Trends in Racial Disparities in Traffic Stops: South Burlington, Vermont 2013-19

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EXECUTIVE SUMMARY

This study of South Burlington traffic stops forms part of a statewide study of Vermont traffic stop data by the authors that includes additional years of data since the Seguino and Brooks (2017) report was issued. 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 fall over time. Finally, we comment on the completeness and quality of the data collected by the South Burlington Police Department.

Our main findings are that in South Burlington:

- The Black share of stopped drivers exceeds their share of the estimated driving population. The data indicate Black drivers were overstopped by 54 to 87%, depending on the measure of the driving population used. Hispanics were not substantively overstopped relative to their estimated share of the driving population.
- Black drivers are less likely to be issued a citation during a traffic stop than white drivers, but they are also more likely to be issued multiple citations during the same stop.
- Black drivers are more likely than white drivers to experience pretextual stops—stops that may be used to investigate "suspicious" behavior and are therefore more prone to racial bias.
- Black driver arrest rates are 40% higher than arrest rates of white drivers.
- Black drivers are more than four times as likely to be searched subsequent to a stop as white drivers. Hispanic drivers were also searched at a higher rate than white drivers, although but there were very few searches of Hispanic drivers in total. Asian drivers were searched at rates similar to white drivers.
- Black and Hispanic drivers are less likely to be found with contraband than white drivers despite their higher search rate, suggestive of racial bias in the decision of whom to search.

In terms of trends over time:

- The total number of stops per year decreased by 40.2% from 2013 to 2019. For Black drivers, however, the stop rate rose 31.2%. The Black stop rate in 2019 increased to more than twice that per estimated white resident.
- The share of investigatory/pretextual stops of Black and Hispanic drivers has been rising, while white shares have remained roughly constant and Asian shares have fallen.
- Since 2015-17, Black-white disparities in arrest rates have modestly declined.
- Both Black and white search rates have increased over time, but the Black/white ratio of search rates has decreased, indicating shrinking racial disparities in search rates, albeit from a very wide starting point. In 2013-2015, Black drivers were searched at more than 7 times the rate of white drivers. In 2017-2019, the difference was 2.7 times. The reason for the decline in search rate disparities is a rising search rate of white drivers (from 0.5% to 1.5%), rather than a decline in the Black search rate.
- The large differences in hit rates seen in the earliest years of the data have shrunk. The Black hit rate is still lower than the white hit rate but the difference in 2017-19 is no longer significant.

Regarding the quality of South Burlington traffic stop data:

- Data was provided for seven years (2013-19) with 67% of stops having missing or unknown values for at least one variable. Much of the missing data was the absence of gender and age data until 2017.
- Race data was missing in 1.2% of stops overall. The quantity of missing data has declined but there is some variability.
- In 2018, 4.2% of stops were missing the legally required race information but in 2019 the race data was 100% complete.

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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 data 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 South Burlington, Vermont for 2013-19. South Burlington Police Department (SBPD) collected data on 22,306 traffic stops during this period of time.

Our study aims to identify whether there are racial disparities in traffic stops and outcomes of stops in Vermont law enforcement agencies. Our focus is primarily on actions that require officer discretion on whom to stop, arrest, and search. For this reason, we exclude externally generated stops in much of the analysis that follows. That said, officer behavior is influenced by agency leadership and culture, the extent of implicit bias, and trainings related to race, as well as policies that shape officer decisions.[2] Not all disparities, where they are found, then should be solely attributed to officer discretion.

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 stop. In Vermont, driver's licenses do not include race/ethnicity of the driver. The race of driver indicated in officer reports on traffic stops is based on officer 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]

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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 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 state the vehicle is registered in, the duration of the stop, officer-level data, and stop IDs would improve the ability to assess the degree, if any, of racial disparities in traffic policing.

In the next section, we provide an overview of the South Burlington data, identify methodological issues of relevance to our analysis, and report on the quality of the traffic stop data. In Section III, we report descriptive data on key indicators and discuss results of the hit rate test. In Section IV, we assess trends over time in racial disparities, using 3-year trends (2013-15, 2014-16, etc.), instead of year by year, to expand the sample size. In Section V, we conduct a logit analysis to estimate 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 the driver's race in the officer's decision to search and in finding contraband. Section VI concludes and in the appendix we provide supplemental data and an analysis of the quality of the agency's 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 officers may not use race or ethnicity to any degree, except that officers 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 groups is comprised of a larger share of younger drivers, 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 police officers 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

[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

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).

II. Data Overview, Methodology, and Data Quality

The data in Table 1 provide an overview of the traffic stop data generated by the SBPD from 2013-19. As can be seen, a total of 22,306 stops were made. Approximately one third of these stops resulted in the issuance of a citation. The percentage of stops that resulted in an arrest for violation was 1.3%, while 1.0% of stopped vehicles were searched. Contraband was found in 1.0% of all stops. The overall contraband hit rate (the number of contraband finds divided by the number of searches) is 76.4%.

Table 1. Search Rate Trends by Race/Ethnicity

	Observations	**Rates**
Total Stops		
incl. EGS	22,306	
excl. EGS	22,160	
2013	3,372	
2014	3,896	
2015	4,242	
2016	3,020	
2017	2,896	
2018	2,719	
2019	2,015	
Citations	7,668	34.6%
Arrests	279	1.3%
Searches	212	1.0%
Contraband	162	0.7%
Contraband as % of searches	162	76.4%

Note: EGS is externally generated stops. All counts of outcomes, rates, and annual data exclude EGS. Rates are outcomes as a percentage of total stops, except where noted.

Our focus is primarily policing decisions based on officer discretion, although it is impossible to entirely disentangle the role of agency culture and leadership from individual officer 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. An officer may be directed to stop a vehicle, for instance, in response to a be-on-the-lookout (BOLO) alert. In this case, the officer did not initiate the stop. In the case of South Burlington, 0.6% or 146 of all stops were externally generated. These exclusions reduce our sample size to 22,160 traffic stops.

A challenging problem in the data, not only for South Burlington but other agencies as well, is that more than one row in the raw data appear 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 officer 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/time 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. In the analysis that follows, we report data only for white, Black, Hispanic, and Asian drivers, omitting Native Americans due to the small sample size that limits our ability to make sound inferences about the results. In the case of South Burlington, over the time period of this study, 2013-19, only 13 drivers were identified as Native American.

Appendix A.3 details information on missing or contradictory data reported by SBPD. Here, we note that in the event there is missing data (sometimes marked as "unknown") those stops are not included in our analysis. For example, the gender of the driver was omitted in 52.3% of traffic stop reports from 2013 to 2019. Age of driver was omitted in 65.7% of all reports. It should be noted that over time, there has been substantial reduction in missing data. Although 2018 was an outlier with 4.2% of stops missing data on driver race, the average over all years is 1.2% of stops missing driver race. Appendix A.4 provides a list of all variables in this report with information on how they are measured.

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.

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

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 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?

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). 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).[6] 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. Officers 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 the appropriate benchmark against which to compare racial shares of stops. 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. While the ideal would be to use only not-at-fault drivers from the DMV data to calculate estimates of racial shares of the driving population, we seek to maximize sample sizes, given the unreliability of estimates that result from the low number of observations for minority

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[6] 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.

racial groups in Vermont.[7] It should be noted, also, there continues to be a notable amount of missing race data in South Burlington accident reports (3.9% in 2019). The SBPD could contribute to the greater reliability of analyses of racial shares of stops by addressing the problem of missing data.

Data on racial shares of stopped drivers and the driving population are shown in Table 2. The share of stops relative to share of population based on U.S. Census data is calculated only for Blacks, Asians, 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, police officers 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, however, 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 in South Burlington comprised 90.4% of all stopped drivers from 2013 through 2019, with Blacks 5.4%, 3.3% Asians, and Hispanics 0.8% of all drivers stopped. Inclusion of externally generated stops does not change these percentages. Black and Hispanic shares of the driving population are lower than their share of stops, whether using the ACS or DMV accident data. For example, the estimates of Black drivers' share of the driving population range from 2.9% to 3.5%, lower than their share of stopped drivers.

[7] 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. Apart from the issue of sample size, another possible flaw of this measure is that 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 is a person of color. In the latter case, white drivers may be more likely to involve the police due to potential implicit bias.

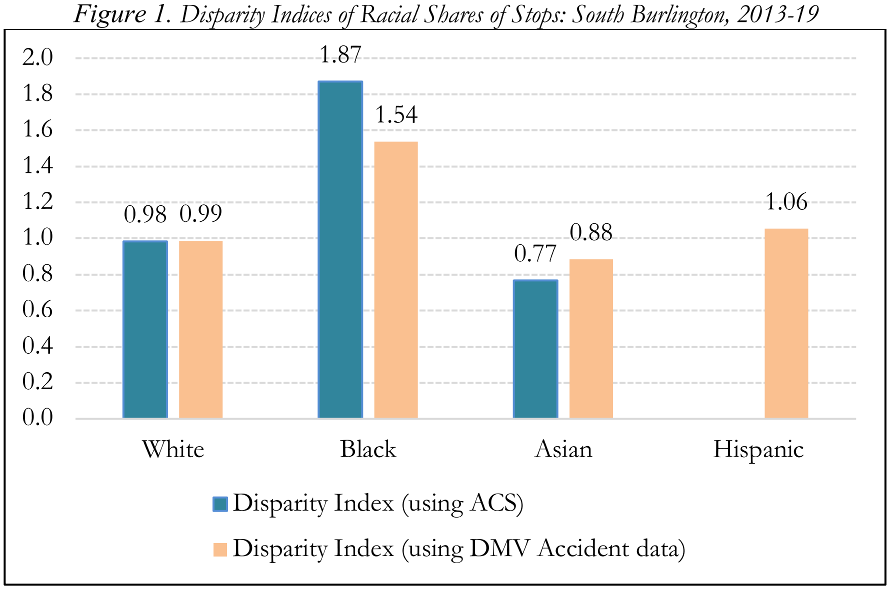
Table 2. Racial Shares of Stops, Reasons for Stops, and Post-Stop Outcomes

	White	Black	Asian	Hispanic
Racial Shares of Stops				
Including externally generated stops	90.4%	5.4%	3.3%	0.8%
Excluding externally generated stops	90.4%	5.4%	3.3%	0.8%
Driver Percentage (ACS)	92.8%	2.9%	4.3%	NA
Driver Percentage (DMV Accident data)	91.6%	3.5%	3.7%	0.8%
Disparity Index (using ACS)	0.98	1.87	0.77	
Disparity Index (using DMV Accident data)	0.99	1.54	0.88	1.06
Stop Reason as % of All Stops				
Safety Stops	71.0%	66.9%	76.5%	70.3%
Moving Violation	70.8%	66.8%	76.5%	70.3%
Suspicion of DWI	0.2%	0.1%	0.0%%	0.0%%
Investigatory/Pretextual Stops	27.4%	30.1%	21.8%	27.6%
Investigatory Stops	0.4%	0.8%	0.1%	0.0%%
Vehicle Equipment	27.0%	29.2%	21.6%	27.6%
Externally Generated Stops	0.6%	1.0%	0.8%	0.0%%
Multiple Reasons	0.1%	0.1%	0.0%%	0.0%%
Unknown Reason	1.0%	1.9%	1.0%	2.2%
Outcome Rates as a % of All Stops				
Warning Rate	63.8%	68.7%	65.6%	60.0%
Ticket Rate	35.1%	29.5%	34.2%	38.9%
Arrest for Violation Rate	1.3%	1.8%	0.4%	1.1%
Arrest for Warrant Rate	0.0%	0.0%%	0.0%%	0.0%%
No Action Rate	0.1%	0.3%	0.1%	0.0%%
Search Rates				
Search rate (excl. searches on warrant)	0.7%	3.1%	0.8%	1.6%
Search rate (incl. searches on warrant)	0.8%	3.5%	0.8%	1.6%
Hit rates (as a % of PC, RS & Warrant Searches)				
Hit rates (incl. all outcomes)	80.9%	65.9%	50.0%	33.3%
Hit rates (excl. warnings as outcomes)	49.4%	31.7%	16.7%	0.0%%
Hit rates (outcome = arrest)	18.5%	12.2%	16.7%	0.0%%

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. All data exclude externally generated stops except where noted.

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 Black drivers during this time period, that ratio ranges from 1.54 (5.4%/3.5%) using the DMV data to 1.87 using ACS data. Put another way, we estimate that Black drivers are stopped at a rate that is from 54% to 87% greater than their share of the driving population. For Hispanic drivers, their share of stops is slightly higher than the estimate of their population share with a DI of 1.06, indicating they are stopped at a rate that is about 6% greater than their share of the driving population. This degree of overstopping is not large enough to be considered noteworthy. In contrast to Black drivers, whether we use the ACS or DMV data, white drivers are stopped at rates slightly below but very close to what would be expected by their estimated population share. The Asian DI ranges from 0.77 to 0.88 (signifying understopping). The Asian DI is lower than even that of white drivers.

Figure 1. Disparity Indices of Racial Shares of Stops: South Burlington, 2013-19



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. They also found that Hispanics are less likely to be stopped. The authors of that study use the local population as a benchmark, and thus their results are most comparable to our ACS stop disparity estimates. As can be seen, racial disparities in South Burlington traffic stops using ACS data are larger than the estimated differential at the national level.

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 weaknesses 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, and the accident data may overestimate minority shares of the driving population, given the possibility that not all accidents involve police reports. Most critical to our analysis, therefore, 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. As a result, 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

Officers 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 officers stop a vehicle to investigate further whether a crime has been committed or not. The law requires that the officer have reasonable suspicion to conduct such as stop, based on specific and articulable facts. (As noted above, externally generated stops are not officer-initiated, but instead result from information from a person other than the officer). Table 2 shows the distribution of reasons for stops by race. By far the most common reason motorists in South Burlington are pulled over is for moving violations (such as speeding). 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 officer 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. In South Burlington, a higher share of Black drivers is stopped for investigatory/pretextual reasons that any other racial group. The Black-white and Black-Asian differences are statistically significant (z=2.11 and z=4.01, respectively). The Hispanic share of stops that are investigatory/pretextual is also higher than that of whites and Asians, and while the Hispanic-white difference is not statistically significant, the Hispanic-Asian difference is (z=1.67). It is also noteworthy that stop reason is missing in 1% of white and Asian stops, but double that in Black and Hispanic stops. Missing data undermine the quality of the data. And it is further worrisome that the share of missing stop reasons differs by race (Appendix Table A.1).

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, once stopped.

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 racial shares of stops.

Table 2 reports South Burlington Police Department's post-stop outcomes by race. In order to make comparisons across racial groups, it is useful to consider 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 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

	Black/white	Asian/white	Hispanic/white
Warning Rate	1.08	1.03	0.94
Ticket Rate	0.84	0.98	1.11
Arrest Rate	1.40	0.33	0.85
Search Rate	4.19	1.15	2.22

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.

There are modest racial differences in the rates at which drivers receive warnings or are ticketed, although the Black-white difference in the share of stops in which a citation is issued is statistically significant (z=3.92). The 0.84 ratio implies that Black drivers are about 16% less likely to be issued a citation. That said, as noted, there may be more than one outcome to a stop, and that means that drivers may be given more than one citation per stop. We find that although Black drivers are issued citations at a lower rate than white drivers, they are more likely to be issued multiple citations during the same stop. Specifically, during the time period of this study, 0.6% of white drivers were given more than one citation compared to 1.3% of Black drivers. This difference is statistically significant (z=3.07).

Black/white arrest rate disparities are more pronounced. (There were just 3 arrests of Asian drivers and two of Hispanic drivers). The ratio of Black to white arrests rates is 1.40, indicating Black drivers are 40% more likely to be arrested subsequent to a stop than white drivers. The difference in arrest rates is not, however, statistically significant.

Search rate data used for Table 3 exclude searches based on a warrant.[8] Black drivers are searched at a rate that is more than 4 times the rate at which white drivers are searched, and

[8] 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 officer impounds the vehicle and seeks a warrant

the difference in search rates is highly statistically significant (z=8.83). There were just 6 searches of Asian drivers during this time period, and although the Asian search rate is slightly higher than the white rate, the difference is not statistically significant. The Hispanic/white ratio is 2.22 although this is not a reliable statistic because of the small sample size—only 3 Hispanic drivers were searched.

The results presented here with regard to higher arrest and search rates of Black drivers as compared to white drivers are consistent with those found in a number of national, state, and local studies—although the search rate disparities are much wider in South Burlington. For example, Pierson, *et al* (2020) report national-level data on nearly 100 million US traffic stops, finding that Black and Hispanic drivers are searched at more than twice the rate of white drivers.[9] In a study of 20 million car stops in North Carolina from 2002-2016, Baumgartner, *et al* (2018) also find evidence of higher arrest and search rates of Black and Hispanic drivers. The ratio of Black to white search rates in North Carolina was roughly 2 to 1, similar to Pierson, *et al* (2020), indicating search rate disparities between Black and white drivers that are much lower than in South Burlington.

Why might we observe racial disparities 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 police officers 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 who 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.[10] Absent racial bias (as compared to racial disparities), we would expect that officers 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 suggests officers 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 officer'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

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from a judge. However, in order to be conservative in our approach to defining officer discretion, we exclude searches on warrant because a judge also participates in the decision to conduct a search.

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

[10] Note that firearms for those 21 and over are not necessarily contraband in Vermont, but for those under 21, firearms would be considered contraband. Cannabis was legalized July 1, 2018 and is no longer contraband. Before that time, cannabis had been decriminalized in 2013 for quantities under one ounce, and possession of less than an ounce was until 2018 considered a misdemeanor.

at racial differences in the severity of contraband, we adopt a method to differentiate the type of contraband by the severity of the outcome as follows: 1) hit rates for all outcomes (warning, ticket, arrest), 2) hit rates in which contraband leads to a ticket(s) and/or an arrest, and 3) the arrest-worthy contraband hit rate (that is, the percentage of searches in which contraband is found and the driver is arrested).

In conducting the hit rate test, we focus on white and Black drivers. The number of searches of Asian and Hispanic drivers are not considered due to the low incidence of searches of these groups. In the case of the overall hit rate and the hit rate that leads to a ticket or arrest, the productivity of searches of Black drivers is lower than that of white drivers. For example, in all searches in which contraband is found, the hit rate for white drivers is 80.9% compared to 65.9% for Black drivers, and the difference is statistically significant (z=2.07). When the outcome of the search is at least a citation and/or an arrest, the Black hit rate is still lower than that of white drivers, 31.7% compared to 49.4%. This difference is also statistically significant (z=2.03). When the outcome of a search is an arrest (signifying more serious contraband found), the Black hit rate is also lower than the white hit rate, although this difference is not statistically significant. These findings suggest that SBPD officers use a lower threshold of evidence to initiate a search of a vehicle with a Black driver.

IV. Trends Over Time

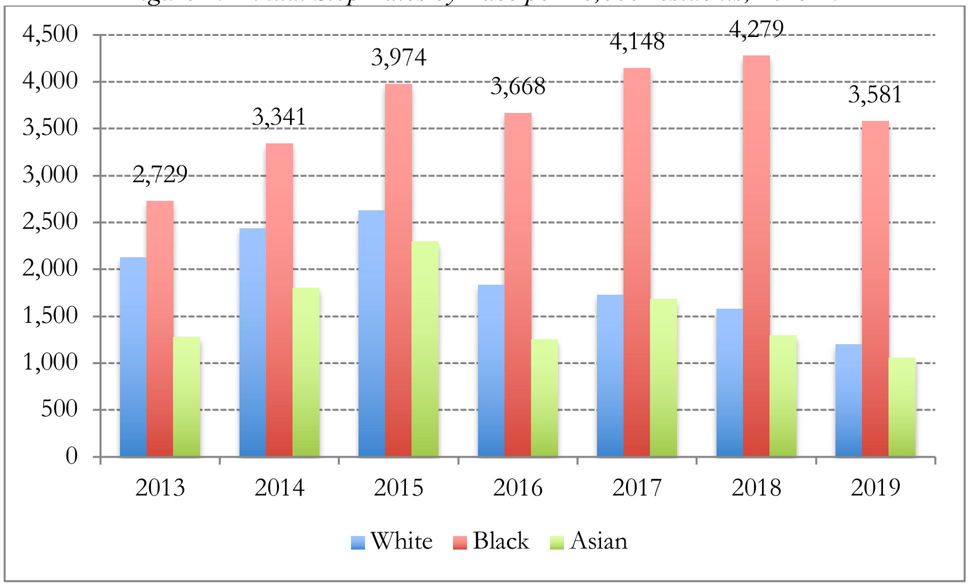
The adoption of fair and impartial policing policies and the availability of traffic stop data may incentivize agencies to review their policies and to conduct trainings on race, policing, and impartial bias. It is therefore useful to explore trends in racial disparities over time to track the effect 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 Table A.2b). The total number of stops has decreased by 40.2% over this period of time. The percentage changes by racial group vary widely, however, with the number of white stops decreasing by 43.7%, and the Asian count falling 17.4%. In contrast, the number of Black drivers stopped *increased* 31.2%. There was no change in the Hispanic number of stops.

For 2019, we estimate that white drivers were stopped at a rate of 1,575 per 10,000 white residents.[11] The Asian stop rate for 2019 was 1,058 per 10,000 Asian residents. In contrast, for Black drivers, the stop rate in 2019 was 3,581 per 10,000 Black residents (Figure 2). The Asian-Black differences in this and other indicators are consistent with critical race theory, which finds that Asians are more likely to be treated as a "model" minority, and thus much less susceptible to racial police bias than Blacks.

[11] ACS 2013-17 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 of South Burlington 15 and older, all multiplied by 10,000.

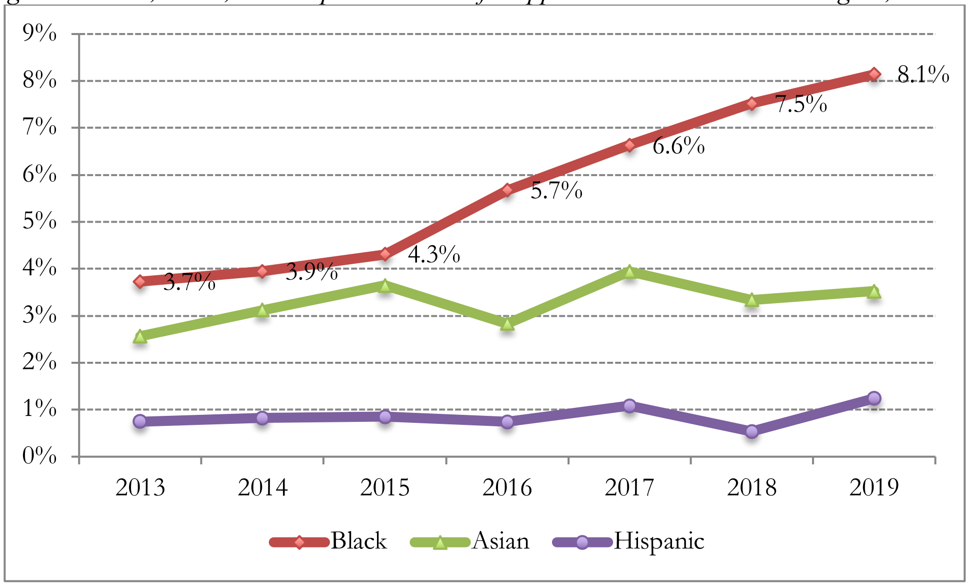
Figure 2. Annual Stop Rates by Race per 10,000 residents, 2013-19



Secondly, we present results here for South Burlington on trends in stop shares, investigatory/pretextual stops, and arrest, search, and hit rates. Due to small sample sizes, we calculate three-year moving trends instead of one-year trends to increase our sample sizes. Specifically, we look at data for 2013-15, 2014-16, etc. (See Table A.2a. for the raw numbers on which the following figures are based).

Figure 3 portrays trends in the Black, Asian, and Hispanic shares of stops. (We focus on minorities in this graph to underscore that outcomes of minority racial groups differ, making it analytically unsound to group all minorities into one category). The Hispanic stop share has increased modestly and Asian stop share has increased from 2.6% to 3.9%. The Black share of stops, however, has more than doubled over this period of time, from 3.7% of all stops in 2013 to 8.1% in 2019. During this time period, the white share of drivers has fallen from 92.9% to 87.0% (calculated from data in Table A.2b).

Figure 3. Black, Asian, and Hispanic Shares of Stopped Drivers in South Burlington, 2013-19



Of interest, as noted, is the percentage of stops that are pretextual. This type of stop is one that is more susceptible to bias than are safety stops, with the latter are based on discernible driver behavior. Figure 4 provides the racial shares of all stops that are investigatory/pretextual as a percentage of all stops. There are two noteworthy observations. The share of stops of Asian drivers that are investigatory/pretextual is lower than for all other groups over the entire time period from 2014-16 to 2017-19, and that share has been falling. The share of this type of stops for white drivers has been relatively constant, while Black and Hispanic drivers have increasingly been the subjects of this type of stop, with the Black-white difference increasing over the past few years. Hispanic drivers, however, experienced the largest percentage increase in this type of stop from 21.4% in 2013 to 30.0% in 2019.

Figure 4. Investigatory/Pretextual Stops as % of All Stops

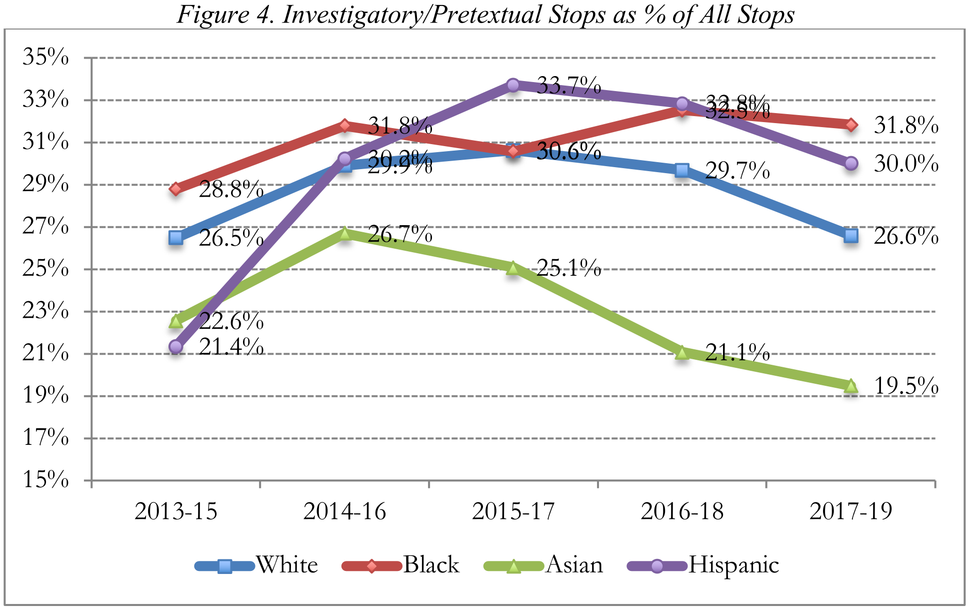
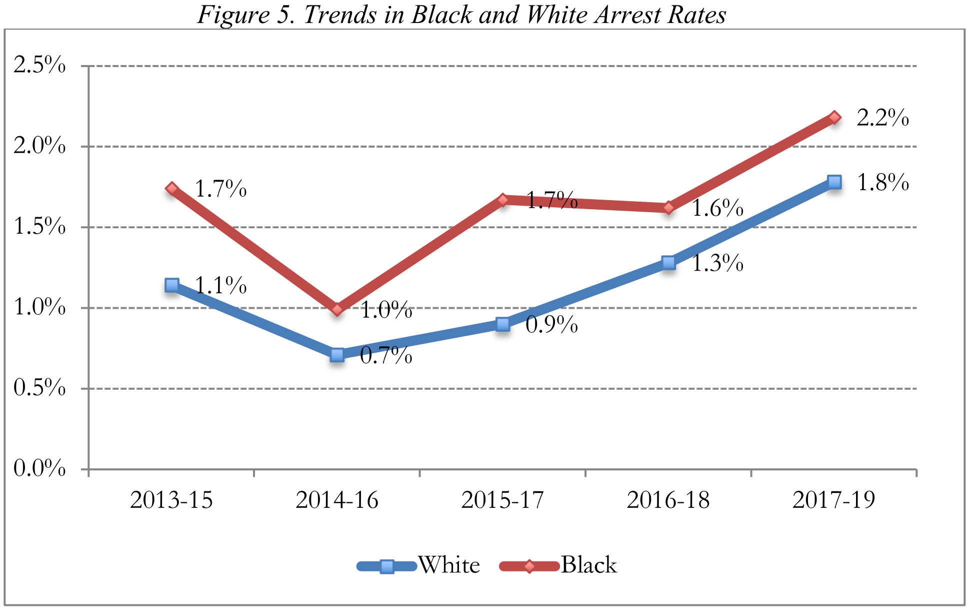


Figure 5 shows trends in white and Black arrest rates. Arrest rates have risen for Black and white drivers since 2013. In all years, the Black arrest rate exceeds the white rate. After widening in 2015-17, the Black-white gap narrowed marginally by 2019 to 1.8% for whites and 2.2% for Blacks. (Asian and Hispanic arrest rate numbers are omitted due to small sample sizes). Thus, while in 2013-15, the ratio of Black to white arrest rates was 1.54 (meaning that Black drivers were roughly 54% more likely to be arrested in a traffic stop compared to white drivers), that ratio has fallen to 1.22.

Figure 5. Trends in Black and White Arrest Rates



White and Black search rates are shown in Figure 6. The number of annual searches of Asian and Hispanic drivers is very small and so we do not include those in Figure 6. Search rates have risen over time for both groups with the percentage of white searches tripling over the period, but the Black search rate continues to be much higher than the white rate. The Black/white disparity in search rates has narrowed albeit from a very large 7.6 times in 2013-2015 to 2.7 times in 2017-2019. The gap narrowed in 2014-16, but since that time, the gap has widened.

Figure 6. White and Black Search Rates Trends and Differentials

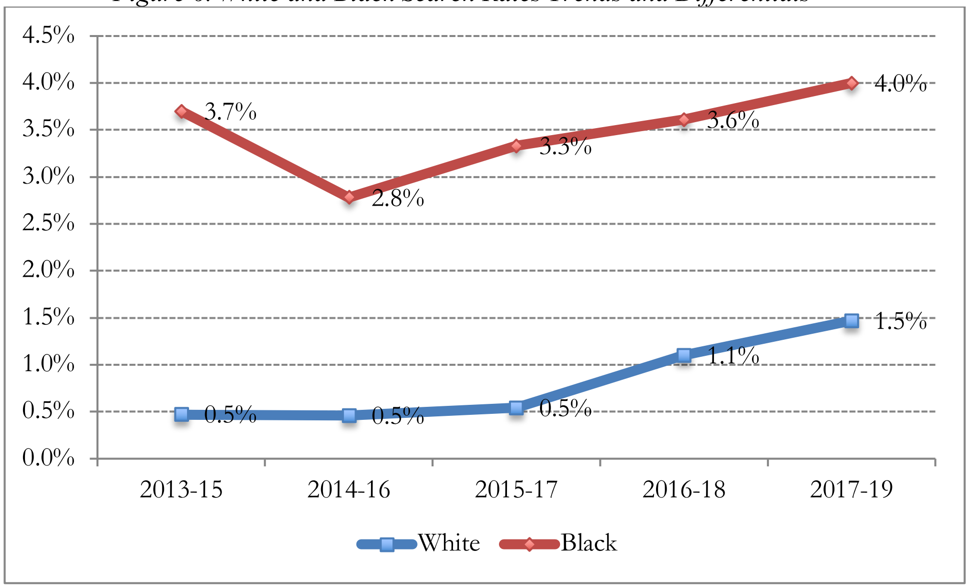
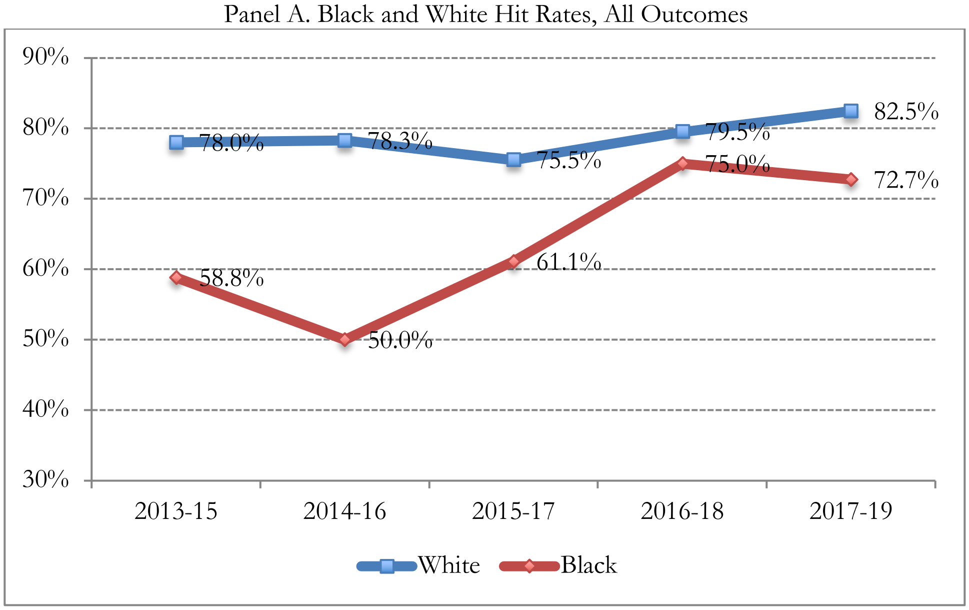


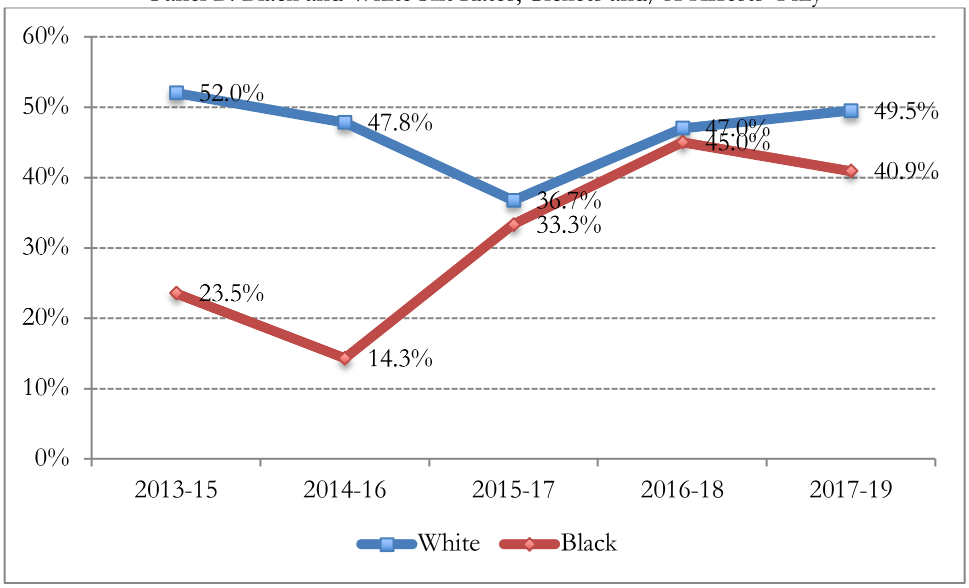
Figure 7, *Panel A*, shows trends in the white and Black contraband hit rates. (Asian and Hispanic hit rates are not shown due to small sample sizes). The Black hit rate has been below the white rate in every time period, but that gap has narrowed since 2013-15 and especially since 2014-2016 when the hit rate disparity reached its maximum. The hit rate difference between Black and white drivers in 2017-19 is not statistically significant (z=1.05).

Figure 7. Trends in Black and White Hit Rates

Panel A. Black and White Hit Rates, All Outcomes



Panel B. Black and White Hit Rates, Tickets and/or Arrests Only



As noted, contraband ranges in severity from relatively minor types to more serious forms of contraband. Focusing our attention on contraband hits that result in a ticket and/or arrest (thus excluding lesser forms of contraband that result in a warning), we find that again the white hit rate is higher than the Black rate in every time period (*Panel B*). Very significant differences were seen in 2013-15 and 2014-2016 but the disparity has decreased since then. The trends in *Panel B* are very similar to those in *Panel A*, showing a slightly widening gap from 2016-18 to 2017-19. We caution that sample sizes are even smaller than in *Panel A*.

V. Logit Analysis

In this analysis, our focus is on searches and their relative efficiency in finding contraband. Our goal is to examine in greater depth the evidence that minority drivers receive less favorable treatment due to their race 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 an officer's decision to conduct 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 in South Burlington.

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:

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

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 other 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.

We also 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 given for a stop divided by the odds of being searched due to a 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 officer indicated more than one reason for the stop), and for reasons unknown (that is, the reason was not stipulated in the incident report). This control helps to eliminate misattribution of race to search disparities if, for example, any racial group is more likely to be stopped under suspicion of 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.

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. Controlling for all of these factors allows us to interpret the race variable, net of the impact of these other control variables.

The South Burlington data pose a challenge in that all gender and age data were missing for the years 2013 to 2017. We therefore estimate the above equation using all data, but dropping gender and age from our model. This implies the time period of analysis is 2013 to 2019. We then repeat the regressions, adding gender and age, which results in using data only for 2017 to 2019, and thus a much smaller sample size. By doing this, we can also examine changes over the two periods.

Results are shown in Table 4. Of primary interest in all models we estimate is whether the race variables are statistically significant (as designated by the asterisks). If they are, this implies that independent of the factors we control for that may lead to the decision to search a vehicle, race influences the officer's decision to search (net of those factors).

We start with a basic model (Model 1 in Table 4), in which race of the driver is our only explanatory variable. The results show that the odds a Black driver is searched are 4.37 times greater than the odds for a white driver. Neither the Hispanic nor Asian odds ratios are statistically significant in this or in any of the other regression models, and this could in part be due to the low numbers of searches of these racial/ethnic groups. There were no searches of Native American drivers.

In Model 2, we add all remaining controls except for gender and age. These include time of day, day of week, and reason for stop. We find that the probability of a search is lower in the morning than in the afternoon. The odds of search at night are more than double those in the afternoon. None of the coefficients on days of the week are statistically significant, except for Monday.

The odds of an investigatory stop leading to a search are more than 25 times greater than 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 statistically significant. The odds of a search when the search stop reason is unknown or missing are 9.2 times greater than a stop due to a moving violation. When the stop reason is vehicle equipment, the odds of a search are 1.66 times greater than if the reason is moving violation. Finally, the odds of a search when the reason is suspicion of DWI are more than 7 times greater when the stop reason is moving violation. The odds a Black driver will be searched in this model, after controlling for other factors, are 3.21, relative to the odds a white driver will be searched. That is, even controlling for other factors, the odds a Black driver is searched in South Burlington are still more than triple the odds a white driver is 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.

In Model 3, we repeat our analysis, now including just two categories of *Reason for Stop*—safety stops (the omitted variable) and pretextual stops. The odds a pretextual stop will result in a search are 2.25 times greater than if the stop reason is a safety stop. The odds a Black driver will be searched in this model, after controlling for other factors, are 3.37, relative to the odds a white driver will be searched.

In Model 4, we add controls for gender and age, thus limiting our analysis to 2017 to 2019. This reduces the sample size by two-thirds. We find that the odds a male driver will be searched are 1.59 times greater than if the driver if female. The odds ratio on age of driver indicates that older drivers have a lower probability of being searched than younger drivers. The odds a Black driver will be searched in this model, after controlling for other factors, are 1.971 relative to the odds a white driver will be searched. Race, in other words, continues to influence an officer's decision to search. That said, because Model 4 reflects search probabilities in 2017-19, the lower odds ratio suggests a narrowing of search rates gaps between white and Black drivers.

In Model 5, we add all controls and use safety and pretextual stops to capture the effect of stop reason on search probabilities by race. The odds of a pretextual stop leading to a search are similar to those in Model 3. The odds a Black driver will be searched in this model are 2.078 greater than the odds a white driver will be searched.

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

	(1)	(2)	(3)	(4)	(5)
	2013-19	2013-19	2013-19	2017-19	2017-19
VARIABLES	Race only	With time and stop reason	With time and pretextual stop control	With all controls and stop reason	With all controls and pretextual stop control
Black	4.372***	3.210***	3.370***	1.971***	2.078***
	(0.776)	(0.591)	(0.607)	(0.495)	(0.509)
Asian	1.028	0.952	0.923	1.175	1.226
	(0.429)	(0.401)	(0.387)	(0.557)	(0.572)
Hispanic	1.997	2.104	1.969	2.165	1.888
	(1.173)	(1.246)	(1.163)	(1.585)	(1.383)
Male				1.586**	1.644**
				(0.334)	(0.343)
Age				0.973***	0.972***
				(0.007)	(0.007)
Morning		0.487**	0.504**	0.445	0.452
		(0.155)	(0.160)	(0.266)	(0.269)
Night		2.399***	2.507***	1.603	1.562
		(0.439)	(0.456)	(0.589)	(0.560)
Saturday		1.256	1.309	0.448	0.446
		(0.444)	(0.461)	(0.379)	(0.376)
Sunday		1.594	1.629	1.426	1.370
		(0.564)	(0.574)	(0.918)	(0.879)
Monday		1.689*	1.844**	1.260	1.377
		(0.465)	(0.503)	(0.611)	(0.661)
Tuesday		1.104	1.199	0.913	0.974
		(0.318)	(0.343)	(0.453)	(0.479)
Wednesday		1.033	1.055	0.857	0.858
		(0.359)	(0.364)	(0.584)	(0.582)
Thursday		1.247	1.287	1.628	1.550
		(0.417)	(0.428)	(0.970)	(0.921)
Investigatory stop		25.21***		19.74***	
		(7.874)		(9.742)	
Suspicion of DWI		7.505***			
		(5.579)			
Unknown stop reason		9.155***		10.88***	
		(2.546)		(3.326)	
Vehicle equipment		1.657***		1.698***	
		(0.259)		(0.348)	
Pretextual stop			2.254***		2.426***
			(0.315)		(0.442)
Constant	0.008***	0.003***	0.003***	0.007***	0.008***
	(0.001)	(0.001)	(0.001)	(0.006)	(0.005)
No. of observations	21,861	21,851	21,861	7,422	7,445

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

Taken together, these results suggest that Black/white disparities in search rates are extremely robust, regardless of the contextual factors controlled for. Moreover, the levels of disparity indicated by the logistic regressions are very similar to the search rate ratio in Figure 6 when using the full dataset but the odds fall when gender and race are added and the sample is thus restricted to 2017-2019.

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:

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

Table 5 reports the results of the probability of contraband found for searches for any outcome of the stop and search (that is, in which the result is 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 less than half the odds a white driver will be found with contraband subsequent to a search. The odds an Asian driver is found with contraband are one quarter of the white odds. The odds of Hispanic drivers being found with contraband are even lower, roughly 1/10 the odds a white driver will be found with contraband. In each of these cases, the odds ratios are 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 80.9% of searched white drivers are found with contraband and thus, 19.1% are not found with contraband. This implies an odds ratio for white drivers of 80.9/19.1= 4.24. In other words, the odds are roughly 4.24 to 1 that a search of a white driver will yield contraband. For Black drivers, we find in Table 2 that 65.9% of them are found with contraband so their odds ratio is 65.9/34.1=1.93. The ratio of these two odds is the coefficient in our regression (1.93/4.24=0.46), very close to the coefficient estimate on race when we formally run the logit regression.

The addition of controls in Model 2 (except gender and race) slightly reduces the odds ratio of finding contraband in searches of Black as compared to white drivers to 0.444. In Model 3, we obtain similar results on the Black to white odds of contraband being found as in Model 2, and searches after pretextual stops are shown to result in a lower probability of finding contraband than if the stop is for safety reasons. That odds ratio is, however, not statistically significant.

In Models 4 and 5, we add gender and race, thus limiting our analysis to 2017-19 due to missing data in previous years. The odds ratios for all racial groups are now no longer statistically significant. And indeed, none of the variables in either model are statistically significant. The much smaller sample size of an already small sample may have contributed to the lack of robustness of the results in these models as compared to Models 1-3. It also reflects the improvement in closing the hit rate gap between white drivers and other racial groups illustrated in Figure 7.

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

	(1) 2013-19	(2) 2013-19	(3) 2013-19	(4) 2017-19	(5) 2017-19
VARIABLES	Race only	With time and stop reason	With time and pretextual stop control	With all controls and stop reason	With all controls and pretextual stop control
Black	0.456**	0.444**	0.442**	0.606	0.618
	(0.176)	(0.178)	(0.176)	(0.375)	(0.380)
Asian	0.237*	0.224*	0.217*	0.377	0.382
	(0.199)	(0.195)	(0.187)	(0.384)	(0.380)
Hispanic	0.118*	0.150	0.150	0.196	0.205
	(0.147)	(0.202)	(0.200)	(0.409)	(0.426)
Male				1.724	1.727
				(0.918)	(0.917)
Age				1.032	1.034
				(0.0290)	(0.0286)
Morning		0.859	0.839	1.85e-07	1.23e-07
		(0.647)	(0.625)	(0.000233)	(0.000187)
Night		1.885	1.888	4.743	5.195
		(0.838)	(0.821)	(5.556)	(5.726)
Saturday		3.232	3.163		
		(3.075)	(3.000)		
Sunday		2.027	2.238	1.094e+07	1.773e+07
		(1.772)	(1.943)	(1.380e+10)	(2.697e+10)
Monday		1.107	1.132	1.640	1.637
		(0.695)	(0.704)	(1.726)	(1.697)
Tuesday		1.837	1.846	2.469	2.523
		(1.250)	(1.254)	(2.795)	(2.828)
Wednesday		1.787	1.821	8.821e+06	1.675e+07
		(1.439)	(1.460)	(1.113e+10)	(2.547e+10)
Thursday		1.530	1.533	4.978	5.043
		(1.186)	(1.187)	(8.187)	(8.215)
Investigatory stop		0.751		0.740	
		(0.527)		(0.829)	
Suspicion of DWI		-			
Unknown stop reason		0.900		0.727	
		(0.578)		(0.517)	
Vehicle equipment		0.883		0.962	
		(0.341)		(0.630)	
Pretextual stop			0.845		0.838
			(0.294)		(0.442)
Constant	4.226***	1.981	1.997	0.0893	0.0774
	(0.844)	(1.346)	(1.335)	(0.172)	(0.142)
No. of observations	212	210	212	124	124

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

To sum up the results of the logistic regressions and focusing on the 2013-19 results, adding controls for a variety of contextual factors has little effect on the size of the 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 and the likelihood of finding contraband are more likely to happen under some conditions as compared to others (e.g., during investigatory stops as compared to motor vehicle stops). But even controlling for these factors, race continues to be a statistically significant factor in an officer's decision to search a vehicle. Moreover, and with regard to the question of racial bias as an explanation for such disparities, the analysis shows that Black, Asian, and Hispanic drivers are all less likely to be found with contraband, a finding that is consistent with oversearching of that group of drivers—a trend, though, that seems to be improving.

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 SBPD traffic stops. We find that Black drivers' share of stops exceeds their estimated share of the driving population. We estimate that Black drivers were overstopped by 54% to 87%, depending on the estimate of the driving population used. Post-stop outcomes also give evidence of racial disparities, with Black drivers more likely than white drivers to be stopped for investigatory/pretextual reasons. That disparity has risen over time. The reason such stops are of interest in evaluating evidence of racial bias is that such stops are more likely to be used to investigate "suspicious" behavior and therefore more prone to racial bias.

There is a noteworthy disparity in Black and white arrests rates, with the Black arrest rate 40% higher than the white arrest rate. Over time, the disparity between Black and white arrest rates has modestly declined. Asian drivers have a sizably lower arrest rate than white drivers.

Black drivers were searched at a rate that was more than 4 times greater than the white search rate. This disparity has declined over time so that by 2019, the Black search rate was 2.7 times greater than the white rate. The reason for this decline is that the white search rate has been rising. The Black hit rate is lower than the white rate though this disparity shrunk by 2019, so much so that the difference in hit rates is not statistically significant.

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 drivers are substantially more likely to be searched than white drivers. They are less likely to be found with contraband.

The total number of traffic stops per year has decreased by 40.2% from 2013 to 2019. But for Black drivers, the number of traffic stops rose 31.2%. As a result, the Black stop rate per 10,000 Black residents in 2019 is more than twice that per estimated 10,000 white residents. Collectively, these results suggest that the race of the driver plays a role in officer decision-making in traffic policing in South Burlington.

In terms of data quality, SBPD's efforts to improve data quality have born fruit. By 2019, there were minimal quantities of missing data.

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APPENDIX

Table A.1. South Burlington Raw Traffic Stop Data, 2013-19

All Years	White	Black	Asian	Hispanic	Native American	Unknown	Total
Total Traffic Stops							
Including externally generated stops	19,936	1,190	722	185	13	260	22,306
Excluding externally generated stops	19,808	1,178	716	185	13	260	22,160
Reasons For Stops							
Safety Stops	14,151	796	552	130	10	90	15,729
Moving Violation	14,119	795	552	130	9	89	15,694
Suspicion of DWI	32	1	0	0	1	1	35
Investigatory/Pretextual Stops	5,458	358	157	51	3	32	6,059
Investigatory Stop	82	10	1	0	0	2	95
Vehicle Equipment	5,376	348	156	51	3	30	5,964
Externally Generated Stop	128	12	6	0	0	0	146
Multiple Reasons - Moving Violation & Suspicion of DWI	0	0	0	0	0	0	0
Multiple Reasons - Moving Violation & Vehicle Equipment	8	1	0	0	0	0	9
Multiple Reasons - Suspicion of DWI & Vehicle Equipment	1	0	0	0	0	0	1
Unknown Stop Reason	190	23	7	4	0	138	362
Outcomes							
Ticket	6,948	348	245	72	5	50	7,668
Warning	12,630	809	470	111	7	76	14,103
No Action Taken	12	3	1	0	0	0	16
Arrest for violation	252	21	3	2	1	0	279
Arrest for warrant	8	0	0	0	0	0	8
Searches							
Total Stops with No Search	19,624	1,136	707	182	13	124	21,786
No Search & Contraband & Arrest for violation	3	0	0	0	0	0	3
No Search & Contraband & No arrest	17	0	0	0	0	0	17
No Search (all others)	19,604	1,136	707	182	13	124	21,766
Total Stops with Unknown Search	22	1	3	0	0	136	162
Total Stops with Search	162	41	6	3	0	0	212
Search with Probable Cause (PC)	100	19	4	1	0	0	124
Stops with PC Searches, No contraband	18	4	2	0	0	0	24
Stops with PC Searches, Unknown contraband	0	0	0	0	0	0	0
Stops with PC Searches, Contraband	82	15	2	1	0	0	100
Outcomes of PC Search							
Stops with PC Searches, Contraband & Warning, No Action or Unknown	32	10	1	1	0	0	44
Stops with PC Searches, Contraband and Ticket	30	5	0	0	0	0	35
Stops with PC Searches, Contraband and Arrest	20	0	1	0	0	0	21
Search with Reasonable Suspicion (RS)	44	17	2	2	0	0	65
Stops with RS Searches, No contraband	11	8	1	2	0	0	22
Stops with RS Searches, Unknown contraband	0	0	0	0	0	0	0
Stops with RS Searches, Contraband	33	9	1	0	0	0	43
Outcomes of RS Search							
Stops with RS Searches, Contraband & Warning, No Action or Unknown	17	3	1	0	0	0	21
Stops with RS Searches, Contraband & Ticket	11	3	0	0	0	0	14
Stops with RS Searches, Contraband & Arrest	5	3	0	0	0	0	8
Search with Warrant	18	5	0	0	0	0	23
Stops with Warrant Searches, No contraband	2	2	0	0	0	0	4
Stops with Warrant Searches, Unknown contraband	0	0	0	0	0	0	0
Stops with Warrant Searches, Contraband	16	3	0	0	0	0	19
Outcomes of Warrant Search							
Stops with Warrant Searches, Contraband & Warning, No Action or Unknown	2	1	0	0	0	0	3
Stops with Warrant Searches, Contraband & Ticket	9	0	0	0	0	0	9
Stops with Warrant Searches, Contraband & Arrest	5	2	0	0	0	0	7

Notes: Except where noted, data exclude externally generated stops. Outcomes of stops with searches are listed in order of severity. If the outcome is a warning, no action taken, or unknown, this implies that no citation or arrest resulted. In stops with searches that result in a citation or arrest, this implies at least one ticket and/or an arrest. And in the final category (stops with searches that result in an arrest), this refers to only those searches in which contraband is found and result at least in an arrest.

Table A.2a. South Burlington Raw Traffic Stop Trend Data (3-year rolling trends)

All Years	White	Black	Asian	Hispanic	Native American	Unknown	Total
Total Traffics Stops							
Excluding externally generated stops							
2013-15	10,530	460	361	93	8	58	11,510
2014-16	10,103	503	359	90	7	96	11,158
2015-17	9,066	540	351	89	6	106	10,158
2016-18	7,524	554	284	67	4	202	8,635
2017-19	6,590	550	271	70	5	144	7,630
Reasons For Stops (excl. externally generated stops and unknown reasons)							
Safety Stops							
2013-15	7,688	324	278	70	5	44	8,409
2014-16	7,030	339	261	60	4	65	7,759
2015-17	6,238	370	260	57	4	49	6,978
2016-18	5,224	365	221	45	4	46	5,905
2017-19	4,756	364	215	49	5	8	5,397
2013-15 (% of stops)	73.5%	71.2%	77.4%	78.7%	62.5%	78.6%	73.6%
2014-16 (% of stops)	70.1%	68.2%	73.3%	69.8%	57.1%	69.2%	70.1%
2015-17 (% of stops)	69.4%	69.4%	74.9%	66.3%	66.7%	64.5%	69.5%
2016-18 (% of stops)	70.3%	67.5%	78.9%	67.2%	100.0%	69.7%	70.4%
2017-19 (% of stops)	73.4%	68.2%	80.5%	70.0%	100.0%	100.0%	73.3%
Pretextual Stops							
2013-15	2,769	131	81	19	3	12	3,015
2014-16	3,000	158	95	26	3	29	3,311
2015-17	2,755	163	87	29	2	27	3,063
2016-18	2,205	176	59	22	0	20	2,482
2017-19	1,723	170	52	21	0	0	1,966
2013-15 (% of stops)	26.5%	28.8%	22.6%	21.4%	37.5%	21.4%	26.4%
2014-16 (% of stops)	29.9%	31.8%	26.7%	30.2%	42.9%	30.9%	29.9%
2015-17 (% of stops)	30.6%	30.6%	25.1%	33.7%	33.3%	35.5%	30.5%
2016-18 (% of stops)	29.7%	32.5%	21.1%	32.8%	0.0%	30.3%	29.6%
2017-19 (% of stops)	26.6%	31.8%	19.5%	30.0%	0.0%	0.0%	26.7%
Outcomes (excl. externally generated stops)							
Tickets (one or more)							
2013-15	3,968	152	123	35	4	31	4,313
2014-16	4,060	161	134	39	3	39	4,436
2015-17	3,443	146	126	36	2	28	3,781
2016-18	2,455	153	99	28	0	19	2,754
2017-19	1,753	143	83	27	1	0	2,007
2013-15 (% of stops)	37.7%	33.0%	34.1%	37.6%	50.0%	53.5%	37.5%
2014-16 (% of stops)	40.2%	32.0%	37.3%	43.3%	42.9%	40.6%	39.8%
2015-17 (% of stops)	38.0%	27.0%	35.9%	40.5%	33.3%	26.4%	37.2%
2016-18 (% of stops)	32.6%	27.6%	34.9%	41.8%	0.0%	9.4%	31.9%
2017-19 (% of stops)	26.6%	26.0%	30.6%	38.6%	20.0%	0.0%	26.3%
Arrests for Violation							
2013-15	120	8	0	0	0	0	128
2014-16	72	5	0	0	0	0	77
2015-17	82	9	1	1	1	0	94
2016-18	96	9	3	2	1	0	111
2017-19	117	12	3	2	1	0	135
2013-15 (% of stops)	1.1%	1.7%	0.0%	0.0%	0.0%	0.0%	1.1%
2014-16 (% of stops)	0.7%	1.0%	0.0%	0.0%	0.0%	0.0%	0.7%
2015-17 (% of stops)	0.9%	1.7%	0.3%	1.1%	16.7%	0.0%	0.9%
2016-18 (% of stops)	1.3%	1.6%	1.1%	3.0%	25.0%	0.0%	1.3%

2017-19 (% of stops)	1.8%	2.2%	1.1%	2.9%	20.0%	0.0%	1.8%
Searches (excl. externally generated stops)							
Searches (PC, RS or Warrant)							
2013-15	50	17	1	1	0	0	69
2014-16	46	14	1	1	0	0	62
2015-17	49	18	1	3	0	0	71
2016-18	83	20	4	2	0	0	109
2017-19	97	22	5	2	0	0	126
2013-15 (% of Stops)	0.5%	3.7%	0.3%	1.1%	0.0%	0.0%	0.6%
2014-16 (% of Stops)	0.5%	2.8%	0.3%	1.1%	0.0%	0.0%	0.6%
2015-17 (% of Stops)	0.5%	3.3%	0.3%	3.4%	0.0%	0.0%	0.7%
2016-18 (% of Stops)	1.1%	3.6%	1.4%	3.0%	0.0%	0.0%	1.3%
2017-19 (% of Stops)	1.5%	4.0%	1.9%	2.9%	0.0%	0.0%	1.7%
Contraband (All Outcomes)							
2013-15	39	10	0	0	0	0	49
2014-16	36	7	0	0	0	0	43
2015-17	37	11	0	1	0	0	49
2016-18	66	15	2	1	0	0	84
2017-19	80	16	3	1	0	0	100
2013-15 (% of Searches)	78.0%	58.8%	0.0%	0.0%	0.0%	0.0%	71.0%
2014-16 (% of Searches)	78.3%	50.0%	0.0%	0.0%	0.0%	0.0%	69.4%
2015-17 (% of Searches)	75.5%	61.1%	0.0%	33.3%	0.0%	0.0%	69.0%
2016-18 (% of Searches)	79.5%	75.0%	50.0%	50.0%	0.0%	0.0%	77.1%
2017-19 (% of Searches)	82.5%	72.7%	60.0%	50.0%	0.0%	0.0%	79.4%
Contraband (Tickets + Arrests)							
2013-15	26	4	0	0	0	0	1
2014-16	22	2	0	0	0	0	1
2015-17	18	6	0	0	0	0	1
2016-18	39	9	1	0	0	0	1
2017-19	48	9	1	0	0	0	1
2013-15 (% of Searches)	52.0%	23.5%	0.0%	0.0%	0.0%	0.0%	1.1%
2014-16 (% of Searches)	47.8%	14.3%	0.0%	0.0%	0.0%	0.0%	1.0%
2015-17 (% of Searches)	36.7%	33.3%	0.0%	0.0%	0.0%	0.0%	1.0%
2016-18 (% of Searches)	47.0%	45.0%	25.0%	0.0%	0.0%	0.0%	1.1%
2017-19 (% of Searches)	49.5%	40.9%	20.0%	0.0%	0.0%	0.0%	0.9%
Contraband (Arrests only)							
2013-15	9	2	0	0	0	0	11
2014-16	7	1	0	0	0	0	8
2015-17	7	2	0	0	0	0	9
2016-18	13	3	1	0	0	0	17
2017-19	19	3	1	0	0	0	23
2013-15 (% of Searches)	18.0%	11.8%	0.0%	0.0%	0.0%	0.0%	15.9%
2014-16 (% of Searches)	15.2%	7.1%	0.0%	0.0%	0.0%	0.0%	12.9%
2015-17 (% of Searches)	14.3%	11.1%	0.0%	0.0%	0.0%	0.0%	12.7%
2016-18 (% of Searches)	15.7%	15.0%	25.0%	0.0%	0.0%	0.0%	15.6%
2017-19 (% of Searches)	19.6%	13.6%	20.0%	0.0%	0.0%	0.0%	18.3%

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							
For year 2013	3,133	126	88	25	1	20	3,393
For year 2014	3,580	155	122	32	2	21	3,912
For year 2015	3,874	184	156	36	5	17	4,272
For year 2016	2,703	170	84	22		58	3,037
For year 2017	2,553	191	113	31	1	31	2,920
For year 2018	2,330	200	88	14	3	113	2,748
For year 2019	1,763	164	71	25	1		2,024
Excluding externally generated stops							
For year 2013	3,115	125	86	25	1	20	3,372
For year 2014	3,567	153	121	32	2	21	3,896
For year 2015	3,848	182	154	36	5	17	4,242
For year 2016	2,688	168	84	22	0	58	3,020
For year 2017	2,530	190	113	31	1	31	2,896
For year 2018	2,306	196	87	14	3	113	2,719
For year 2019	1,754	164	71	25	1	0	2,015
Percentage Change YoY							
2013 vs 2014	14.5%	22.4%	40.7%	28.0%	100.0%	5.0%	15.5%
2014 vs 2015	7.9%	19.0%	27.3%	12.5%	150.0%	-19.1%	8.9%
2015 vs 2016	-30.2%	-7.7%	-45.5%	-38.9%	-100.0%	241.2%	-28.8%
2016 vs 2017	-5.9%	13.1%	34.5%	40.9%		-46.6%	-4.1%
2017 vs 2018	-8.9%	3.2%	-23.0%	-54.8%	200.0%	264.5%	-6.1%
2018 vs 2019	-23.9%	-16.3%	-18.4%	78.6%	-66.7%	-100.0%	-25.9%
Stops per 10,000 residents							
For year 2013	2,127	2,729	1,282				
For year 2014	2,436	3,341	1,803				
For year 2015	2,628	3,974	2,295				
For year 2016	1,836	3,668	1,252				
For year 2017	1,728	4,148	1,684				
For year 2018	1,575	4,279	1,297				
For year 2019	1,198	3,581	1,058				

Appendix A.3. Data Quality and Methodology

The South Burlington Police Department (SBPD) traffic stop data used in this study consists of 22,977 rows, spanning seven years (2013-2019). Each row corresponds to a single outcome resulting from a traffic stop (there may be multiple outcomes of a stop). Date and time of stops are not required by legislation, although some agencies have chosen to provide date and time. South Burlington began supplying this data in 2018. 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.3a shows the counts and percentages of missing or unknown data values. Missing data is when the officer fails to record data on a particular field. Unknown is where the officer 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 SBPD supplies.

Table A.3a. 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												
2013	3,372	0	0	3,372	20	3,372	16	2	2	3	1,512	61
2014	3,896	0	0	3,896	21	3,896	24	5	5	2	1,445	99
2015	4,242	0	0	4,242	17	4,242	44	12	12	1	1,242	92
2016	3,020	0	0	3,020	58	36	18	0	0	1	1,173	105
2017	2,896	2,896	0	9	31	20	49	31	31	38	1,068	48
2018	2,719	0	2,719	15	113	19	173	112	112	166	1,011	30
2019	2,015	0	2,015	2	0	1	38	0	0	0	1,572	62
All Years	22,160	2,896	4,734	14,556	260	11,586	362	162	162	211	9,023	497
Percentage of Blank or Unknown Rows												
2013	3,372	0.0%	0.0%	100.0%	0.6%	100.0%	0.5%	0.1%	0.1%	0.1%	1,512	4.0%
2014	3,896	0.0%	0.0%	100.0%	0.5%	100.0%	0.6%	0.1%	0.1%	0.1%	1,445	6.9%
2015	4,242	0.0%	0.0%	100.0%	0.4%	100.0%	1.0%	0.3%	0.3%	0.0%	1,242	7.4%
2016	3,020	0.0%	0.0%	100.0%	1.9%	1.2%	0.6%	0.0%	0.0%	0.0%	1,173	9.0%
2017	2,896	100.0%	0.0%	0.3%	1.1%	0.7%	1.7%	1.1%	1.1%	1.3%	1,068	4.5%
2018	2,719	0.0%	100.0%	0.6%	4.2%	0.7%	6.3%	4.1%	4.1%	5.3%	1,011	3.0%
2019	2,015	0.0%	100.0%	0.1%	0.0%	0.1%	1.9%	0.0%	0.0%	0.0%	1,572	3.9%
All Years	22,160	13.1%	21.4%	65.7%	1.2%	52.3%	1.6%	0.7%	0.7%	0.9%	9,023	5.5%

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 SBPD data shows that required field values are sometimes missing or incorrect. The number of fields with problem values has been reduced starting in 2017. Missing or unknown values for driver age and gender have been the most common. By 2019, however, there was no missing data for most fields.

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

Table A.3b. Stops With at Least One Missing/Unknown Data Value

Stop Years	Total Stops	Stops Missing Value(s)	% of Stops Missing Value(s)
2013	3,372	3,372	100.0%
2014	3,896	3,896	100.0%
2015	4,242	4,242	100.0%
2016	3,020	3,020	100.0%
2017	2,896	80	2.8%
2018	2,719	193	7.1%
2019	2,015	41	2.0%
All Years	22,160	14,844	67.0%

Note: These data exclude those rows missing date/time of stop.

Table A.3c reports data on missing or unknown values by race. We would expect data to be missing at the same rates across racial groups. It is concerning therefore that stop reason is missing at almost double the rates for Black and Hispanic drivers, compared to white drivers.

Table A.3c. Missing or Unknown Values and Race of Driver

	White	Black	Asian	Hispanic	Unknown
Count of Blank or Unknown Rows					
Total Stops (excl. EGS)	19,808	1,178	716	185	260
Unknown Stop Reason	190	23	7	4	138
Unknown Stop Outcome	14	1	1	0	195
Unknown if Search occurred	22	1	3	0	136
Unknown if Contraband found subsequent to a search	0	0	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	1.0%	1.9%	1.0%	2.2%	53.1%
Unknown Stop Outcome as % of all outcomes	0.1%	0.1%	0.1%	0.0%	60.6%
Unknown if Search occurred as % of all stops	0.1%	0.1%	0.4%	0.0%	52.3%
Unknown if Contraband found as % of all searches	0.0%	0.0%	0.0%	0.0%	0.0%
Unknown Outcome if contraband found as % of all searches	0.6%	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 South Burlington for all years except 2017, the Stop IDs were directly usable to tie together multiple outcomes for stops. In 2017, no Stop IDs were provided at all. However, the dates, times and other fields were available to derive Stop IDs for that year (Table A.3d).

Table A.3d. South Burlington Stop IDs

Year	Usable Stop ID	Could Derive Stop IDs	Stop Count	Row Count
2013	Yes		3,393	3,445
2014	Yes		3,912	3,918
2015	Yes		4,272	4,281
2016	Yes		3,037	3,105
2017	No	Yes	2,920	2,971
2018	Yes		2,748	3,197
2019	Yes		2,024	2,060

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

* Does not appear in all reports