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

Stephanie Seguino
Professor
Department of Economics
University of Vermont
Burlington, VT 05401
stephanie.seguino@uvm.edu

Nancy Brooks
Visiting Associate Professor
Dept. of City and Regional Planning
Cornell University
Ithaca, NY USA 14853
nb275@cornell.edu

Pat Autilio
Data Analyst
P.O. Box 728
Quechee, VT 05059
diversifiedpat@gmail.com

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EXECUTIVE SUMMARY

This study of Williston 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) study 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 Williston PD.

Our main findings are that in Williston:

- Black and Hispanic shares of stopped drivers exceed their shares of the estimated driving population. The data indicate Black drivers were overstopped by 65% to 196%, depending on the measure of the driving population used. Hispanics were overstopped by 57% relative to their estimated share of the driving population.
- The Black arrest rate is almost double the arrest rate of white drivers.
- Black drivers are twice as likely to be searched subsequent to a stop as white drivers. In contrast, there were no searches of Asian drivers from 2012-19 and Hispanic drivers were searched at a similar rate to white drivers.
- Black and Hispanic drivers are less likely to be found with contraband than white drivers. Overall, 20.9% of searches of white drivers that yielded contraband resulted in an arrest, compared to 0.0% of Black and Hispanic drivers.

In terms of trends in racial disparities:

- Over time, Black-white disparities in arrest rates declined but then widened again in 2017-19. Both Black and white search rates have fallen over time, but the Black/white ratio of search rates has risen, indicating widening racial disparities in searches.
- The contraband hit rate leading to any outcome (warning, ticket, arrest) for white drivers has fallen slightly since 2013-15, and the Black hit rate has risen, closing the disparity in hit rates. However, hits that lead to a ticket or an arrest (suggesting more serious contraband) continue to occur at a higher rate for white than Black drivers.
- The total number of stops per year rose by 18.8% from 2013 to 2019. For Black drivers, however, the stop rate rose 136.6%, compared to 13.7% for white drivers. The Black stop rate in 2019 was more than 4 times that per estimated white resident and almost 9 times that of Asian drivers. There were twice as many stops of Black drivers in 2019 than their estimated population.

Regarding quality of the data, we found:

- Data was provided for eight years (2012-19) with about 17% of traffic stop reports having missing or unknown values for at least one variable. Race data was missing in 1.1% of all traffic stop reports. Almost all of the stops with missing race had no other missing information, and this is a cause for concern. The quantity of missing data has declined substantially since 2012, however.

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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 Williston, Vermont for 2012-19. Williston Police Department (WPD) collected data on 24,146 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]

In the next section, we provide an overview of the Williston data, identify methodological issues of relevance to our analysis, and report on the quality of Williston's traffic stop data.

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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 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 (2012-14, 2013-15, 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 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 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 WPD from 2012-19. As can be seen, a total of 24,146 stops were made. 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 Williston, 3.1% or 746 of all stops were externally generated. These exclusions reduce our sample size to 23,400 traffic stops.

Approximately one quarter of discretionary stops (not externally generated, in other words) resulted in the issuance of a citation. The percentage of stops that resulted in an arrest was 3.1%, while 1.6% of stopped vehicles were searched. And contraband was found in 1.3% of all stops. The overall contraband hit rate (the number of contraband finds divided by the number of searches) is 81.2%.

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

Table 1. Overview of the Data, 2012-19

	Observations	Rates
Total Stops		
incl. EGS	24,146	
excl. EGS	23,400	
2012	393	
2013	3,587	
2014	3,338	
2015	3,433	
2016	1,811	
2017	2,819	
2018	3,756	
2019	4,263	
Citations	6,045	25.8%
Arrests	735	3.1%
Searches	378	1.6%
Contraband	307	1.3%
Contraband as % of searches	307	81.2%

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

A challenging problem in the data, not only for Williston 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 Williston, over the time period of this study, 2012-19, only 16 drivers were identified as Native American.

Appendix Tables A.1 and A.3a-3c detail information on missing or contradictory data reported by WPD. The race of the driver was omitted in 258 rows of data or in 1.1% of all rows from 2012 to 2019.[6] Here, we note that in the event there is missing race data (sometimes marked as "unknown") those stops are not included in our analysis. In all but 6 of those 258 stops, race was the only missing field. We question why an officer can record all other information about the stop but fail to record race, a field that is legally required. We

[6] This excludes externally generated stops.

note that the stops of drivers with unknown race were slightly more likely to be subject to pretextual stops and significantly more likely to receive warnings (z=3.70) than white drivers. 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?

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).[7] 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

[7] 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.

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.[8]

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, 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. 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 Williston comprised 92.9% of all stopped drivers from 2012 through 2019, with Blacks 3.8%, Asians 2.2% and Hispanics 1.1% 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 1.3% to 2.3%, lower than their share of stopped drivers.

[8] 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.

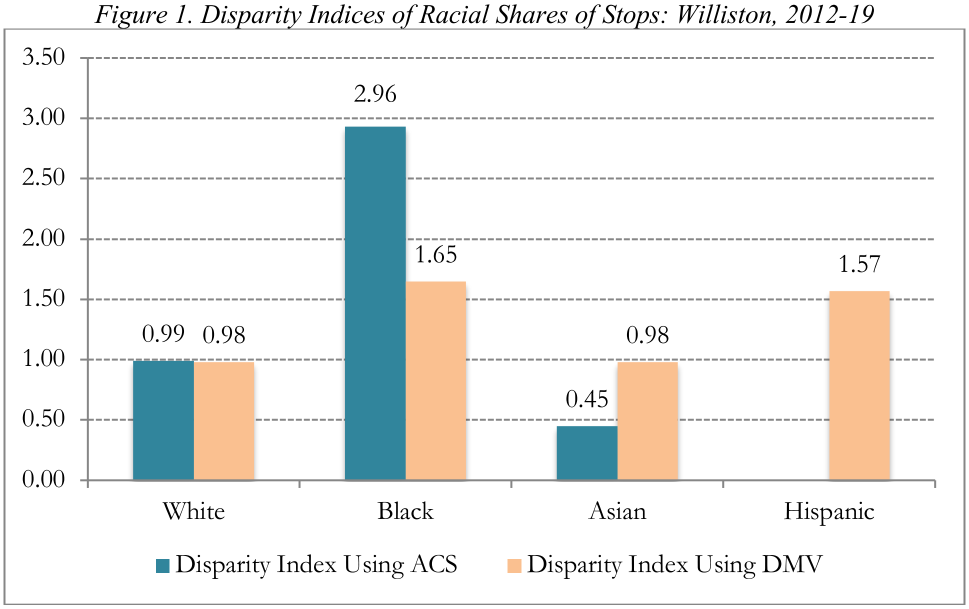
Table 2. Racial Shares of Stops, Reasons for Stops, and Post-Stop Outcomes

All Years	White	Black	Asian	Hispanic
Racial Shares of Stops				
Including externally generated stops	92.8%	3.9%	2.2%	1.1%
Excluding externally generated stops	92.9%	3.8%	2.2%	1.1%
Driver Percentage (ACS)	94.0%	1.3%	4.8%	
Driver Percentage (DMV Accident data)	94.4%	2.3%	2.2%	0.7%
Disparity Index (using ACS)	1.00	2.96	0.45	
Disparity Index (using DMV Accident data)	0.99	1.65	0.98	1.57
Stop Reason as % of All Stops				
Safety Stops	55.5%	54.6%	60.0%	57.7%
Moving Violation	55.4%	54.6%	59.8%	57.4%
Suspicion of DWI	0.1%		0.2%	0.4%
Investigatory/Pretextual Stops	40.4%	39.6%	35.4%	37.0%
Investigatory Stops	5.8%	4.1%	4.8%	5.3%
Vehicle Equipment	34.6%	35.5%	30.6%	31.7%
Externally Generated Stops	3.0%	4.9%	3.7%	3.8%
Multiple Reasons	0.2%	0.1%		0.4%
Unknown Reason	0.9%	0.9%	1.0%	1.1%
Outcome Rates as a % of All Stops				
Warning Rate	70.6%	62.7%	70.5%	57.3%
Ticket Rate	25.6%	30.1%	27.5%	37.7%
Arrest for Violation Rate	3.1%	5.8%	2.4%	5.1%
Arrest for Warrant Rate	0.1%	0.6%	0.0%	0.0%
No Action Rate	0.4%	0.3%	0.0%	0.4%
Search Rates				
Search rate (excl. searches on warrant)	1.5%	3.2%	0.0%	1.6%
Search rate (incl. searches on warrant)	1.6%	3.2%	0.0%	1.6%
Hit rates (as a % of PC, RS & Warrant Searches)				
Hit rates (incl. all outcomes)	83.1%	60.7%	NA	75.0%
Hit rates (excl. warnings as outcomes)	58.1%	46.4%	NA	50.0%
Hit rates (outcome = arrest)	20.9%	0.0%	NA	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 are for 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 during this time period, that ratio ranges from 1.65 (3.8%/2.3%) using the DMV data to 2.96 using ACS data. Put another way, Black drivers are stopped at a rate that is from 65% to 196% greater than their share of the driving population. Hispanics, too, are overstopped relative to their share of the driving population, with a DI of 1.57, indicating they are stopped at a rate that is about 57% greater than their share of the driving population. In contrast, whether we use the ACS or DMV data, white drivers are understopped as compared to what would be expected while the Asian DI ranges from 0.45 (signifying understopping) to 0.98, approximately the same DI for white drivers in the latter case.

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



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 Williston traffic stops using ACS data are similar to 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 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). Table 2 shows the distribution of reasons for stops by race. The most common reason motorists in Williston 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 Williston, in contrast to some other law enforcement agencies, there are no meaningful differences by race in the share of stops that are investigatory/pretextual.

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 Williston 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	0.89	1.00	0.81
Ticket Rate	1.18	1.07	1.47
Arrest Rate	1.89	NA	NA
Search Rate	2.09	NA	1.03

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.

Black and Hispanic drivers are less likely to receive a warning than white drivers (11% and 19% less likely, respectively). They are more likely to be issued a citation than white drivers (18% and 47%, respectively) and those differences are statistically significant (z=3.06 and z=4.48, respectively). The rate at which Asian drivers is ticketed is 7% higher than the white rate but the Asian-white difference is not statistically significant

There were no arrests of Asian drivers and only one arrest of a Hispanic driver, and therefore we only report the Black/white arrest rate. Blacks are almost twice as likely to be arrested subsequent to a stop as white drivers. The difference in arrest rates is statistically significant (z=4.53).

Search rate data used for Table 3 exclude searches based on a warrant.[9] Black drivers are searched at a rate that is slightly more than double that of white drivers, a difference that is statistically significant (z=3.95). In contrast, there were no searches of Asian drivers during this time period. The Hispanic/white ratio is 1.03, although this is based on only one search of a Hispanic driver and thus this statistic is not reliable because of the small sample size.

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,

[9] 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.

and local studies. 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.[10] 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 similar to those in Williston.

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.[11] 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 at the racial differences in the severity of contraband found, 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.

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 83.1% compared to 60.7% for Black drivers, and the difference is statistically significant (z=2.45). When the

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

[11] 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.

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, 46.4% compared to 58.1%. This difference is not statistically significant, likely attributable to the small sample size. When the outcome of a search is an arrest (signifying more serious contraband found), the Black hit rate is 0% (no searches resulted in an arrest), compared to a white hit rate of 20.9%.

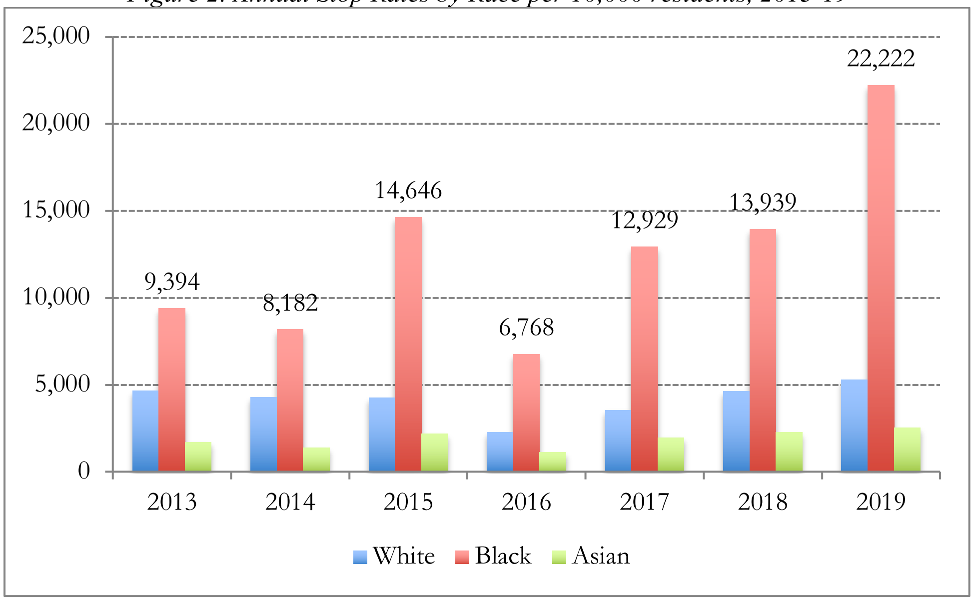
IV. Trends Over Time

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 Appendix Table A.2b). We focus on the trends from 2013 to 2019 because the number of stops reported for 2012 appear to be a partial summary with only 403 stops in total. The total number of stops has increased by 18.8% during this period of time (again, excluding externally generated stops). The percentage increases by racial group vary widely, however, with stops of white drivers increasing by 13.7% and for Black drivers, 136.6%. The increase in stops of Hispanic drivers is similar to the increase for Black drivers, at 132.0%. Stops of Asian drivers increased 40.0%. For 2019, we estimate that white drivers were stopped at a rate of 5,308 per 10,000 white residents (a much higher white stop rate than in some other cities and towns).[12] In contrast, for Black drivers, the stop rate in 2019 was 22,222 per 10,000—that is, the stop rate per capita is more than double the estimated number in the local population in that year (Figure 2). Although the Asian stop rate has risen since 2013, the stop rate per 10,000 estimated Asian residents is less than half the white rate in 2019 and little more than one tenth the Black stop rate. The Asian-Black differences in this and other indicators is 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 bias than Blacks. For all drivers, the stop rates in Williston are very high relative to the national average of 8.6% (or 860 out of 10,000) of drivers stopped per year.[13]

[12] ACS data is used to calculate an estimated rate per 10,000 residents. Because we do not have ACS estimates of Hispanics, this racial category is omitted from Figure 2. Stop rates are calculated, using white drivers as an example, as: [(number of stops of white drivers/number of white residents 15+)*10,000]. Similarly, the stop rate of Black and Asian drivers is their stop numbers divided by the number of Black and Asian residents of Williston 15 and older, all multiplied by 10,000.
[13] U.S. Department of Justice (2018: 1).

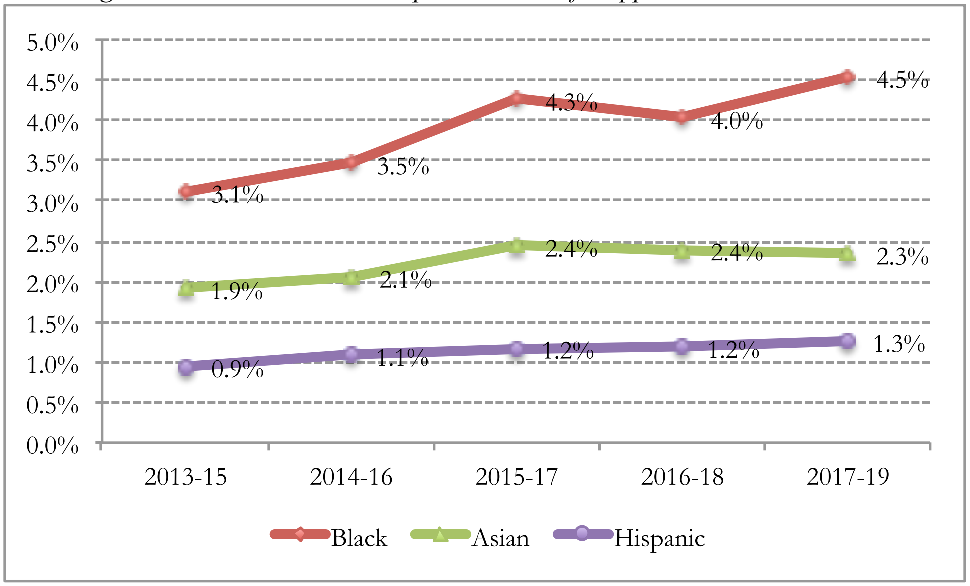
Figure 2. Annual Stop Rates by Race per 10,000 residents, 2013-19



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

Figure 3 portrays trends in Black, Asian, and Hispanic shares of stopped drivers. Stop shares have risen for all minority groups, with the Black share increasing the most, the Asian share also rising, and the Hispanic share relatively constant. During this time period, the white share of stops fell from 93.9% in 2013-15 to 91.8% in 2017-19 (calculated from data in Appendix Table A.2b).

Figure 3. Black, Asian, and Hispanic Shares of Stopped Drivers in Williston



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, the latter which are based on discernible driver behavior. Figure 4 provides the share of all stops that are investigatory/pretextual as a percentage of all stops. There are two noteworthy observations. In earlier periods, the Black and Asian stop shares that were pretextual exceeded those of whites, but by 2017-19, white drivers' share of pretextual stops exceeds that of all other racial groups. Unlike other indicators we have looked at thus far, this one does not show evidence of racial disparities to the disadvantage of minorities. It is also noteworthy, that for all groups, the share of stops that are investigatory/pretextual has been rising over time, suggesting a shift away from a public safety focus of traffic policing. It would be useful to for the Williston Police Department to shed light on the rising number of stops over time, and the greater emphasis on pretextual stops.

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

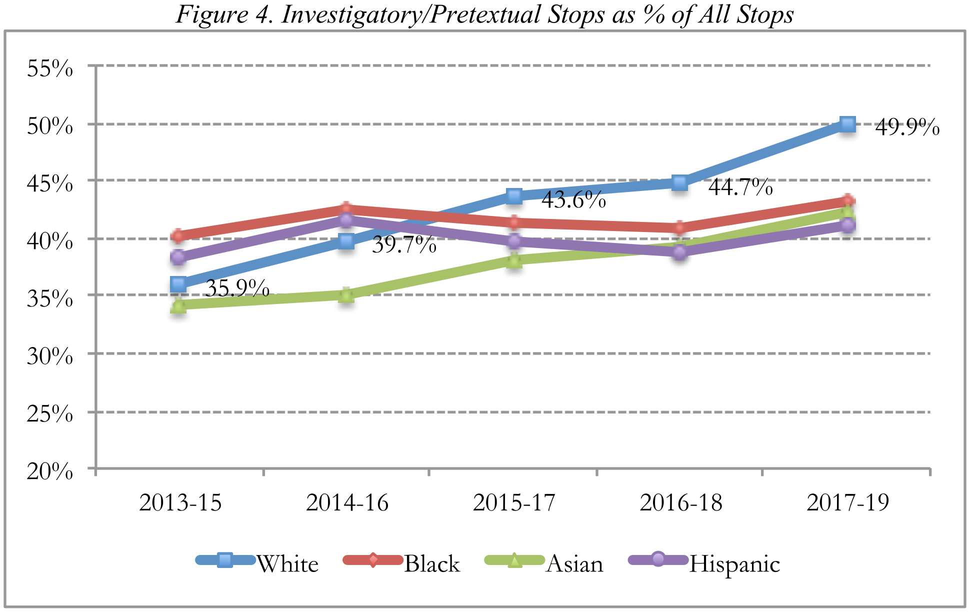
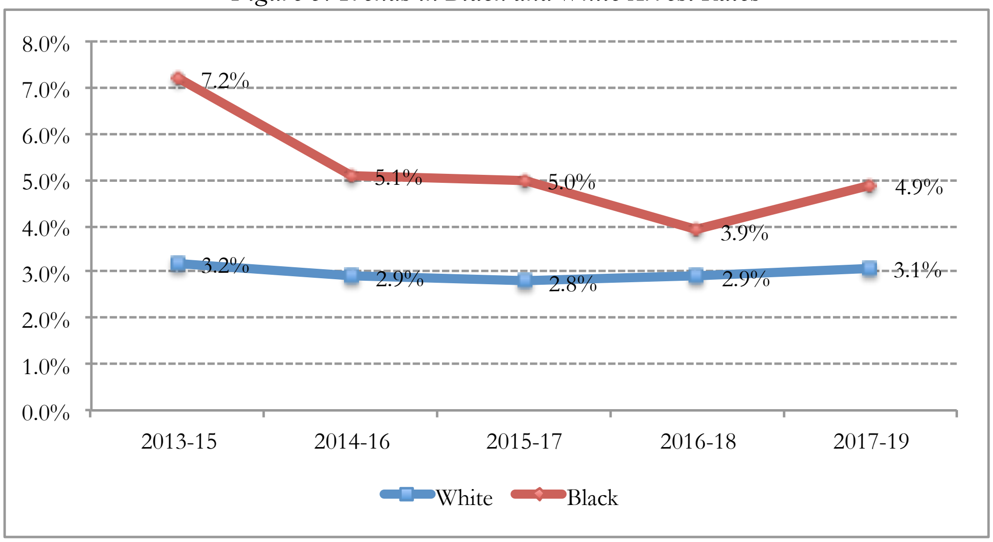


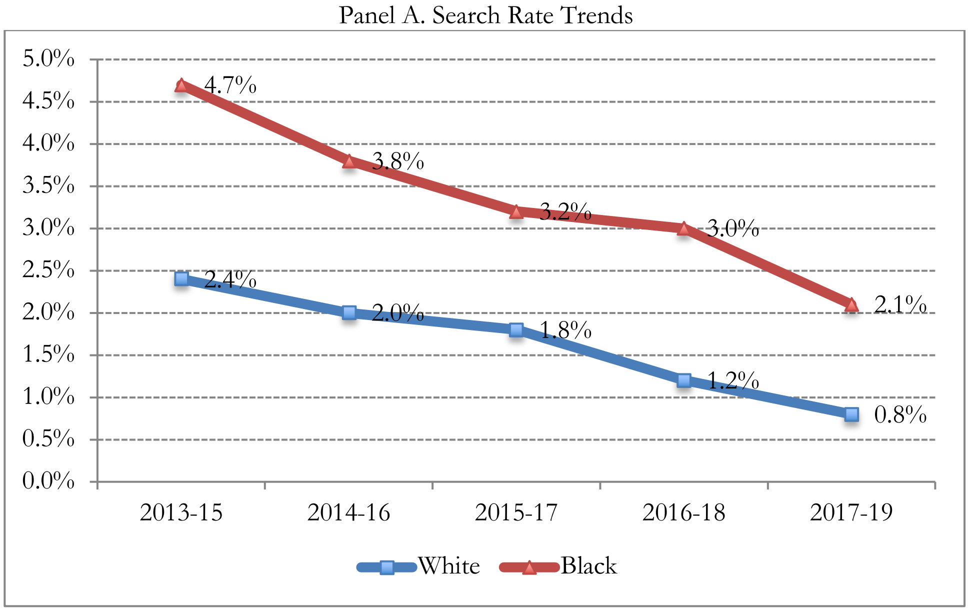
Figure 5 shows trends in the Black and white arrest rates. In all years, the Black arrest rate exceeds the white rate, and this gap has narrowed substantially since 2013-19. (Asian and Hispanic arrest rate numbers are omitted due to small sample sizes). Thus, while in 2013-15, the ratio of Black to white arrest rates was 2.28 (meaning that Black drivers were more than twice as likely to be arrested in a traffic stop compared to white drivers), that ratio has fallen to 1.60. Although there continues to be a notably higher arrest rate of Black drivers, the lower ratio is a positive trend in terms of racial equity.

Figure 5. Trends in Black and White Arrest Rates



White and Black search rates are shown in Figure 6. In *Panel A*, we observe that both Black and white search rates have fallen over time. But as the data in *Panel B* show, the white rate has fallen more in percentage terms since 2013-15 than the Black search rate, and so by 2017-19, Black drivers were 2.63 times more likely to be searched than white drivers in Williston in 2017-19—a wider disparity than in 2013-15. (The number of annual searches of Asian and Hispanic drivers is very small and so we do not include those in Figure 6).

Figure 6. White and Black Search Rates Trends and Differentials



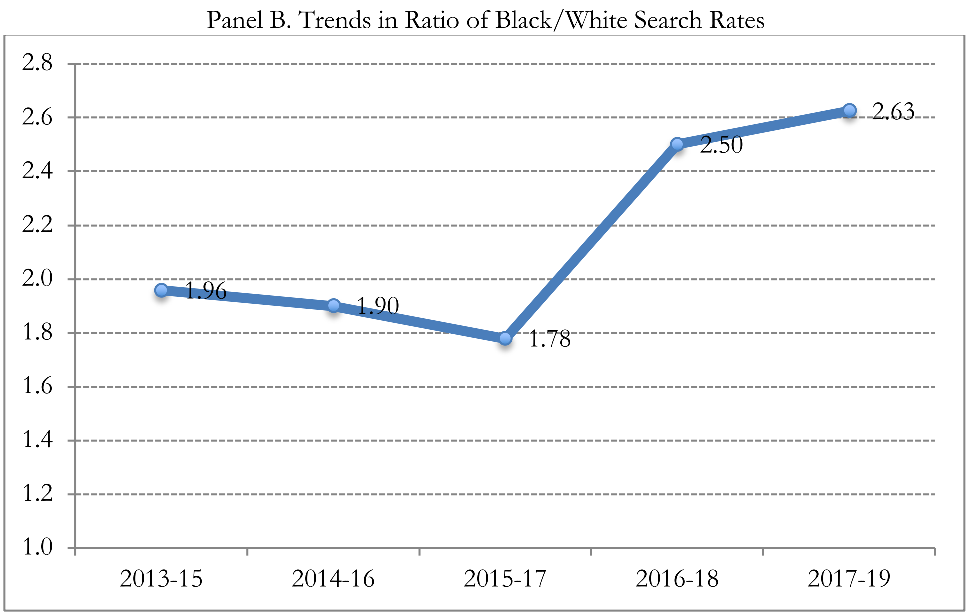
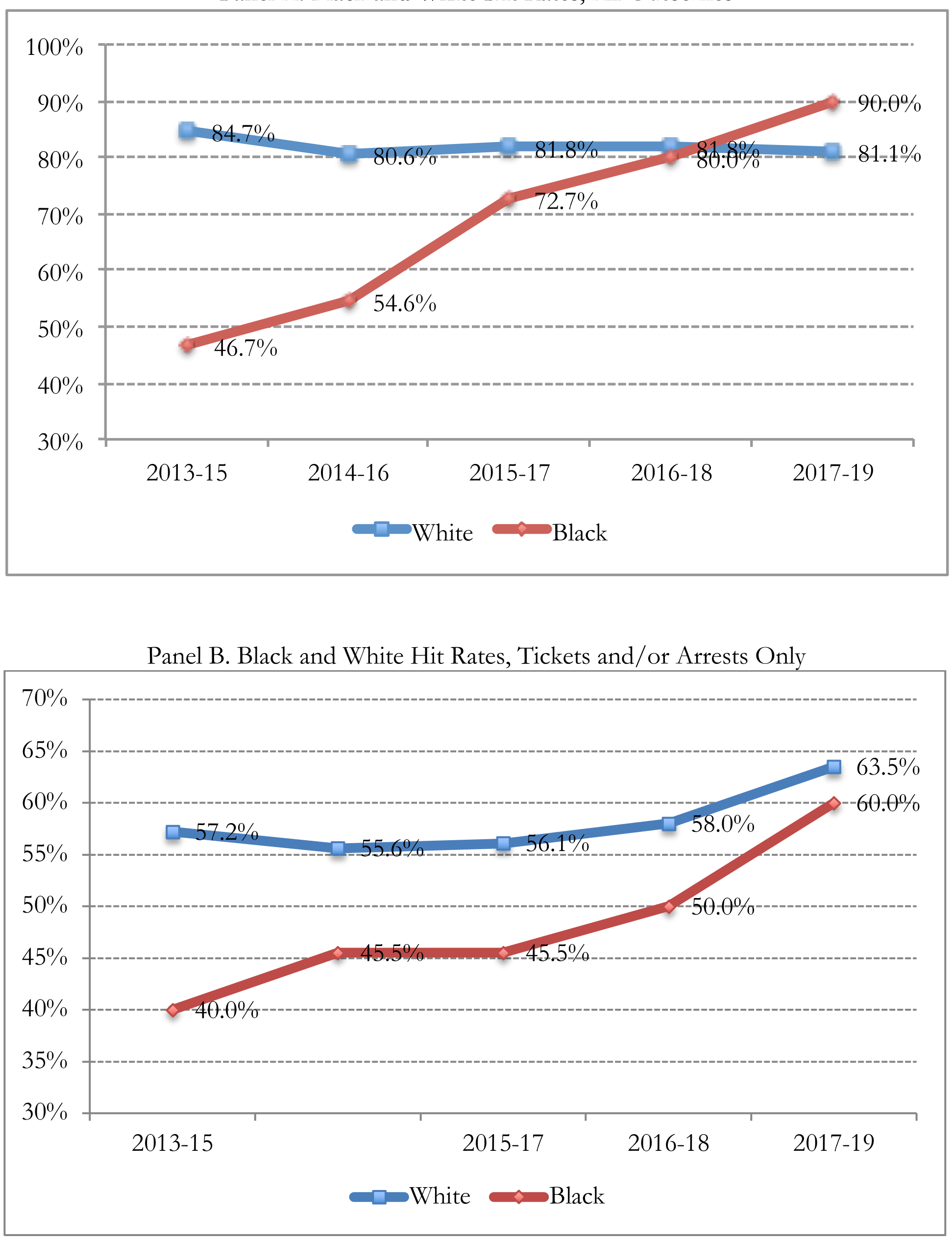


Figure 7, *Panel A*, shows trends in the white and Black contraband hit rates. The Black hit rate was below the white rate until 2017-19, which would appear to be a positive development. (Asian and Hispanic hit rates are not shown due to small sample sizes). The hit rate difference between Black and white drivers in 2017-19 is not statistically significant (z=0.17), however, and that is in part due to small sample sizes.

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 the white hit rate is higher than the Black rate in every time period (although, again we caution that sample sizes are even smaller than in *Panel A*), and when it comes to hits that lead to an arrest in every time period, the Black hit rate was 0%, while the white rate has consistently hovered around 20%. Given that law enforcement agencies often explain Black-white search rate disparities as a function of a belief about Black involvement in drug trafficking (which, if contraband is found, typically would lead to an arrest), the differentials between search rates and hit rates suggest oversearching of Black drivers in Williston.

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 Williston.

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 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 can help to eliminate misattribution of race to search disparities if, for example, any racial group is more likely to be DWI. In the second method, we disaggregate the reasons for a stop into safety stops and pretextual stops. The omitted variable in this case is safety stops. In this case, the coefficient on the *Pretextual Stop* variable indicates the odds of being searched if the stop was pretextual (investigatory or vehicle equipment) divided by the odds of being searched due to moving violation.

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.

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 the factors we control for that may lead to an officer's decision to search a vehicle, race influences the officer's decision to search (net of those factors).

We report results on five 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 the odds ratio of a search of a Black driver relative to a white driver is 2.02. That is, Black drivers have twice the odds of being searched as compared to white drivers. Neither the Hispanic nor Native American 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 Asian drivers.

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 1.57 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 greater in the morning than at night. The odds of a morning or evening search are lower than in the afternoon. The odds of a search are lower on Sunday through Tuesday are lower than Fridays. The coefficients on the other days of the week are not significant, suggesting similar odds to a search on a Friday.

The odds of an investigatory stop leading to a search are about twice 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 a stop due to suspicion of DWI will lead to a search is more than 9 times higher than if the reason for the stop is motor vehicle equipment. The coefficients on the remaining reasons for a stop are not statistically significant. The odds a Black driver will be searched in this model, after controlling for other factors, is 2.01 relative to the odds a white driver will be searched. That is, even controlling for other factors, the odds a Black driver will be searched in Williston, are still double that of 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, the odds of a driver being searched are slightly higher than it is a safety stop, but this coefficient is not statistically significant.

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

	(1)	(2)	(3)
Variables	Race only	With all controls and stop reason	With all controls and pretextual stop control
Black	2.024***	2.012***	1.979***
	(0.404)	(0.433)	(0.426)
Hispanic	0.983	1.222	1.296
	(0.499)	(0.630)	(0.665)
Native American	4.081	5.178	4.923
	(4.221)	(5.634)	(5.341)
Male		1.571***	1.531***
		(0.194)	(0.189)
Age		0.940***	0.941***
		(0.00515)	(0.005)
Morning		0.676**	0.680**
		(0.107)	(0.108)
Night		0.373***	0.350***
		(0.0457)	(0.0425)
Saturday		1.043	1.009
		(0.173)	(0.167)
Sunday		0.498***	0.514***
		(0.112)	(0.115)
Monday		0.569***	0.591**
		(0.122)	(0.126)
Tuesday		0.470***	0.485***
		(0.108)	(0.111)
Wednesday		1.116	1.112
		(0.197)	(0.196)
Thursday		0.915	0.890
		(0.163)	(0.158)
Investigatory stop		2.066***	
		(0.380)	
Multiple reasons		1.807	
		(1.344)	
Suspicion of DWI		9.493***	
		(6.231)	
Unknown reason		0.902	
		(0.916)	
Vehicle equipment		0.865	
		(0.109)	
Pretextual stop			1.036
			(0.116)
Constant	0.016***	0.132***	0.141***
	(0.000888)	(0.0393)	-0.042
Observations	22,547	19,049	19,049

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. 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:

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

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 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 one third the odds a white driver will be found with contraband subsequent to a search. The difference is statistically significant. The odds a Hispanic driver is found with contraband is slightly more than half that of a white driver, but this difference in odds is not statistically significant.

Because of the importance of the hit rate in our analysis, let's describe more precisely what the odds ratio coefficient means using the results from this simple regression. From Table 2, we find that 83.1% of searched white drivers are found with contraband and thus, 17.7% are not found with contraband. This implies an odds ratio for white drivers of 83.1/17.7= 4.73. In other words, the odds are roughly 4.7 to 1 that a search of a white driver will yield contraband. For Black drivers, we find in Table 2 that 60.7% of them are found with contraband so their odds ratio is 60.7/39.3=1.54. The ratio of these two odds is the coefficient in our regression (1.54/4.73=0.33), 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 0.247. That is, the odds of finding contraband in a search of a Black driver is now only about one quarter of the white odds of contraband being found 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, and pretextual stops are shown to result in a higher probability of finding contraband than if the reason for the stop is for safety reasons. That odds ratio is, however, not statistically significant.

To sum up the results of the logistic regressions, adding controls for a variety of contextual factors has little effect on racial disparities in the probability of being searched and of contraband being found during a search. This is not to say that the controls were not meaningful or significant. Searches 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 drivers are less likely to be found with contraband, a finding that is consistent with oversearching of that group of drivers. This analysis is based on all the years of data. As we noted in the previous section, the hit disparity is decreasing.

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

Variables	(1) Race only	(2) With all controls and stop reason	(3) With all controls and pretextual stop control
Black	0.313***	0.247***	0.256***
	(0.129)	(0.119)	(0.121)
Hispanic	0.608	0.896	1.057
	(0.708)	(1.178)	(1.346)
Male		2.069**	2.102**
		(0.659)	(0.659)
Age		0.950***	0.952***
		(0.0130)	(0.0127)
Morning		0.527	0.518
		(0.217)	(0.211)
Night		0.572	0.726
		(0.203)	(0.250)
Saturday		1.575	1.439
		(0.727)	(0.657)
Sunday		1.537	0.952
		(0.943)	(0.543)
Monday		0.857	0.591
		(0.471)	(0.310)
Tuesday		1.183	0.929
		(0.702)	(0.544)
Wednesday		2.080	1.785
		(1.069)	(0.898)
Thursday		1.765	1.648
		(0.908)	(0.825)
Investigatory stop		0.561	
		(0.246)	
Vehicle equipment		2.971***	
		(1.242)	
Pretextual stop			1.546
			(0.480)
Constant	4.931***	5.877**	5.810**
	(0.710)	(4.300)	(4.197)
Observations	376	349	355

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 and 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. We find evidence of racial disparities using a variety of indicators. Black and Hispanic drivers are stopped at a rate that exceeds their share of the estimated driving population. Calculations of stop rates per 10,000 residents by race show that the stop rate of white drivers is 5,308, compared to 22,222 for Black drivers. The Asian stop rate per 10,000 residents is just 2,547. The stop rates in Williston are much higher than the national average.

Though racial disparities in investigatory/pretextual stops have fallen, this type of stop has increased in frequency from 36.1% of all stops in 2013-15 to 49.3% in 2017-19. This suggests a shift away from a public safety approach to traffic policing. As we have noted, investigatory/pretextual stops leave more room for implicit bias to influence policing decisions.

While arrest rate disparities have fallen modestly since 2013-15, the Black-white search rate disparity has widened. The gap between Black and white hit rates has declined over time for all outcomes. If we exclude hits that result in a warning (thus suggesting less serious contraband) and focus only on those that result in an arrest or ticket, white hit rates exceed those of Black drivers in every time period. Further, it is noteworthy that roughly 20% of white searches resulted in arrest-worthy contraband being found, and yet, in no year were there any arrests of Black drivers as a result of 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.

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APPENDIX

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

All Years	White	Black	Asian	Hispanic	Native American	Unknown	Total
Total Traffic Stops							
Including externally generated stops	22,154	925	517	265	16	269	24,146
Excluding externally generated stops	21,493	880	498	255	16	258	23,400
Reasons For Stops							
Safety Stops	12,291	505	310	153	12	137	13,408
Moving Violation	12,263	505	309	152	12	137	13,378
Suspicion of DWI	28	0	1	1	0	0	30
Investigatory/Pretextual Stops	8,957	366	183	98	4	115	9,723
Investigatory Stop	1,286	38	25	14	0	11	1,374
Vehicle Equipment	7,671	328	158	84	4	104	8,349
Externally Generated Stop	661	45	19	10	0	11	746
Multiple Reasons - Moving Violation & Suspicion of DWI	1	0	0	0	0	0	1
Multiple Reasons - Moving Violation & Vehicle Equipment	39	1	0	1	0	0	41
Multiple Reasons - Suspicion of DWI & Vehicle Equipment	1	0	0	0	0	0	1
Unknown Stop Reason	204	8	5	3	0	6	226
Outcomes							
Ticket	5,503	265	137	96	4	40	6,045
Warning	15,171	552	351	146	12	211	16,443
No Action Taken	94	3	0	1	0	3	101
Arrest for violation	659	51	12	13	0	0	735
Arrest for warrant	16	5	0	0	0	0	21
Searches							
Total Stops with No Search	21,059	847	498	249	15	252	22,920
No Search & Contraband & Arrest for violation	5	0	0	0	0	0	5
No Search & Contraband & No arrest	85	1	1	1	0	0	88
No Search (all others)	20,969	846	497	248	15	252	22,827
Total Stops with Unknown Search	90	5	0	2	0	5	102
Total Stops with Search	344	28	0	4	1	1	378
Search with Probable Cause (PC)	230	20	0	4	1	0	255
Stops with PC Searches, No contraband	33	5	0	1	0	0	39
Stops with PC Searches, Unknown contraband	6	0	0	0	0	0	6
Stops with PC Searches, Contraband	191	15	0	3	1	0	210
Outcomes of PC Search							
Stops with PC Searches, Contraband & Warning, No Action or Unknown	50	4	0	1	1	0	56
Stops with PC Searches, Contraband and Ticket	92	11	0	2	0	0	105
Stops with PC Searches, Contraband and Arrest	49	0	0	0	0	0	49
Search with Reasonable Suspicion (RS)	97	8	0	0	0	0	105
Stops with RS Searches, No contraband	15	6	0	0	0	0	21
Stops with RS Searches, Unknown contraband	1	0	0	0	0	0	1
Stops with RS Searches, Contraband	81	2	0	0	0	0	83
Outcomes of RS Search							
Stops with RS Searches, Contraband & Warning, No Action or Unknown	35	0	0	0	0	0	35
Stops with RS Searches, Contraband & Ticket	30	2	0	0	0	0	32
Stops with RS Searches, Contraband & Arrest	16	0	0	0	0	0	16
Search with Warrant	17	0	0	0	0	1	18
Stops with Warrant Searches, No contraband	3	0	0	0	0	1	4
Stops with Warrant Searches, Unknown contraband	0	0	0	0	0	0	0
Stops with Warrant Searches, Contraband	14	0	0	0	0	0	14
Outcomes of Warrant Search							
Stops with Warrant Searches, Contraband & Warning, No Action or Unknown	1	0	0	0	0	0	1
Stops with Warrant Searches, Contraband & Ticket	6	0	0	0	0	0	6
Stops with Warrant Searches, Contraband & Arrest	7	0	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. Williston 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	6,902	182	125	53	4	52	7,318
2013-15	9,626	319	196	97	8	112	10,358
2014-16	7,896	293	174	92	5	122	8,582
2015-17	7,351	340	195	94	7	76	8,063
2016-18	7,632	333	198	98	6	119	8,386
2017-19	9,828	486	251	135	8	130	10,838
Reasons For Stops (excl. externally generated stops and unknown reasons)							
Safety Stops							
2012-14	4,700	117	87	32	4	31	4,971
2013-15	6,104	188	129	58	7	59	6,545
2014-16	4,722	166	113	52	4	65	5,122
2015-17	4,102	198	120	56	4	36	4,516
2016-18	4,149	195	118	60	4	61	4,587
2017-19	4,860	274	142	79	5	70	5,430
2012-14 (% of stops)	69.0%	65.7%	69.6%	62.8%	100.0%	60.8%	68.8%
2013-15 (% of stops)	64.1%	59.9%	65.8%	61.7%	87.5%	54.6%	63.9%
2014-16 (% of stops)	60.3%	57.6%	64.9%	58.4%	80.0%	55.6%	60.3%
2015-17 (% of stops)	56.4%	58.6%	61.9%	60.2%	57.1%	50.0%	56.6%
2016-18 (% of stops)	55.3%	59.1%	60.8%	61.2%	66.7%	52.1%	55.6%
2017-19 (% of stops)	50.1%	56.9%	57.7%	59.0%	62.5%	54.3%	50.7%
Pretextual Stops							
2012-14	2,117	61	38	19	0	20	2,255
2013-15	3,424	126	67	36	1	49	3,703
2014-16	3,104	122	61	37	1	52	3,377
2015-17	3,168	140	74	37	3	36	3,458
2016-18	3,357	135	76	38	2	56	3,664
2017-19	4,844	208	104	55	3	59	5,273
2012-14 (% of stops)	31.1%	34.3%	30.4%	37.3%	0.0%	39.2%	31.2%
2013-15 (% of stops)	35.9%	40.1%	34.2%	38.3%	12.5%	45.4%	36.1%
2014-16 (% of stops)	39.7%	42.4%	35.1%	41.6%	20.0%	44.4%	39.7%
2015-17 (% of stops)	43.6%	41.4%	38.1%	39.8%	42.9%	50.0%	43.4%
2016-18 (% of stops)	44.7%	40.9%	39.2%	38.8%	33.3%	47.9%	44.4%
2017-19 (% of stops)	49.9%	43.2%	42.3%	41.0%	37.5%	45.7%	49.3%

Table 2a. continued

All Years	White	Black	Asian	Hispanic	Native American	Unknown	Total
Outcomes (excl. externally generated stops)							
Tickets (one or more)							
2012-14	1,962	62	44	25	2	12	2,107
2013-15	2,497	107	61	39	2	12	2,718
2014-16	2,038	86	51	40	0	12	2,227
2015-17	1,691	86	54	28	0	2	1,861
2016-18	2,036	92	52	39	1	24	2,244
2017-19	2,344	142	59	46	2	26	2,619
2012-14 (% of stops)	28.4%	34.1%	35.2%	47.2%	50.0%	23.1%	28.8%
2013-15 (% of stops)	25.9%	33.5%	31.1%	40.2%	25.0%	10.7%	26.2%
2014-16 (% of stops)	25.8%	29.4%	29.3%	43.5%	0.0%	9.8%	26.0%
2015-17 (% of stops)	23.0%	25.3%	27.7%	29.8%	0.0%	2.6%	23.1%
2016-18 (% of stops)	26.7%	27.6%	26.3%	39.8%	16.7%	20.2%	26.8%
2017-19 (% of stops)	23.9%	29.2%	23.5%	34.1%	25.0%	20.0%	24.2%
Arrests for Violation							
2012-14	219	18	1	2	0	0	240
2013-15	304	23	3	3	0	0	333
2014-16	228	15	3	4	0	0	250
2015-17	204	17	4	4	0	0	229
2016-18	220	13	5	6	0	0	244
2017-19	303	24	8	8	0	0	343
2012-14 (% of stops)	3.2%	9.9%	0.8%	3.8%	0.0%	0.0%	3.3%
2013-15 (% of stops)	3.2%	7.2%	1.5%	3.1%	0.0%	0.0%	3.2%
2014-16 (% of stops)	2.9%	5.1%	1.7%	4.4%	0.0%	0.0%	2.9%
2015-17 (% of stops)	2.8%	5.0%	2.1%	4.3%	0.0%	0.0%	2.8%
2016-18 (% of stops)	2.9%	3.9%	2.5%	6.1%	0.0%	0.0%	2.9%
2017-19 (% of stops)	3.1%	4.9%	3.2%	5.9%	0.0%	0.0%	3.2%
Searches (excl. externally generated stops)							
Searches (PC, RS or Warrant)							
2012-14	181	12	0	1	1	1	196
2013-15	229	15	0	3	1	1	249
2014-16	160	11	0	2	0	1	174
2015-17	132	11	0	2	0	0	145
2016-18	88	10	0	0	0	0	98
2017-19	74	10	0	1	0	0	85
2012-14 (% of Stops)	2.6%	6.6%	0.0%	1.9%	25.0%	1.9%	2.7%
2013-15 (% of Stops)	2.4%	4.7%	0.0%	3.1%	12.5%	0.9%	2.4%
2014-16 (% of Stops)	2.0%	3.8%	0.0%	2.2%	0.0%	0.8%	2.0%
2015-17 (% of Stops)	1.8%	3.2%	0.0%	2.1%	0.0%	0.0%	1.8%

Table A.2a continued

	White	Black	Asian	Hispanic	Native American	Unknown	Total
2016-18 (% of Stops)	1.2%	3.0%	0.0%	0.0%	0.0%	0.0%	1.2%
2017-19 (% of Stops)	0.8%	2.1%	0.0%	0.7%	0.0%	0.0%	0.8%
Contraband (All Outcomes)							
2012-14	154	4	0	1	1	0	160
2013-15	194	7	0	2	1	0	204
2014-16	129	6	0	1	0	0	136
2015-17	108	8	0	1	0	0	117
2016-18	72	8	0	0	0	0	80
2017-19	60	9	0	1	0	0	70
2012-14 (% of Searches)	85.1%	33.3%	0.0%	100.0%	100.0%	0.0%	81.6%
2013-15 (% of Searches)	84.7%	46.7%	0.0%	66.7%	100.0%	0.0%	81.9%
2014-16 (% of Searches)	80.6%	54.6%	0.0%	50.0%	0.0%	0.0%	78.2%
2015-17 (% of Searches)	81.8%	72.7%	0.0%	50.0%	0.0%	0.0%	80.7%
2016-18 (% of Searches)	81.8%	80.0%	0.0%	0.0%	0.0%	0.0%	81.6%
2017-19 (% of Searches)	81.1%	90.0%	0.0%	100.0%	0.0%	0.0%	82.4%
Contraband (Tickets + Arrests)							
2012-14	103	3	0	1	0	0	2
2013-15	131	6	0	1	0	0	1
2014-16	89	5	0	0	0	0	1
2015-17	74	5	0	0	0	0	1
2016-18	51	5	0	0	0	0	1
2017-19	47	6	0	1	0	0	2
2012-14 (% of Searches)	56.9%	25.0%	0.0%	100.0%	0.0%	0.0%	0.9%
2013-15 (% of Searches)	57.2%	40.0%	0.0%	33.3%	0.0%	0.0%	0.5%
2014-16 (% of Searches)	55.6%	45.5%	0.0%	0.0%	0.0%	0.0%	0.6%
2015-17 (% of Searches)	56.1%	45.5%	0.0%	0.0%	0.0%	0.0%	0.7%
2016-18 (% of Searches)	58.0%	50.0%	0.0%	0.0%	0.0%	0.0%	1.1%
2017-19 (% of Searches)	63.5%	60.0%	0.0%	100.0%	0.0%	0.0%	2.6%
Contraband (Arrests only)							
2012-14	36	0	0	0	0	0	36
2013-15	45	0	0	0	0	0	45
2014-16	31	0	0	0	0	0	31
2015-17	26	0	0	0	0	0	26
2016-18	17	0	0	0	0	0	17
2017-19	17	0	0	0	0	0	17
2012-14 (% of Searches)	19.9%	0.0%	0.0%	0.0%	0.0%	0.0%	18.4%
2013-15 (% of Searches)	19.7%	0.0%	0.0%	0.0%	0.0%	0.0%	18.1%
2014-16 (% of Searches)	19.4%	0.0%	0.0%	0.0%	0.0%	0.0%	17.8%
2015-17 (% of Searches)	19.7%	0.0%	0.0%	0.0%	0.0%	0.0%	17.9%

Table A.2a continued

	White	Black	Asian	Hispanic	Native American	Unknown	Total
2016-18 (% of Searches)	19.3%	0.0%	0.0%	0.0%	0.0%	0.0%	17.3%
2017-19 (% of Searches)	23.0%	0.0%	0.0%	0.0%	0.0%	0.0%	20.0%

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	380	9	10	3	0	1	403
2013	3,448	95	64	26	3	5	3,641
2014	3,281	90	54	27	1	53	3,506
2015	3,278	155	88	50	4	62	3,637
2016	1,734	69	41	22	0	16	1,882
2017	2,671	141	76	27	3	0	2,918
2018	3,441	138	86	52	3	105	3,825
2019	3,921	228	98	58	2	27	4,334
Excluding externally generated stops							
2012	371	8	10	3	0	1	393
2013	3,398	93	63	25	3	5	3,587
2014	3,133	81	52	25	1	46	3,338
2015	3,095	145	81	47	4	61	3,433
2016	1,668	67	41	20	0	15	1,811
2017	2,588	128	73	27	3	0	2,819
2018	3,376	138	84	51	3	104	3,756
2019	3,864	220	94	57	2	26	4,263
Annual Percentage Change							
2012 to 2013	815.9%	1062.5%	530.0%	733.3%	--	400.0%	812.7%
2013 to 2014	-7.8%	-12.9%	-17.5%	0.0%	-66.7%	820.0%	-6.9%
2014 to 2015	-1.2%	79.0%	55.8%	88.0%	300.0%	32.6%	2.9%
2015 to 2016	-46.1%	-53.8%	-49.4%	-57.5%	-100.0%	-75.4%	-47.3%
2016 to 2017	55.2%	91.0%	78.1%	35.0%	0%%	-100.0%	55.7%
2017 to 2018	30.5%	7.8%	15.1%	88.9%	0.0%	--	33.2%
2018 to 2019	14.5%	59.4%	11.9%	11.8%	-33.3%	-75.0%	13.5%
Stops per 10,000 residents							
2012	510	808	271				
2013	4,668	9,394	1,707				
2014	4,304	8,182	1,409				
2015	4,251	14,646	2,195				
2016	2,291	6,768	1,111				
2017	3,555	12,929	1,978				
2018	4,637	13,939	2,276				
2019	5,308	22,222	2,547				

Appendix A.3. Data Quality and Methodology

The Williston Police Department (WPD) traffic stop data used in this study consists of 24,995 rows, spanning eight 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. Williston does supply this data. 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 WPD 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												
2012	393	31	0	6	1	0	10	7	11	7	0	0
2013	3,587	247	0	13	5	8	29	30	30	32	638	10
2014	3,338	125	0	200	46	41	27	35	38	145	620	14
2015	3,433	120	0	288	61	4	20	20	20	21	582	58
2016	1,811	1,811	0	246	15	5	5	5	5	4	604	96
2017	2,819	2,819	8	0	0	0	47	2	2	1	617	15
2018	3,756	3,756	14	2,919	104	11	75	3	3	3	494	5
2019	4,263	4,263	20	67	26	49	13	0	0	0	614	1
All Years	23,400	13,172	42	3,739	258	118	226	102	109	213	4,169	199
Percentage of Blank or Unknown Rows												
2012	393	7.9%	0.0%	1.5%	0.3%	0.0%	2.5%	1.8%	2.8%	1.6%	0	0.0%
2013	3,587	6.9%	0.0%	0.4%	0.1%	0.2%	0.8%	0.8%	0.8%	0.8%	638	1.6%
2014	3,338	3.7%	0.0%	6.0%	1.4%	1.2%	0.8%	1.1%	1.1%	4.2%	620	2.3%
2015	3,433	3.5%	0.0%	8.4%	1.8%	0.1%	0.6%	0.6%	0.6%	0.6%	582	10.0%
2016	1,811	100.0%	0.0%	13.6%	0.8%	0.3%	0.3%	0.3%	0.3%	0.2%	604	15.9%
2017	2,819	100.0%	0.3%	0.0%	0.0%	0.0%	1.6%	0.1%	0.1%	0.0%	617	2.4%
2018	3,756	100.0%	0.4%	77.7%	2.8%	0.3%	2.0%	0.1%	0.1%	0.1%	494	1.0%
2019	4,263	100.0%	0.5%	1.6%	0.6%	1.2%	0.3%	0.0%	0.0%	0.0%	614	0.2%
All Years	23,400	56.3%	0.2%	16.0%	1.1%	0.5%	0.9%	0.4%	0.5%	0.9%	4,169	4.8%

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 WPD data shows that required field values are sometimes missing or incorrect. The inclusion and quality of the data has improved year-over-year by 2019 (although it is unclear as to why age of driver continues to be missing so frequently) and hopefully, problems of missing data will not reemerge. Williston also has substantially lowered the number of accident reports missing the race of the driver.

Table A.3b shows the number and percentage of WPD 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	393	19	4.8%
2013	3,587	51	1.4%
2014	3,338	249	7.5%
2015	3,433	355	10.3%
2016	1,811	250	13.8%
2017	2,819	49	1.7%
2018	3,756	2,951	78.6%
2019	4,263	112	2.6%
All Years	23,400	4,036	17.3%

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

Table A.3c shows data on missing or unknown values and race of driver. We would expect data to be missing at the same rates across racial groups. In general, this holds for Williston. It is concerning, however, that 2% of searches of white drivers are missing data on contraband found, compared to 0% for other racial groups.

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)	21,493	880	498	255	258
Unknown Stop Reason	204	8	5	3	6
Unknown Stop Outcome	197	9	0	2	5
Unknown if Search occurred	90	5	0	2	5
Unknown if Contraband found subsequent to a search	7	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	0.9%	0.9%	1.0%	1.1%	2.2%
Unknown Stop Outcome as % of all outcomes	0.9%	1.0%	0.0%	0.8%	1.9%
Unknown if Search occurred as % of all stops	0.4%	0.6%	0.0%	0.8%	1.9%
Unknown if Contraband found as % of all searches	2.0%	0.0%	0.0%	0.0%	0.0%
Unknown Outcome if contraband found as % of all searches	0.3%	0.0%	0.0%	0.0%	0.0%

B. Stop IDs

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

For the 8 years of data available from Williston, the Stop IDs provided were not directly usable to tie together multiple outcomes for stops. For 2012 through 2016, the dates, times and other fields were available to derive Stop IDs. For 2017 through 2019, dates but not times were provided. This is insufficient to associate outcomes, so each row was treated as a separate stop (Table A.3d).

Table A.3d. Williston Stop IDs

Year	Usable Stop ID	Could Derive Stop IDs	Stop Count	Row Count
2012	No	Yes	403	444
2013	No	Yes	3,641	3,986
2014	No	Yes	3,506	3,675
2015	No	Yes	3,637	3,807
2016	No	Yes	1,882	2,006
2017	No	No	2,918	2,918
2018	No	No	3,825	3,825
2019	No	No	4,334	4,334

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