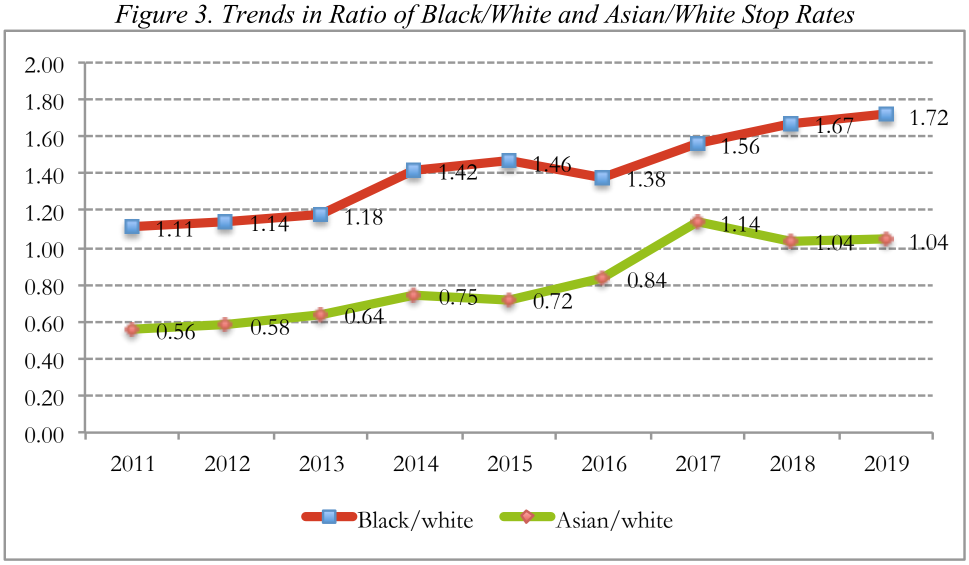
[13] ACS data is used to calculate an estimated rate per 10,000 residents. Because we do not have ACS estimates of Hispanics, this racial category is omitted from Figure 2. Stop rates are calculated, using white drivers as an example, as: [(number of stops of white drivers/number of white residents 15+)*10,000]. Similarly, the stop rate of Black and Asian drivers is their stop numbers divided by the number of Black and Asian residents Vermont 15 and older, all multiplied by 10,000.

Figure 2. Trends in Stops Rates per 10,000 Residents



To more easily compare trends in Black and Asian stop rates, as compared to white rates, Figure 3 plots the ratio of Black to white stop rates and Asian to white stop rates. The Black-white ratio was 1.11 in 2011, meaning that Black drivers were stopped a rate that was about 11% greater than white drivers in year. The Black/white ratio has risen over time to 1.72 in 2019. That is, by 2019, the Black stop rate was more than 70% greater than the white rate. The Asian stop rate was roughly half the white rate in 2011, and by 2019, the Asian rate is slightly higher than the white rate.

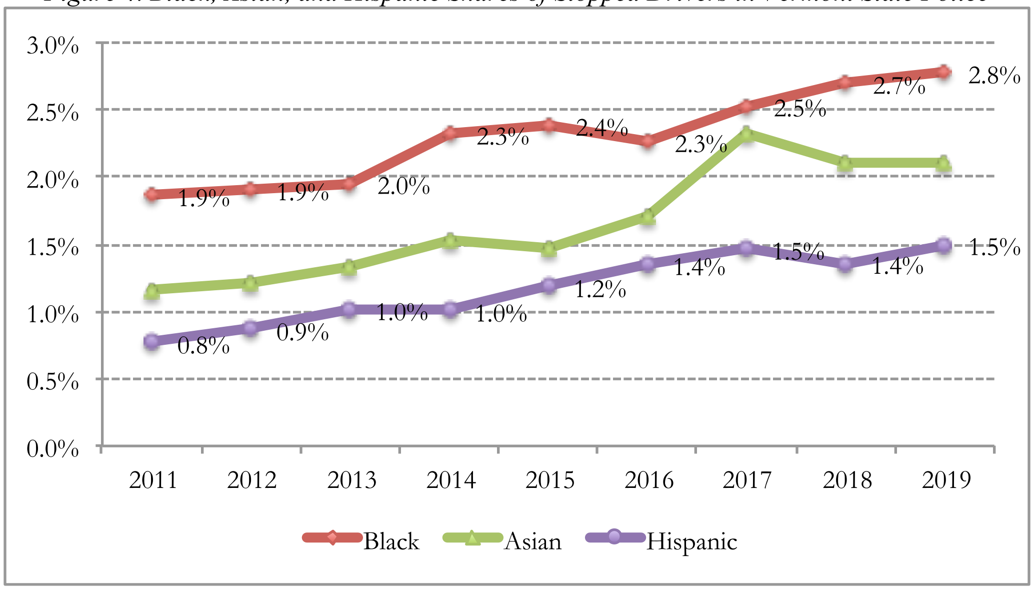
Figure 3. Trends in Ratio of Black/White and Asian/White Stop Rates



We also present data on trends in stop shares, arrest, search, and hit rates. (See Tables A.2a and A.2b for the raw numbers on which the following figures are based).

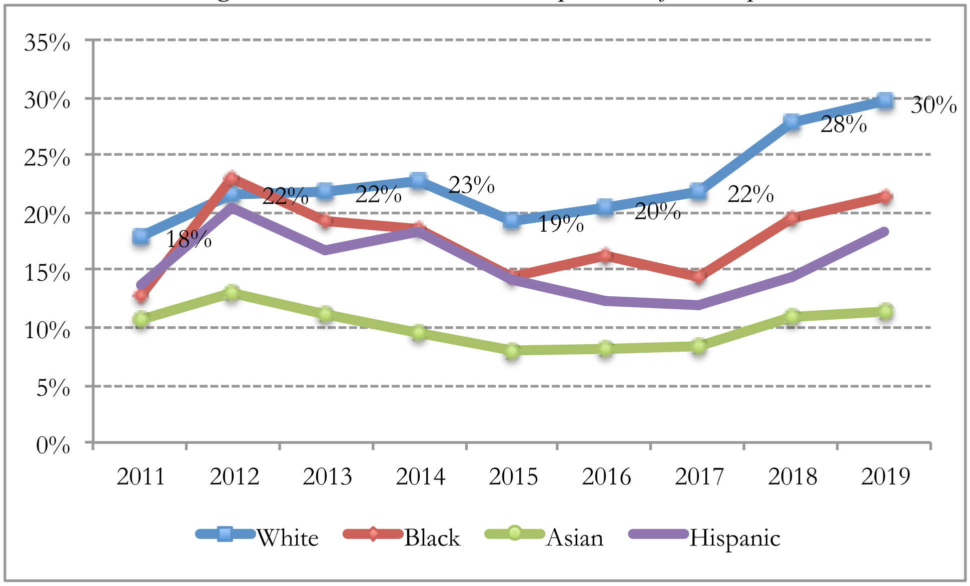
Figure 4 portrays trends in the Black, Asian, and Hispanic shares of stopped drivers. The Black share of stopped drivers has risen by about 50% percent over this time period, and the Hispanic and Asian shares have almost doubled. Although it might be assumed that the rising share of Black and Asian drivers is primarily a result of demographic changes in Vermont's population data over the last several years, both ACS and DMV data indicate that racial shares have been relatively stable.

Figure 4. Black, Asian, and Hispanic Shares of Stopped Drivers in Vermont State Police



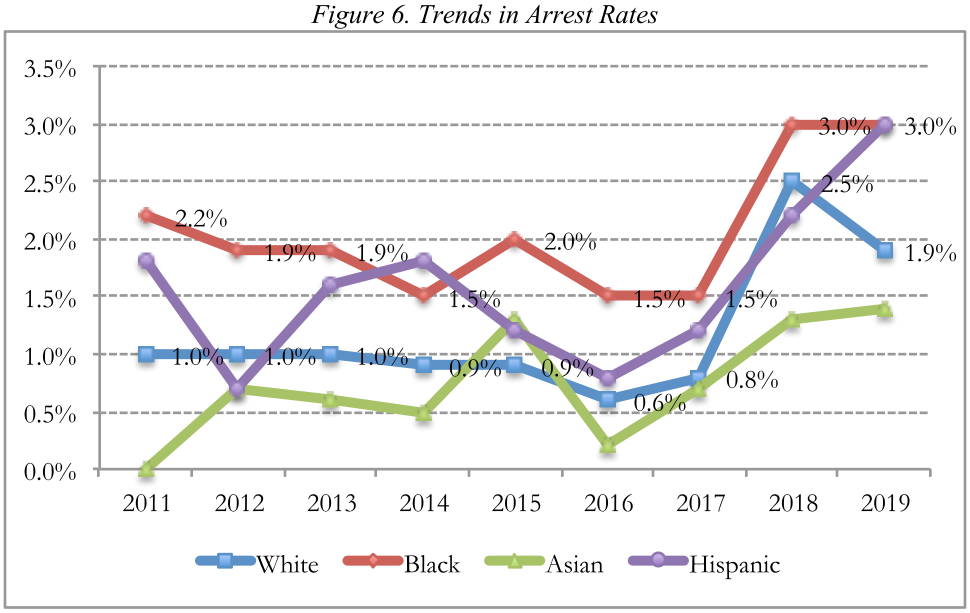
Of interest, as noted, is the percentage of stops that are pretextual—that is, for which the reason for the stop is investigatory or vehicle equipment. This type of stop is one that is more likely to be susceptible to bias than a safety stop. Figure 5 shows trends in pretextual stops as a share of all stops by race. In contrast to other agencies (and our hypothesis), white drivers experience higher rates of investigatory/pretextual stops than all other racial groups. That said, since 2016, the share of stops that are pretextual has been rising for white drivers and has fluctuated for Black and Hispanic drivers with an upswing in the last few years. For example, 20% of stops of white drivers were pretextual in 2016, rising to 30% by 2019.

Figure 5. Trends in Pretextual Stops as % of All Stops



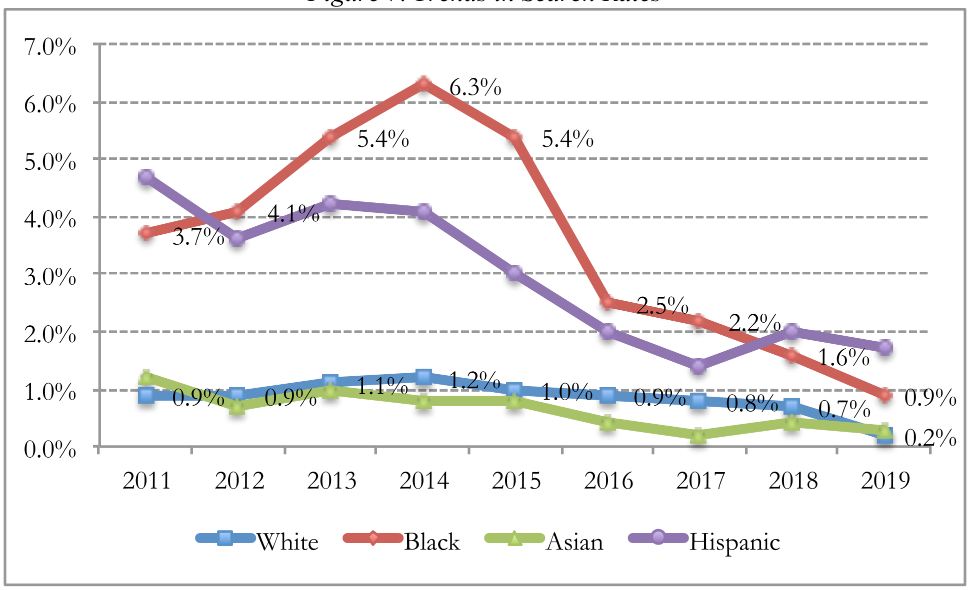
In all years, the Black arrest rate exceeds the white rate (Figure 6). The size of this disparity has varied over time, with 2016 the year with the widest gap in arrest rates. By 2019, the Black arrest rate was 60% higher than the white rate (2.9% compared to 1.8%). The Asian arrest rate in most years is below the white rate. (For 2011-2016, sample sizes of Asian and Hispanic arrest rates are quite small, but by 2017, the larger sample sizes make inferences more reliable). The Hispanic arrest rate has been higher than the white rate in most years, and by 2019 the Hispanic-white disparity was similar to the Black-white disparity.

Figure 6. Trends in Arrest Rates



Search rate trends by race are shown in Figure 7. Vehicle search rates of white drivers were relatively low in 2011 but have fallen significantly over this time period, from 0.9% in 2011 to just 0.2% in 2019. Although the Black search rate started from a much higher rate in 2011 at 3.7%, it too has fallen, such that by 2019, the Black search rate was 0.9%, the same rate that white drivers were searched in the first year of analysis. During that same time period, the Hispanic search rate fell from 4.5% to 1.7%. The Asian search rate has been very close to the white search rate over this time period.

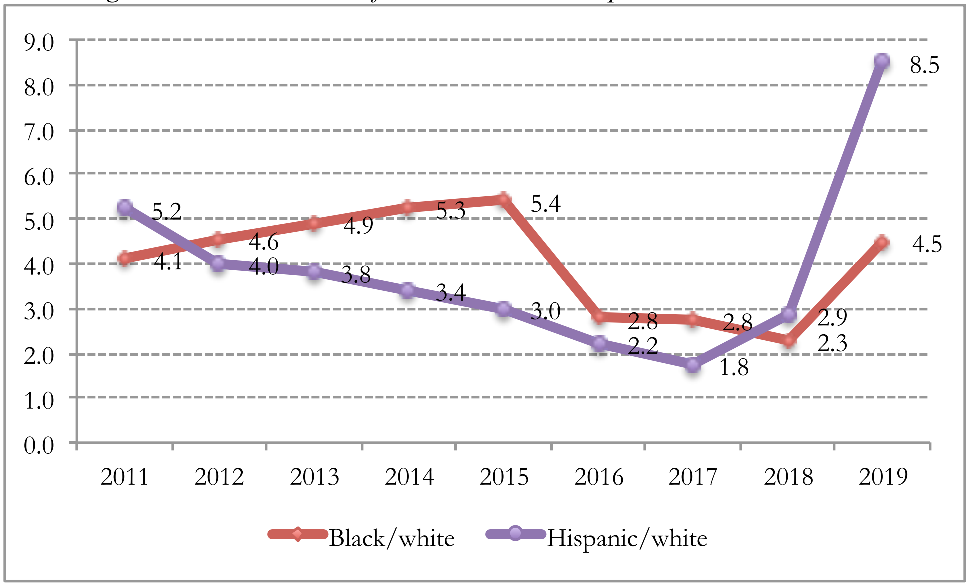
Figure 7. Trends in Search Rates



Although search rates have been declining for all racial groups from 2011 to 2019, search rate disparities have been volatile and in recent years have been increasing. In Figure 8, we plot the ratio of the Black-to-white and Hispanic-to-white search rates. A search rate tells us the probability (or the odds) of a driver being searched. The Black/white and Hispanic/white ratios indicate the relative rates of being searched—that is, the percentage likelihood a person of one racial group will be searched relative to a person from the other (in this case, white) racial group will be searched.

Starting in 2011, the likelihood a Black driver would be searched was 5 times greater than likelihood for a white driver. And the probability a Hispanic driver would be searched was 4 times greater. Those disparities fell by one half by 2017. However, since that time, search rate disparities have widened noticeably. By 2019, Hispanic drivers were 8.5 times more likely to be searched than white drivers while the corresponding rate for Black-to-white drivers rose to 4.5. Thus, although search rates have decreased overall, the unequal treatment by race has not.

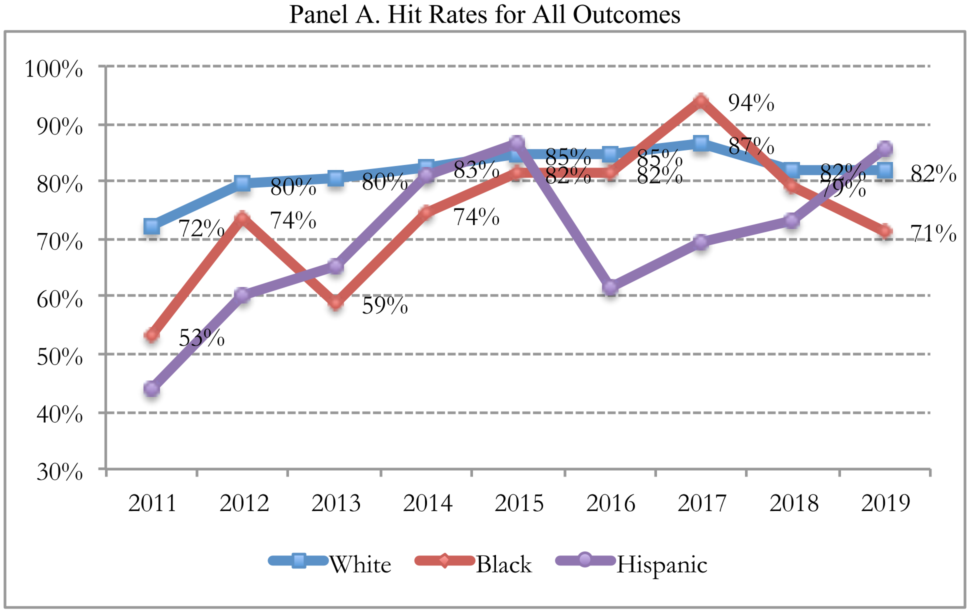
Figure 8. Trends in Ratio of Black/White and Hispanic/White Search Rates

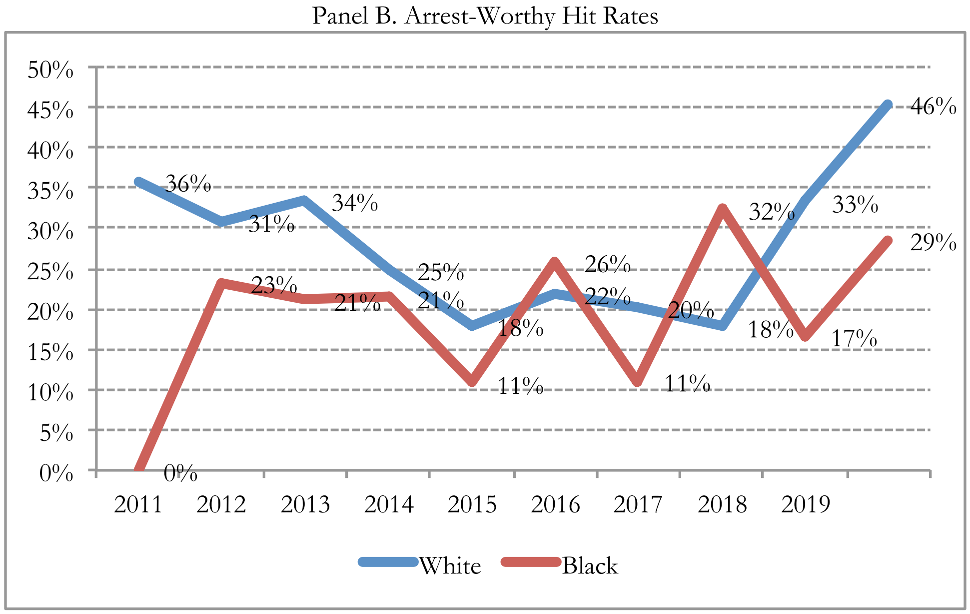


Panel A of Figure 9 shows trends in white, Black, and Hispanic contraband hit rates. Asian hit rates are not shown due to small sample sizes. As the graph indicates, hit rates have been rising for all racial groups over this time period, suggesting higher search productivity. This could be evidence of more efficient policing. It is noteworthy that hit rate disparities have narrowed since 2011. By 2019, the Hispanic hit rate was slightly higher than the white rate (but that difference is not statistically significant). In contrast, the Black hit rate in 2019, was lower than the white rate. The data do suggest, however, a convergence of Black and white hit rates over time, while there is no clear pattern with regard to Hispanic-white hit rate disparities.

Figure 9. Contraband Hit Rates

Panel A. Hit Rates for All Outcomes





The Black-white trend and disparity in hit rates is similar when we exclude warnings or no action taken (not shown here, and ignoring Hispanic-white trends for this type of hit rate due to small sample sizes). Although sample sizes are small when we restrict our focus to arrest-worthy hit rates, it is useful to consider Black and white trends, given the stated focus of law enforcement agencies on drug enforcement and stereotypes about racial differences in drug trafficking. *Panel B* of Figure 9 shows those trends. In most years the Black rate is below that white rate, and that gap widened in 2018 and 2019.

In sum, VSP trends in racial disparities are mixed. There is no evidence of drivers of color disproportionately being targeted for pretextual stops and hit rate disparities for all outcomes have narrowed. But arrest rate disparities have risen since 2017 as have search rate disparities, even given the notable decline in overall search rates.

V. Logit Analysis

In this analysis, our focus is on searches and contraband. Our goal is to examine further for evidence that minority drivers receive less favorable treatment by controlling for possible confounding variables. To do this, we use multivariate logistic regression analysis to calculate the probability of a search occurring and separately, contraband being found, controlling for other factors that may influence the decision to search or of contraband being found. Why is this useful? Some driving behaviors and circumstances may co-vary with race, and could be the dominant reason behind a search rather than the race of the driver. Failing to control for such factors risks misattributing search rate differences to race rather than the explicit behavior of the driver. If, even after controlling for factors like gender, age, reason for stop, and time of day, which we are able to control for, we still find that race is a statistically significant predictor of a search, then that provides additional evidence that the race of the driver, independent of these other factors, influences traffic policing by Vermont State Police.

A. Probability of a Search

We first report results from the probability of a driver being searched by race. The full model takes this general form:

$$\begin{aligned}\textit{Probability of Search} = {} & \beta_0 + \beta_b{*}\textit{Black} + \beta_a{*}\textit{Asian} + \beta_h{*}\textit{Hispanic} + \beta_{na}{*}\textit{Native American} + \\ & \beta_m{*}\textit{Male} + \beta_{age}{*}\textit{Age} + \beta_k{*}\textit{Time of Day}_k + \beta_i{*}\textit{Day of Week}_i + \\ & \beta_j{*}\textit{Reason for Stop}_j + \beta_k{*}\textit{Year}_k + \textit{Residual.}\end{aligned}$$

Dummy variables for each racial group are included, with white the excluded racial category. The coefficients, reported in Table 4, for each of the driver race variables can be interpreted as the odds of a search for a driver of that race as compared to the odds for white drivers with the same characteristics. This is called the *odds ratio*, because it is the ratio of the odds of a non-white driver being searched over the odds that a white driver is searched. An odds ratio of 1 indicates equal probabilities of being searched. A ratio that is greater than one indicates a group is more likely to be searched than the omitted or benchmark group (that is, white drivers). Finally, an odds ratio that is less than 1 is indicative of a lower probability of a group being searched relative to the omitted group.

The coefficient on *Male* indicates the odds a male driver will be searched as compared to the odds a female driver will be searched. We include a control for the driver's age, measured in years, as an explanatory variable. We also control for time of day, with the excluded category the *afternoon*. We control for day of the week, with *Friday* the omitted day. The coefficients on days of the week indicate the odds of being searched on those days as compared to Fridays.

We control for the reason for the stop in two ways. First, we include all reasons for a stop as explanatory variables. The excluded category for this set of variables is *moving violation*. The coefficients on the *Reason for Stop* variables indicate the odds of being searched for each reason for stop divided by the odds of being searched due to moving violation, where the reason is one of the following: suspicion of driving while under the influence (DWI), investigatory stop, multiple reasons for a stop (where the trooper indicated more than one reason for the stop), for reasons unknown (that is, the reason was not stipulated in the incident report), and vehicle equipment. This control can help to eliminate misattribution of race to search disparities, if for example, any racial group is more likely to be DWI. In the second method, we disaggregate the reasons for a stop into safety stops and pretextual stops. The omitted variable in this case is *safety stops*. In this case, the coefficient on the *Pretextual Stop* variable indicates the odds of being searched if the stop was pretextual (investigatory or vehicle equipment) divided by the odds of being searched due to moving violation.

We also include year dummies, with 2010 the omitted year. The odds ratio on years indicates changes in the odds of a search occurring in a given year as compared to the odds in 2010. Controlling for all of these factors allows us to interpret the race variable, net of the impact of these other control variables. Results are shown in Table 4. Of primary interest is whether the race variables are statistically significant (as designated by the asterisks). If they are, this implies that independent of any other factors that may lead to a trooper's decision to search a vehicle, race influenced the trooper's decision to initiate a search.

We report results on four variations of our basic model. We start with a basic model (Model 1 in Table 4), in which race of the driver is our only explanatory variable. (We omit reporting coefficients on days of the week in order to focus attention on our main variables of interest).[14] The results show that, compared to white drivers, Black drivers are about 4 times more likely to be searched than white drivers. (This represents the ratio of the odds of a Black driver being search compared to the odds of a white driver being searched). In contrast, the odds an Asian driver will be searched are about 30% lower than the odds a white driver being searched (the odds ratio is 0.618). The odds ratio for Hispanic drivers is 3.396. That is, the odds a trooper will search a Hispanic driver are almost 3 and a half times greater than the white odds of a search. Finally, the odds a trooper will search the vehicle of Native American drivers are almost 3 times greater than the odds a white driver will be searched.

In Model 2, adding controls for gender, age of driver, time of day, day of week, and reason for stop, we find that the odds of a male driver being searched are more than double the odds a female driver will be searched. The odds ratio on age indicates a lower probability of being searched, the older the driver, and this is statistically significant. The probability of a search is substantially lower in the morning than in the afternoon. The odds of an evening search are more than 50% greater than in the afternoon.

The odds of an investigatory stop leading to a search are more than 6 times the odds for a stop initiated due to a moving violation. The odds ratio on all other reasons for a search as compared to a stop based on a moving violation are also greater than the odds of a search when the reason for the stop is moving violation, and all are statistically significant. The odds a Black driver will be searched in this model, after controlling for other factors, compared to the odds for a white driver is 3.357. That is, even controlling for other factors, the odds a Black driver will be searched in Vermont State Police are more than 3 times greater than the odds a white driver will be searched. The coefficient continues to be statistically significant at the one percent level. That is, we can reject the null hypothesis that there is no difference in search rates between Black and white drivers with a high degree of certainty. Similarly, the odds Hispanic and Native American drivers will be searched continue to be significantly higher than the white odds, after controlling for other factors that might influence the decision to search. In contrast, the odds Asian drivers are searched continue to be lower than the white odds.

[14] Full results, however, are available on request.

Table 4. Odds Ratios of Probability of a Search (Compared to White Drivers)

VARIABLES	(1) Race only	(2) With all controls and stop reason	(3) With all controls, year dummies, and stop reason	(4) With all controls and pretextual stop control
Black	4.043***	3.357***	3.570***	3.358***
	(0.226)	(0.192)	(0.206)	(0.192)
Asian	0.618***	0.603***	0.648***	0.597***
	(0.096)	(0.095)	(0.102)	(0.094)
Hispanic	3.396***	3.048***	3.276***	3.043***
	(0.281)	(0.256)	(0.276)	(0.255)
Native American	2.954***	2.967***	2.865***	2.913***
	(0.903)	(0.921)	(0.892)	(0.900)
Male		2.073***	2.068***	2.084***
		(0.078)	(0.078)	(0.078)
Age		0.947***	0.947***	0.947***
		(0.001)	(0.001)	(0.001)
Morning		0.631***	0.629***	0.632***
		(0.031)	(0.031)	(0.031)
Night		1.581***	1.526***	1.588***
		(0.053)	(0.053)	(0.053)
		(0.067)	(0.067)	(0.064)
Investigatory stop		6.235***	6.334***	
		(0.387)	(0.395)	
Multiple stop reasons		3.435***	3.061***	
		(0.562)	(0.501)	
Suspicion of DWI		5.628***	6.431***	
		(0.730)	(0.839)	
Unknown stop reason		6.584***	10.91***	
		(1.349)	(2.277)	
Vehicle equipment		1.443***	1.517***	
		(0.052)	(0.055)	
2011			0.961	
			(0.083)	
2012			1.009	
			(0.085)	
2013			1.144*	
			(0.093)	
2014			1.220**	
			(0.099)	
2015			1.023	
			(0.087)	
2016			0.874	
			(0.075)	
2017			0.812**	
			(0.068)	
2018			0.623***	
			(0.055)	
2019			0.206***	
			(0.023)	
Pretextual stop				1.737***
				(0.056)
Constant	0.008***	0.011***	0.013***	0.011***
	(0.0001)	(0.0001)	(0.001)	(0.001)
No. of observations	484,948	482,758	482,758	482,758

Note: Standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

In Model 3, we add year dummies to our model. The coefficients on the years convey the odds of a search occurring in each year (of all racial groups) relative to the odds of a search occurring in 2010. Recalling that an odds ratio below 1 indicates lower odds of a search in a given year relative to 2010, these results indicate that by 2019, the odds of a search occurring had fallen 80% since 2010, consistent to what was found in the descriptive data analysis. Still, the higher odds of a search of Black and Hispanic drivers persist, even after controlling for falling overall search rates.

Finally, in Model 4, we include two categories of *Reason for Stop*—safety stops (the omitted variable) and pretextual stops. The results indicate that when the reason for the stop is pretextual, the odds drivers will be searched are about 1.7 times greater than the odds of a search if the reason is a safety stop.

Taken together, these results suggest that Black/white, Hispanic/white, and Native American/white disparities in search rates are extremely robust, regardless of the contextual factors controlled for. The use of more rigorous statistical techniques does not in any meaningful way change the nature of the descriptive data findings.

B. The Probability of Finding Contraband

We conduct logistic regression analysis to assess the role of race in the probability of finding contraband, subsequent to a search. As in the analysis of search rates, we control for other factors that may influence the probability of contraband being found to avoid erroneously attributing to race the effect of other factors. Again, we exclude externally generated stops and searches based on a warrant. The equation we estimate is as follows:

$$\begin{aligned} \textit{Probability of Finding Contraband} = {} & \beta_0 + \beta_b * \textit{Black} + \beta_a * \textit{Asian} + \beta_h * \textit{Hispanic} + \beta_{na} * \textit{Native} \\ & \textit{American} + \beta_m * \textit{Male} + \beta_{age} * \textit{Age} + \beta_k * \textit{Time of Day}_k + \beta_i * \textit{Day of Week}_i \\ & + \beta_j * \textit{Reason for Stop}_j + \beta_k * \textit{Year}_k + \textit{Residual.} \end{aligned}$$

Table 5 reports the results of the probability of contraband being found for searches for any outcome of the stop and search (that is, in which the result was a warning, a citation, or an arrest) for all years for which we have data. The results shown for Model 1, where the only explanatory variable is race of the driver, indicate that the odds of a search of a Black driver yielding contraband are about 40% less than the odds a white driver will be found with contraband subsequent to a search. The difference is statistically significant. Similarly, the odds a Hispanic driver will be found with contraband are about half the white odds. The odds a Native American driver will be found with contraband are about one fourth the white odds. The odds ratios for Hispanic and Native American drivers are both statistically significant. The Asian odds are also lower than the white odds of finding contraband, but this odds ratio is not statistically significant.

Because of the importance of the hit rate in our analysis, let's describe more precisely what the odds ratio coefficient means using the results from this simple regression. From Table 2, we find that 81.3% of searched white drivers are found with contraband and thus, 18.7% are not found with contraband. This implies an odds ratio for white drivers of 81.3/18.7= 4.35. In other words, the odds a search of a white driver will yield contraband are more than 4 times the odds of not finding contraband. For Black drivers, we find in Table 2 that 72.0% of them are found with contraband so their odds ratio is 72.0/28.0=2.57. The ratio of these two odds is the coefficient in our regression (2.57/4.35 =0.59), the coefficient estimate on race when we formally run the logit regression in Model 1.

The addition of controls in Model 2 does not meaningfully change the odds ratio of finding contraband in searches of Black, Asian, or Hispanic drivers as compared to white drivers. The odds ratio on Native Americans is no longer significant, however. It is notable that although investigatory stops are more than 6 times more likely to lead to a search of a vehicle than stops initiative due to a moving violation, those searches are only 1.5 times more likely to lead to contraband being found compared to stops due to moving violations.

In Model 3, we add year dummy variables to capture trends in the overall contraband hit rate over time relative to 2010. The results show that in most years, the odds of finding contraband are greater than in 2010, suggesting a greater productivity of searches.

In Model 4, we obtain similar results on the Black/white and Hispanic/white odds of contraband being found as in Models 1-3, while pretextual stops are shown to result in a slightly higher probability of finding contraband than if the reason for the stop is for safety reasons, the coefficient estimate is not statistically significant.[15]

[15] In results not reported here (but available on request), we recoded warnings as no contraband in order to focus on more serious types of contraband, specifically those that lead to a ticket or an arrest. We obtain broadly similar odds ratios on Black as compared to white drivers.

Table 5. Odds Ratios of Probability of Finding Contraband (Compared to White Drivers)

	(1)	(2)	(3)	(4)
VARIABLES	Race only	With all controls and stop reason	With all controls, year dummies, and stop reason	With all controls and pretextual stop control
Black	0.590***	0.590***	0.568***	0.596***
	(0.073)	(0.075)	(0.074)	(0.076)
Asian	0.734	0.653	0.654	0.670
	(0.268)	(0.241)	(0.245)	(0.247)
Hispanic	0.472***	0.494***	0.496***	0.489***
	(0.083)	(0.089)	(0.091)	(0.087)
Native American	0.275**	0.357	0.439	0.360
	(0.167)	(0.229)	(0.289)	(0.231)
Male		1.246**	1.323***	1.248**
		(0.115)	(0.124)	(0.115)
Age		0.972***	0.970***	0.972***
		(0.003)	(0.004)	(0.003)
Morning		0.761**	0.800*	0.759**
		(0.090)	(0.096)	(0.089)
Night		0.933	0.916	0.926
		(0.080)	(0.079)	(0.078)
Investigatory stop		1.584***	1.471**	
		(0.270)	(0.253)	
Multiple stop reasons		3.021*	2.880*	
		(1.832)	(1.751)	
Suspicion of DWI		0.753	0.777	
		(0.219)	(0.229)	
Unknown stop reason		0.105***	0.0949***	
		(0.046)	(0.042)	
Vehicle equipment		1.053	1.081	
		(0.094)	(0.099)	
2011			0.989	
			(0.186)	
2012			1.659***	
			(0.318)	
2013			1.645***	
			(0.302)	
2014			2.094***	
			(0.390)	
2015			2.776***	
			(0.572)	
2016			2.418***	
			(0.489)	
2017			3.001***	
			(0.613)	
2018			2.261***	
			(0.467)	
2019			2.381***	
			(0.668)	
Pretextual stop				1.102
				(0.090)
Constant	4.362***	9.090***	4.798***	9.064***
No. of observations	4,366	4,328	4,328	4,328

Note: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

To sum up the results of the logistic regressions, adding controls for a variety of contextual factors has little effect on racial disparities in the probability of being searched and of contraband being found during a search. This is not to say that the controls were not meaningful or significant. Searches are more likely to happen under some conditions as compared to others (e.g., during investigatory stops as compared to moving violation stops). But even controlling for these factors, race continues to be a statistically significant factor in a trooper's decision to search a vehicle. With regard to the question of racial bias as an explanation for such disparities, the analysis shows that Black and Hispanic drivers are less likely to be found with contraband.

VI. Conclusion

Vermont has embarked on a long-term project of using data to expand awareness of traffic policing and race. Because traffic stops are the most frequent interaction people have with the police, combined with the large number of traffic stops in any given year, data on stops can be a useful tool for understanding the extent of racial disparities in these interactions. They are, in other words, a way of holding up a mirror to ourselves.

In this report, we provide descriptive data on racial disparities in Vermont State Police traffic stops. We find that Black drivers' share of stops is close to or slightly above their share of the driving population, while the results on stop shares of Hispanic and Asian drivers indicate these groups are stopped at rates below or roughly equal to their share of the driving population. Post-stop outcomes give mixed evidence of racial disparities. In contrast to our hypothesis, white drivers were more likely than other racial groups of drivers to be stopped for investigatory/pretextual reasons. That said, Black and Hispanic drivers have higher arrest rates than white drivers, while Asian drivers are arrested at a lower rate. And although overall search rates have declined over the last 10 years, search rates of Black and Hispanic drivers are proportionately much higher than white search rates, indicative of disparate treatment by VSP troopers. This is especially noteworthy because Black and Hispanic drivers are less likely to be found with contraband. With regard to all types of contraband, the hit rate disparity has been declining especially for Black compared to white drivers. The arrest-worthy hit rate disparity between Black and white drivers is still noteworthy, with white drivers more likely to be arrested subsequent to a search than Black drivers.

We also report on a statistical analysis that controls for other factors that may influence the probability of being searched or of contraband being found during a search. Those results demonstrate that while other factors also contribute to the likelihood of either of those outcomes, racial disparities continue to exist when those factors are controlled for. In particular, Black, Hispanic, and Native American drivers are substantially more likely to be searched than white drivers. Black and Hispanic drives are less likely to be found with contraband, using more sophisticated statistical techniques.

For several years, VSP has engaged in a variety of trainings to address racial disparities and potential bias in policing, and therefore trends over time are of much interest since they can be indicative of how effective trainings and other efforts by VSP have been. Moreover, since 2016, VSP has conducted intensive trainings on data collection and adopted policies that have virtually eliminated missing data, thus substantially improving the reliability of VSP traffic stop data. Despite these efforts, we observe that Black stop rates (per 10,000 Black residents) have been rising faster than white stop rates. Of course, drivers on the road include those from out of state and DMV accident data may be a better measure of racial shares of drivers on Vermont roads. Except for 2019, in which the Black share of drivers using the DMV accident data was 3%, the Black share has been relatively stable at around 2.1%. In other words, accident data do not show a notable increase in the Black share of drivers that might explain the rising stop rates of Black drivers relative to white drivers.

Collectively, these results suggest that the race of the driver plays a role in trooper decision-making in traffic policing in Vermont—although the role that race plays in terms of whom to stop is less pronounced. Rather, it is in post-stop outcomes where we observe racial disparities. This concerning finding coexists with some other positive aspects of Vermont State Police's policing. The VSP has used race data in traffic policing as a management tool and as a means to make troopers conscious of these disparities. Seguino and Brooks (2020) outline other steps the agency has taken to address racial disparities that may be due to bias, a process that may take time to bear fruit.

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APPENDIX

Table A.1. Vermont State Police Raw Traffic Stop Data, 2010-19

All Years	**White**	**Black**	**Asian**	**Hispanic**	**Native American**	**Unknown**	**Total**
Total Traffic Stops							
Including externally generated stops	469,881	11,402	8,298	5,799	472	4,977	500,829
Excluding externally generated stops	460,892	11,113	8,212	5,683	458	4,883	491,241
Reasons For Stops							
Safety Stops	354,908	9,085	7,392	4,802	385	3,767	380,339
Moving Violation	353,593	9,049	7,369	4,782	385	3,758	378,936
Suspicion of DWI	1,315	36	23	20	0	9	1,403
Investigatory/Pretextual Stops	103,052	1,964	802	862	71	756	107,507
Investigatory Stop	6,268	132	38	48	2	61	6,549
Vehicle Equipment	96,784	1,832	764	814	69	695	100,958
Externally Generated Stop	8,989	289	86	116	14	94	9,588
Multiple Reasons - Moving Violation & Suspicion of DWI	34	0	1	1	0	2	38
Multiple Reasons - Moving Violation & Vehicle Equipment	1,236	23	3	5	1	8	1,276
Multiple Reasons - Suspicion of DWI & Vehicle Equipment	14	0	0	0	0	0	14
Unknown Stop Reason	1,648	41	14	13	1	350	2,067
Outcomes							
Ticket	173,774	4,780	4,097	2,596	218	2,060	187,525
Warning	283,968	6,122	4,041	2,982	237	2,481	299,831
No Action Taken	1,532	41	18	22	0	5	1,618
Arrest for violation	5,492	231	64	96	6	9	5,898
Arrest for warrant	163	8	0	5	0	0	176
Searches							
Total Stops with No Search	455,743	10,719	8,158	5,515	447	4,480	485,062
No Search & Contraband & Arrest for violation	76	2	1	3	0	0	82
No Search & Contraband & No arrest	302	10	3	4	2	4	325
No Search (all others)	455,365	10,707	8,154	5,508	445	4,476	484,655
Total Stops with Unknown Search	1,353	33	12	12	0	367	1,777
Total Stops with Search	3,796	361	42	156	11	36	4,402
Search with Probable Cause (PC)	2,749	238	23	94	4	17	3,125
Stops with PC Searches, No contraband	315	40	2	17	2	1	377
Stops with PC Searches, Unknown contraband	23	3	0	0	0	0	26
Stops with PC Searches, Contraband	2,411	195	21	77	2	16	2,722
Outcomes of PC Search							
Stops with PC Searches, Contraband & Warning, No Action or Unknown	411	53	1	25	0	5	495
Stops with PC Searches, Contraband and Ticket	1,307	93	11	37	1	9	1,458
Stops with PC Searches, Contraband and Arrest	693	49	9	15	1	2	769
Search with Reasonable Suspicion (RS)	822	97	16	57	6	17	1,015
Stops with RS Searches, No contraband	325	54	7	34	3	12	435
Stops with RS Searches, Unknown contraband	3	0	0	0	0	0	3
Stops with RS Searches, Contraband	494	43	9	23	3	5	577
Outcomes of RS Search							
Stops with RS Searches, Contraband & Warning, No Action or Unknown	128	12	3	8	0	0	151
Stops with RS Searches, Contraband & Ticket	211	19	5	10	2	3	250
Stops with RS Searches, Contraband & Arrest	155	12	1	5	1	2	176
Search with Warrant	225	26	3	5	1	2	262
Stops with Warrant Searches, No contraband	42	4	1	0	0	1	48
Stops with Warrant Searches, Unknown contraband	3	0	0	0	0	0	3
Stops with Warrant Searches, Contraband	180	22	2	5	1	1	211
Outcomes of Warrant Search							
Stops with Warrant Searches, Contraband & Warning, No Action or Unknown	12	4	0	1	0	1	18
Stops with Warrant Searches, Contraband & Ticket	43	8	0	0	0	0	51
Stops with Warrant Searches, Contraband & Arrest	125	10	2	4	1	0	142

Table A.2a. Vermont State Police Raw Traffic Stop Trend Data

All Years	White	Black	Asian	Hispanic	Native American	Unknown	Total
Total Traffics Stops							
Excluding externally generated stops							
2010	21,230	401	255	178	21	538	22,623
2011	42,996	821	524	342	39	780	45,502
2012	46,808	920	596	420	49	1,154	49,947
2013	51,106	1,033	716	548	65	746	54,214
2014	48,304	1,179	787	514	49	564	51,397
2015	39,598	997	625	500	38	865	42,623
2016	46,390	1,103	847	661	43	165	49,209
2017	58,578	1,573	1,457	913	62	10	62,593
2018	52,931	1,523	1,201	765	45	60	56,525
2019	52,951	1,563	1,204	842	47	1	56,608
Reasons For Stops (excl. externally generated stops and unknown reasons)							
Safety Stops							
2010	18,213	351	244	160	18	413	19,399
2011	34,909	708	467	294	35	574	36,987
2012	36,331	704	518	331	35	932	38,851
2013	39,502	824	636	454	54	554	42,024
2014	36,850	949	710	416	40	388	39,353
2015	31,679	841	571	429	36	719	34,275
2016	36,782	922	777	579	39	129	39,228
2017	45,669	1,345	1,336	803	57	9	49,219
2018	37,939	1,220	1,066	653	36	49	40,963
2019	37,034	1,221	1,067	683	35	0	40,040
2010 (% of Stops)	85.8%	87.5%	95.7%	89.9%	85.7%	76.8%	85.8%
2011 (% of Stops)	81.2%	86.2%	89.1%	86.0%	89.7%	73.6%	81.3%
2012 (% of Stops)	77.6%	76.5%	86.9%	78.8%	71.4%	80.8%	77.8%
2013 (% of Stops)	77.3%	79.8%	88.8%	82.9%	83.1%	74.3%	77.5%
2014 (% of Stops)	76.3%	80.5%	90.2%	80.9%	81.6%	68.8%	76.6%
2015 (% of Stops)	80.0%	84.4%	91.4%	85.8%	94.7%	83.1%	80.4%
2016 (% of Stops)	79.3%	83.6%	91.7%	87.6%	90.7%	78.2%	79.7%
2017 (% of Stops)	78.0%	85.5%	91.7%	88.0%	91.9%	90.0%	78.6%
2018 (% of Stops)	71.7%	80.1%	88.8%	85.4%	80.0%	81.7%	72.5%
2019 (% of Stops)	69.9%	78.1%	88.6%	81.1%	74.5%	0.0%	70.7%
Pretextual Stops							
2010	2,840	48	7	17	3	63	2,978
2011	7,705	105	56	47	4	142	8,059
2012	10,137	212	77	86	13	184	10,709
2013	11,149	199	79	91	11	106	11,635

2014	10,929	220	75	94	9	94	11,421
2015	7,624	143	50	71	2	124	8,014
2016	9,436	178	69	82	4	32	9,801
2017	12,788	228	121	109	5	1	13,252
2018	14,776	296	132	110	8	9	15,331
2019	15,668	335	136	155	12	1	16,307
2010 (% of Stops)	13.4%	12.0%	2.8%	9.6%	14.3%	11.7%	13.2%
2011 (% of Stops)	17.9%	12.8%	10.7%	13.7%	10.3%	18.2%	17.7%
2012 (% of Stops)	21.7%	23.0%	12.9%	20.5%	26.5%	15.9%	21.4%
2013 (% of Stops)	21.8%	19.3%	11.0%	16.6%	16.9%	14.2%	21.5%
2014 (% of Stops)	22.6%	18.7%	9.5%	18.3%	18.4%	16.7%	22.2%
2015 (% of Stops)	19.3%	14.3%	8.0%	14.2%	5.3%	14.3%	18.8%
2016 (% of Stops)	20.3%	16.1%	8.2%	12.4%	9.3%	19.4%	19.9%
2017 (% of Stops)	21.8%	14.5%	8.3%	11.9%	8.1%	10.0%	21.2%
2018 (% of Stops)	27.9%	19.4%	11.0%	14.4%	17.8%	15.0%	27.1%
2019 (% of Stops)	29.6%	21.4%	11.3%	18.4%	25.5%	100.0%	28.8%
Outcomes (excl. externally generated stops)							
Tickets (one or more)							
2010	9,268	219	132	89	13	249	9,970
2011	16,719	370	259	178	18	383	17,927
2012	17,687	379	302	179	25	538	19,110
2013	16,362	399	323	247	31	274	17,636
2014	17,006	479	369	212	23	177	18,266
2015	14,767	419	295	210	18	357	16,066
2016	18,688	490	413	315	20	66	19,992
2017	25,195	763	810	471	35	6	27,280
2018	19,096	607	602	325	18	9	20,657
2019	18,986	655	592	370	17	1	20,621
2010 (% of Stops)	43.7%	54.6%	51.8%	50.0%	61.9%	46.3%	44.1%
2011 (% of Stops)	38.9%	45.1%	49.4%	52.1%	46.2%	49.1%	39.4%
2012 (% of Stops)	37.8%	41.2%	50.7%	42.6%	51.0%	46.6%	38.3%
2013 (% of Stops)	32.0%	38.6%	45.1%	45.1%	47.7%	36.7%	32.5%
2014 (% of Stops)	35.2%	40.6%	46.9%	41.3%	46.9%	31.4%	35.5%
2015 (% of Stops)	37.3%	42.0%	47.2%	42.0%	47.4%	41.3%	37.7%
2016 (% of Stops)	40.3%	44.4%	48.8%	47.7%	46.5%	40.0%	40.6%
2017 (% of Stops)	43.0%	48.5%	55.6%	51.6%	56.5%	60.0%	43.6%
2018 (% of Stops)	36.1%	39.9%	50.1%	42.5%	40.0%	15.0%	36.5%
2019 (% of Stops)	35.9%	41.9%	49.2%	43.9%	36.2%	100.0%	36.4%
Arrests for Violation							
2010	208	5	0	5	1	2	221
2011	416	18	0	6	1	1	442

2012	447	17	4	3	0	1	472
2013	508	20	4	9	0	0	541
2014	454	18	4	9	2	3	490
2015	359	20	8	6	0	1	394
2016	288	17	2	5	1	0	313
2017	487	23	10	11	0	0	531
2018	1,339	46	15	17	0	1	1,418
2019	986	47	17	25	1	0	1,076
2010 (% of Stops)	1.0%	1.3%	0.0%	2.8%	4.8%	0.4%	1.0%
2011 (% of Stops)	1.0%	2.2%	0.0%	1.8%	2.6%	0.1%	1.0%
2012 (% of Stops)	1.0%	1.9%	0.7%	0.7%	0.0%	0.1%	1.0%
2013 (% of Stops)	1.0%	1.9%	0.6%	1.6%	0.0%	0.0%	1.0%
2014 (% of Stops)	0.9%	1.5%	0.5%	1.8%	4.1%	0.5%	1.0%
2015 (% of Stops)	0.9%	2.0%	1.3%	1.2%	0.0%	0.1%	0.9%
2016 (% of Stops)	0.6%	1.5%	0.2%	0.8%	2.3%	0.0%	0.6%
2017 (% of Stops)	0.8%	1.5%	0.7%	1.2%	0.0%	0.0%	0.9%
2018 (% of Stops)	2.5%	3.0%	1.3%	2.2%	0.0%	1.7%	2.5%
2019 (% of Stops)	1.9%	3.0%	1.4%	3.0%	2.1%	0.0%	1.9%
Searches (excl. externally generated stops)							
Searches (PC, RS or Warrant)							
2010	184	10	0	11	1	4	210
2011	379	30	6	16	2	17	450
2012	433	38	4	15	1	3	494
2013	542	56	7	23	3	1	632
2014	555	74	6	21	3	7	666
2015	392	54	5	15	0	4	470
2016	406	27	3	13	1	0	450
2017	461	34	3	13	0	0	511
2018	345	24	5	15	0	0	389
2019	99	14	3	14	0	0	130
2010 (% of Stops)	0.9%	2.5%	0.0%	6.2%	4.8%	0.7%	0.9%
2011 (% of Stops)	0.9%	3.7%	1.2%	4.7%	5.1%	2.2%	1.0%
2012 (% of Stops)	0.9%	4.1%	0.7%	3.6%	2.0%	0.3%	1.0%
2013 (% of Stops)	1.1%	5.4%	1.0%	4.2%	4.6%	0.1%	1.2%
2014 (% of Stops)	1.2%	6.3%	0.8%	4.1%	6.1%	1.2%	1.3%
2015 (% of Stops)	1.0%	5.4%	0.8%	3.0%	0.0%	0.5%	1.1%
2016 (% of Stops)	0.9%	2.5%	0.4%	2.0%	2.3%	0.0%	0.9%
2017 (% of Stops)	0.8%	2.2%	0.2%	1.4%	0.0%	0.0%	0.8%
2018 (% of Stops)	0.7%	1.6%	0.4%	2.0%	0.0%	0.0%	0.7%
2019 (% of Stops)	0.2%	0.9%	0.3%	1.7%	0.0%	0.0%	0.2%
Contraband (All Outcomes)							

2010	135	1	0	4	1	3	144
2011	274	16	2	7	1	5	305
2012	344	28	4	9	1	2	388
2013	436	33	6	15	1	1	492
2014	458	55	5	17	2	7	544
2015	332	44	5	13	0	4	398
2016	343	22	2	8	0	0	375
2017	399	32	3	9	0	0	443
2018	283	19	5	11	0	0	318
2019	81	10	0	12	0	0	103
2010 (% of Searches)	73.4%	10.0%	0.0%	36.4%	100.0%	75.0%	68.6%
2011 (% of Searches)	72.3%	53.3%	33.3%	43.8%	50.0%	29.4%	67.8%
2012 (% of Searches)	79.5%	73.7%	100.0%	60.0%	100.0%	66.7%	78.5%
2013 (% of Searches)	80.4%	58.9%	85.7%	65.2%	33.3%	100.0%	77.8%
2014 (% of Searches)	82.5%	74.3%	83.3%	81.0%	66.7%	100.0%	81.7%
2015 (% of Searches)	84.7%	81.5%	100.0%	86.7%	0.0%	100.0%	84.7%
2016 (% of Searches)	84.5%	81.5%	66.7%	61.5%	0.0%	0.0%	83.3%
2017 (% of Searches)	86.6%	94.1%	100.0%	69.2%	0.0%	0.0%	86.7%
2018 (% of Searches)	82.0%	79.2%	100.0%	73.3%	0.0%	0.0%	81.7%
2019 (% of Searches)	81.8%	71.4%	0.0%	85.7%	0.0%	0.0%	79.2%
Contraband (Tickets + Arrests)							
2010	111	1	0	1	1	0	114
2011	223	12	2	5	1	3	246
2012	248	14	3	3	1	2	271
2013	335	22	6	12	1	1	377
2014	389	42	5	11	2	6	455
2015	289	35	5	10	0	4	343
2016	297	19	1	7	0	0	324
2017	342	24	2	6	0	0	374
2018	233	16	4	8	0	0	261
2019	67	6	0	8	0	0	81
2010 (% of Searches)	60.3%	10.0%	0.0%	9.1%	100.0%	0.0%	54.3%
2011 (% of Searches)	58.8%	40.0%	33.3%	31.3%	50.0%	17.7%	54.7%
2012 (% of Searches)	57.3%	36.8%	75.0%	20.0%	100.0%	66.7%	54.9%
2013 (% of Searches)	61.8%	39.3%	85.7%	52.2%	33.3%	100.0%	59.7%
2014 (% of Searches)	70.1%	56.8%	83.3%	52.4%	66.7%	85.7%	68.3%
2015 (% of Searches)	73.7%	64.8%	100.0%	66.7%	0.0%	100.0%	73.0%
2016 (% of Searches)	73.2%	70.4%	33.3%	53.9%	0.0%	0.0%	72.0%
2017 (% of Searches)	74.2%	70.6%	66.7%	46.2%	0.0%	0.0%	73.2%
2018 (% of Searches)	67.5%	66.7%	80.0%	53.3%	0.0%	0.0%	67.1%
2019 (% of Searches)	67.7%	42.9%	0.0%	57.1%	0.0%	0.0%	62.3%

Contraband (Arrests only)							
2010	66	0	0	1	1	0	68
2011	117	7	0	4	1	1	130
2012	145	8	2	0	0	1	156
2013	135	12	3	2	0	0	152
2014	100	8	1	3	1	1	114
2015	86	14	2	4	0	1	107
2016	82	3	0	0	0	0	85
2017	82	11	2	2	0	0	97
2018	115	4	2	2	0	0	123
2019	45	4	0	6	0	0	55
2010 (% of Searches)	35.9%	0.0%	0.0%	9.1%	100.0%	0.0%	32.4%
2011 (% of Searches)	30.9%	23.3%	0.0%	25.0%	50.0%	5.9%	28.9%
2012 (% of Searches)	33.5%	21.1%	50.0%	0.0%	0.0%	33.3%	31.6%
2013 (% of Searches)	24.9%	21.4%	42.9%	8.7%	0.0%	0.0%	24.1%
2014 (% of Searches)	18.0%	10.8%	16.7%	14.3%	33.3%	14.3%	17.1%
2015 (% of Searches)	21.9%	25.9%	40.0%	26.7%	0.0%	25.0%	22.8%
2016 (% of Searches)	20.2%	11.1%	0.0%	0.0%	0.0%	0.0%	18.9%
2017 (% of Searches)	17.8%	32.4%	66.7%	15.4%	0.0%	0.0%	19.0%
2018 (% of Searches)	33.3%	16.7%	40.0%	13.3%	0.0%	0.0%	31.6%
2019 (% of Searches)	45.5%	28.6%	0.0%	42.9%	0.0%	0.0%	42.3%

Table A.2b. Trends in Total Stops by Year

All Years	White	Black	Asian	Hispanic	Native American	Unknown	Total
Total Traffics Stops							
Including externally generated stops							
2010	21,651	418	257	182	21	547	23,076
2011	43,907	851	531	351	40	794	46,474
2012	47,727	949	606	431	51	1,174	50,938
2013	52,231	1,068	727	555	68	763	55,412
2014	49,458	1,208	792	523	51	575	52,607
2015	40,692	1,024	633	509	41	886	43,785
2016	47,265	1,132	851	675	43	166	50,132
2017	59,301	1,604	1,472	929	64	10	63,380
2018	53,762	1,548	1,210	780	46	61	57,407
2019	53,887	1,600	1,219	864	47	1	57,618
Excluding externally generated stops							
2010	21,230	401	255	178	21	538	22,623
2011	42,996	821	524	342	39	780	45,502
2012	46,808	920	596	420	49	1,154	49,947
2013	51,106	1,033	716	548	65	746	54,214
2014	48,304	1,179	787	514	49	564	51,397
2015	39,598	997	625	500	38	865	42,623
2016	46,390	1,103	847	661	43	165	49,209
2017	58,578	1,573	1,457	913	62	10	62,593
2018	52,931	1,523	1,201	765	45	60	56,525
2019	52,951	1,563	1,204	842	47	1	56,608
Percentage Change YoY (Excl. EGS)							
2010 vs 2011	102.5%	104.7%	105.5%	92.1%	85.7%	45.0%	101.1%
2011 vs 2012	8.9%	12.1%	13.7%	22.8%	25.6%	48.0%	9.8%
2012 vs 2013	9.2%	12.3%	20.1%	30.5%	32.7%	-35.4%	8.5%
2013 vs 2014	-5.5%	14.1%	9.9%	-6.2%	-24.6%	-24.4%	-5.2%
2014 vs 2015	-18.0%	-15.4%	-20.6%	-2.7%	-22.5%	53.4%	-17.1%
2015 vs 2016	17.2%	10.6%	35.5%	32.2%	13.2%	-80.9%	15.5%
2016 vs 2017	26.3%	42.6%	72.0%	38.1%	44.2%	-93.9%	27.2%
2017 vs 2018	-9.6%	-3.2%	-17.6%	-16.2%	-27.4%	500.0%	-9.7%
2018 vs 2019	0.0%	2.6%	0.3%	10.1%	4.4%	-98.3%	0.2%
Stops per 10,000 residents (Excl. EGS)							
2010	423	465	233				428
2011	857	953	479				862
2012	933	1,067	545				946
2013	1,019	1,199	654				1,027
2014	963	1,368	719				973
2015	790	1,157	571				807
2016	925	1,280	774				932
2017	1,168	1,825	1,331				1,185
2018	1,056	1,767	1,097				1,070
2019	1,056	1,813	1,100				1,072

Appendix A.3. Data Quality and Methodology

The Vermont State Police (VSP) traffic stop data used in this study consists of 20,590 rows, spanning nine years (2014-2019). Each row corresponds to a single outcome resulting from a traffic stop. There can multiple outcomes of a stop, and as a result, there were 20,040 stops over this time period. Date and time of stops are not required by legislation, although some agencies have chosen to provide date and time. Because date and time are useful for many types of analysis, the existence and quality of that field of data is reported in this section as well.

A. Missing or Unknown Data Values by Field

Table A.3 shows the counts and percentages of missing or unknown data values. Missing data is when the trooper fails to record data on a particular field. Unknown is where the trooper records "unknown" as a value in a field. In either case, we lack data on that variable and thus we group missing and unknown together in assessing the quality of the data VSP supplies.

Table A.3. Fields with Missing or Unknown Values

Stop Years	Stops	Stop ID	Stop Date/Time	Age	Race	Gender	Stop Reason	Search Reason	Contra-band	Stop Outcome	Reported Accidents	Race in Reported Accidents
Count of Blank or Unknown Rows												
2010	22,623	1,084	0	76	538	115	191	194	195	235	0	0
2011	45,502	1,623	0	184	780	337	319	356	358	452	0	0
2012	49,947	1,380	0	103	1,154	255	220	235	238	322	0	0
2013	54,214	1,535	0	106	746	412	387	379	385	486	0	0
2014	51,397	1,665	0	163	564	331	392	386	397	547	0	0
2015	42,623	1,468	1	463	865	208	118	121	122	201	0	0
2016	49,209	49,209	0	53	165	54	60	56	59	75	0	0
2017	62,593	62,593	0	25	10	43	4	0	0	0	0	0
2018	56,525	56,525	0	35	60	21	165	26	26	25	0	0
2019	56,608	56,608	0	10	1	5	211	24	24	27	0	0
All Years	491,241	233,690	1	1,218	4,883	1,781	2,067	1,777	1,804	2,370	0	0
Percentage of Blank or Unknown Rows												
2010	22,623	4.8%	0.0%	0.3%	2.4%	0.5%	0.8%	0.9%	0.9%	1.0%	0	0.0%
2011	45,502	3.6%	0.0%	0.4%	1.7%	0.7%	0.7%	0.8%	0.8%	1.0%	0	0.0%
2012	49,947	2.8%	0.0%	0.2%	2.3%	0.5%	0.4%	0.5%	0.5%	0.6%	0	0.0%
2013	54,214	2.8%	0.0%	0.2%	1.4%	0.8%	0.7%	0.7%	0.7%	0.9%	0	0.0%
2014	51,397	3.2%	0.0%	0.3%	1.1%	0.6%	0.8%	0.8%	0.8%	1.0%	0	0.0%
2015	42,623	3.4%	0.0%	1.1%	2.0%	0.5%	0.3%	0.3%	0.3%	0.5%	0	0.0%
2016	49,209	100.0%	0.0%	0.1%	0.3%	0.1%	0.1%	0.1%	0.1%	0.2%	0	0.0%
2017	62,593	100.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0	0.0%
2018	56,525	100.0%	0.0%	0.1%	0.1%	0.0%	0.3%	0.1%	0.1%	0.0%	0	0.0%
2019	56,608	100.0%	0.0%	0.0%	0.0%	0.0%	0.4%	0.0%	0.0%	0.1%	0	0.0%
All Years	491,241	47.6%	0.0%	0.3%	1.0%	0.4%	0.4%	0.4%	0.4%	0.5%	0	0.0%

The definitions for missing or unknown values by field are:

- Age – Blank or 0
- Race – Blank, "Business", "Unknown - U" or "Other – U"
- Gender – Blank, Business, NA or "Transgendered - T"
- Stop Reason – Blank or "O = Other violation"
- Search Reason – Blank
- Search Outcome – Blank
- Stop Result – Blank.

Analysis of the VSP data shows that required field values are sometimes missing or incorrect. Except for the optional Date/Time field, the number of fields with problem values has been reduced starting in 2017. Missing or unknown values for driver race have been the most common. This is concerning since race is the key variable of interest in traffic stop data. Although missing race data has declined since 2014, even in 2019, race is missing in 3.6% of all rows of data. About 6% of accident reports had missing race data in 2019. This category of data is not required by the legislation, but it is important as a benchmark for assessing racial share of stops and agencies should consider placing more emphasis on ensuring accident reports are complete.

Table A.3b shows the number and percentage of VSP traffic stop reports with at least one field with a missing/unknown value.

Table A.3b. Stops With at Least

Stop Years	Total Stops	Stops Missing Value(s)	% of Stops Missing Value(s)
2010	22,623	794	3.5%
2011	45,502	1,427	3.1%
2012	49,947	1,645	3.3%
2013	54,214	1,542	2.8%
2014	51,397	1,332	2.6%
2015	42,623	1,526	3.6%
2016	49,209	319	0.7%
2017	62,593	71	0.1%
2018	56,525	258	0.5%
2019	56,608	259	0.5%
All Years	491,241	9,173	1.9%

Table A.3c provides data on the relationship between missing or unknown values and race of driver. We would expect that, absent any anomalies in data reporting, the percentage of missing data by race would be roughly equal. (There would be no reason to expect that the percentage of stops that are missing the reason for the stop would be higher or lower for any one racial group than another). This is in fact what we found for VSP. Further, we would expect that for those stops for which the race of the driver is unknown, the percentage with missing data on say, stop reason, should be similar to that for each racial group. This, however, is not the case for VSP.

Table A.3c. Missing or Unknown Values by Race

	White	Black	Asian	Hispanic	Unknown
Count of Blank or Unknown Rows					
Total Stops (excl. EGS)	460,892	11,113	8,212	5,683	4,883
Unknown Stop Reason	1,648	41	14	13	350
Unknown Stop Outcome	1,924	48	16	16	366
Unknown if Search occurred	1,353	33	12	12	367
Unknown if Contraband found to a search	24	3	0	0	0
Unknown Outcome if contraband found	1	0	0	0	0
Percentage of Blank or Unknown Rows					
Unknown Stop Reason as % of all stops	0.4%	0.4%	0.2%	0.2%	7.0%
Unknown Stop Outcome as % of all outcomes	0.4%	0.4%	0.2%	0.3%	7.4%
Unknown if Search occurred as % of all stops	0.3%	0.3%	0.2%	0.2%	7.5%
Unknown if Contraband found as % of all searches	0.6%	0.8%	0.0%	0.0%	0.0%
Unknown Outcome if contraband found as % of all searches	0.0%	0.0%	0.0%	0.0%	0.0%

B. Stop IDs

Most Vermont traffic stop data files contain only one stop outcome per row (where an outcome can be one arrest, one ticket, one warning, etc.). However, a single traffic stop can have multiple outcomes. For example, it is possible for a single stop to result in multiple tickets being issued, or other combinations such as a ticket and a warning, and so forth. It is important to be able to collect multiple outcomes into stops to avoid overcounting as well as to recognize stops where more than one ticket is issued. Identifying multiple outcomes for a stop can be a challenge. Some datasets provide stop IDs that enable this association. When stop IDs are present, each one of a stop's outcomes will have the same stop ID and so can be associated and analyzed together. When stop IDs are absent, a heuristic approach is used to attempt to group together outcomes. This technique associates outcomes using a combination of fields with matching values. Typically, the following set of fields is used to identify incidents: agency, date/time, age, gender, and race.

For the 6 out of ten years of data available from Vermont State Police, the Stop IDs provided were not directly usable to tie together multiple outcomes for stops. However, the dates, times and other fields were available to derive Stop IDs (Table A.3d).

Table A.3d. Vermont State Police Stop IDs

Stop Years	Usable Stop IDs	Could Derive Stop IDs	Stop Count	Row Count
2010	Partial	Yes	23,076	24,479
2011	Partial	Yes	46,474	48,652
2012	Partial	Yes	50,938	52,568
2013	Partial	Yes	55,412	57,235
2014	Partial	Yes	52,607	54,689
2015	Partial	Yes	43,785	45,662
2016	No	Yes	50,130	51,597
2017	No	Yes	63,380	64,093
2018	No	Yes	57,405	57,964
2019	No	Yes	57,618	58,093

Table A.4. Variable Definitions

Variable	Formula
Total Traffic Stops	
Including externally generated stops	Count of all stops
Excluding externally generated stops	Count of all stops except where stop reason is "externally generated stop"
Reasons For Stops	
Safety Stops	Count of all stops where stop reason is "moving violation" or "suspicion of DWI"
Moving Violation	Count of all stops where stop reason is "moving violation"
Suspicion of DWI	Count of all stops where stop reason is "suspicion of DWI"
Investigatory/Pretextual Stops	Count of all stops where stop reason is "investigatory stop" or "vehicle equipment"
Investigatory Stop	Count of all stops where stop reason is "investigatory stop"
Vehicle Equipment	Count of all stops where stop reason is "vehicle equipment"
Externally Generated Stop	Count of all stops where stop reason is "externally generated stop"
Multiple Reasons - Moving Violation & Suspicion of DWI	Count of all stops where stop reasons include both "moving violation" and "suspicion of DWI"
Multiple Reasons - Moving Violation & Vehicle Equipment	Count of all stops where stop reasons include both "moving violation" and "vehicle equipment"
Multiple Reasons - Suspicion of DWI & Vehicle Equipment	Count of all stops where stop reasons include both "suspicion of DWI" and "vehicle equipment"
Unknown Stop Reason	Count of all stops where stop reason is "unknown"
Outcomes (excl. EGS)	
Ticket	Count of all stops where at least one ticket was issued.
Warning	Count of all stops where at least one warning was issued.
No action taken	Count of all stops where no action was taken was issued.
Arrest for violation	Count of all stops where there was an arrest for violation.
Arrest for warrant	Count of all stops where there was an arrest for warrant.
Searches	
Total stops with no search	Count of all stops where search reason was "no search"
No Search & Contraband & Arrest for violation	Count of all stops where search reason was "no search" and stop search outcome was "contraband" and there was an arrest for violation
No Search & Contraband & No Arrest	Count of all stops where search reason was "no search" and stop search outcome was "contraband" and there was not an arrest for violation
No Search (all others)	Count of all stops where search reason was "no search" and stop search outcome was not "contraband"
Total Stops with Unknown Search	Count of all stops where search reason was "unknown"
Total Stops with Search	Count of all stops where search reason was one of "probable cause," "reasonable suspicion," or "warrant"
Search with Probable Cause (PC)	Count of all stops where search reason was "probable cause"
Stops with PC Searches, No contraband	Count of all stops where search reason was "probable cause" and search outcome was "no contraband" or "no search"

Variable	Formula
Stops with PC Searches, Unknown contraband	Count of all stops where search reason was “probable cause” and search outcome was “unknown”
Stops with PC Searches, Contraband	Count of all stops where search reason was “probable cause” and search outcome was “contraband”
Outcomes of PC Search	
Stops with PC Searches, Contraband & Warning, No Action or Unknown*	Count of all stops where search reason was “probable cause” and search outcome was “contraband” and one or more of the following outcomes were recorded: “warning,” “no action,” or “unknown” but no tickets or arrests
Stops with PC Searches, Contraband and Ticket*	Count of all stops where search reason was “probable cause” and search outcome was “contraband” and one or more tickets were issued but no arrest
Stops with PC Searches, Contraband and Arrest*	Count of all stops where search reason was “probable cause” and search outcome was “contraband” and one or more arrests were made (for Violation or Warrant)
Search with Reasonable Suspicion (RS)	Count of all stops where search reason was “reasonable suspicion”
Stops with RS Searches, No contraband	Count of all stops where search reason was “reasonable suspicion” and search outcome was “no contraband” or “no search”
Stops with RS Searches, Unknown contraband	Count of all stops where search reason was “reasonable suspicion” and search outcome was “unknown”
Stops with RS Searches, Contraband	Count of all stops where search reason was “reasonable suspicion” and search outcome was “contraband”
Outcomes of RS Search	
Stops with RS Searches, Contraband & Warning, No Action or Unknown	Count of all stops where search reason was “reasonable suspicion” and search outcome was “contraband” and one or more of the following outcomes were recorded: “warning,” “no action,” or “unknown” but no tickets or arrests
Stops with RS Searches, Contraband & Ticket*	Count of all stops where search reason was “reasonable suspicion” and search outcome was “contraband” and one or more tickets were issued but no arrest
Stops with RS Searches, Contraband & Arrest*	Count of all stops where search reason was “reasonable suspicion” and search outcome was “contraband” and one or more arrests were made (for Violation or Warrant)
Search with Warrant	Count of all stops where search reason was “warrant”.
Stops with Warrant Searches, No contraband	Count of all stops where search reason was “warrant” and search outcome was “no contraband” or “no search”
Stops with Warrant Searches, Unknown contraband	Count of all stops where search reason was “warrant” and search outcome was “unknown”
Stops with Warrant Searches, Contraband	Count of all stops where search reason was “warrant” and search outcome was “contraband”
Outcomes of Warrant Search	
Stops with Warrant Searches, Contraband & Warning, No Action or Unknown	Count of all stops where search reason was “warrant” and search outcome was “contraband” and one or more of the following outcomes were recorded: “warning,” “no action,” or “unknown” but no tickets or arrests
Stops with Warrant Searches, Contraband & Ticket*	Count of all stops where search reason was “warrant” and search outcome was “contraband” and one or more tickets were issued but no arrest

Variable	Formula
Stops with Warrant Searches, Contraband & Arrest*	Count of all stops where search reason was "warrant" and search outcome was "contraband" and one or more arrests were made
Racial Shares of Stops	
Including externally generated stops	Number of stops for a race divided by number of stops for all races
Excluding externally generated stops	Number of non-EGS for a race divided by number of non-EGS for all races
Racial share of stops (ACS)	Percentage of area residents of a particular race as determined by the American Community Survey (ACS) five-year estimates for 2013-2017 (See https://www.census.gov/programs-surveys/acs)
Racial share of stops (DMV accident data)	Percentage of area drivers of a particular race as determined by Vermont DMV Accident data for 2013-18.
Disparity Index (using ACS)	For a particular race, the Disparity Index (ACS) is the % of non-EGS for that race divided by the % of area residents for that race based on the ACS 5-year estimates from 2013-2017.
Disparity Index (using DMV Accident data)	For a particular race, the Disparity Index (DMV) is the % of non-EGS stops for that race by the % of area drivers for that race based on Vermont DMV accident data for 2013-2018.
Stop Reason as % of All Stops	
Safety Stops	% of all stops where stop reason is "moving violation" or "suspicion of DWI"
Moving Violation	% of all stops where stop reason is "moving violation"
Suspicion of DWI	% of all stops where stop reason is "suspicion of DWI"
Investigatory/Pretextual Stops	% of all stops where stop reason is "investigatory stop" or "vehicle equipment"
Investigatory Stops	% of all stops where stop reason is "investigatory stop"
Vehicle Equipment	% of all stops where stop reason is "vehicle equipment"
Externally Generated Stops	% of all stops where stop reason is "externally generated stop"
Multiple Reasons	% of all stops where there are multiple stop reasons in the following combinations: "moving violation" and "suspicion of DWI" or "moving violation" and "vehicle equipment" or "suspicion of DWI" and "vehicle equipment"
Unknown Reason	% of all stops where stop reason is "unknown"
Outcome Rates as a % of All Stops	
Warning Rate	% of non-EGS stops where at least one warning was issued
Ticket Rate	% of non-EGS stops where at least one ticket was issued
Arrest for Violation Rate	% of non-EGS stops where there was an arrest for violation
Arrest for Warrant Rate	% of non-EGS stops where there was an arrest for warrant
No Action Rate	% of non-EGS stops where there was no action taken
Search Rates	
Search rate (excl. searches on warrant)	% of non-EGS stops where the search reason was "probable cause" or "reasonable suspicion"

Variable	Formula
Search rate (incl. searches on warrant)	% of non-EGS stops where the search reason was "probable cause," "reasonable suspicion," or "warrant search"
Hit rates (as a % of PC, RS, & Warrant Searches)	
Hit rates (incl. all outcomes)	% of non-EGS stops where the search reason was "probable cause," "reasonable suspicion," or "warrant" and contraband was found
Hit rates (excl. warnings as outcomes)	% of non-EGS where the search reason was "probable cause," "reasonable suspicion," or "warrant" and contraband was found, and the stop resulted in at least one ticket or arrest
Hit rates (outcome = arrest)	% of non-EGS stops where the search reason was "probable cause," "reasonable suspicion." or "warrant" and contraband was found, and the stop resulted in an arrest for violation or warrant