Trends in Racial Disparities in Traffic Stops: Burlington, Vermont 2012-19

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EXECUTIVE SUMMARY

This study of Burlington traffic stops forms part of a statewide report of Vermont traffic stop data for 2012-2019. In each study of individual law enforcement agencies, we examine the data for racial disparities in several areas: racial share of stops, tickets vs. warnings, reasons for stops, arrest rates, search rates, and contraband "hit" rates. We also examine trends to determine whether racial disparities change over time. Finally, we comment on the completeness and quality of the data collected by the Burlington Police Department (BDP).

Our main findings are that during this period of time in Burlington:

- The Black share of drivers stopped exceeds their share of the estimated driving population. The data indicate Black drivers were overstopped by between 28% to 59%, depending on the measure of the driving population used. The shares of stops of all other racial groups were at or below their share of the driving population.
- Black drivers were ticketed at a higher rate than white drivers, and are also more likely to be given multiple tickets per stop. Hispanic drivers were also more likely to receive a ticket than white drivers (and thus less likely to receive a warning).
- The arrest rate of Black drivers was roughly 69% greater than that of white drivers during the entire period. Over the period 2017-2019, though, the arrest rate of Black drivers was 366% that of white drivers.
- Black drivers were significantly more likely to experience an investigatory stop compared to white drivers.
- Black drivers were about 3.8 times more likely to be searched subsequent to a stop than white drivers and Hispanic drivers were searched at a rate that is 2.5 times greater than that of white drivers. Asian drivers were less likely to be searched than white drivers.
- Black, Hispanic, and Asian drivers were less likely to be found with contraband than white drivers when we consider all outcomes of a stop (warnings, tickets, arrests). Minority-white differences in hit rates are not statistically significant, but are nevertheless noteworthy, especially given the higher search rates of Black and Hispanic drivers. In our more sophisticated logit analysis, however, the lower Black odds of being found with contraband relative to whites is statistically significant.

With regard to trends over time:

- Trend analysis shows that the share of stopped drivers who are Black has risen over time, exceeding estimates of their share of the driving population.
- The Black/white arrest rate differential and the Black/white search rate differential have worsened considerably.
- The racial disparities in the hit rate have decreased.
- There has been a steady decline in the annual number of traffic stops over time, with the total number of stops falling 64.8% from 2012 to 2019. The decline in

stops of white drivers, however, was greater (67%) than the stops of Black drivers (54%), Asian drivers (50%), and Hispanic drivers (53%).

- We estimate that by 2019, white drivers were stopped at a rate of 489 per 10,000 white residents, compared to 959 Blacks per 10,000 Black residents.

Regarding data quality, our main findings are:

- Data quality is poor, with a continued high rate of missing data. In fact, in 2019, the quantity of missing data for a number of critical categories (e.g., race of driver, gender, stop outcome) is greater than in 2012. Looking at the entire dataset, 13.4% of stops had at least one missing value over the entire time period but that increased to 14.7% in 2019. Particularly problematic is that the race of driver was omitted in 3.8% of all traffic stop reports in 2019. And yet race is the central focus of traffic data analysis and legally required.
- Burlington Police Department's data quality is notably worse than a number of other Vermont law enforcement agencies, some of which have reduced missing race data to 0%. BPD is encouraged to follow the practice of agencies such as Vermont State Police, which has conducted in-depth training of its troopers on traffic stop data collection, virtually eliminating missing data.

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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 Burlington, Vermont for 2012-2019. Burlington Police Department (BPD) collected data on 35,979 traffic stops during this period of time.

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

The law requires that the following traffic stop data be collected and made available to the public: race, age, and gender of driver; reason for stop; type of search, if any; evidence found during the search, if any; and the outcome of stop. In Vermont, driver's licenses do not include race/ethnicity of the driver. The race of driver indicated in traffic stop reports 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]

In the next section, we provide an overview of the data, identify methodological issues of relevance to our analysis, and assess the quality of BPD data. We report descriptive data on key indicators in Section III of this report, and we discuss results of the hit rate test as well.

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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 numbers would improve the ability to assess the degree, if any, of racial disparities in traffic policing.

In Section IV, we assess trends over time in racial disparities, using 3-year trends (2012-2014, 2013-15, etc.), instead of year by year in order to expand the sample size. In Section V, we conduct a logit analysis to determine the probability of a search and of finding contraband, based on a variety of factors (such as age, gender, and reason for the stop) in addition to the race of the driver. This analysis helps us to control for the context of the stop, thereby better isolating the role of race of driver in a search or finding of contraband. Section VI concludes and in the appendix we provide supplemental data and data that underlie our 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 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

[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

more reason for concern. We conduct a similar analysis of the probability of contraband being found in a search (Section V).

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 the names of all racial groups should be capitalized. We capitalize black but not white, as proposed by the *Columbia Journal Review*.[5] We made these decisions, not because we believe our approach is "right" but rather to note how fluid and rapidly changing race language can be, and to underscore that we are aware of the complexities of race language in the U.S.

II. Data Overview, Methodology, and Data Quality

The data in Table 1 provide an overview of the traffic stop data generated by the Burlington Police Department (BDP) from 2012-19.[6] As can be seen, a total of 35,979 stops were made. A little less than a quarter of these stops resulted in the issuance of a citation.

Our focus is primarily on 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 stop is not initiated by the officer. In the case of Burlington, 3.1% or 1,125 of all stops were externally generated. These exclusions reduce our sample size to 34,854 traffic stops. The percentage of these stops that resulted in an arrest for violation[7] was 0.9%, while 1.4% of stopped vehicles were searched. Contraband was found in 1.0% of all stops, and in 69.6% of all searches.

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

[6] It should be noted that 2012-15 data for Burlington is the data used in Seguino and Brooks (2017), obtained from Burlington Police Department in 2016. Data for 2016-18 was obtained from the Crime Research Group website, which hosts traffic stop data for the state. And 2019 data was obtained directly from BPD.

[7] We exclude arrests for warrant since we are focusing on officer discretion. There were a total of 4 arrests on warrant.

Table 1. Overview of Data

	Observations	Rates
Total Stops		
incl. EGS	35,979	
excl. EGS	34,854	
2012	5,557	
2013	4,753	
2014	5,633	
2015	5,181	
2016	5,551	
2017	3,475	
2018	2,698	
2019	2,006	
Citations	8,277	23.7%
Arrests	311	0.9%
Searches	503	1.4%
Contraband	350	1.0%
Contraband as % of Searches	350	69.6%

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

A challenging problem in the data, not only for Burlington but other agencies as well, is that more than one row in the raw data appeared to refer to the same stop in a number of cases. This typically occurs if there is more than one outcome to a stop. For example, the 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 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, however, we report data on 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 for that group. In the case of Burlington, over the time period of this study 2012-2019, only 19 drivers were identified by officers as Native American.

Appendix Tables A.1 and A.3a-A.3c detail information on missing data. The race of the driver was omitted in 5.1% of all traffic stop reports from 2012 to 2019.[8] This is a serious problem given that race of driver is the key factor motivating traffic stop data collection. (We must drop the stops for which race of driver is missing from our analysis, thus reducing

[8] This excludes externally generated stops.

the sample size and reliability of our analysis if officers are more likely to code nonwhite drivers as unknown race or leave the race field empty). Race was also missing in almost 10% of BPD accident reports. Of much concern is that data quality has worsened over time. For example, while the reason for a stop was missing in 2.8% of all rows of data in 2012, by 2019, that was up to 12.3% (in 2016, reason for a stop was missing in 20.2% of rows of data). Appendix A.4 provides a list of all variables in this report with information on how they are measured.

III. Descriptive Data Analysis of Traffic Stops

A. Racial Shares of Traffic Stops

A straightforward method for identifying racial disparities in traffic stops is to compare the racial shares of traffic stops with estimates of the racial share of the driving population. We use that method here. In theory, we would expect that each racial group's share of stops is roughly equal to their share of the driving population, absent any known systematic differences in driving behavior by race/ethnicity. One of the challenges is how to measure racial shares of the driving population, known as the "benchmarking problem." In other words, against what benchmark do we measure the racial shares of the drivers stopped to determine whether racial groups are overstopped or understopped?

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

Two alternative benchmarks, therefore, are typically used to estimate racial disparities in traffic stops. One relies on the U.S. Census Bureau's estimate of racial shares of the population 15 years and older, using the American Community Survey (ACS) for 2013-17. This benchmark is not without its faults. Not everyone over 15 drives a vehicle and not everyone drives with the same degree of frequency. For example, on average, whites drive more than Blacks and Hispanics, a phenomenon related to income and wealth inequality by race (Tal and Handy 2005).[9] 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

[9] 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.

reported to the Department of Motor Vehicles (DMV). This approach has emerged as an alternative method to determine an appropriate benchmark against which to compare racial shares of stops. 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 racial groups in Vermont.[10] The failure of BPD officers to report race in about 10% of accidents also impacts the reliability of this benchmark.

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 rely on for traffic stops and so we can calculate the Hispanic share of drivers using that metric.

White drivers in Burlington comprised 86.7% of all stopped drivers from 2012 through 2019, with Blacks 8.4%, Asians 4.3% and Hispanics 0.7% of all drivers stopped. Inclusion of externally generated stops does not markedly 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 5.3% to 6.5%, lower than their share of stopped drivers.

[10] 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

All Years	White	Black	Asian	Hispanic
Racial Shares of Stops				
Including externally generated stops	86.7%	8.4%	4.3%	0.7%
Excluding externally generated stops	86.6%	8.3%	4.3%	0.7%
Driver Percentage (ACS)	87.9%	5.3%	6.8%	
Driver Percentage (DMV Accident data)	87.1%	6.5%	5.3%	0.8%
Disparity Index (using ACS)	0.99	1.59	0.63	
Disparity Index (using DMV Accident data)	1.00	1.28	0.81	0.87
Stop Reason as % of All Stops				
Safety Stops	52.2%	51.5%	57.9%	56.8%
Moving Violation	51.8%	51.0%	57.3%	56.4%
Suspicion of DWI	0.4%	0.5%	0.6%	0.4%
Investigatory/Pretextual Stops	37.0%	36.7%	32.4%	40.7%
Investigatory Stops	0.7%	1.6%	0.6%	0.9%
Vehicle Equipment	36.3%	35.1%	31.8%	39.8%
Externally Generated Stops	3.2%	3.2%	2.8%	2.1%
Multiple Reasons	0.5%	0.8%	0.6%	
Unknown Reason	7.2%	7.9%	6.3%	0.4%
Outcome Rates as a % of All Stops				
Warning Rate	74.9%	69.2%	75.3%	70.6%
Ticket Rate	23.6%	29.8%	22.8%	33.3%
Arrest for Violation Rate	0.9%	1.5%	0.9%	0.9%
Arrest for Warrant Rate	0.1%	0.1%	0.0%	0.0%
No Action Rate	0.1%	0.1%	0.0%	0.0%
Search Rates				
Search rate (excl. searches on warrant)	1.1%	4.2%	0.4%	2.6%
Search rate (incl. searches on warrant)	1.2%	4.3%	0.5%	2.6%
Hit rates (as a % of PC, RS & Warrant Searches)				
Hit rates (incl. all outcomes)	72.2%	65.3%	57.1%	50.0%
Hit rates (excl. warnings as outcomes)	41.5%	45.8%	57.1%	50.0%
Hit rates (outcome = arrest)	10.1%	10.2%	28.6%	16.7%

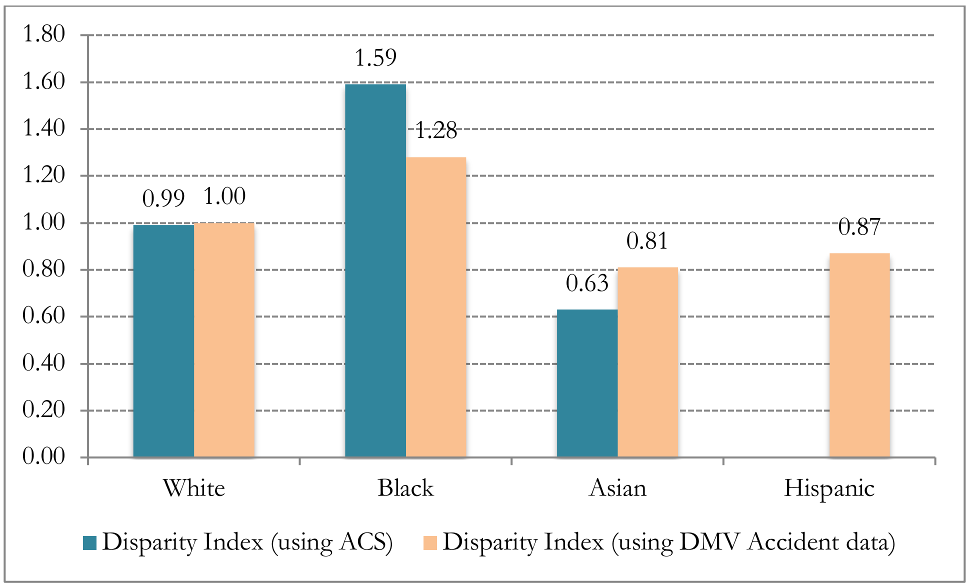
Note: ACS refers to the American Community Survey. NA is "not applicable." U.S. Census Bureau data record Hispanics as an ethnicity, not race. Hispanics may be white or non-white. In contrast, Vermont law enforcement agencies treat the category of Hispanics as a mutually exclusive racial category. We 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.

The Disparity Index (DI) is used as a way to compare racial shares of stops and driving population across groups (Table 2 and Figure 1). The DI is simply the ratio of the racial share of stopped drivers divided by the racial share of the driving population. A DI that is greater than 1 indicates a group is overstopped relative to what would be expected, given its share of the driving population, and a ratio of less than 1 indicates a group is understopped. For Blacks in Burlington during this time period, that ratio ranges from 1.28 to (8.4%/6.5%)

using the DMV accident data to 1.59 (8.4%/5.3%) using ACS data. This implies the share of drivers stopped who are perceived to be Black exceeds their share of the driving population by between 28% and 59%. All other groups have a DI that is at or below 1, meaning they are stopped at a rate equal to or less than their estimated share of the driving population.

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 than their population share. The authors use the local population as a benchmark, and thus their results are most comparable to our ACS stop disparity estimates. As can be seen, racial disparities in Burlington traffic stops using ACS data are about the same as the estimated differential at the national level.

Figure 1. Disparity Indices of Racial Shares of Stops: Burlington, 2012-19



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

B. Reasons for Stops

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 making the stop). Table 2 shows the distribution of reasons for stops by race. The most common reason motorists in Burlington are pulled over is for moving violations (such as speeding), regardless of race of the driver. The second most common reason is vehicle equipment (such as a faulty taillight). Other reasons for stops are far less common.

Following Baumgartner, *et al* (2018), we categorize stops into two groups: *safety stops* and *investigatory/pretextual stops*. Safety stops have a clear purpose of promoting public safety. These include stops due to moving violation or suspicion of DWI. Pretextual stops (whose reasons are investigatory or vehicle equipment), legal under U.S. law, involve an officer stopping a driver for a traffic violation, minor or otherwise, to allow the 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. The percentage of these stops is slightly lower for Black drivers (36.7% compared to 37.0% for white drivers). This difference is very small and not statistically significant. However, the Black share of stops that are "investigatory" is more than double that of the white share of stops (1.6%) compared to 0.7% and that difference is statistically significant (z=5.13). Such stops are due to suspicion, making them more susceptible to racial bias. The Hispanic share of stops that are investigatory/pretextual is higher than the white share, and this is due to the relatively higher share of Hispanic stops for which the reason is vehicle equipment. The difference, however, is not statistically significant. The Asian share of stops that are "investigatory" is lower than of whites, but that difference is not statistically significant.

C. Post-Stop Outcomes

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

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

Table 2 reports 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 1 indicates the minority group is more likely to experience a particular outcome than white drivers, and a ratio of less than 1 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	0.92	1.01	0.94
Ticket rate	1.26	0.97	1.41
Arrest rate	1.69	0.99	1.01
Search Rate	3.93	0.41	2.45

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

Black drivers are 8% less likely to be given a warning than white drivers. This also holds for Hispanic drivers who are 6% less likely than whites to receive a warning. Asian drivers are slightly more likely than white drivers to receive a warning, although the disparity is much smaller (1%). In contrast, Black and Hispanic drivers are 26% and 41%, respectively, more likely to receive a citation than white drivers, and Asian drivers are slightly less likely to receive a citation. As noted above, 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 in addition to Black drivers being more likely to be issued a citation in Burlington, they are also more likely to be issued more than one citation per stop. Specifically, during the time period of this study, 3.6% of white drivers were given more than one citation compared to 5.4% of Black drivers. This difference is statistically significant ($z=4.87$).

Black drivers are 69% more likely to be arrested in Burlington than white drivers. Asian and Hispanic arrest rates are equal to white arrest rates.

Search rate data used for Table 3 exclude searches based on a warrant.[11] Black drivers are searched at a rate that is almost 4 times greater than that of white drivers, and the difference in Black and white search rates is very statistically significant (z=13.75). In contrast, Asians are about 40% less likely to be searched than a white driver, with only 7 Asian drivers searched from 2012 to 2019. The Hispanic/white search rate ratio is 2.45, signifying Hispanic drivers are searched at a rate that is more than twice the rate of white drivers in Burlington. Again, we caution that the small number of Asian and Hispanic searches requires us to view the search rates with some caution.

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. For example, Pierson, *et al* (2020) report national-level data on nearly 100 million US traffic stops, finding that Black drivers are searched at more than twice the rate of white drivers.[12] 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 drivers. The ratio of Black to white search rates in North Carolina was roughly 2 to 1. The Black/white search rate disparity in Burlington almost twice as large as the national-level and North Carolina disparities, however.

Why might we observe racial differences in search rates? Search rate disparities may be justified if some groups (in this case, Blacks) are more likely to be carrying contraband than white drivers. Police may search vehicles, for example, in an attempt to interdict drugs (a reason that numerous 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 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.[13] 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 is consistent with the argument that 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.

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[11] 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 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.
[12] Pierson, *et al* (2020) do not report racial differences in arrest rates.
[13] Note that firearms for those 21 and over are not necessarily contraband in Vermont, but for those under 21, firearms would be considered contraband.

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

In conducting the hit rate test, we focus on white and Black drivers. The number of searches of Asian and Hispanic drivers is small, preventing a reliable hit rate comparison of these groups to white drivers. In searches that result in any outcome, the hit rate for white drivers is 72.2% compared to 65.3% for Black drivers, but this difference is not statistically significant (Table 2). The Black hit rate for searches that result in a ticket and/or arrest only is slightly higher than the corresponding white rate (45.8% compared to 41.5%), but this difference is also not statistically significant. The Black and white hit rates for arrests only are roughly equal. We caution that the number of searches resulting in an arrest upon discovery of contraband is very small, making comparisons less reliable in this case. This form of the hit rate test is not conclusive, although we return to this issue in Section V where we conduct a more statistically sophisticated logit analysis. In that analysis, we find that the odds of finding contraband in a search of the vehicle of a Black driver are lower than of finding contraband in the search of the vehicle of a white driver, and that difference is statistically significant.

IV. Trends Over Time

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

First, we examine trends in the number of stops per year in total and by race (for raw data, see Table A.2b). From 2012 to 2019 the total number of stops decreased by about 64.8% although the decrease was larger for white drivers than all other racial/ethnic groups. Stops of white drivers fell 67%, compared to 54% for Black drivers, 50% for Asian drivers, and 53% for Hispanic drivers.

For 2019, we estimate that white drivers were stopped at a rate of 489 per 10,000 white residents[14] compared to 1,443 in 2012. For Black drivers, the rate in 2012 was 2,013 per 10,000 Black residents, falling to 959 in 2019. In all years, the Asian stop rate per 10,000 residents is lower than the white rate, but the gap is narrowing. For example, in 2012, the Asian stop rate was 796, falling to 404 in 2019 (Figure 2).

[14] 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 rates of Black and Asian drivers are their stop numbers divided by the number of Black and Asian residents of Burlington 15 and older, all multiplied by 10,000.

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

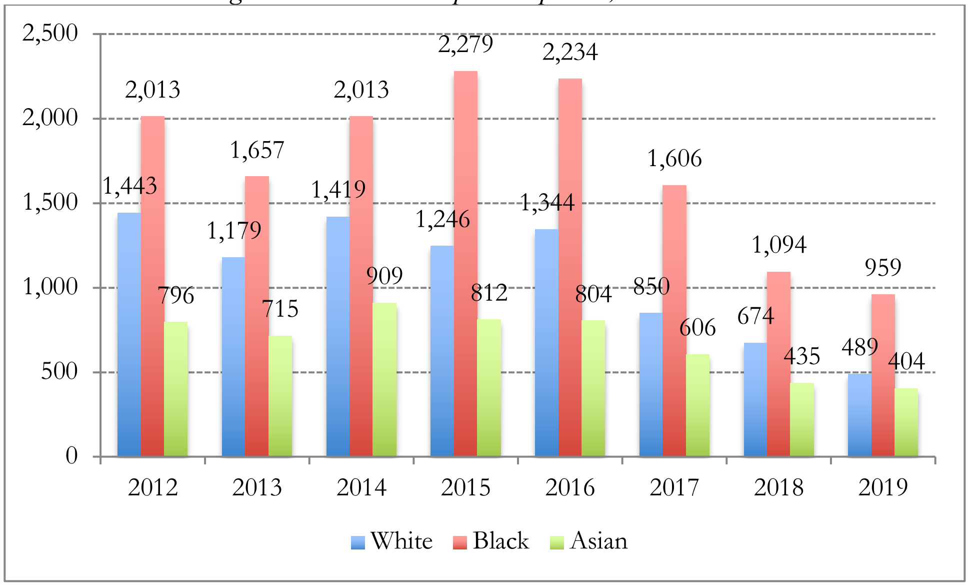
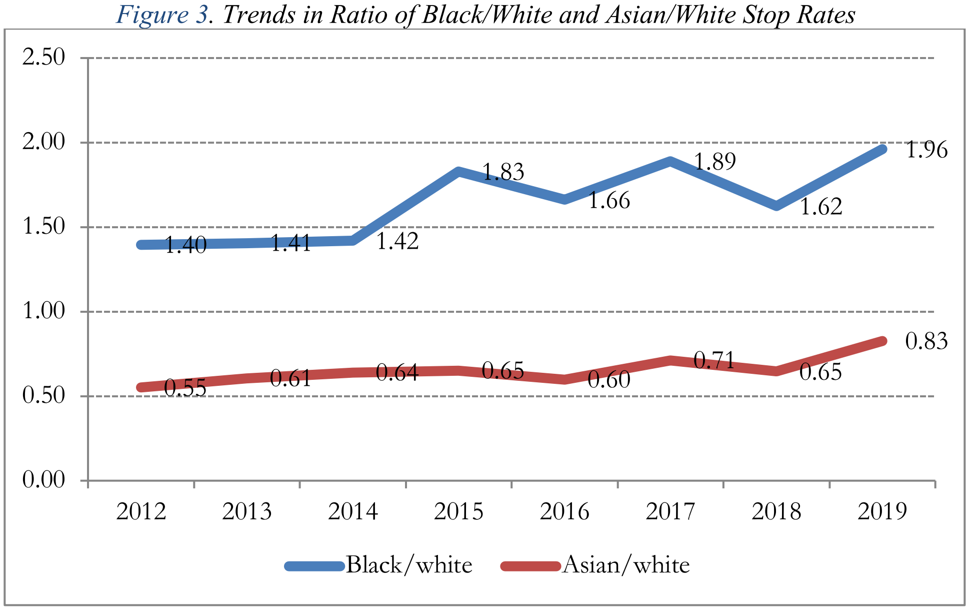


Figure 3 plots the ratio of Black to white stop rates and Asian to white stop rates. The Black-white ratio has risen over time from 1.4 in 2012 to 1.96 in 2019. This means that by 2019, the Black stop rate was almost double the white stop rate. The Asian to white stop rate has also risen, although the Asian stop rate, which was about half that of white drivers in 2012 and is now just 83% of the white stop rate, is in each year lower than the white rate.

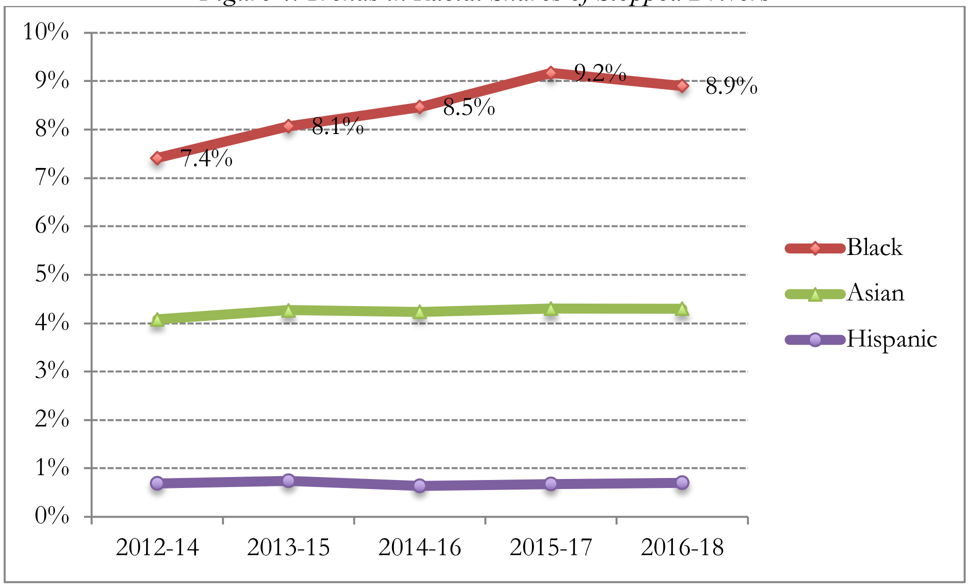
Figure 3. Trends in Ratio of Black/White and Asian/White Stop Rates



Secondly, we present data on trends in stop shares, 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 2012-14, 2013-15, etc. (See Table A.2a. for the raw numbers on which the following figures are based).

Figure 4 portrays trends in the share of stops of Black, Asian, and Hispanic drivers. It is noteworthy that the Black share of stopped drivers has risen by about 20% percent over this time period, while the Asian and Hispanic shares have remained relatively constant.

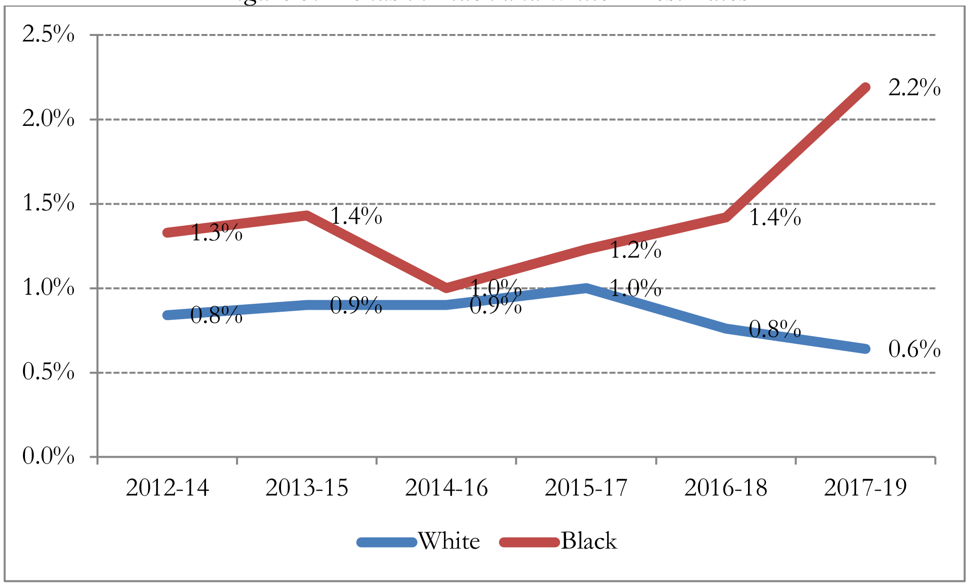
Figure 4. Trends in Racial Shares of Stopped Drivers



In all years, the Black arrest rate exceeds the white rate (Figure 5). Asian and Hispanic arrest rates are omitted due to small sample sizes. The Black-white gap had narrowed by 2014-16, but since that time, has continued to widen such that by 2017-19, the gap is more than double what it was in 2012-14. Using data from just 2017-2019, we find the Black/white arrest disparity has increased to 3.7 and is statistically significant (z=4.47).[15] This implies that in 2017-19 time period, Black drivers were more than 3 and a half times more likely to be arrested during a traffic stop than white drivers.

[15] This is similar to the differential found by BPD for all arrests (Lowe and Stetson 2020).

Figure 5. Trends in Black and White Arrest Rates



Racial trends in search rates are shown in Figure 6. Asian and Hispanic arrest rate numbers are omitted due to small sample sizes. While search rates of white drivers have remained relatively constant from 2012 to 2019, the Black search rate over that period of time increased, rising to 5.1% in 2017-19.

Figure 6. Black and White Search Rate Trends

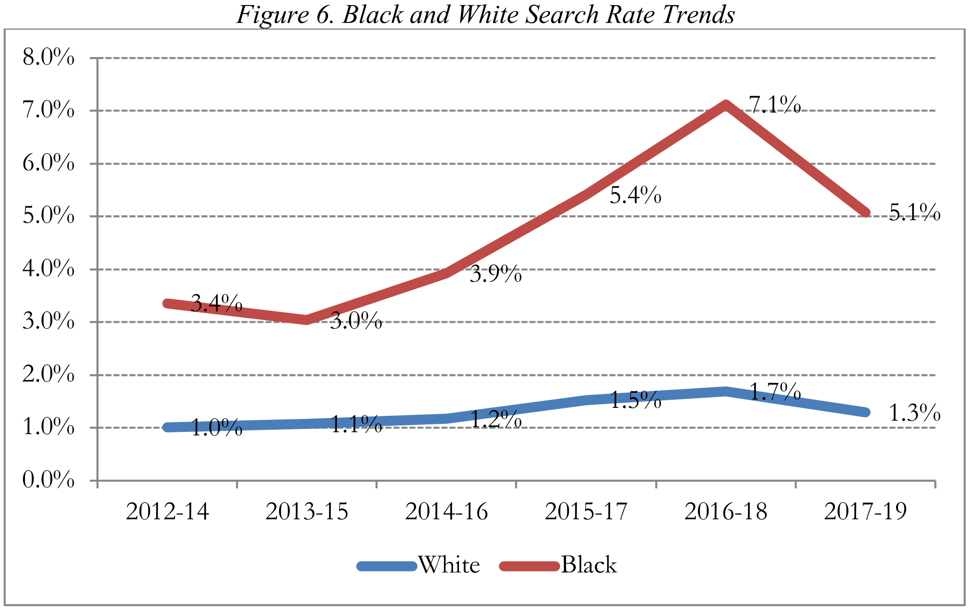
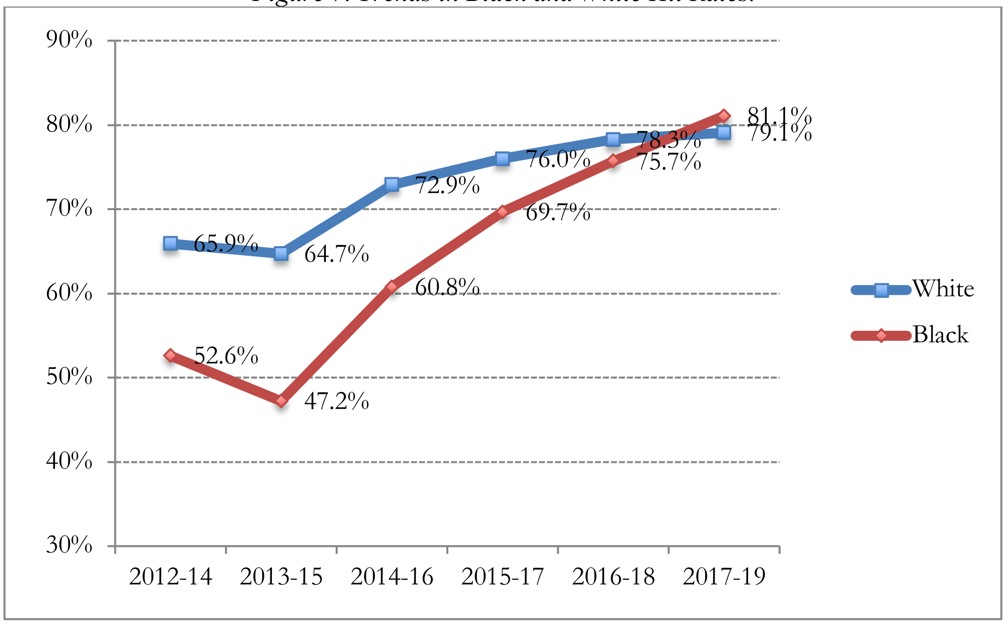


Figure 7 shows trends in white and Black contraband hit rates. The white hit rate was higher than the Black rate in 5 out of 6 of the time periods for which we have data. By 2017-19, the gap has narrowed considerably and the 2017-19 disparity is not statistically significant. (Asian and Hispanic hit rates are not shown due to small sample sizes).

Figure 7. Trends in Black and White Hit Rates.



V. Logit Analysis

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

A. The 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:

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

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

The coefficient on *Male* indicates the odds a male driver will be searched as compared to the odds a female driver will be searched. We include a control for the driver's age, measured in years, as an explanatory variable. We also control for time of day, with the excluded category the afternoon. The coefficients on days of the week indicate the odds of being searched on those days as compared to Fridays. Controlling for all of these factors allows us to interpret the race variable, net of the impact of these other control variables.

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

Results are shown in Table 4. Of primary interest is whether the race variables are statistically significant (as designated by the asterisks). If they are, this implies that independent of any other factors that may lead to an officer's decision to search a vehicle, race influenced the officer's decision to initiate a search.

We report results on three variations of our basic model. We start with a basic model (Model 1 in Table 4), in which race of the driver is our only explanatory variable. The results show that, compared to Black drivers are 3.671 times more likely to be searched. (This represents the ratio of the odds of a Black driver being search compared to the odds of a white driver being searched). Hispanic drivers are 2.172 times more likely to be searched. In contrast, Asian drivers are less than half as likely to be searched as white drivers. In all cases, these odds ratios are statistically significant. The number of Native American drivers was very small and so was omitted.

In Model 2, adding controls for gender, age of driver, time of day, day of week, and reason for stop, we find that the odds of a male driver being searched are 1.924 times greater than the odds a female driver will be searched. The odds ratio on age indicates a lower probability of being searched, the older the driver. The probability of a search is lower in the morning than in the afternoon. The odds of an evening search are greater than in the afternoon. None of the coefficients on days of the week are statistically significant.

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

VARIABLES	(1) Race only	(2) With all controls and stop reason	(3) With all controls and pretextual stop control
Black	3.671***	3.093***	3.227***
	(0.399)	(0.359)	(0.370)
Asian	0.410**	0.388**	0.395**
	(0.157)	(0.149)	(0.152)
Hispanic	2.172*	2.052*	2.083*
	(0.906)	(0.869)	(0.876)
Male		1.924***	1.959***
		(0.226)	(0.230)
Age		0.957***	0.957***
		(0.005)	(0.005)
Morning		0.431***	0.421***
		(0.0868)	(0.0846)
Night		1.285**	1.284**
		(0.141)	(0.140)
Saturday		0.767	0.765
		(0.128)	(0.127)
Sunday		0.753	0.744
		(0.137)	(0.135)
Monday		0.806	0.804
		(0.142)	(0.141)
Tuesday		0.891	0.877
		(0.157)	(0.153)
Wednesday		0.850	0.829
		(0.149)	(0.145)
Thursday		0.913	0.902
		(0.153)	(0.151)
Investigatory stop		7.385***	
		(1.656)	
Multiple stop reasons		2.506**	
		(1.068)	
Suspicion of DWI		2.096	
		(1.090)	
Unknown stop reason		0.729	
		(0.238)	
Vehicle equipment		1.014	
		(0.107)	
Pretextual stop			1.133
			(0.111)
Constant	0.012***	0.017***	0.017***
	(0.001)	(0.005)	(0.005)
No. of observations	32,818	31,220	31,220

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

The odds of an investigatory stop leading to a search are 7.385 times the odds for a stop initiated due to a moving violation. The odds ratio of a search when multiple stop reasons are listed is more than double the odds when a stop is due to moving violation. All other reasons for a search as compared to a stop based on a moving violation are not statistically significant.

The odds a Black driver will be searched in this model, after controlling for other factors, are 3.093 relative to the odds of a white driver being searched. That is, even controlling for other factors, the odds a Black driver will be searched in Burlington are 3 times the odds a white driver will be searched. The coefficient continues to be statistically significant at the one percent level. That is, we can reject the null hypothesis that there is no difference in search rates between Black and white drivers with a high degree of certainty.

In Model 3, we include two categories of *Reason for Stop*—safety stops (the omitted variable) and pretextual stops. The results indicate that when the reason for the stop is pretextual, drivers are slightly more likely to be searched than if the reason is a safety stop, but this odds ratio is not statistically significant. The odds a Black driver will be searched in this model are 3.227 times the white odds.

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. The use of more rigorous statistical techniques does not in any meaningful way change the nature of the descriptive data findings.

B. The Probability of Finding Contraband

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

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

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 was a warning, a citation, or an arrest) for all years for which we have data. The results shown for Model 1, where the only explanatory variable is race of the driver, indicate that the odds of a search of a Black driver yielding contraband are about 25% less than the odds a white driver will be found with contraband subsequent to a search. The difference is not statistically significant, however. The odds Asian and Hispanic drivers are found with contraband are also lower than the white odds, but neither of these odds ratios is 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 72.2% of searched white drivers are found with contraband and thus, 27.8% are not found with contraband. This implies an odds ratio for white drivers of 72.2/27.8= 2.60. In other words, the odds are roughly 2.6 to 1 that a search of a white driver will yield contraband. For Black drivers, we report in Table 2 that 65.3% of them are found with contraband so their odds ratio is 65.3/34.7=1.88. The ratio of these two odds is the coefficient in our regression (1.88/2.60 =0.723), very close to the coefficient estimate on race when we formally run the logit regression.

The addition of controls in Model 2 reduces the odds ratio of finding contraband in searches of Black as compared to white drivers to 0.621 and this odds ratio is statistically significant. That is, the odds of finding contraband in a search of a Black driver is about one third less than the white odds after controlling for other relevant variables. In Model 3, we obtain similar results on the Black to white odds of contraband being found as in Model 2, but here, pretextual stops are shown to result in a lower probability of finding contraband than if the reason for the stop is for safety reasons. That odds ratio is, however, not statistically significant.[16]

To sum up the results of the logistic regressions, the race of the driver influences the odds of a search and of finding contraband. Adding controls for a variety of contextual factors has little effect on racial disparities in the probability of being searched and of contraband being found during a search. This is not to say that the controls were not meaningful or significant. Searches are more likely to happen under some conditions as compared to others (e.g., during investigatory stops as compared to 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 drivers are less likely to be found with contraband, a finding that is consistent with oversearching of that group of drivers. As noted above in our trend analysis, despite these overall findings of significant oversearching, we are heartened by the decline in the racial gap in the odds of contraband being found over time.

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

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

VARIABLES	(1) Race only	(2) With all controls and stop reason	(3) All controls using pretextual stop control
Black	0.724	0.621*	0.617*
	(0.165)	(0.157)	(0.155)
Asian	0.514	0.437	0.426
	(0.397)	(0.349)	(0.339)
Hispanic	0.386	0.305	0.296
	(0.318)	(0.265)	(0.256)
Male		1.719**	1.652*
		(0.453)	(0.430)
Age		0.983	0.984
		(0.0111)	(0.0110)
Morning		0.873	0.895
		(0.377)	(0.385)
Night		1.110	1.095
		(0.277)	(0.271)
Saturday		0.857	0.878
		(0.305)	(0.309)
Sunday		1.608	1.570
		(0.672)	(0.653)
Monday		1.432	1.381
		(0.560)	(0.537)
Tuesday		1.262	1.246
		(0.491)	(0.481)
Wednesday		1.550	1.531
		(0.618)	(0.608)
Thursday		0.735	0.748
		(0.260)	(0.264)
Investigatory stop		0.873	
		(0.390)	
Multiple stop reasons		2.413	
		(2.697)	
Suspicion of DWI		0.350	
		(0.359)	
Unknown stop reason		2.053	
		(1.698)	
Vehicle equipment		0.840	
		(0.198)	
Pretextual stop			0.926
			(0.203)
Constant	2.594***	1.480	1.554
	(0.312)	(0.970)	(1.008)
No. of observations	476	431	431

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

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 traffic stops in Burlington. We find that race of driver influences traffic policing for, net of other factors. Black drivers' share of stops exceeds their estimated share of the driving population by between 28% to 59%. In contrast, white, Asian, and Hispanic shares of stopped drivers are lower than would be expected, given their estimated shares of the driving population. Black arrest rates are also disproportionately high as compared to white arrest rates, and the Black-white differences has widened, such that by 2017-19, the arrest rate of Black drivers was 366% of the white rate. Put differently, Black drivers in Burlington are more than 3 ½ times more likely to be arrested subsequent to a stop than white drivers.

Black drivers continue to have higher search rates than white drivers, and that disparity has risen since 2012-15 when the Black/white ratio of search rates was 3.32, rising to 3.93 in 2017-19.

Over time, there has been a decline in the number of traffic stops in Burlington. The decline in stops of white drivers was greater than the decline for all other racial groups. That said, the lower number of traffic stops has also coincided with a decline in the Black-white hit rate disparity.

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, and are less likely to be found with contraband. These results suggest that the race of the driver plays a role in officer decision-making in traffic policing in Burlington.

Of particular note is the poor quality of BPD's traffic stop data (as well as race in accident reports). In contrast to other agencies that have reduced the quantity of missing data, BPD even in 2019 has a large amount of missing or unknown values. Fully 12.9% of traffic stops are missing at least one value. The race of driver was missing in 3.8% of stops in 2019 and stop reason had an especially large amount of missing data in that year—12.3%. This is especially worrisome, since as we have noted, investigatory/pretextual stops are the type of stops that are influenced by officer suspicion rather than actual driving behavior, and as such are more prone to bias than safety stops.

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APPENDIX

Table A.1. Burlington Raw Traffic Stop Data, 2012-19

All Years	**White**	**Black**	**Asian**	**Hispanic**	**Native American**	**Unknown**	**Total**
Total Traffic Stops							
Including externally generated stops	29,588	2,851	1,451	236	19	1,834	35,979
Excluding externally generated stops	28,652	2,760	1,411	231	17	1,783	34,854
Reasons For Stops							
Safety Stops	15,449	1,468	840	134	8	710	18,609
Moving Violation	15,338	1,455	832	133	8	705	18,471
Suspicion of DWI	111	13	8	1	0	5	138
Investigatory/Pretextual Stops	10,933	1,045	470	96	8	398	12,950
Investigatory Stop	196	45	8	2	0	8	259
Vehicle Equipment	10,737	1,000	462	94	8	390	12,691
Externally Generated Stop	936	91	40	5	2	51	1,125
Multiple Reasons - Moving Violation & Suspicion of DWI	3	0	2	0	0	0	5
Multiple Reasons - Moving Violation & Vehicle Equipment	140	19	7	0	0	7	173
Multiple Reasons - Suspicion of DWI & Vehicle Equipment	5	3	0	0	0	0	8
Unknown Stop Reason	2,122	225	92	1	1	668	3,109
Outcomes							
Ticket	6,756	823	322	77	3	296	8,277
Warning	21,456	1,911	1,062	163	14	915	25,521
No Action Taken	23	2	0	0	0	11	36
Arrest for violation	247	40	12	2	0	10	311
Arrest for warrant	24	4	0	0	0	1	29
Searches							
Total Stops with No Search	28,106	2,619	1,392	225	17	1,697	34,056
No Search & Contraband & Arrest for violation	0	0	0	0	0	1	1
No Search & Contraband & No arrest	41	1	4	0	0	6	52
No Search (all others)	28,065	2,618	1,388	225	17	1,690	34,003
Total Stops with Unknown Search	201	23	12	0	0	59	295
Total Stops with Search	345	118	7	6	0	27	503
Search with Probable Cause (PC)	215	77	3	6	0	21	322
Stops with PC Searches, No contraband	45	24	1	3	0	6	79
Stops with PC Searches, Unknown contraband	0	0	0	0	0	0	0
Stops with PC Searches, Contraband	170	53	2	3	0	15	243
Outcomes of PC Search							
Stops with PC Searches, Contraband & Warning, No Action or Unknown	79	18	0	0	0	10	107
Stops with PC Searches, Contraband and Ticket	69	29	1	2	0	3	104
Stops with PC Searches, Contraband and Arrest	22	6	1	1	0	2	32
Search with Reasonable Suspicion (RS)	90	38	3	0	0	3	134
Stops with RS Searches, No contraband	39	16	2	0	0	1	58
Stops with RS Searches, Unknown contraband	0	0	0	0	0	0	0
Stops with RS Searches, Contraband	51	22	1	0	0	2	76
Outcomes of RS Search							
Stops with RS Searches, Contraband & Warning, No Action or Unknown	22	5	0	0	0	2	29
Stops with RS Searches, Contraband & Ticket	23	13	0	0	0	0	36
Stops with RS Searches, Contraband & Arrest	6	4	1	0	0	0	11
Search with Warrant	40	3	1	0	0	3	47
Stops with Warrant Searches, No contraband	12	1	0	0	0	3	16
Stops with Warrant Searches, Unknown contraband	0	0	0	0	0	0	0
Stops with Warrant Searches, Contraband	28	2	1	0	0	0	31
Outcomes of Warrant Search							
Stops with Warrant Searches, Contraband & Warning, No Action or Unknown	5	0	0	0	0	0	5
Stops with Warrant Searches, Contraband & Ticket	16	0	1	0	0	0	17
Stops with Warrant Searches, Contraband & Arrest	7	2	0	0	0	0	9

Table A.2a. 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							
2012-14	13,396	1,132	623	106	10	676	15,943
2013-15	12,743	1,185	627	109	15	888	15,567
2014-16	13,289	1,300	650	98	14	1,014	32,730
2015-17	11,403	1,219	572	90	7	916	28,414
2016-18	9,505	983	475	78	0	683	23,448
2017-19	6,671	729	372	65	0	342	16,358
Reasons For Stops (excl. externally generated stops and unknown reasons)							
Safety Stops							
2012-14	7,396	583	370	63	8	391	8,811
2013-15	7,088	640	388	63	6	541	8,726
2014-16	7,155	686	373	60	5	448	17,454
2015-17	5,992	660	330	50	0	308	14,680
2016-18	4,915	512	271	49	0	110	11,714
2017-19	3,631	409	232	39	0	29	8,680
2012-14 (% of stops)	57.0%	54.4%	61.5%	59.4%	80.0%	62.4%	57.3%
2013-15 (% of stops)	57.7%	56.2%	63.8%	58.3%	42.9%	65.1%	58.2%
2014-16 (% of stops)	58.8%	57.7%	62.0%	61.9%	38.5%	65.8%	59.2%
2015-17 (% of stops)	59.9%	60.9%	64.5%	56.2%	0.0%	66.2%	60.3%
2016-18 (% of stops)	61.5%	61.1%	66.1%	62.8%	0.0%	69.6%	61.8%
2017-19 (% of stops)	62.1%	64.0%	69.7%	60.0%	0.0%	76.3%	62.7%
Pretextual Stops							
2012-14	5,572	488	232	43	2	236	6,573
2013-15	5,196	498	220	45	8	290	6,257
2014-16	5,013	504	229	37	8	233	12,048
2015-17	4,016	424	182	39	6	157	9,648
2016-18	3,083	326	139	29	0	48	7,250
2017-19	2,214	230	101	26	0	9	5,160
2012-14 (% of stops)	43.0%	45.6%	38.5%	40.6%	20.0%	37.6%	42.7%
2013-15 (% of stops)	42.3%	43.8%	36.2%	41.7%	57.1%	34.9%	41.8%
2014-16 (% of stops)	41.2%	42.4%	38.0%	38.1%	61.5%	34.2%	40.8%
2015-17 (% of stops)	40.1%	39.1%	35.6%	43.8%	100.0%	33.8%	39.7%
2016-18 (% of stops)	38.6%	38.9%	33.9%	37.2%	0.0%	30.4%	38.2%
2017-19 (% of stops)	37.9%	36.0%	30.3%	40.0%	0.0%	23.7%	37.3%
Outcomes (excl. externally generated stops)							
Tickets (one or more)							
2012-14	3,448	347	141	27	3	187	4,153
2013-15	3,377	384	149	28	2	226	4,166
2014-16	3,408	418	170	31	2	192	8,442
2015-17	2,693	385	146	35	0	106	6,730
2016-18	1,923	264	108	34	0	30	4,718
2017-19	1,119	168	64	29	0	8	2,776
2012-14 (% of stops)	25.7%	30.7%	22.6%	25.5%	30.0%	27.7%	26.1%
2013-15 (% of stops)	26.5%	32.4%	23.8%	25.7%	13.3%	25.5%	26.8%
2014-16 (% of stops)	25.7%	32.2%	26.2%	31.6%	14.3%	18.9%	25.8%
2015-17 (% of stops)	23.6%	31.6%	25.5%	38.9%	0.0%	11.6%	23.7%
2016-18 (% of stops)	20.2%	26.9%	22.7%	43.6%	0.0%	4.4%	20.1%
2017-19 (% of stops)	16.8%	23.1%	17.2%	44.6%	0.0%	2.3%	17.0%
Arrests for Violation							
2012-14	113	15	6	0	0	5	139

2013-15	115	17	6	0	0	4	142
2014-16	119	13	7	1	0	4	288
2015-17	114	15	5	1	0	5	280
2016-18	72	14	4	1	0	3	188
2017-19	43	16	3	1	0	1	128
2012-14 (% of stops)	0.8%	1.3%	1.0%	0.0%	0.0%	0.7%	0.9%
2013-15 (% of stops)	0.9%	1.4%	1.0%	0.0%	0.0%	0.5%	0.9%
2014-16 (% of stops)	0.9%	1.0%	1.1%	1.0%	0.0%	0.4%	0.9%
2015-17 (% of stops)	1.0%	1.2%	0.9%	1.1%	0.0%	0.6%	1.0%
2016-18 (% of stops)	0.8%	1.4%	0.8%	1.3%	0.0%	0.4%	0.8%
2017-19 (% of stops)	0.6%	2.2%	0.8%	1.5%	0.0%	0.3%	0.8%
Searches (excl. externally generated stops)							
Searches (PC, RS or Warrant)							
2012-14	135	38	2	1	0	9	185
2013-15	136	36	2	2	0	9	185
2014-16	155	51	4	5	0	12	454
2015-17	175	66	5	5	0	16	534
2016-18	161	70	5	3	0	16	510
2017-19	86	37	1	0	0	6	260
2012-14 (% of Stops)	1.0%	3.4%	0.3%	0.9%	0.0%	1.3%	1.2%
2013-15 (% of Stops)	1.1%	3.0%	0.3%	1.8%	0.0%	1.0%	1.2%
2014-16 (% of Stops)	1.2%	3.9%	0.6%	5.1%	0.0%	1.2%	1.4%
2015-17 (% of Stops)	1.5%	5.4%	0.9%	5.6%	0.0%	1.8%	1.9%
2016-18 (% of Stops)	1.7%	7.1%	1.1%	3.9%	0.0%	2.3%	2.2%
2017-19 (% of Stops)	1.3%	5.1%	0.3%	0.0%	0.0%	1.8%	1.6%
Contraband (All Outcomes)							
2012-14	89	20	1	1	0	6	117
2013-15	88	17	1	0	0	5	111
2014-16	113	31	2	2	0	8	312
2015-17	133	46	3	2	0	10	388
2016-18	126	53	3	2	0	10	388
2017-19	68	30	1	0	0	3	204
2012-14 (% of Searches)	65.9%	52.6%	50.0%	100.0%	0.0%	66.7%	63.2%
2013-15 (% of Searches)	64.7%	47.2%	50.0%	0.0%	0.0%	55.6%	60.0%
2014-16 (% of Searches)	72.9%	60.8%	50.0%	40.0%	0.0%	66.7%	68.7%
2015-17 (% of Searches)	76.0%	69.7%	60.0%	40.0%	0.0%	62.5%	72.7%
2016-18 (% of Searches)	78.3%	75.7%	60.0%	66.7%	0.0%	62.5%	76.1%
2017-19 (% of Searches)	79.1%	81.1%	100.0%	0.0%	0.0%	50.0%	78.5%
Contraband (Tickets + Arrests)							
2012-14	52	14	1	1	0	3	3
2013-15	59	12	1	0	0	2	1
2014-16	64	18	2	2	0	1	3
2015-17	81	30	3	2	0	2	4
2016-18	66	37	3	2	0	2	5
2017-19	36	24	1	0	0	1	4
2012-14 (% of Searches)	38.5%	36.8%	50.0%	100.0%	0.0%	33.3%	1.4%
2013-15 (% of Searches)	43.4%	33.3%	50.0%	0.0%	0.0%	22.2%	0.8%
2014-16 (% of Searches)	41.3%	35.3%	50.0%	40.0%	0.0%	8.3%	0.8%
2015-17 (% of Searches)	46.3%	45.5%	60.0%	40.0%	0.0%	12.5%	0.8%
2016-18 (% of Searches)	41.0%	52.9%	60.0%	66.7%	0.0%	12.5%	0.9%
2017-19 (% of Searches)	41.9%	64.9%	100.0%	0.0%	0.0%	16.7%	1.7%
Contraband (Arrests only)							
2012-14	18	4	0	0	0	1	23
2013-15	17	3	0	0	0	1	21
2014-16	12	2	1	1	0	0	32
2015-17	16	4	2	1	0	1	48

2016-18	9	8	2	1	0	1	42
2017-19	5	7	1	0	0	1	28
2012-14 (% of Searches)	13.3%	10.5%	0.0%	0.0%	0.0%	11.1%	12.4%
2013-15 (% of Searches)	12.5%	8.3%	0.0%	0.0%	0.0%	11.1%	11.4%
2014-16 (% of Searches)	7.7%	3.9%	25.0%	20.0%	0.0%	0.0%	7.0%
2015-17 (% of Searches)	9.1%	6.1%	40.0%	20.0%	0.0%	6.3%	9.0%
2016-18 (% of Searches)	5.6%	11.4%	40.0%	33.3%	0.0%	6.3%	8.2%
2017-19 (% of Searches)	5.8%	18.9%	100.0%	0.0%	0.0%	16.7%	10.8%

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							
2012	4,992	424	211	30	2	148	5,807
2013	4,099	340	196	39	1	300	4,975
2014	4,837	410	239	39	7	265	5,797
2015	4,295	476	213	34	9	357	5,384
2016	4,587	458	213	27	0	420	5,705
2017	2,867	327	160	31	0	151	3,536
2018	2,262	221	115	22	0	115	2,735
2019	1,649	195	104	14	0	78	2,040
Excluding externally generated stops							
2012	4,784	401	205	30	2	135	5,557
2013	3,908	330	184	38	1	292	4,753
2014	4,704	401	234	38	7	249	5,633
2015	4,131	454	209	33	7	347	5,181
2016	4,454	445	207	27	0	418	5,551
2017	2,818	320	156	30	0	151	3,475
2018	2,233	218	112	21	0	114	2,698
2019	1,620	191	104	14	0	77	2,006
Percentage Change YoY (excl. EGS)							
2012 vs 2013	-18.3%	-17.7%	-10.2%	26.7%	-50.0%	116.3%	-14.5%
2013 vs 2014	20.4%	21.5%	27.2%	0.0%	600.0%	-14.7%	18.5%
2014 vs 2015	-12.2%	13.2%	-10.7%	-13.2%	0.0%	39.4%	-8.0%
2015 vs 2016	7.8%	-2.0%	-1.0%	-18.2%	-100.0%	20.5%	7.1%
2016 vs 2017	-36.7%	-28.1%	-24.6%	11.1%	NA	-63.9%	-37.4%
2017 vs 2018	-20.8%	-31.9%	-28.2%	-30.0%	NA	-24.5%	-22.4%
2018 vs 2019	-27.5%	-12.4%	-7.1%	-33.3%	NA	-32.5%	-25.7%
Stops per 10,000 residents (excl. EGS)							
2012	1,443	2,013	796				
2013	1,179	1,657	715				
2014	1,419	2,013	909				
2015	1,246	2,279	812				
2016	1,344	2,234	804				
2017	850	1,606	606				
2018	674	1,094	435				
2019	489	959	404				

Appendix A.3. Data Quality and Methodology

The Burlington Police Department (BDP) traffic stop data used in this study consists of 25,025 rows, spanning nine years (2012-2019). 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. 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 BDP supplies.

Table A.3a. Fields with Missing or Unknown Values

Stop Years	Stop s	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												
2012	5,557	1	0	82	135	88	160	62	62	49	0	0
2013	4,753	0	0	116	292	116	150	126	126	90	2,415	232
2014	5,633	3	0	38	249	42	79	30	30	58	2,257	229
2015	5,181	1	0	128	347	201	233	77	77	79	2,147	238
2016	5,551	0	0	1,084	418	1,119	1,232	0	0	954	1,953	206
2017	3,475	0	0	537	151	567	566	0	0	449	2,125	191
2018	2,698	0	0	281	114	291	439	0	0	249	2,293	214
2019	2,006	0	0	165	77	176	250	0	0	149	2,201	212
All Years	34,854	5	0	2,431	1,783	2,600	3,109	295	295	2,077	15,391	1,522
Percentage of Blank or Unknown Rows												
2012	5,557	0.0%	0.0%	1.5%	2.4%	1.6%	2.8%	1.1%	1.1%	0.8%	0	0.0%
2013	4,753	0.0%	0.0%	2.4%	6.1%	2.4%	3.0%	2.7%	2.7%	1.6%	2,415	9.6%
2014	5,633	0.1%	0.0%	0.7%	4.4%	0.8%	1.4%	0.5%	0.5%	0.9%	2,257	10.2%
2015	5,181	0.0%	0.0%	2.5%	6.7%	3.9%	4.3%	1.5%	1.5%	1.4%	2,147	11.1%
2016	5,551	0.0%	0.0%	19.5%	7.5%	20.2%	21.6%	0.0%	0.0%	15.7%	1,953	10.6%
2017	3,475	0.0%	0.0%	15.5%	4.4%	16.3%	16.0%	0.0%	0.0%	12.0%	2,125	9.0%
2018	2,698	0.0%	0.0%	10.4%	4.2%	10.8%	16.1%	0.0%	0.0%	8.5%	2,293	9.3%
2019	2,006	0.0%	0.0%	8.2%	3.8%	8.8%	12.3%	0.0%	0.0%	7.0%	2,201	9.6%
All Years	34,854	0.0%	0.0%	7.0%	5.1%	7.5%	8.6%	0.9%	0.9%	5.4%	15,391	9.9%

Note: These data exclude externally generated stops.

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 BDP data shows that required field values are sometimes missing or incorrect. The inclusion and quality of the data has worsened since 2012. There is a good deal of work to do to improve the quality of these data, including ensuring that the race of the driver is identified in all incident reports as well as the reason for the stop. Further, 9.9% of accident reports had missing race data. Although accident data reports are not required by the legislation, this data source offers is useful benchmark for assessing the racial share of stops and agencies should consider placing more emphasis on ensuring accident reports are complete.

Table A.3b shows the number and percentage of BDP traffic stop reports 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)
2012	5,557	292	5.3%
2013	4,753	464	9.8%
2014	5,633	352	6.3%
2015	5,181	589	11.4%
2016	5,551	1,493	26.9%
2017	3,475	702	20.2%
2018	2,698	499	18.5%
2019	2,006	295	14.7%
All Years	34,854	4,686	13.4%

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

Table A.3c reports on missing or unknown values and race of driver. We would expect data to be missing at the same rates across racial groups. That holds in general for Burlington's traffic stop data. However, when race is missing, there are high rates of missing data for other fields as well, such as *Stop Reason* and *Stop Outcome*.

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)	28,652	2,760	1,411	231	1,783
Unknown Stop Reason	2,122	225	92	1	668
Unknown Stop Outcome	1,269	136	64	0	608
Unknown if Search occurred	201	23	12	0	59
Unknown if Contraband found subsequent to a search	0	0	0	0	0
Unknown Outcome if contraband found	0	0	0	0	0
Percentage of Blank or Unknown Rows					
Unknown Stop Reason as % of all stops	7.2%	7.9%	6.3%	0.4%	36.4%
Unknown Stop Outcome as % of all outcomes	4.0%	4.3%	4.2%	0.0%	31.7%
Unknown if Search occurred as % of all stops	0.7%	0.8%	0.9%	0.0%	3.3%
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	0.0%	0.0%	0.0%	0.0%	0.0%

B. Stop IDs

Most Vermont traffic stop data files contain only one stop outcome per row (where an outcome can be one arrest, one ticket, one warning, etc.). However, a single traffic stop can have multiple outcomes. For example, it is possible for a single stop to result in multiple tickets being issued, or other combinations such as a ticket and a warning, and so forth. It is important to be able to collect multiple outcomes into stops to avoid overcounting as well as to recognize stops where more than one ticket is issued. Fortunately, the Burlington stop data has a different structure from all other Vermont agencies. Each row in the data corresponds to a single stop and has details about how many citations or warnings were issued. s a result, no special processing for Stop IDs was required.

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