

Trends in Racial Disparities in Traffic Stops: Bennington, Vermont 2014-19

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EXECUTIVE SUMMARY

This study of Bennington traffic stops forms part of a statewide study of Vermont traffic stop data for 2011-2019. In each study of individual law enforcement agencies, we examine the data for racial disparities in several areas: racial share of stops, tickets vs. warnings, reasons for stops, arrest rates, search rates, and contraband “hit” rates. We also examine trends to determine whether racial disparities change over time. Finally, we comment on the completeness of the data collected by the Bennington Police Department (BPD).

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

- Black and Hispanic shares of drivers stopped exceed their shares of the estimated driving population. The data indicate Black drivers were overstopped by between 55% to 236%, depending on the measure of the driving population used. Hispanics were overstopped by 93% relative to their estimated share of the driving population.
- The arrest rate of Black drivers was 26% higher than the white arrest rate, and the Hispanic arrest rate was more than double the white rate.
- Black drivers were almost 4 times more likely to be searched subsequent to a stop than white drivers. Hispanic drivers were 60% more likely to be searched and the Asian search rate was less than half the white search rate.
- The likelihood of finding contraband of any kind was similar for Black and white drivers, but white drivers were much more likely to be found with contraband that led to an arrest.

In terms of trends:

- From 2015 to 2019, the number of traffic stops has risen about 65% in Bennington. Overall, Bennington has a high volume of stops relative to its population size. Black drivers are stopped at a rate that is more than double their estimated resident population.
- Over time, the Black-white and Hispanic white arrest rate disparities have worsened. Search rates of Black drivers have decreased and the Black-white search rate disparity has narrowed but it is still almost 3 times greater than the rate white drivers are searched.

Regarding data quality, we find:

- Race of the driver was omitted in 3.3% of stops—or 806 stops. To put that magnitude in perspective, during the entire period studied, there were only 613 recorded stops of Black drivers. Moreover, in more than 98% of the stops with no race recorded, all other fields (except age) were complete. In virtually all of the stops, age data is missing even though it is a legally required field. There has been no reduction in missing data over time. In fact, the proportion of stops missing the race of the driver has risen over time so that by 2019, 4.9% of traffic reports fail to record race of driver. This is concerning, since the goal of the legislation to require traffic stop data collection was precisely to identify racial

disparities. Bennington Police Department could benefit from additional attention to this problem so as to improve the quality and reliability of its 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 results for all agencies for which we had data, but due to small sample sizes for a number of agencies, we were only able to make statistical inferences on racial disparities for the state as a whole and for the larger cities and towns.

With several additional years of data and thus larger sample sizes, it is possible to provide statistical analysis for a larger number of agencies. It is also possible for us to evaluate trends over time. This report, which will form a component of a statewide report, analyzes data for Bennington, Vermont for 2014-2019.² Bennington Police Department (BPD) collected data on 25,037 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.³

The law requires that the following traffic stop data be collected and made available to the public: race, age, and gender of driver; reason for stop; type of search, if any; evidence found during the search, if any; and the outcome of the stop. In Vermont, driver's licenses do not include race/ethnicity of the driver. The race of driver indicated in incident reports on traffic stops is based on 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.⁴

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

¹ The bill is 20 V.S.A. § 2366.

² Bennington Police Department supplied only partial data for 2016 (January – August).

³ 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.

⁴ 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.

report descriptive data on key indicators in Section III of this report, and we discuss results of the hit rate test as well. In Section IV, we assess trends over time in racial disparities, using 3-year trends (2014-16, 2015-17, 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 information on missing data.⁵

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 has a larger proportion of younger drivers compared to other racial groups, for example, racial disparities may be expected. Race may also correlate with traffic stop disparities for reasons outside the control of law enforcement. For example, U.S. minorities have higher poverty rates than white Americans. This may result in a larger share of minorities driving with a suspended license due to the accumulation of unpaid parking or traffic citations. Racial disparities in this case are not necessarily due to bias of 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

⁵ 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*.⁶ 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 Bennington City Police Department (BPD) from 2014-19. As can be seen, a total of 25,037 stops were made. The percentage of stops in which a citation was issued is 64.5%, a percentage higher than any other agency we examined (the state average is 37.5%).

Table 1. Overview of the Data, 2014-19

	Observations	Rates
<i>Total Stops</i>		
incl. EGS	25,037	
excl. EGS	24,656	
<i>2014</i>	584	
<i>2015</i>	3,134	
<i>2016</i>	3,315	
<i>2017</i>	6,372	
<i>2018</i>	5,957	
<i>2019</i>	5,294	
<i>Citations</i>	15,899	64.5%
<i>Arrests</i>	371	1.5%
<i>Searches</i>	321	1.3%
<i>Contraband</i>	236	1.0%
<i>Contraband as % of Searches</i>	236	73.5%

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

⁶ To see the reasoning for this rule, see <https://www.cjr.org/analysis/capital-b-black-styleguide.php>.

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 Bennington, 1.5% (381 stops) of all stops were externally generated. These exclusions reduce our sample size to 24,656 traffic stops. The percentage of these stops that resulted in an arrest for violation⁷ was 1.5%, while 1.3% of stopped vehicles were searched. And contraband was found in 1.0% of all stops. Almost three quarters of searches (73.5%) yielded any type of contraband.

A challenging problem in the data, not only for Bennington 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 Bennington, over the time period of this study 2014-2019, 26 drivers were identified by officers as Native American.

Appendix Tables A.3a-3c detail information on missing data. In Bennington traffic reports, the race of the driver was omitted in 806 stops or in 3.3% of all stops. To put that magnitude into context, during the entire period there were only 630 recorded stops of Black drivers. Moreover, in more than 95% of the stops with no race recorded, all other fields were complete. We believe it is concerning that officers were able to record all information about a stop but failed to record race, a field that is legally required. We must drop the stops for which race of driver is missing from our analysis, thus reducing the sample size and reliability of our analysis.

Even more concerning is that data quality for race has not improved over time. In 2019, 4.2% of all traffic stop reports were missing race of driver. In every year except 2015, Bennington's first year of race data collection, the number of stops with drivers of unknown race has exceeded the number with identified Black drivers. Even in 2015, there were 101 stops with Black recorded as the driver's race and only a slightly lower 91 with unknown race recorded. Stop reason was missing in about 4.9% of all stops as well. Age information is missing from almost all stops even though it is a legally required field. Bennington Police

⁷ We exclude arrests for warrant since we are focusing on officer discretion. In the case of Bennington, however, there were no arrests on warrant over this time period.

Department should pay additional attention to this problem so as to improve the quality and reliability of their data. Appendix Table 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). This benchmark is not without its faults. Not everyone over 15 drives a vehicle and not everyone drives with the same degree of frequency. For example, on average, whites drive more than Blacks and Hispanics, a phenomenon related to income and wealth inequality by race (Tal and Handy 2005).⁸ Thus, there may be reason to question whether the racial composition of the population in an area is the same as the racial composition of drivers on the road. That said, this benchmark could be enlightening, especially when coupled with alternative benchmarks.

The second benchmark we use is the racial composition of drivers involved in accidents in Vermont. 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 an appropriate benchmark against which to compare racial shares of stops. This measure, too, has some weaknesses. It may overestimate Black and Hispanic shares of drivers due to racial dynamics in the U.S. Take, for example, the case of two white drivers involved in a minor traffic accident. These drivers may be more likely to

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

exchange insurance information and go on their way without calling the police than if one of the drivers is white and the other a person of color. In the latter case, white drivers may be more likely to involve the police due to potential implicit bias.

Alpert, *et al* (2004) recommend using only racial shares of not-at-fault drivers under the theoretical assumption that not-at-fault drivers represent a random sample of the driving population. In contrast, at-fault drivers may not comprise a random sample. For example, younger drivers are typically found to be lower quality drivers. Thus, age may be correlated with at-fault accidents, and the age composition of drivers may differ by race. We use all data from the DMV (including at-fault drivers), however, in order to maximize sample sizes, given the unreliability of estimates that result from the low number of observations for minority racial groups in Vermont.⁹

Data on racial shares of stopped drivers and the driving population are shown in Table 2. The share of stops relative to the share of population based on U.S. Census data is calculated only for Blacks, Asians, 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 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 Bennington comprised 94.3% of all stopped drivers from 2014 through 2019, with Blacks 2.6%, Asians 1.5% and Hispanics 1.5% of all drivers stopped. Inclusion of externally generated stops does not substantively change these percentages. Black and Hispanic shares of the driving population are lower than their share of stops, whether using the ACS population data or DMV accident data. For example, the estimates of Black drivers' share of the driving population range from 0.8% to 1.7%, lower than their share of stopped drivers (2.6%).

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

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

All Years	White	Black	Asian	Hispanic
Racial Shares of Stops				
<i>Including externally generated stops</i>	94.2%	2.7%	1.4%	1.6%
<i>Excluding externally generated stops</i>	94.3%	2.6%	1.5%	1.5%
<i>Driver Percentage (ACS)</i>	98.3%	0.8%	0.9%	
<i>Driver Percentage (DMV Accident data)</i>	95.9%	1.7%	1.5%	0.8%
<i>Disparity Index (using ACS)</i>	0.98	3.36	1.64	
<i>Disparity Index (using DMV Accident data)</i>	0.98	1.55	0.97	1.93
Stop Reason as % of All Stops				
<i>Safety Stops</i>	71.7%	72.1%	89.7%	74.5%
<i>Moving Violation</i>	71.6%	72.1%	89.4%	74.0%
<i>Suspicion of DWI</i>	0.1%	0%	0.3%	0.5%
<i>Investigatory/Pretextual Stops</i>	23.9%	22.0%	8.3%	20.2%
<i>Investigatory Stops</i>	2.5%	2.3%	0.3%	1.9%
<i>Vehicle Equipment</i>	21.4%	19.7%	8.0%	18.3%
<i>Externally Generated Stops</i>	1.5%	2.9%	0.9%	2.4%
<i>Multiple Reasons</i>	0.3%	0.2%	0%	0.3%
<i>Unknown Reason</i>	2.6%	2.8%	1.2%	2.7%
Outcome Rates as a % of All Stops				
<i>Warning Rate</i>	32.0%	35.4%	22.5%	36.7%
<i>Ticket Rate</i>	64.9%	62.1%	76.0%	59.2%
<i>Arrest for Violation Rate</i>	1.5%	1.9%	1.2%	3.5%
<i>Arrest for Warrant Rate</i>	0.1%	0.3%	0%	0%
<i>No Action Rate</i>	1.0%	0.2%	0.3%	0.8%
<i>Search Rates</i>				
<i>Search rate (excl. searches on warrant)</i>	1.2%	4.6%	0.6%	1.9%
<i>Search rate (incl. searches on warrant)</i>	1.2%	4.9%	0.6%	1.9%
<i>Hit rates (as a % of PC, RS & Warrant Searches)</i>				
<i>Hit rates (incl. all outcomes)</i>	72.9%	77.4%	100.0%	85.7%
<i>Hit rates (excl. warnings as outcomes)</i>	69.3%	67.7%	100.0%	85.7%
<i>Hit rates (outcome = arrest)</i>	19.9%	6.5%	50.0%	28.6%

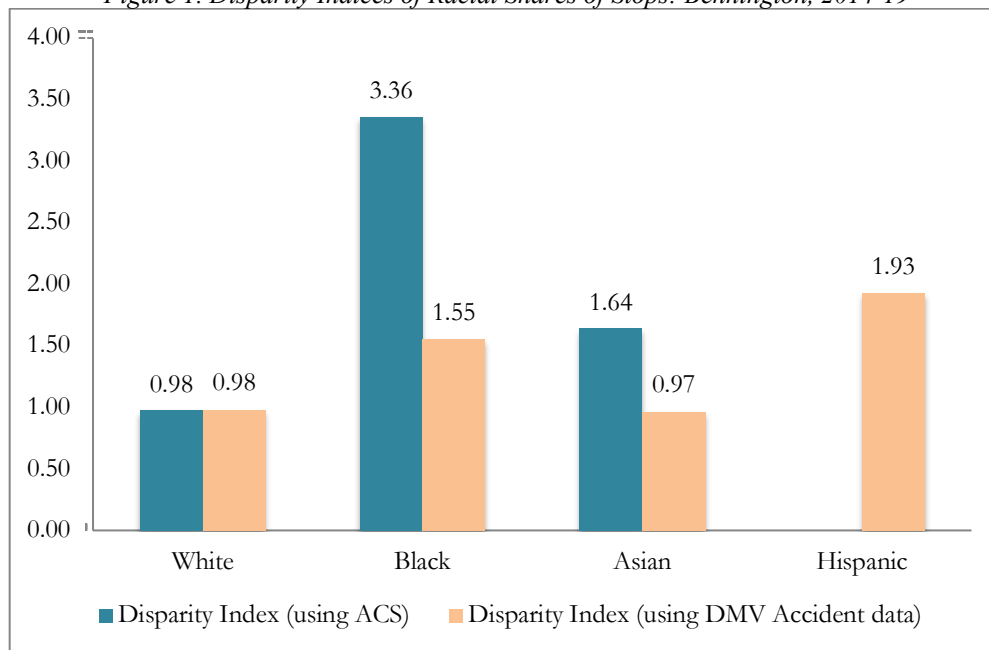
Note: ACS refers to the American Community Survey. NA is “not applicable.” U.S. Census Bureau data record Hispanics as an ethnicity, not race. Hispanics may be white or non-white. In contrast, Vermont law enforcement agencies treat the category of Hispanics as a mutually exclusive racial category. We 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 Bennington during this time period, that ratio ranges from 1.55 (2.6%/1.7%) using the DMV data to 3.36 (2.6%/0.8%) using ACS data. This implies the share of drivers stopped who are perceived to be Black is between 55% and 236% greater than their share of the estimated driving population. Hispanics, too, are overstopped relative to their share of the driving population, with a DI of 1.93. Put another way, Hispanic drivers are stopped at a rate this is almost double their estimated share of the driving population. In contrast, whether we use the ACS or DMV data, white drivers are stopped at a rate proportionate to their driving population share, while Asian drivers are overstopped by 64% using the ACS estimate and are stopped at a proportionate rate using the DMV estimates.

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

Figure 1. Disparity Indices of Racial Shares of Stops: Bennington, 2014-19



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

heavily on post-stop outcomes to assess racial disparities in policing. We turn to that topic in the next section.

B. Reasons for Stops

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. By far the most common reason motorists in Bennington 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 includes 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 Bennington the share of investigatory stops is about the same for Black and white drivers. The Asian share of stops that are "investigatory" is lower than that of white drivers. For Hispanics, the share of investigatory stops is slightly lower than the white rate. That said, neither the Asian nor Hispanic sample sizes are large enough to make reliable inferences.

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 vehicle 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 who have been stopped by race, and therefore can assess racial differences in post-stop outcomes with greater precision than stops.

Table 2 reports Bennington 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 the white search rate). A ratio that is greater than one indicates the minority group is more likely to experience a particular outcome than white drivers, and a ratio of less than one indicates the minority group is less likely to experience a particular outcome.

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

	Black/white	Asian/white	Hispanic/white
<i>Warning Rate</i>	1.11	0.71	1.15
<i>Ticket Rate</i>	0.96	1.17	0.91
<i>Arrest for Violation Rate</i>	1.26	0.77	2.34
<i>Search rate</i>	3.87	0.49	1.18

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 11% more likely to be given a warning than white drivers, and receive tickets at about the same rate as white drivers. Hispanic drivers are 15% more likely than white drivers to receive a warning, and are 9% less likely to be issued a citation. Asian drivers are 17% more likely than white drivers to receive a citation. None of these differences are statistically significant.

Black drivers are 26% more likely to be arrested in Bennington than white drivers (a difference that is not statistically significant). Hispanic drivers are 2.34 times more likely to be arrested subsequent to a stop than white drivers, a difference that is significant ($z=3.12$). In contrast, Asian drivers are less likely to be arrested than white drivers but because of the small number of Asian drivers who are arrested, the finding is not statistically significant.

Search rate data used for Table 3 exclude searches based on a warrant.¹⁰ Black drivers are searched at a rate that is almost 4 times greater than that of white drivers, a difference that is statistically significant ($z=7.96$). Specifically, while 1.2% of white drivers were searched

¹⁰ Searches resulting from a warrant could reasonably be described as discretionary because they are the result of a driver refusing to consent to a search. In those cases, the 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.

during this period of time, 4.6% of Black drivers were searched. There was only 2 searches of Asian drivers, and 7 searches of Hispanic drivers from 2014-19.

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.¹¹ 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, similar to Pierson, *et al*'s (2020) results. The Black/white search rate disparity in Bennington, however, is nearly twice the size of the national-level and North Carolina disparities.

Why might we observe racial differences in search rates? Search rate disparities may be justified if some groups (in this case, Blacks) are more likely to be carrying contraband than white drivers. Police may search vehicles, for example, in an attempt to interdict drugs (a reason that numerous 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.¹² 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.

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

In conducting the hit rate test, we focus on white and Black drivers. The number of searches of Asian and Hispanic drivers is small, preventing hit rate comparisons of these groups to

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

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

whites. We find that the productivity of searches of Black drivers is slightly higher than that of white drivers in searches that result in any outcome, although the difference is not significant ($z=0.54$). On the other hand, the Black hit rate as compared to the white hit rate is slightly lower for outcomes that lead at least to a ticket and/or arrest, but again the differences are not statistically significant ($z=0.43$). From 2015-2019, the years for which we have more complete data, the Black hit rate is significantly lower than the white hit rate where the contraband leads to an arrest ($z=2.39$). This is notable, given the negative stereotypes held of Blacks that can lead to higher search rates.

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 2015 (our first year of complete data)¹³ to 2019 the total number of stops increased by 65%. Stops of white drivers increased by 62.2%, stops of Black drivers increased by only 38% between 2015 and 2019, but the pattern for Black drivers is volatile. The number of stops of Black drivers more than tripled between 2016 and 2017 then decreased from 2017 to 2019. Although smaller in number, stops of Asian drivers tripled and stops of Hispanic drivers increased by 81%.

For 2019, we estimate that white drivers were stopped at a rate of 6,611 per 10,000 residents over 15¹⁴ compared to 3,983 in 2015 (Figure 2). That said, the white stop rate has been as high as 8,053 per 10,000 white residents (in 2017) during this time period. For Black drivers, the rate in 2015 was a large 16,102 per 10,000 rising to an even higher 22,203 in 2019—more than two stops per estimated Black resident in Bennington. It ballooned to 29,831 in 2017—almost 3 stops per year per estimated Black Bennington resident (for comparison, the estimated rate per 10,000 for all stops in Vermont that year was 3,326—a little over 10% of the rate at which Bennington was then stopping Black drivers). In all years except 2015, the Asian stop rate per 10,000 residents has been significantly higher than the white rate. For example, in 2019, the Asian stop rate was 10,597 compared to 6,611 for whites. For all drivers, the stop rates in Bennington are very high relative to the national average of 8.6%¹⁵ (or 860 out of 10,000) of drivers stopped per year.

¹³ BPD has only supplied partial data for 2016, as well, covering January through August. Because it is a much larger sample size than the 2014 data, we use it in our analysis.

¹⁴ 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 South Burlington 15 and older, all multiplied by 10,000. Population sizes by race are calculated from ACS 2013-17 data.

¹⁵ U.S. Department of Justice (2018: 1).

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

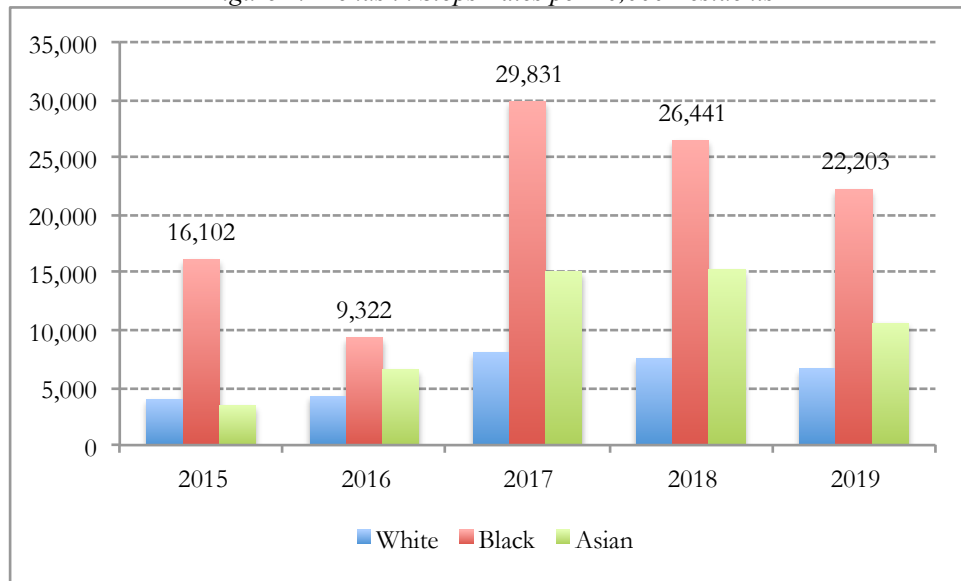
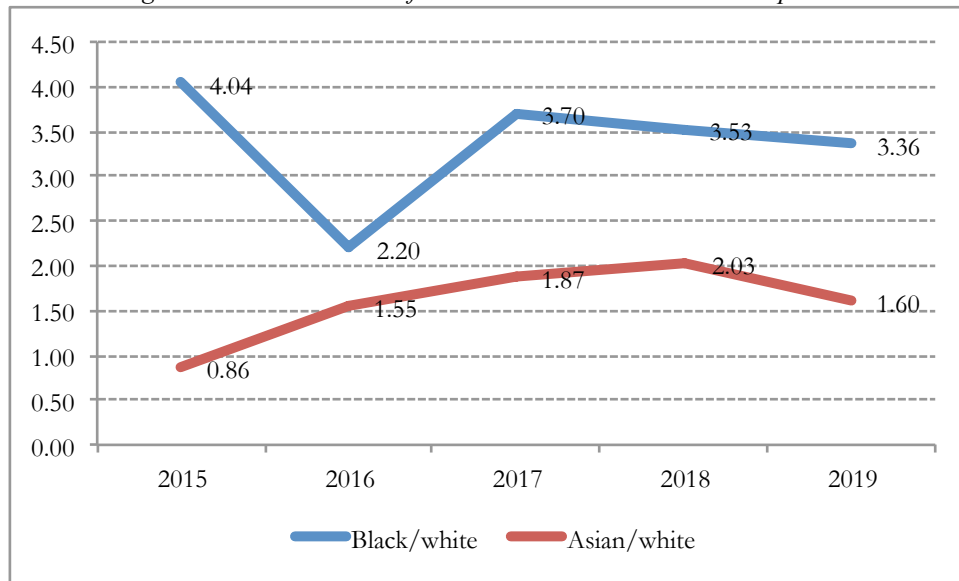


Figure 3 plots the ratio of Black to white stop rates and Asian to white stop rates. Because of partial data for 2014, we examine trends from 2015 to 2019. The Black-white ratio was 4 in 2015, meaning that Black drivers were stopped at a rate per capita 4 times larger than white drivers in that year. The Black/white ratio dipped in 2016 but has remained relatively constant around 3.5 times from 2017 to 2019. The Asian to white rate has fluctuated over this time period, starting at a rate a little lower than white drivers'. In 2019, the Asian stop rate rose to 60% higher than the white stop rate, after declining from a rate double that of white drivers.

Thus, the very high stop rates in Bennington are accompanied with disproportionately high stop rates of Black and Asians, relative to whites. Bennington is unusual in that racial disparities are typically limited to Blacks relative to whites and sometimes Hispanics relative to whites. Asian drivers tend to get more favorable treatment in other jurisdictions, in contrast to Bennington, where they are stopped at disproportionately high rates.

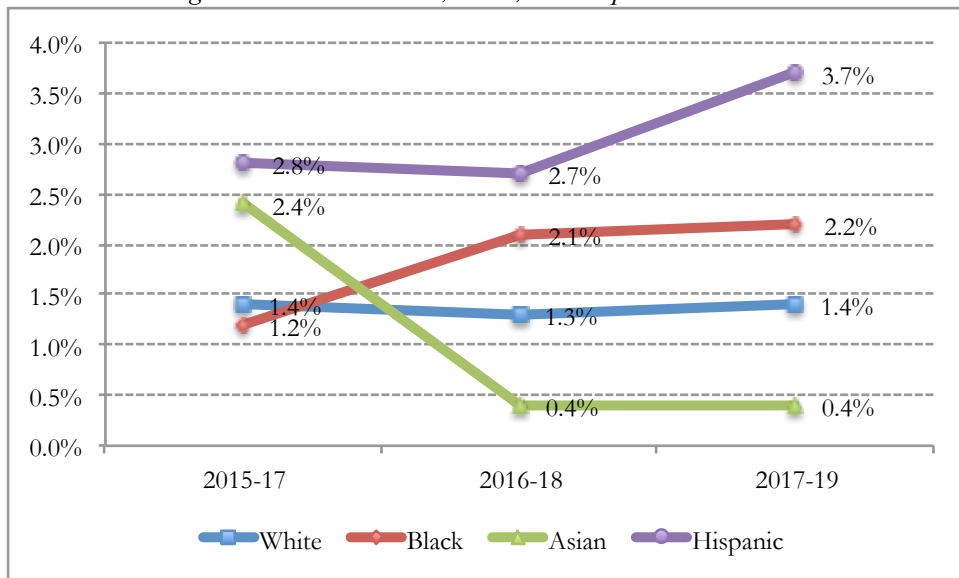
Figure 3. Trends in Ratio of Black/White and Asian/White Stop Rates



We also present data on trends 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 2015-17, 2016-17, etc. (See Appendix Table A.2a. for the raw numbers on which the following figures are based).

The Black arrest rate exceeded the white rate beginning in 2016-18 (Figure 4) and in 2017-19, was 57% higher than the white rate. The Hispanic-white difference in arrest rates is even wider, and has grown over time. In 2017-19, the Hispanic arrest rate was more than 2 and a half times greater than the white rate. The Asian arrest rate fell below the white rate in 2016-18, declining further to less than a third of the white rate in 2017-19.

Figure 4. Trends in White, Black, and Hispanic Arrest Rates



White and Black trends in search rates are shown in Figure 5. (Asian and Hispanic combined searches totaled 9 over this entire time period and are thus omitted due to sample size limitations). Search rates for white drivers have been relatively stable over this entire time period. In contrast, the Black search rate has fallen, reaching 3.0% in 2017-19. This narrowing search rate gap is a positive development although it should be noted that even with this progress, in 2017-19, Black drivers were searched at a rate that was 2.7 times greater than the white search rate.

Figure 5. Trends in Black and White Search Rates

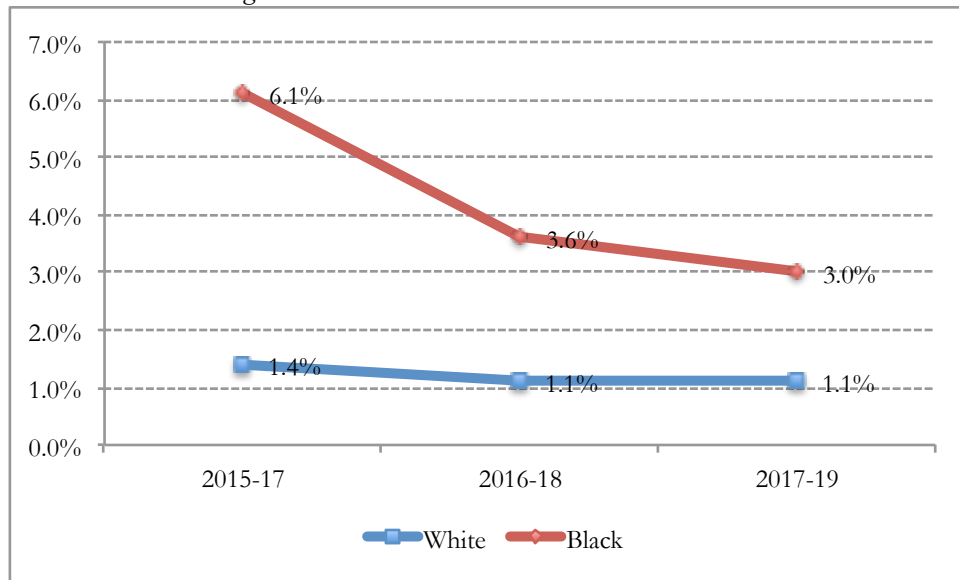
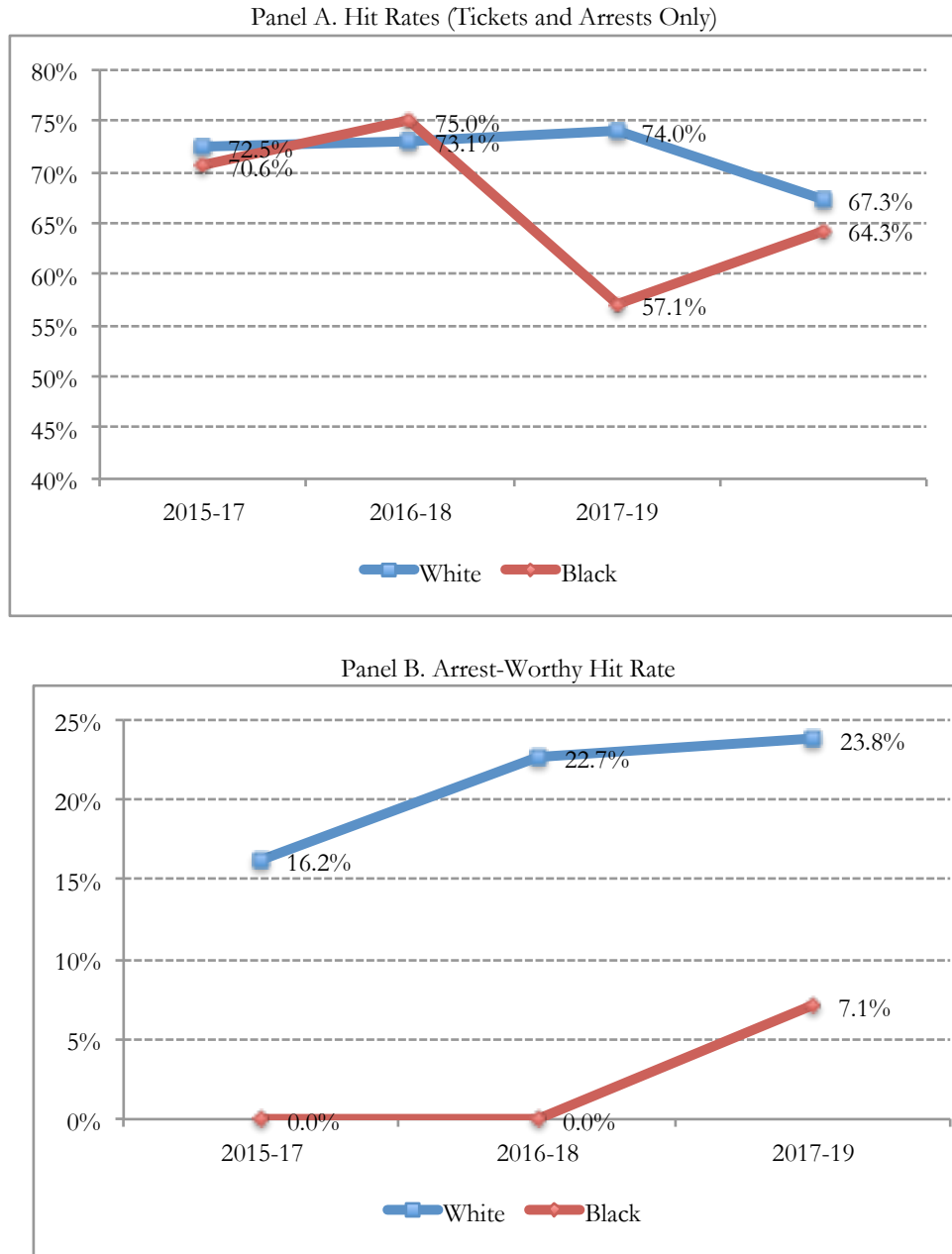


Figure 6, *Panel A* shows trends in white and Black contraband hit rates that result in at least one citation and/or arrest. Asian and Hispanic hit rates are not shown due to small sample sizes. As the graph indicates, since 2016, the Black hit rate has been below the white hit rate, although the gap narrowed in 2017-19.

Police officers often explain the higher Black search rate (shown in Figure 5) by their assumption that people of color from out of state are disproportionately trafficking drugs in Vermont. The arrest-worthy hit rate is therefore of much interest since searches that result in illegal drugs being found are more likely to result in an arrest of the driver. *Panel B* show the percentage of searches in which drivers were arrested, subsequent to the finding of contraband. As that figure shows, the arrest-worthy contraband hit rate for Black drivers has been 0% in 2 out of 3 periods, rising to 7.1% in 2017-2019. This is much lower than the white hit rate which rose from 16.3% in 2015-17 to 23.8%. As mentioned earlier, over this period from 2015-2019, this difference in the arrest-worthy hit rate is statistically significant.

Figure 6. Trends in White and Black Hit Rates



V. Logit Analysis

In this analysis, our focus is on searches and contraband. Our goal is to examine further for evidence that minority drivers receive less favorable treatment by controlling for possible confounding variables. To do this, we use multivariate logistic regression analysis to calculate the probability of a search occurring and separately, contraband being found, controlling for other factors that may influence the decision to search or of contraband being found. Why is this useful? Some driving behaviors and circumstances may co-vary with race, and could be the dominant reason behind a search rather than the

race of the driver. Failing to control for such factors risks misattributing search rate differences to race rather than the explicit behavior of the driver. If, even after controlling for factors like gender, age, reason for stop, and time of day, which we are able to control for, we still find that race is a statistically significant predictor of a search, then that provides additional evidence that the race of the driver, independent of these other factors, influences traffic policing in Bennington.

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:

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

Dummy variables for each racial group are included, with white the excluded racial category. The coefficients, reported in Table 4, for each of the driver race variables can be interpreted as the odds of a search for a driver of that race as compared to the odds for white drivers with the same characteristics. This is called the *odds ratio*, because it is the ratio of the odds of a non-white driver being searched over the odds that a white driver is searched. An odds ratio of 1 indicates equal probabilities of being searched. A ratio that is greater than one indicates a group is more likely to be searched than the omitted or benchmark group (that is, white drivers). Finally, an odds ratio that is less than 1 is indicative of a lower probability of a group being searched relative to the omitted group. (It is typical to include a control for driver age, but BPD has not reported driver age since 2014, despite this being a legally required category).

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 also control for time of day, with the excluded category the *afternoon*. We control for day of the week, with *Friday* the omitted day. The coefficients on days of the week indicate the odds of being searched on those days as compared to Fridays.

We control for the reason for the stop in two ways. First, we include all reasons for a stop as explanatory variables. The excluded category for this set of variables is *moving violation*. The coefficients on the *Reason for Stop* variables indicate the odds of being searched for each reason for stop divided by the odds of being searched due to moving violation, where the reason is one of the following: suspicion of driving while under the influence (DWI), investigatory stop, multiple reasons for a stop (where the 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 due to moving violation.

Controlling for all of these factors allows us to interpret the race variable, net of the impact of these other control variables. Results are shown in Table 4. Of primary interest is whether the race variables are statistically significant (as designated by the asterisks). If they are, this implies that independent of any other factors that may lead to 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 white drivers, Black drivers are 4.2 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). In contrast, the odds an Asian driver will searched are less than half the white odds. The odds ratio for Hispanic drivers is 1.6. The odds a Native American driver is searched are more than 3 times the white odds. The Asian, Hispanic, and Native American odds ratios are not statistically significant in this or in any of the other regression models, however.

In Model 2, adding controls for gender, time of day, day of week, and reason for stop, we find that the odds of a male driver being searched are 1.8 times greater than the odds a female driver will be searched. The probability of a search is substantially lower in the morning than in the afternoon. The odds of an evening search are more than double the odds in the afternoon. Odds of a search on Saturdays, Mondays and Tuesdays are higher than on Friday.

The odds of an investigatory stop leading to a search are more than double the odds for a stop initiated due to a moving violation. The odds of a search for stops due to suspicion of DWI and when there is an unknown stop reason are higher than the odds for a moving violation stop. The odds a Black driver will be searched in this model, after controlling for other factors, compared to the odds for a white driver, are 3.197. That is, even controlling for other factors, the odds a Black driver will be searched in Bennington are about 3 times greater than the odds a white driver will be searched. The coefficient continues to be statistically significant at the one percent level. That is, we can reject the null hypothesis that there is no difference in search rates between Black and white drivers with a high degree of certainty.

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

VARIABLES	(1)	(2)	(3)
	Race only	With all controls and stop reason	With all controls and pretextual stop control
Black	4.149*** (0.805)	3.197*** (0.638)	3.200*** (0.634)
Asian	0.461 (0.328)	0.419 (0.301)	0.449 (0.321)
Hispanic	1.547 (0.598)	1.221 (0.479)	1.300 (0.506)
Native American	3.296 (3.370)	2.817 (2.905)	2.984 (3.072)
Male		1.778*** (0.233)	1.804*** (0.235)
Morning		0.654*** (0.100)	0.639*** (0.100)
Night		2.328*** (0.307)	2.249*** (0.293)
Saturday		1.475** (0.282)	1.462** (0.279)
Sunday		0.925 (0.214)	0.989 (0.227)
Monday		1.713*** (0.339)	1.723*** (0.340)
Tuesday		1.878*** (0.370)	1.903*** (0.374)
Wednesday		1.042 (0.237)	1.031 (0.234)
Thursday		1.363 (0.285)	1.389 (0.290)
Investigatory Stop		2.125*** (0.555)	
Multiple stop reasons		2.613 (1.894)	
Suspicion of DWI		17.07*** (10.24)	
Unknown stop reason		4.725*** (1.187)	
Vehicle Equipment		0.961 (0.136)	
Pretextual stop			1.244* (0.151)
Constant	0.013*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
Observations	23,546	23,446	23,446

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

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 drivers will be searched are about 25% greater than the odds of a search if the reason is a safety stop.

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 5. 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:

$$\begin{aligned} \text{Probability of Finding Contraband} = & \beta_0 + \beta_B * \text{Black} + \beta_A * \text{Asian} + \beta_H * \text{Hispanic} + \beta_{Na} * \text{Native} \\ & \text{American} + \beta_M * \text{Male} + \beta_K * \text{Time of Day}_k + \beta_I * \text{Day of Week}_i + \beta_J * \text{Reason} \\ & \text{for Stop}_j + \text{Residual.} \end{aligned}$$

Table 5 reports the results of the probability of contraband being found for searches for any outcome of the stop and search (that is, in which the result was a warning, a citation, or an arrest) for all years for which we have data. The results shown for Model 1, where the only explanatory variable is race of the driver, indicate that the odds of a search of a Black driver yielding contraband are about 40% greater than the odds a white driver will be found with contraband subsequent to a search. The difference is not, however, 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 72.9% of searched white drivers are found with contraband and thus, 29.1% are not found with contraband. This implies an odds ratio for white drivers of $72.1/29.9 = 2.51$. In other words, the odds are roughly even that a search of a white driver will yield contraband. For Black drivers, we find in Table 2 that 77.4% of them are found with contraband so their odds ratio is $77.4/22.6 = 3.46$. The ratio of these two odds is the coefficient in our regression ($3.46/2.51 = 1.39$), very close to the coefficient estimate on race when we formally run the logit regression.

The addition of controls in Model 2 lowers the odds ratio of finding contraband in searches of Black as compared to white drivers to 1.08. Again, that coefficient is statistically insignificant. 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 higher probability of finding contraband than if the reason for the stop is for safety reasons. The odds ratio on pretextual stops, however, is not statistically significant.¹⁶

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. The odds ratios are even lower than those reported in Table 5. The coefficient is not statistically significant but the results are instructive.

Although the Black-white differences in the odds of contraband found during a search are not significant, we note two things. First, the relatively high percentage of stops for which the race of the driver is missing (6.6%) reduces the quality of the data, affecting measurement of all racial disparities in this study if the missing data is not random (that is, if for some reason, it is correlated with the race of the driver). BPD would be advised to dedicate efforts to improving the quality of the data and eliminating the problem of missing data in all categories, not just race. Second, the wide disparity in search rates is notable, even though the coefficients on the contraband odds ratio of Blacks relative to whites is statistically insignificant. More data would be helpful, and it may well show that contraband hit rates have converged, a positive development. Or, with more data, the hit rate difference may prove to be statistically significant, suggesting racial bias in the decision to search.

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

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

	(1)	(2)	(3)
VARIABLES	Race only	With all controls and stop reason	With all controls and pretextual stop control
Black	1.436 (0.682)	1.098 (0.547)	1.147 (0.566)
Hispanic	2.068 (2.252)	2.243 (2.570)	2.213 (2.505)
Male		1.662* (0.501)	1.707* (0.507)
Morning		0.558 (0.203)	0.540* (0.194)
Night		0.814 (0.265)	0.777 (0.251)
Saturday		2.120 (1.047)	2.109 (1.036)
Sunday		0.599 (0.313)	0.617 (0.319)
Monday		1.151 (0.536)	1.172 (0.543)
Tuesday		1.091 (0.500)	1.086 (0.493)
Wednesday		1.304 (0.720)	1.336 (0.732)
Thursday		1.495 (0.784)	1.550 (0.784)
Investigatory Stop		1.073 (0.732)	
Multiple		0.312 (0.472)	
Suspicion of DWI		0.299 (0.318)	
Unknown		1.134 (0.694)	
Vehicle Equipment		0.616 (0.196)	
Pretextual			0.742 (0.209)
Constant	2.901*** (0.399)	1.482 (0.907)	1.390 (0.837)
Observations	315	315	315

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.

Though data often and usually are imperfect, that does not preclude their usefulness. Efforts to improve data quality—and especially to eliminate missing race data—are important and should continue to be pursued. This is particularly so in the case of Bennington where race of driver was missing in 3.3% of all reports and the number of stops with drivers of unknown race is *twice as large* as the number with a recorded Black driver.

In this report, we provide descriptive data on racial disparities in Bennington Police Department's traffic stops. We find that Black drivers' share of stops exceed their estimated share of the driving population by a large margin—between 55% to 236%. Post-stop outcomes also give evidence of racial disparities.

There is a disparity in Black and white arrests rates. The Hispanic arrest rate was about 3 times greater than the white rate and that disparity has widened over time. From 2014 to 2019, Black drivers were searched at a rate that was almost 4 times greater than of white drivers. Although this disparity has narrowed over time but is still almost 3 times higher than the search rate of white drivers.

We also report on a statistical analysis that controls for additional factors that may influence the probability of being searched. Those results demonstrate that while other factors also contribute to the likelihood of search, 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. The results of the regressions exploring the probability of contraband indicated that statistically speaking, Black and white hit rates were equal, when we consider all outcomes to a stop. However, when we consider contraband that leads to an arrest, the white arrest-worthy hit rate exceeded the Black rate.

In addition to these results, some interesting aspects of BPD policing emerge from the data we analyzed. Traffic stops have increased by 65% in the last five years. There are more stops of Black drivers in Bennington than the resident Black population. In fact, there are 2.2 stops per Black resident, compared to 0.6 per white resident. Both of which are very large numbers compared to the national average of .086 stops per resident.

Bennington's traffic stop data is not of an adequate quality. Missing data are rampant and legally required data (age of driver) are not reported. Nor does the missing data appear to be randomly distributed.

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APPENDIX

Table A.1. Bennington Raw Traffic Stop Data, 2014-19

All Years	White	Black	Asian	Hispanic	Native American	Unknown	Total
Total Traffic Stops							
<i>Including externally generated stops</i>	22,822	649	349	377	26	814	25,037
<i>Excluding externally generated stops</i>	22,480	630	346	368	26	806	24,656
Reasons For Stops							
<i>Safety Stops</i>	16,359	468	313	281	20	599	18,040
Moving Violation	16,344	468	312	279	20	598	18,021
Suspicion of DWI	15	0	1	2	0	1	19
<i>Investigatory/Pretextual Stops</i>	5,456	143	29	76	4	169	5,877
Investigatory Stop	579	15	1	7	1	18	621
Vehicle Equipment	4,877	128	28	69	3	151	5,256
<i>Externally Generated Stop</i>	342	19	3	9	0	8	381
<i>Multiple Reasons - Moving Violation & Suspicion of DWI</i>	0	0	0	0	0	0	0
<i>Multiple Reasons - Moving Violation & Vehicle Equipment</i>	73	1	0	1	0	0	75
<i>Multiple Reasons - Suspicion of DWI & Vehicle Equipment</i>	0	0	0	0	0	0	0
<i>Unknown Stop Reason</i>	592	18	4	10	2	38	664
Outcomes							
<i>Ticket</i>	14,589	391	263	218	12	426	15,899
<i>Warning</i>	7,185	223	78	135	11	337	7,969
<i>No Action Taken</i>	224	1	1	3	1	10	240
<i>Arrest for violation</i>	340	12	4	13	1	1	371
<i>Arrest for warrant</i>	11	2	0	0	0	0	13
Searches							
<i>Total Stops with No Search</i>	21,912	591	343	358	24	770	23,998
No Search & Contraband & Arrest for violation	13	0	0	0	0	0	13
No Search & Contraband & No arrest	29	4	1	1	0	0	35
No Search (all others)	21,870	587	342	357	24	770	23,950
<i>Total Stops with Unknown Search</i>	291	8	1	3	1	33	337
<i>Total Stops with Search</i>	277	31	2	7	1	3	321
<i>Search with Probable Cause (PC)</i>	197	21	2	6	1	3	230
Stops with PC Searches, No contraband	45	5	0	1	1	1	53
Stops with PC Searches, Unknown contraband	7	0	0	0	0	0	7
Stops with PC Searches, Contraband	145	16	2	5	0	2	170
<i>Outcomes of PC Search</i>							
<i>Stops with PC Searches, Contraband & Warning, No Action or Unknown</i>	7	1	0	0	0	0	8
<i>Stops with PC Searches, Contraband and Ticket</i>	97	15	1	4	0	1	118
<i>Stops with PC Searches, Contraband and Arrest</i>	41	0	1	1	0	1	44
<i>Search with Reasonable Suspicion (RS)</i>	70	8	0	1	0	0	79
Stops with RS Searches, No contraband	18	1	0	0	0	0	19
Stops with RS Searches, Unknown contraband	1	0	0	0	0	0	1
Stops with RS Searches, Contraband	51	7	0	1	0	0	59
<i>Outcomes of RS Search</i>							
<i>Stops with RS Searches, Contraband & Warning, No Action or Unknown</i>	3	1	0	0	0	0	4
<i>Stops with RS Searches, Contraband & Ticket</i>	38	4	0	0	0	0	42
<i>Stops with RS Searches, Contraband & Arrest</i>	10	2	0	1	0	0	13
<i>Search with Warrant</i>	10	2	0	0	0	0	12
Stops with Warrant Searches, No contraband	4	0	0	0	0	0	4
Stops with Warrant Searches, Unknown contraband	0	1	0	0	0	0	1
Stops with Warrant Searches, Contraband	6	1	0	0	0	0	7
<i>Outcomes of Warrant Search</i>							
<i>Stops with Warrant Searches, Contraband & Warning, No Action or Unknown</i>	0	1	0	0	0	0	1
<i>Stops with Warrant Searches, Contraband & Ticket</i>	2	0	0	0	0	0	2
<i>Stops with Warrant Searches, Contraband & Arrest</i>	4	0	0	0	0	0	4

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

All Years	White	Black	Asian	Hispanic	Native American	Unknown	Total
Total Traffic Stops							
<i>Excluding externally generated stops</i>							
2014-16	6,475	167	72	94	9	216	7,033
2015-17	11,753	326	168	182	12	380	12,821
2016-18	14,293	387	247	226	13	478	15,644
2017-19	16,005	463	274	274	17	590	17,623
Reasons For Stops (excl. externally generated stops and unknown reasons)							
<i>Safety Stops</i>							
2014-16	5,344	135	69	80	8	186	5,822
2015-17	9,146	261	157	155	11	308	10,038
2016-18	10,514	280	222	169	12	361	11,558
2017-19	11,015	333	244	201	12	413	12,218
2014-16 (% of stops)	82.9%	81.3%	95.8%	85.1%	88.9%	86.1%	83.1%
2015-17 (% of stops)	78.8%	81.1%	93.5%	86.1%	91.7%	81.3%	79.2%
2016-18 (% of stops)	75.7%	74.7%	91.0%	77.9%	92.3%	77.6%	76.0%
2017-19 (% of stops)	71.7%	74.8%	90.4%	76.4%	80.0%	74.8%	72.3%
<i>Pretextual Stops</i>							
2014-16	1,105	31	3	14	1	30	1,184
2015-17	2,468	61	11	25	1	71	2,637
2016-18	3,374	95	22	48	1	104	3,644
2017-19	4,351	112	26	62	3	139	4,693
2014-16 (% of stops)	17.1%	18.7%	4.2%	14.9%	11.1%	13.9%	16.9%
2015-17 (% of stops)	21.3%	18.9%	6.6%	13.9%	8.3%	18.7%	20.8%
2016-18 (% of stops)	24.3%	25.3%	9.0%	22.1%	7.7%	22.4%	24.0%
2017-19 (% of stops)	28.3%	25.2%	9.6%	23.6%	20.0%	25.2%	27.8%
Outcomes (excl. externally generated stops)							
<i>Tickets (one or more)</i>							
2014-16	5,287	135	60	72	7	165	5,726
2015-17	8,434	233	129	118	8	224	9,146
2016-18	9,351	235	189	131	6	242	10,154
2017-19	9,302	256	203	146	5	261	10,173
2014-16 (% of stops)	81.7%	80.8%	83.3%	76.6%	77.8%	76.4%	81.4%
2015-17 (% of stops)	71.8%	71.5%	76.8%	64.8%	66.7%	59.0%	71.3%
2016-18 (% of stops)	65.4%	60.7%	76.5%	58.0%	46.2%	50.6%	64.9%
2017-19 (% of stops)	58.1%	55.3%	74.1%	53.3%	29.4%	44.2%	57.7%
<i>Arrests for Violation</i>							
2014-16	112	2	3	3	0	0	120
2015-17	165	4	4	5	0	1	179
2016-18	189	8	1	6	0	1	205
2017-19	228	10	1	10	1	1	251
2014-16 (% of stops)	1.7%	1.2%	4.2%	3.2%	0.0%	0.0%	1.7%
2015-17 (% of stops)	1.4%	1.2%	2.4%	2.8%	0.0%	0.3%	1.4%
2016-18 (% of stops)	1.3%	2.1%	0.4%	2.7%	0.0%	0.2%	1.3%
2017-19 (% of stops)	1.4%	2.2%	0.4%	3.7%	5.9%	0.2%	1.4%
Searches (excl. externally generated stops)							
<i>Searches (PC, RS or Warrant)</i>							
2014-16	109	17	0	1	0	1	128
2015-17	167	20	1	3	0	2	193
2016-18	154	14	2	5	0	1	176
2017-19	168	14	2	6	1	2	193
2014-16 (% of Stops)	1.7%	10.2%	0.0%	1.1%	0.0%	0.5%	1.8%

2015-17 (% of Stops)	1.4%	6.1%	0.6%	1.7%	0.0%	0.5%	1.5%
2016-18 (% of Stops)	1.1%	3.6%	0.8%	2.2%	0.0%	0.2%	1.1%
2017-19 (% of Stops)	1.1%	3.0%	0.7%	2.2%	5.9%	0.3%	1.1%
<i>Contraband (All Outcomes)</i>							
2014-16	84	14	0	1	0	1	100
2015-17	130	16	1	3	0	2	152
2016-18	119	10	2	4	0	1	136
2017-19	118	10	2	5	0	1	136
2014-16 (% of Searches)	77.1%	82.4%	0.0%	100.0%	0.0%	100.0%	78.1%
2015-17 (% of Searches)	77.8%	80.0%	100.0%	100.0%	0.0%	100.0%	78.8%
2016-18 (% of Searches)	77.3%	71.4%	100.0%	80.0%	0.0%	100.0%	77.3%
2017-19 (% of Searches)	70.2%	71.4%	100.0%	83.3%	0.0%	50.0%	70.5%
<i>Contraband (Tickets + Arrests)</i>							
2014-16	79	12	0	1	0	1	3
2015-17	122	15	1	3	0	2	4
2016-18	114	8	2	4	0	1	4
2017-19	113	9	2	5	0	1	4
2014-16 (% of Searches)	72.5%	70.6%	0.0%	100.0%	0.0%	100.0%	2.7%
2015-17 (% of Searches)	73.1%	75.0%	100.0%	100.0%	0.0%	100.0%	2.3%
2016-18 (% of Searches)	74.0%	57.1%	100.0%	80.0%	0.0%	100.0%	2.3%
2017-19 (% of Searches)	67.3%	64.3%	100.0%	83.3%	0.0%	50.0%	1.9%
<i>Contraband (Arrests only)</i>							
2014-16	15	1	0	0	0	0	16
2015-17	27	0	1	0	0	1	29
2016-18	35	0	1	0	0	1	37
2017-19	40	1	1	2	0	1	45
2014-16 (% of Searches)	13.8%	5.9%	0.0%	0.0%	0.0%	0.0%	12.5%
2015-17 (% of Searches)	16.2%	0.0%	100.0%	0.0%	0.0%	50.0%	15.0%
2016-18 (% of Searches)	22.7%	0.0%	50.0%	0.0%	0.0%	100.0%	21.0%
2017-19 (% of Searches)	23.8%	7.1%	50.0%	33.3%	0.0%	50.0%	23.3%

2014-16	11	1	0	0	0	0	12
2015-17	23	0	1	0	0	1	25
2016-18	31	0	1	0	0	1	33
2017-19	40	1	1	2	0	1	45
2014-16 (% of Searches)	11.7%	6.7%	0.0%	0.0%	0.0%	0.0%	10.8%
2015-17 (% of Searches)	15.1%	0.0%	100.0%	0.0%	0.0%	50.0%	14.2%
2016-18 (% of Searches)	22.3%	0.0%	50.0%	0.0%	0.0%	100.0%	20.8%
2017-19 (% of Searches)	23.8%	7.1%	50.0%	33.3%	0.0%	50.0%	23.3%

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

All Years	White	Black	Asian	Hispanic	Native American	Unknown	Total
Total Traffic Stops							
<i>Including externally generated stops</i>							
2014	557	17	5	7		19	605
2015	2,964	102	23	50	3	91	3,233
2016	3,113	57	45	42	6	110	3,373
2017	5,892	182	101	97	3	183	6,458
2018	5,488	158	104	94	4	187	6,035
2019	4,808	133	71	87	10	224	5,333
<i>Excluding externally generated stops</i>							
2014	537	17	5	7	0	18	584
2015	2,876	95	23	48	3	89	3,134
2016	3,062	55	44	39	6	109	3,315
2017	5,815	176	101	95	3	182	6,372
2018	5,416	156	102	92	4	187	5,957
2019	4,774	131	71	87	10	221	5,294
<i>Percentage Change YoY (Excl. EGS)</i>							
2014 vs 2015	435.6%	458.8%	360.0%	585.7%		394.4%	436.6%
2015 vs 2016	6.5%	-42.1%	91.3%	-18.8%	100.0%	22.5%	5.8%
2016 vs 2017	89.9%	220.0%	129.6%	143.6%	-50.0%	67.0%	92.2%
2017 vs 2018	-6.9%	-11.4%	1.0%	-3.2%	33.3%	2.8%	-6.5%
2018 vs 2019	-11.9%	-16.0%	-30.4%	-5.4%	150.0%	18.2%	-11.1%
<i>Stops per 10,000 residents (Excl. EGS)</i>							
2014	744	2,881	746				795
2015	3,983	16,102	3,433				4,177
2016	4,240	9,322	6,567				4,418
2017	8,053	29,831	15,075				8,493
2018	7,500	26,441	15,224				7,939
2019	6,611	22,203	10,597				7,056

Appendix A.3. Data Quality and Methodology

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

A. Missing or Unknown Data Values by Field

Table A.3 shows the counts and percentages of missing or unknown data values. Missing data is when the 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 BPD supplies.

Table A.3. Fields with Missing or Unknown Values

Stop Years	Stops	Stop ID	Stop Date/Time	Age	Race	Gender	Stop Reason	Search Reason	Contra-band	Stop Outcome	Reported Accidents	Race in Reported Accidents
Count of Blank or Unknown Rows												
2014	584	0	0	584	18	4	2	2	3	2	771	34
2015	3,134	0	0	3,134	89	52	13	9	11	11	844	52
2016	3,315	3,315	0	3,187	109	18	6	5	5	10	797	73
2017	6,372	6,372	0	6,372	182	41	95	22	22	48	699	17
2018	5,957	5,957	0	5,953	187	66	285	143	144	378	725	17
2019	5,294	5,294	0	5,294	221	38	263	156	156	400	410	13
All Years	24,656	20,938	0	24,524	806	219	664	337	341	849	5,066	228
Percentage of Blank or Unknown Rows												
2014	584	0.0%	0.0%	100.0%	3.1%	0.7%	0.3%	0.3%	0.5%	0.3%	771	4.4%
2015	3,134	0.0%	0.0%	100.0%	2.8%	1.7%	0.4%	0.3%	0.4%	0.4%	844	6.2%
2016	3,315	100.0%	0.0%	96.1%	3.3%	0.5%	0.2%	0.2%	0.2%	0.3%	797	9.2%
2017	6,372	100.0%	0.0%	100.0%	2.9%	0.6%	1.5%	0.4%	0.4%	0.7%	699	2.4%
2018	5,957	100.0%	0.0%	99.9%	3.1%	1.1%	4.7%	2.4%	2.4%	6.0%	725	2.3%
2019	5,294	100.0%	0.0%	100.0%	4.2%	0.7%	4.9%	3.0%	3.0%	7.1%	410	3.2%
All Years	24,656	84.9%	0.0%	99.5%	3.3%	0.9%	2.7%	1.4%	1.4%	3.3%	5,066	4.5%

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

Table A.3b shows the number and percentage of BPD 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)
2014	584	584	100.0%
2015	3,134	3,134	100.0%
2016	3,315	3,191	96.3%
2017	6,372	6,372	100.0%
2018	5,957	5,955	100.0%
2019	5,294	5,294	100.0%
All Years	24,656	24,530	99.5%

Table A.3c provides data on the relationship between missing or unknown values and race of driver. We would expect data to be missing at the same rates across racial groups. It is concerning therefore that the share of stops missing stop outcome for Black and Hispanics drivers is higher than for white and Asian drivers.

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

	White	Black	Asian	Hispanic	Unknown
Count of Blank or Unknown Rows					
<i>Total Stops (excl. EGS)</i>	22,480	630	346	368	806
<i>Unknown Stop Reason</i>	592	18	4	10	38
<i>Unknown Stop Outcome</i>	758	30	3	16	40
<i>Unknown if Search occurred</i>	291	8	1	3	33
<i>Unknown if Contraband found to a search</i>	4	0	0	0	0
<i>Unknown Outcome if contraband found</i>	3	0	0	0	0
Percentage of Blank or Unknown Rows					
<i>Unknown Stop Reason as % of all stops</i>	2.6%	2.8%	1.2%	2.7%	4.7%
<i>Unknown Stop Outcome as % of all outcomes</i>	3.2%	4.5%	0.9%	4.2%	4.9%
<i>Unknown if Search occurred as % of all stops</i>	1.3%	1.3%	0.3%	0.8%	4.1%
<i>Unknown if Contraband found as % of all searches</i>	1.4%	0.0%	0.0%	0.0%	0.0%
<i>Unknown Outcome if contraband found as % of all searches</i>	1.1%	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 four of the six years of data available from Bennington, the Stop IDs provided were not directly usable to tie together multiple outcomes for stops. However, the dates, times and other fields were available to derive Stop IDs (Table A.3d).

Table A.3d. Bennington Stop IDs

Stop Years	Usable Stop IDs	Could Derive Stop IDs	Stop Count	Row Count
2014	Yes		605	605
2015	Yes		3,233	3,233
2016	No	Yes	3,373	3,589
2017	No	Yes	6,458	6,768
2018	No	Yes	6,035	6,437
2019	No	Yes	5,333	5,711

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	
<i>Safety Stops</i>	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”
<i>Investigatory/Pretextual Stops</i>	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”
<i>Multiple Reasons - Moving Violation & Suspicion of DWI</i>	Count of all stops where stop reasons include both “moving violation” and “suspicion of DWI”
<i>Multiple Reasons - Moving Violation & Vehicle Equipment</i>	Count of all stops where stop reasons include both “moving violation” and “vehicle equipment”
<i>Multiple Reasons - Suspicion of DWI & Vehicle Equipment</i>	Count of all stops where stop reasons include both “suspicion of DWI” and “vehicle equipment”
<i>Unknown Stop Reason</i>	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	
<i>Total stops with no search</i>	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”
<i>Total Stops with Unknown Search</i>	Count of all stops where search reason was “unknown”
<i>Total Stops with Search</i>	Count of all stops where search reason was one of “probable cause,” “reasonable suspicion,” or “warrant”
<i>Search with Probable Cause (PC)</i>	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”
<i>Outcomes of PC Search</i>	
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”
<i>Outcomes of RS Search</i>	
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”
<i>Outcomes of Warrant Search</i>	
<i>Stops with Warrant Searches, Contraband & Warning, No Action or Unknown</i>	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	
<i>Safety Stops</i>	% 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”
<i>Investigatory/Pretextual Stops</i>	% 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”
<i>Externally Generated Stops</i>	% of all stops where stop reason is “externally generated stop”
<i>Multiple Reasons</i>	% 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”
<i>Unknown Reason</i>	% of all stops where stop reason is “unknown”
Outcome Rates as a % of All Stops	
<i>Warning Rate</i>	% of non-EGS stops where at least one warning was issued
<i>Ticket Rate</i>	% of non-EGS stops where at least one ticket was issued
<i>Arrest for Violation Rate</i>	% of non-EGS stops where there was an arrest for violation
<i>Arrest for Warrant Rate</i>	% of non-EGS stops where there was an arrest for warrant
<i>No Action Rate</i>	% of non-EGS stops where there was no action taken
<i>Search Rates</i>	
<i>Search rate (excl. searches on warrant)</i>	% of non-EGS stops where the search reason was “probable cause” or “reasonable suspicion”

Variable	Formula
<i>Search rate (incl. searches on warrant)</i>	% of non-EGS stops where the search reason was “probable cause,” “reasonable suspicion,” or “warrant search”
<i>Hit rates (as a % of PC, RS, & Warrant Searches)</i>	
<i>Hit rates (incl. all outcomes)</i>	% of non-EGS stops where the search reason was “probable cause,” “reasonable suspicion,” or “warrant” and contraband was found
<i>Hit rates (excl. warnings as outcomes)</i>	% 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
<i>Hit rates (outcome = arrest)</i>	% 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