Trends in Racial Disparities in Traffic Stops: Rutland, Vermont 2011-19

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EXECUTIVE SUMMARY

This study of Rutland traffic stops forms part of a statewide report 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 and quality of the data collected by the Rutland Police Department (RPD).

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

- Black and Hispanic shares of drivers stopped exceed their shares of the estimated driving population. The data indicate Black drivers were overstopped by between 79% to 151%, depending on the measure of the driving population used. Hispanics were overstopped by 36% relative to their estimated share of the driving population.
- Black and Hispanic drivers were slightly less likely than white drivers to be stopped for safety reasons, and slightly more likely to experience pretextual stops—stops more prone to be used to investigate "suspicious" behavior and therefore more prone to racial bias.
- Black drivers are more likely than white drivers to be issued more than one citation per stop.
- The arrest rate of Black drivers was 2 times that of white drivers, and the Hispanic arrest rate was 3 times that of white drivers.
- Black drivers were about 4.7 times more likely to be searched subsequent to a stop than white drivers and Hispanic drivers were searched at a rate that is 38% higher than that of white drivers. Asian drivers were less likely to be searched than white drivers.
- Black and Hispanic drivers were less likely to be found with contraband than white drivers despite their higher search rates. For Black and white drivers, the difference in hit rates is statistically significant.

In terms of trends:

- Trends in the share of stopped drivers who are Black and the Black/white arrest differentials have worsened.
- Over time, the racial disparities in the contraband hit rate have decreased.
- There is significant volatility in the number of traffic stops per year, with stops in 2015 being roughly twice the average number per year. The number of stops has declined since 2017 to roughly 40% of the number of stops in 2015. Our sense is that this is a positive trend especially as the period of reduced number of traffic stops coincides with the reduction in the Black/white hit rate disparity.

Regarding data quality, our main findings are:

- Data quality has varied inconsistently over time. Data was provided for 8 complete years (2012-2019) and one partial year (2011) with 12.2% of all traffic stop reports having missing or unknown values for at least one variable. Race data was missing in 2.2% of traffic stop reports for the 2011-19 period, and 3.0% of stops were missing reason for the stop in 2019, up from 0% in 2011.

- In addition, there are concerns that the stops with race missing are not random.

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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 greater number of agencies. It is also possible to evaluate trends over time. This report, which will form a component of a statewide report, analyzes data for Rutland, Vermont for 2011-2019. Rutland Police Department (RPD) collected data on 22,874 traffic stops during this period of time.

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

The law requires that the following traffic stop data be collected and made available to the public: race, age, and gender of driver; reason for stop; type of search, if any; evidence found during the search, if any; and the outcome of stop. In Vermont, driver's licenses do not include race/ethnicity of the driver. The race of driver indicated in 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.[3]

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

[1] The bill is 20 V.S.A. § 2366.
[2] For example, some agencies have a policy that a stopped driver found to be driving with a suspended license is automatically given a citation. Thus, not all officer decisions are the result of discretion. To some extent, the results reflect the role of leadership, training, agency culture, and policies.
[3] Additional data would have been helpful to include in our analysis, but this would require a change to the legislation that has not yet been forthcoming. For example, the type of contraband found, the state the vehicle is registered in, the duration of the stop, officer-level data, and stop numbers would improve the ability to assess the degree, if any, of racial disparities in traffic policing.

hit rate test as well. In Section IV, we assess trends over time in racial disparities, using 3-year trends (2012-2014, 2013-15, etc.), instead of year by year, to expand the sample size. In Section V, we conduct a logit analysis to determine the probability of a search and of finding contraband, based on a variety of factors (such as age, gender, and reason for the stop) in addition to the race of the driver. This analysis helps us to control for the context of the stop thereby better isolating the role of race of driver in a search or finding of contraband. Section VI concludes and in the appendix we provide supplemental data and data that underlie our analysis of the quality of the agency's data.[4]

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

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

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

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

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

A note on language used in this report is warranted. Race is not a biological category but rather, is a socially constructed concept. Moreover, language about race is fluid, and reflects political changes over time. For example, Hispanic has become less politically acceptable and is now widely replaced by Latinx (a gender neutral form of Latina/o). We retain the use of Hispanic in this report only because this is terminology used in police traffic stop data reports. Second, in just the last year, the term BIPOC (Black, Indigenous, and other People of Color) has come to replace people of color or minorities. We determined the term is still too new to be widely familiar and thus retain older terminology for these conceptual categories. And finally, the capitalization of black and white groups is contested, with some arguing for black to be capitalized but not white and more recently, some argue 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 Rutland City Police Department (RPD) from 2011-19. As can be seen, a total of 22,874 stops were made. More than half of these stops resulted in the issuance of a citation.

Our focus is primarily on policing decisions based on officer discretion although it is impossible to entirely disentangle the role of agency culture and leadership from individual officer decisions. In order to restrict our attention to discretionary decisions and actions, in the following analysis we exclude stops that are externally generated. Externally generated stops are those that rely on external information to initiate a stop. An officer may be directed to stop a vehicle, for instance, in response to a be-on-the-lookout (BOLO) alert. In this case, the officer does not initiate the stop. In the case of Rutland, 7.4% or 1,694 of all stops were externally generated (a very high percentage, compared to other agencies). These exclusions reduce our sample size to 21,180 traffic stops. The percentage of these stops that resulted in an arrest for violation[6] was 2.1%, while 1.3% of stopped vehicles were searched. Contraband was found in 0.9% of all stops, and in 74.3% of all searches.

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

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

Table 1. Overview of the Data, 2011-19

	Observations	Rates
Total Stops		
incl. EGS	22,874	
excl. EGS	21,180	
2011	355	
2012	1,771	
2013	2,238	
2014	2,618	
2015	4,515	
2016	2,298	
2017	2, 972	
2018	2,635	
Citations	11,954	56.4%
Arrests	440	2.1%
Searches	265	1.3%
Contraband	197	0.9%
Contraband as % of searches	197	74.3%

Note: EGS is externally generated stops. All rates, annual totals, and outcome data exclude EGS. Rates are outcomes as a percentage of all stops, except where noted. RPD provided partial 2011 data, which preceded the legislation mandating traffic stop data collection.

A challenging problem in the data, not only for Rutland 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 Rutland, over the time period of this study 2011-2019, only 16 drivers were identified as Native American.

Appendix Tables A.1 and A.3a-A.3c detail information on missing data. Missing data does not appear to be random. For example, for the 457 stops where race of driver is not known, less than 1% of those stops had any other missing information about the stop. Why would an officer record all other information on the stop but fail to record the race, a field that is legally required? Having this almost complete information about the drivers whose race is unrecorded allows us to analyze their treatment compared to other drivers. There is significant evidence that the treatment of these drivers in which race is unknown is statistically dissimilar from the treatment of other drivers. Specifically, 77.1% of drivers with unknown race had safety stops (compared to 66% overall, z=4.98) and 76.2% of those stops resulted in tickets (compared to just 56% of stops overall, z=8.42). Again, this does not appear to be random missing information.

Providing complete data is required in order for the public to have full confidence in the quality of Rutland's traffic stop data. The quantity of missing data has varied over time, with 29.0% of all traffic stop reports having missing data (for all variables) in 2011, rising to 100.0% in 2019. The race of the driver was omitted in 2.0% of all traffic stop reports from 2011 to 2019.[7] 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 standard 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

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[7] This excludes externally generated stops.

[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.

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. Alpert, *et al* (2004) recommend using only racial shares of not-at-fault drivers under the theoretical assumption that not-at-fault drivers represent a random sample of the driving population. In contrast, at-fault drivers may not comprise a random sample. For example, younger drivers are typically found to be lower quality drivers. Thus, age may be correlated with at-fault accidents, and the age composition of drivers may differ by race. While the ideal would be to use only not-at-fault drivers from the DMV data to calculate estimates of racial shares of the driving population, we seek to maximize sample sizes, given the unreliability of estimates that result from the low number of observations for minority racial groups in Vermont.[9] It should be noted that RPD accident reports are missing race of driver in 3.4% of all cases. This is problematic, and to improve the accuracy of racial shares of stops, there should be no unknowns or missing data in accidents.

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

White drivers in Rutland comprised 95.1% of all stopped drivers from 2011 through 2019, with Blacks 3.0%, Asians 0.9% and Hispanics 1.0% of all drivers stopped. Inclusion of externally generated stops does not change these percentages. Black and Hispanic shares of the driving population are lower than their share of stops, whether using the ACS or DMV accident data. For example, the estimates of Black drivers' share of the driving population range from 1.2% to 1.7%, lower than their share of stopped drivers.

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

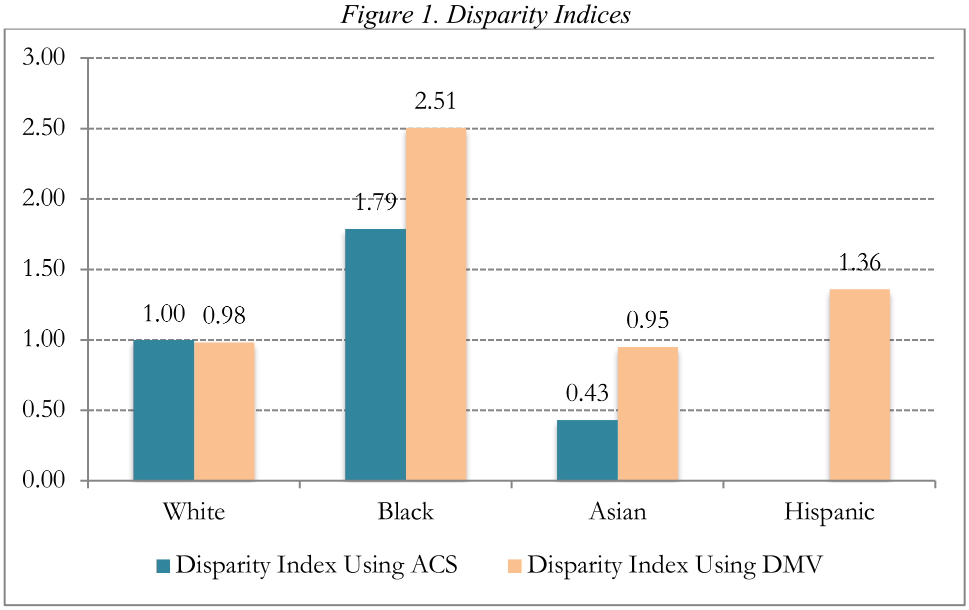
All Years	White	Black	Asian	Hispanic
Total Traffic Stops				
Including externally generated stops	95.1%	3.0%	0.9%	1.0%
Excluding externally generated stops	95.1%	3.0%	0.9%	1.0%
Driver Percentage (ACS)	96.4%	1.7%	2.0%	NA
Driver Percentage (DMV Accident data)	97.0%	1.2%	0.9%	0.7%
Disparity Index (using ACS)	1.00	1.79	0.43	NA
Disparity Index (using DMV Accident data)	0.98	2.51	0.95	1.36
Stop Reason as % of All Stops				
Safety Stops	66.0%	64.4%	74.0%	61.7%
Moving Violation	65.6%	64.0%	73.4%	60.8%
Suspicion of DWI	0.4%	0.4%	0.5%	0.9%
Investigatory/Pretextual Stops	25.5%	26.2%	17.2%	27.6%
Investigatory Stops	1.6%	3.1%	2.6%	0.5%
Vehicle Equipment	23.9%	23.1%	14.6%	27.1%
Externally Generated Stops	7.5%	7.7%	7.8%	7.9%
Multiple Reasons	0.5%	0.7%	0%	0.5%
Unknown Reason	0.6%	0.9%	1.0%	2.3%
Outcome Rates as a % of All Stops (except externally generated stops)				
Warning Rate	43.3%	47.7%	44.6%	49.8%
Ticket Rate	56.2%	51.4%	54.2%	48.2%
Arrest for Violation Rate	2.0%	4.0%	1.1%	6.1%
Arrest for Warrant Rate	0.0%	0%	0%	0.5%
No Action Rate	0.2%	0%	0%	0%
Search Rates				
Search rate (excl. searches on warrant)	1.1%	5.1%	0.6%	1.5%
Search rate (incl. searches on warrant)	1.2%	5.5%	0.6%	1.5%
Hit rates (as a % of PC, RS & Warrant Searches)				
Hit rates (incl. all outcomes)	77.4%	52.9%	100.0%	66.7%
Hit rates (excl. warnings as outcomes)	73.5%	50.0%	100.0%	66.7%
Hit rates (outcome = arrest)	20.4%	14.7%	100.0%	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.

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 Rutland during this time period, that ratio ranges from 1.79 to (3.0%/1.7%) using the ACS data to 2.52 (3.0%/1.2%) using DMV data. This implies the share of drivers stopped who are perceived to be Black is between 77% and 151% greater than their share of the driving population. Hispanics, too, are overstopped relative to their share of the driving population, with a DI of 1.36. Put another way, Hispanic drivers are stopped at a rate this is about 36% greater than their share of the driving population. In contrast, whether we use the ACS or DMV data, white and Asian drivers are understopped as compared to what would be expected, given their population shares.

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

Figure 1. Disparity Indices



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

B. Reasons for Stops

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

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

If negative stereotypes were operative in Vermont (and there is no reason to think they would not be), we would expect Black and Hispanic drivers to have higher shares of investigatory/pretextual stops as compared to white and Asian drivers. While the percentage of these stops is slightly higher for Black drivers (26.2% compared to 25.5% for white drivers), this difference is very small and not statistically significant. However, the Black share of stops that are "investigatory" is almost double that of the white share of stops (3.1% compared to 1.6% and that difference is statistically significant (z=2.97). Such stops are due to suspicion, making them more susceptible to racial bias. The Asian share of stops that are "investigatory" is also higher than that of whites, but that difference is not statistically significant.

C. Post-Stop Outcomes

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

Specifically, we ask whether drivers of different racial groups experience systematically different outcomes.

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

Table 2 reports Rutland 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.

Black drivers are 10% more likely to be given a warning than white drivers. Although this may suggest more favorable treatment of Black drivers, it is possible this is a result of the overstopping of Black drivers for investigatory reasons, which may result in no evidence of wrongdoing and therefore a warning. This also holds for Hispanic drivers, who are 15% more likely than whites to receive a warning. Asian drivers are also slightly more likely than white drivers to receive a warning, although the disparity is much smaller (3%).

As noted above, there may be more than one outcome to a stop, and that means that drivers may be given more than one citation per stop (e.g., for multiple infractions). We find that although Black drivers are less likely to be issued a citation than white drivers in Rutland, they are more likely to be issued more than one citation per stop. Specifically, during the time period of this study, 4.8% of white drivers were given more than one citation compared to 6.6% of Black drivers. This difference is statistically significant (z=2.09).

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

	Black/white	Asian/white	Hispanic/white
Warning rate	1.10	1.03	1.15
Ticket rate	0.91	0.96	0.86
Arrest rate	1.98	0.56	3.00
Search Rate	4.67	0.51	1.38

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 almost twice as likely to be arrested in Rutland as white drivers and Hispanic drivers are three times more likely to be arrested subsequent to a stop than white drivers. In contrast, while 2% of white drivers are arrested subsequent to a stop during this time period (Table 2), the arrest rate for Asian drivers is roughly half that rate.

Search rate data used for Table 3 exclude searches based on a warrant.[10] Black drivers are searched at a rate that is more than 4 and a half times greater than that of white drivers, a difference that is very statistically significant (z=9.21). In contrast, Asians are about half as likely to be searched as a white driver, with only 1 Asian driver searched and the Hispanic/white ratio is 1.38, signifying Hispanic are searched at a rate that is about 38% higher than white drivers in Rutland. Again, we caution that the small number of Asian and Hispanic searches requires us to view the search rates with some caution.

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

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

Whether or not there is racial bias (implicit or explicit) in search racial disparities is a question that can be assessed by examining the productivity of searches, that is, the percentage of searches that result in contraband being found, often called the "hit" rate. Contraband in Vermont ranges from underage cigarette possession to stolen goods, to illegal drugs.[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.

[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.

[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.

Vermont law enforcement agencies are only required to report on whether or not contraband is found and are not required to report the type of contraband. As a way to get at the severity of contraband found, we differentiate by contraband 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 whites. The productivity of searches of Black drivers is lower than that of white drivers for all three hit rates. In searches that result in any outcome, the hit rate for white drivers is 77.4% compared to 52.9% for Black drivers, and this difference is statistically significant (z=3.04). Similarly, the difference between the Black and white hit rates for outcomes that lead at least to a ticket and/or arrest is also statistically significant (z=2.79). The Black hit rate for arrests only (14.7%) is also lower than that of whites (20.4%), but that difference is not statistically significant. Again, however, we caution that the number of searches resulting in an arrest upon discovery of contraband is very small, making comparisons less reliable in this case.

IV. Trends Over Time

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

First, we examine trends in the number of stops per year in total and by race (for raw data, see Table A.2b). From 2012 (our first year of complete data) to 2019 the total number of stops increased by about 2.4% although the increase was larger for Black drivers than white drivers (47.6% compared to 1.9%, respectively). There has been significant variation in the number of stops from year to year with stops in 2015 about three times greater than the number in 2019. This variation is perplexing and should be explained, especially with regard to how Rutland determines the optimal volume of traffic stop policing consistent with public safety.

For 2019, we estimate that white drivers were stopped at a rate of 1,266 per 10,000 white residents[13] compared to 1,243 in 2012. That said, the white stop rate has been as high as 3,375 per 10,000 white residents (in 2015) during this time period. For Black drivers, the rate in 2012 was 1,892 per 10,000 rising to 2,793 in 2019. In all years, the Asian stop rate per 10,000 residents is substantially lower than the white rate. For example, even in 2015 when

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

stop rates were high for all racial groups, the Asian stop rate was 1,423 compared to 3,375 for whites and 4,820 for Blacks (Figure 2).

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

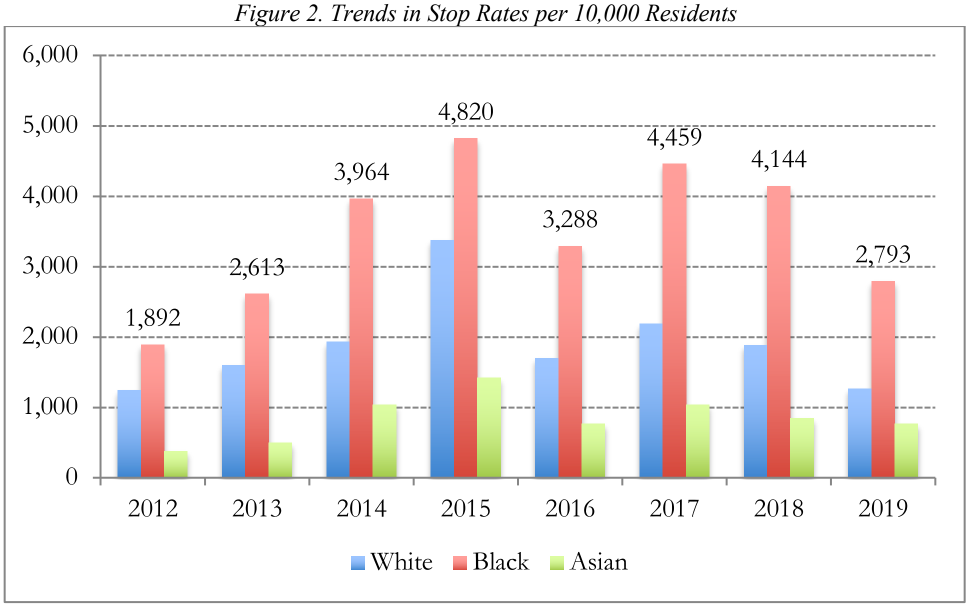
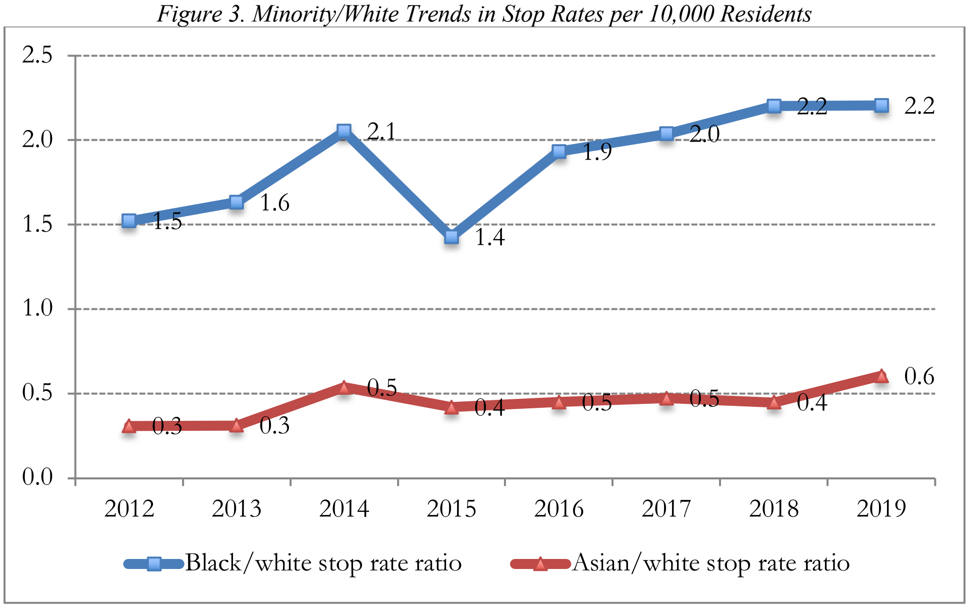


Figure 3 plots the ratio of Black to white stop rates and Asian to white stop rates. The Black-white ratio has risen over time from 1.5 in 2012 to 2.2 in 2019. The Asian to white rate has also risen, although the Asian stop rate, which was one third that of white drivers in 2012 and is now just 60% of the white stop rate, is in each year lower than the white rate.

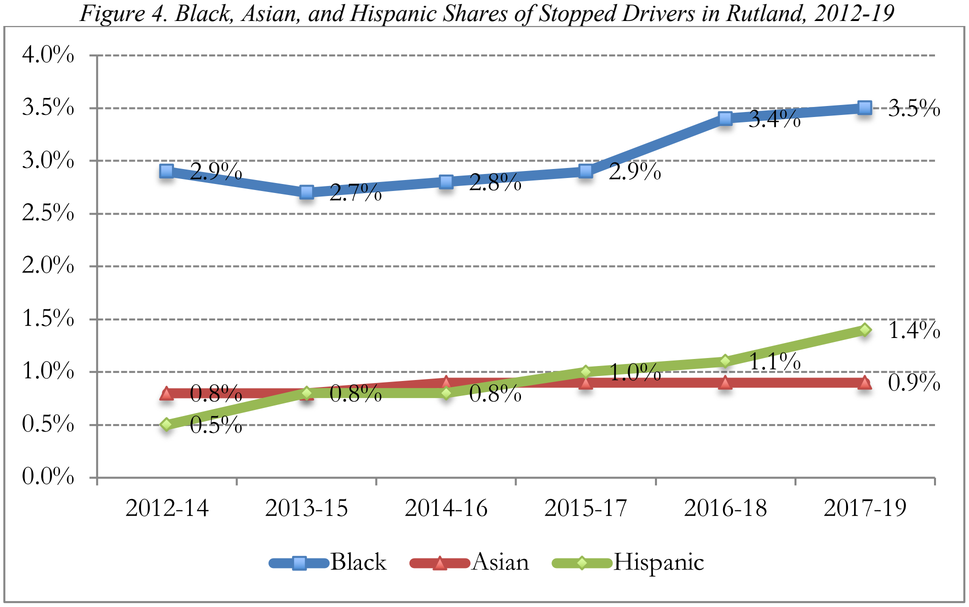
Figure 3. Minority/White Trends in Stop Rates per 10,000 Residents



Secondly, we present data on trends in stop shares, and arrest, search, and hit rates. Due to small sample sizes, we calculate three-year moving trends instead of one-year trends to increase our sample sizes. Specifically, we look at data for 2012-14, 2013-15, etc. (See Table A.2a. for the raw numbers on which the following figures are based).

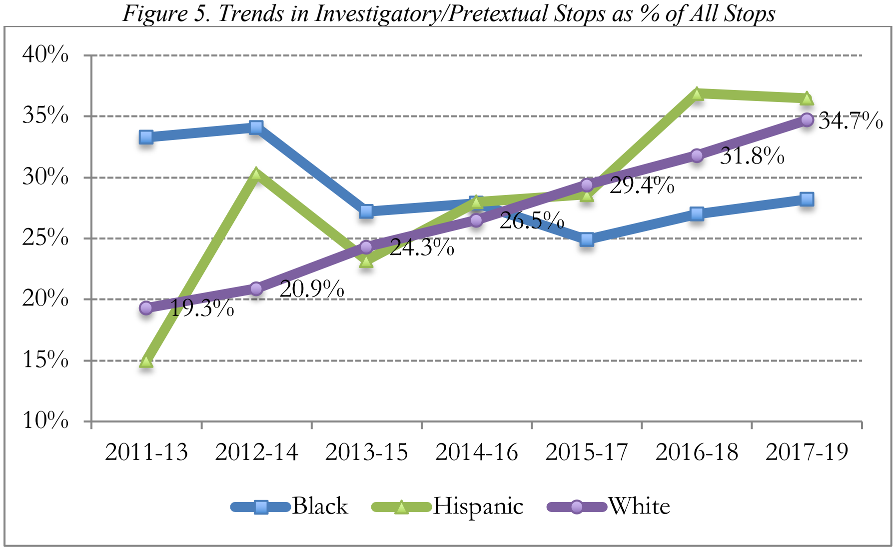
Figure 4 portrays trends in the share of stops of Black, Asian, and Hispanic drivers. It is noteworthy that the Black share of stopped drivers has risen by almost 25 percent over this time period, while the Hispanic share has almost doubled (albeit from a low base), and the Asian share is relatively constant.

Figure 4. Black, Asian, and Hispanic Shares of Stopped Drivers in Rutland, 2012-19



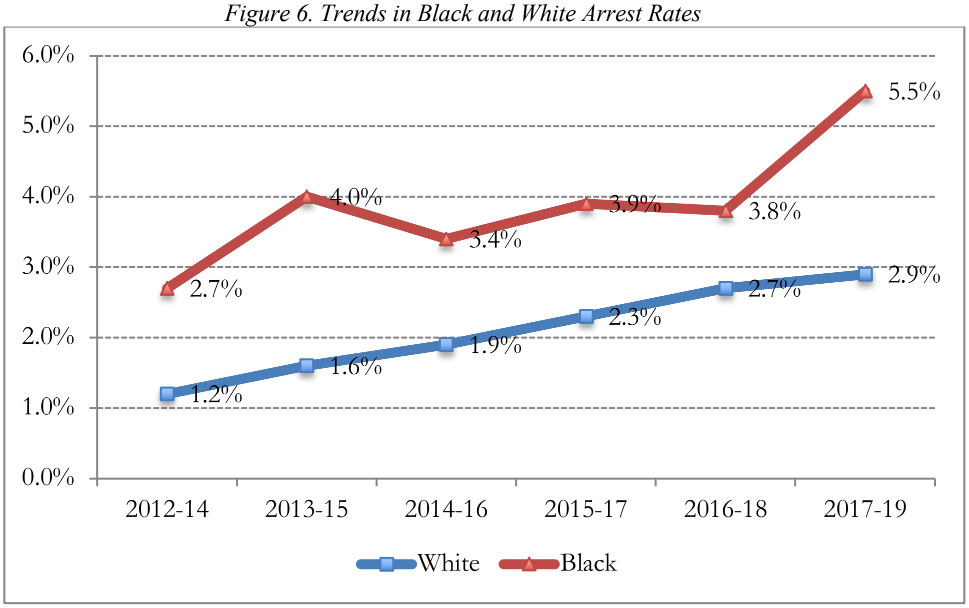
Of interest, as noted, is the percentage of stops that are pretextual—that is, for which the reason for the stop is investigatory or vehicle equipment. This type of stop is one that is more likely to be susceptible to bias than a safety stop. Figure 5 shows trends in investigatory/pretextual stops as a share of all stops by race (excluding Asians due to the small sample size). The share of Hispanic stops for which the reason for the stop is pretextual has been rising since 2012-14, almost doubling by 2019. Black pretextual stop shares fell until 2015-17 at which time they began modestly rising again. In contrast, the white pretextual share of stops has also been rising and by 2017-19, that share exceeded the Black share. While the closing gap between Black and white pretextual shares may be a sign of some progress is closing racial disparities over time, the growing Hispanic pretextual share is noteworthy as an indicator that implicit bias may play a role in whom to stop and for what reason.

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



In all years, the Black arrest rate exceeds the white rate, and this gap widened substantially in 2017-19 after having narrowed for the previous 3 periods of time (Figure 6). Asian and Hispanic arrest rate numbers are omitted due to small sample sizes.

Figure 6. Trends in Black and White Arrest Rates



Racial trends in search rates are shown in Figure 7. Search rates for all racial groups of drivers have risen in Rutland since 2014-16, although the Black search rate had declined significantly in previous years. By 2017-19, white, Asian, and Hispanic search rates are quite similar in magnitude. Although the Black-white disparity in search rates has improved since 2012-14, Figure 7 makes clear that Black drivers are treated very differently than other racial groups when it comes to the decision to search such that the Black/white search rate ratio in 2017-19 is 2.8. This implies that Black drivers are still almost 3 times as likely to be searched as white drivers.

Figure 7. Search Rate Trends by Race/Ethnicity

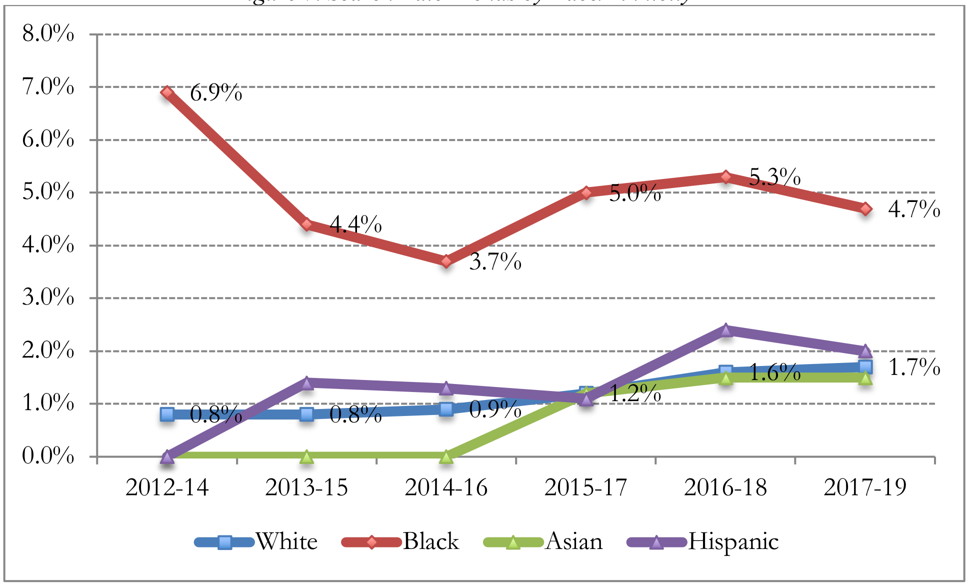
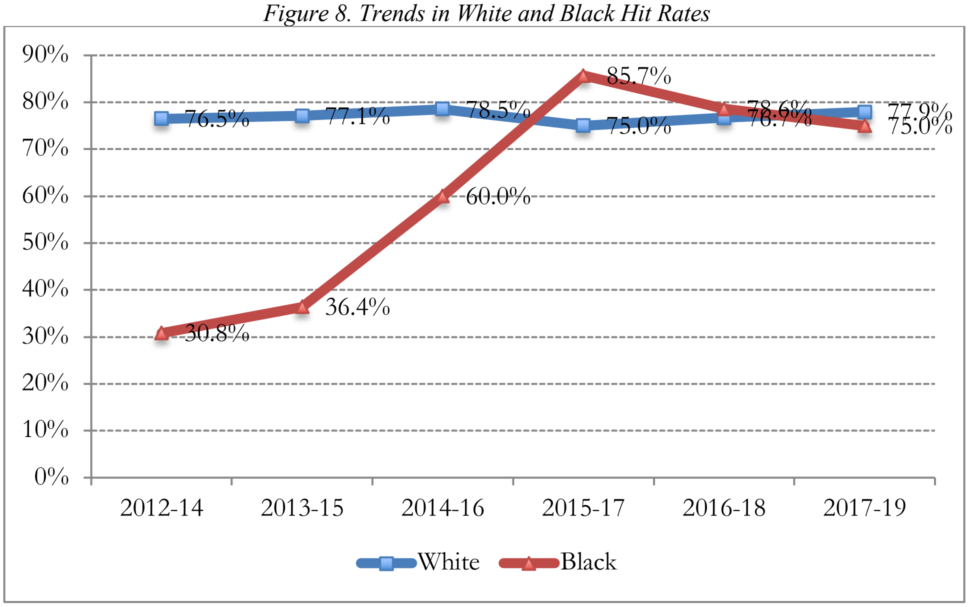


Figure 8 shows trends in white and Black contraband hit rates. The white hit rate was higher than the Black rate in four out of 6 of the time periods for which we have data. Nevertheless, the gap has narrowed considerably since 2012-14, and the 2017-19 disparity is not statistically significant. Asian and Hispanic hit rates are not shown due to small sample sizes. The trend is very similar for contraband hit rates that result in a ticket and/or arrest (in other words, if we exclude warnings or no action taken as outcomes of searches). This is a positive development.

Figure 8. 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 Rutland.

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 characteristics. This is called the *odds ratio*, because it is the ratio of the odds of a non-white driver being searched over the odds that a white driver is searched. An odds ratio of 1 indicates equal probabilities of being searched. A ratio that is greater than one indicates a group is more likely to be searched than the omitted or benchmark group (that is, white drivers). Finally, an odds ratio that is less than 1 is indicative of a lower probability of a group being searched relative to the omitted group.

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

We control for the reason for the stop in two ways. First, we include all reasons for a stop as explanatory variables. The excluded category for this set of variables is moving violation. The coefficients on the *Reason for Stop* variables indicate the odds of being searched for each reason for stop divided by the odds of being searched due to moving violation, where the reason is one of the following: suspicion of driving while under the influence (DWI), investigatory stop, multiple reasons for a stop (where the 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 4.971 times more likely to be searched than white drivers. (This represents the ratio of the odds of a Black driver being search compared to the odds of a white driver being searched). In contrast, Asian drivers are a little less than half has likely to be searched as white drivers. Hispanic drivers are 1.332 times more likely to be searched. Neither the Asian nor Hispanic 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. The number of Native American drivers was small and so was omitted.

In Model 2, adding controls for gender, age of driver, time of day, day of week, and reason for stop, we find that the odds of a male driver being searched are 1.477 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 in the afternoon. The odds of an evening search are greater than in the afternoon, but this is not statistically significant. None of the coefficients on days of the week are statistically significant.

The odds of an investigatory stop leading to a search are 15 times the odds for a stop initiated due to a moving violation. This is noteworthy because Black drivers are more likely to be subject to an investigatory search than white drivers. The odds ratio on all other reasons for a search as compared to a stop based on a moving violation are also statistically significant. Vehicle equipment stops, however, are unique in being less likely to lead to a search than a stop based on a moving violation. The odds a Black driver will be searched in this model, after controlling for other factors, are 3.494. That is, even controlling for other factors, the odds a Black driver will be searched in Rutland, are 3 and a half times more likely to 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.

Because Black drivers in Rutland are more likely to be subject to investigatory stops/pretextual stops than white drivers, we should be careful interpreting the smaller coefficient on the Black/white odds ratio in Model 2 as being a more accurate measure of disparity compared to the model without controls for type of stop.

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

VARIABLES	(1) Race only	(2) With all controls and stop reason	(3) With all controls and pretextual stop control
Black	4.971***	3.494***	3.796***
	(0.938)	(0.751)	(0.787)
Asian	0.489	0.373	0.505
	(0.492)	(0.381)	(0.509)
Hispanic	1.332	1.179	1.187
	(0.780)	(0.709)	(0.699)
Male		1.477***	1.438**
		(0.217)	(0.207)
Age		0.966***	0.966***
		(0.006)	(0.006)
Morning		0.388***	0.383***
		(0.106)	(0.104)
Night		1.193	1.111
		(0.171)	(0.155)
Saturday		0.862	0.874
		(0.204)	(0.201)
Sunday		0.686	0.648*
		(0.179)	(0.166)
Monday		0.844	0.820
		(0.201)	(0.192)
Tuesday		0.865	0.780
		(0.210)	(0.186)
Wednesday		0.770	0.737
		(0.192)	(0.180)
Thursday		0.926	0.897
		(0.215)	(0.204)
Investigatory stop		15.11***	
		(2.791)	
Multiple stop reasons		4.476***	
		(2.126)	
Suspicion of DWI		2.864*	
		(1.723)	
Unknown reason		6.908***	
		(2.540)	
Vehicle equipment		0.616**	
		(0.119)	
Pretextual stop			1.550***
			(0.209)
Constant	0.012***	0.021**	0.024***
	(0.001)	(0.001)	(0.001)
No. of observations	20,686	18,704	18,704

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, drivers are about 55% more likely to be searched than 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 7. The use of more rigorous statistical techniques does not in any meaningful way change the nature of the descriptive data findings.

B. The Probability of Finding Contraband

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

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

Table 5 reports the results of the probability of contraband found for searches for any outcome of the stop and search (that is, in which the result was a warning, a citation, or an arrest) for all years for which we have data. The results shown for Model 1, where the only explanatory variable is race of the driver, indicate that the odds of a search of a Black driver yielding contraband are about 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 are about 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 77.4% of searched white drivers are found with contraband and thus, 22.6% are not found with contraband. This implies an odds ratio for white drivers of 77.4/22.6= 3.43. In other words, the odds are roughly 3.4 to 1 that a search of a white driver will yield contraband. For Black drivers, we find in Table 2 that 52.9% of them are found with contraband so their odds ratio is 52.9/47.1=1.12. The ratio of these two odds is the coefficient in our regression (1.12/3.43 =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 0.256. 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, 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. That odds ratio is, however, not statistically significant.[14]

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

VARIABLES	(1) Race only	(2) With all controls and stop reason	(3) With all controls and pretextual stop control
Black	0.328***	0.256***	0.257***
	(0.124)	(0.122)	(0.119)
Hispanic	0.583	0.560	0.491
	(0.720)	(0.712)	(0.619)
Male		1.557	1.529
		(0.547)	(0.527)
Age		0.993	0.999
		(0.0157)	(0.0153)
Morning		0.564	0.573
		(0.355)	(0.352)
Night		1.960*	1.987**
		(0.683)	(0.683)
Saturday		0.853	0.909
		(0.465)	(0.490)
Sunday		1.316	1.219
		(0.819)	(0.750)
Monday		0.758	0.758
		(0.409)	(0.403)
Tuesday		0.736	0.814
		(0.413)	(0.450)
Wednesday		2.683	2.716
		(1.852)	(1.842)
Thursday		1.438	1.667
		(0.839)	(0.955)
Investigatory stop		1.662	
		(0.722)	
Multiple reasons for stop		1.293	
		(1.501)	
Vehicle equipment		1.060	
		(0.478)	
Pretextual stop			1.498
			(0.496)
Constant	3.431***	1.271	1.093
	(0.546)	(1.104)	(0.941)
Observations	263	223	235

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

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

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/pretextual 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 substantially less likely to be found with contraband, a finding that is consistent with oversearching of that group of drivers. As noted above in our trend analysis, despite these overall findings of significant oversearching, it is noteworthy that the degree of oversearching appears to be declining.

VI. Conclusion

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

In this report, we provide descriptive data on racial disparities in traffic stops in Rutland. We find that Black and Hispanic drivers' share of stops exceeds their estimated share of the driving population, while white and Asian driver shares are lower than would be expected. With regard to the Black-white arrest rate disparity, Black drivers are about twice as likely to be arrested as white drivers. Trends in racial disparities are mixed. The Black-white gap in investigatory/pretextual reasons for a stop has shown some improvement, narrowing by 2017-19. The arrest rate for both white and Black drivers has roughly doubled since 2012-14 and there is little evidence that the Black-white disparity in arrests rates has diminished. Black drivers continue to have higher search rates than white drivers, although the Black/white ratio of search rates has declined from 8.25 in 2012-14 to 2.87 in 2017-19.

We also report on a statistical analysis that controls for other factors that may influence the probability of being searched or of contraband being found during a search. Those results demonstrate that while other factors also contribute to the likelihood of either of those outcomes, racial disparities continue to exist when those factors are controlled for. In particular, Black drivers are substantially more likely to be searched than white drivers, and are less likely to be found with contraband. These results suggest that the race of the driver plays a role in officer decision-making in traffic policing in Rutland.

Over time, there has been a decline in the number of traffic stops in Rutland. The decline in stops occurred even as the Black/white stop rate disparity rose. That said, the lower number of traffic stops has also coincided with a decline in the Black-white hit rate disparity.

The quality of Rutland's traffic stop data, while showing some improvement over time, could be further improved. Eight years into data collection, there continue to be a notable percentage of stops with missing data, and in particular, missing data on race and stop reason.

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APPENDIX

Table A.1. Rutland Raw Traffic Stop Data, 2011-19

All Years	**White**	**Black**	**Asian**	**Hispanic**	**Native American**	**Unknown**	**Total**
Total Traffic Stops							
Including externally generated stops	21,301	675	192	214	16	476	22,874
Excluding externally generated stops	19,711	623	177	197	15	457	21,180
Reasons For Stops							
Safety Stops	14,053	435	142	132	12	367	15,141
Moving Violation	13,964	432	141	130	12	367	15,046
Suspicion of DWI	89	3	1	2	0	0	95
Investigatory/Pretextual Stops	5,434	177	33	59	3	86	5,792
Investigatory Stop	347	21	5	1	1	3	378
Vehicle Equipment	5,087	156	28	58	2	83	5,414
Externally Generated Stop	1,590	52	15	17	1	19	1,694
Multiple Reasons - Moving Violation & Suspicion of DWI	6	0	0	0	0	0	6
Multiple Reasons - Moving Violation & Vehicle Equipment	93	5	0	1	0	0	99
Multiple Reasons - Suspicion of DWI & Vehicle Equipment	1	0	0	0	0	0	1
Unknown Stop Reason	126	6	2	5	0	4	143
Outcomes							
Ticket	11,086	320	96	95	9	348	11,954
Warning	8,540	297	79	98	6	105	9,125
No Action Taken	32	0	0	0	0	2	34
Arrest for violation	401	25	2	12	0	0	440
Arrest for warrant	3	0	0	1	0	0	4
Searches							
Total Stops with No Search	19,463	589	176	194	15	452	20,889
No Search & Contraband & Arrest for violation	2	2	0	0	0	0	4
No Search & Contraband & No arrest	39	1	0	3	0	0	43
No Search (all others)	19,422	586	176	191	15	452	20,842
Total Stops with Unknown Search	22	0	0	0	0	4	26
Total Stops with Search	226	34	1	3	0	1	265
Search with Probable Cause (PC)	163	18	1	1	0	0	183
Stops with PC Searches, No contraband	33	8	0	0	0	0	41
Stops with PC Searches, Unknown contraband	0	0	0	0	0	0	0
Stops with PC Searches, Contraband	130	10	1	1	0	0	142
Outcomes of PC Search							
Stops with PC Searches, Contraband & Warning, No Action or Unknown	4	1	0	0	0	0	5
Stops with PC Searches, Contraband and Ticket	91	6	0	1	0	0	98
Stops with PC Searches, Contraband and Arrest	35	3	1	0	0	0	39
Search with Reasonable Suspicion (RS)	54	14	0	2	0	1	71
Stops with RS Searches, No contraband	14	7	0	1	0	0	22
Stops with RS Searches, Unknown contraband	0	0	0	0	0	0	0
Stops with RS Searches, Contraband	40	7	0	1	0	1	49
Outcomes of RS Search							
Stops with RS Searches, Contraband & Warning, No Action or Unknown	5	0	0	0	0	0	5
Stops with RS Searches, Contraband & Ticket	27	5	0	1	0	1	34
Stops with RS Searches, Contraband & Arrest	8	2	0	0	0	0	10
Search with Warrant	9	2	0	0	0	0	11
Stops with Warrant Searches, No contraband	4	1	0	0	0	0	5
Stops with Warrant Searches, Unknown contraband	0	0	0	0	0	0	0
Stops with Warrant Searches, Contraband	5	1	0	0	0	0	6
Outcomes of Warrant Search							
Stops with Warrant Searches, Contraband & Warning, No Action or Unknown	0	0	0	0	0	0	0
Stops with Warrant Searches, Contraband & Ticket	2	1	0	0	0	0	3
Stops with Warrant Searches, Contraband & Arrest	3	0	0	0	0	0	3

Table A.2a. Rutland 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	6,115	188	50	33	3	238	6,627
2013-15	8,847	253	77	70	3	121	9,371
2014-16	8,977	268	84	76	2	24	9,431
2015-17	9,307	279	84	93	4	18	9,785
2016-18	7,395	264	69	85	6	86	7,905
2017-19	6,838	253	69	101	11	113	7,385
Reasons For Stops (excl. externally generated stops and unknown reasons)							
Safety Stops							
2012-14	4,817	122	37	23	2	194	5,195
2013-15	6,663	182	56	53	2	98	7,054
2014-16	6,551	191	65	54	2	16	6,879
2015-17	6,510	208	67	65	3	11	6,864
2016-18	4,966	187	59	53	4	60	5,329
2017-19	4,369	176	59	61	9	83	4,757
2011-13 (% of stops)	80.7%	66.7%	75.0%	85.0%	50.0%	83.8%	80.5%
2012-14 (% of stops)	79.1%	66.0%	74.0%	69.7%	66.7%	81.5%	78.8%
2013-15 (% of stops)	75.7%	72.8%	72.7%	76.8%	66.7%	81.0%	75.7%
2014-16 (% of stops)	73.5%	72.1%	77.4%	72.0%	100.0%	80.0%	73.5%
2015-17 (% of stops)	70.6%	75.1%	80.7%	71.4%	75.0%	78.6%	70.8%
2016-18 (% of stops)	68.2%	73.1%	86.8%	63.1%	66.7%	73.2%	68.5%
2017-19 (% of stops)	65.3%	71.8%	88.1%	63.5%	81.8%	73.5%	65.8%
Pretextual Stops							
2012-14	1,271	63	13	10	1	44	1,402
2013-15	2,135	68	21	16	1	23	2,264
2014-16	2,357	74	19	21	0	4	2,475
2015-17	2,714	69	16	26	1	3	2,829
2016-18	2,319	69	9	31	2	22	2,452
2017-19	2,326	69	8	35	2	30	2,470
2011-13 (% of stops)	19.3%	33.3%	25.0%	15.0%	50.0%	16.3%	19.5%
2012-14 (% of stops)	20.9%	34.1%	26.0%	30.3%	33.3%	18.5%	21.3%
2013-15 (% of stops)	24.3%	27.2%	27.3%	23.2%	33.3%	19.0%	24.3%
2014-16 (% of stops)	26.5%	27.9%	22.6%	28.0%	0.0%	20.0%	26.5%
2015-17 (% of stops)	29.4%	24.9%	19.3%	28.6%	25.0%	21.4%	29.2%
2016-18 (% of stops)	31.8%	27.0%	13.2%	36.9%	33.3%	26.8%	31.5%
2017-19 (% of stops)	34.7%	28.2%	11.9%	36.5%	18.2%	26.6%	34.2%

Note. All data exclude externally generated stops.

Table A.2a. continued

All Years	White	Black	Asian	Hispanic	Native American	Unknown	Total
Outcomes (excl. externally generated stops)							
Tickets (one or more)							
2012-14	4,728	143	37	24	3	207	5,142
2013-15	5,842	165	54	44	3	107	6,215
2014-16	5,414	142	57	43	2	14	5,672
2015-17	4,797	121	44	48	2	11	5,023
2016-18	3,109	99	31	30	3	33	3,305
2017-19	2,385	92	22	35	5	45	2,584
2011-13 (% of stops)	84.4%	84.3%	70.8%	85.0%	100.0%	90.3%	84.7%
2012-14 (% of stops)	77.3%	76.1%	74.0%	72.7%	100.0%	87.0%	77.6%
2013-15 (% of stops)	66.0%	65.2%	70.1%	62.9%	100.0%	88.4%	66.3%
2014-16 (% of stops)	60.3%	53.0%	67.9%	56.6%	100.0%	58.3%	60.1%
2015-17 (% of stops)	51.5%	43.4%	52.4%	51.6%	50.0%	61.1%	51.3%
2016-18 (% of stops)	42.0%	37.5%	44.9%	35.3%	50.0%	38.4%	41.8%
2017-19 (% of stops)	34.9%	36.4%	31.9%	34.7%	45.5%	39.8%	35.0%
Arrests for Violation							
2012-14	74	5	0	3	0	0	82
2013-15	144	10	0	5	0	0	159
2014-16	168	9	0	6	0	0	183
2015-17	215	11	1	7	0	0	234
2016-18	200	10	2	4	0	0	216
2017-19	199	14	2	4	0	0	219
2011-13 (% of stops)	0.9%	2.0%	0.0%	10.0%	0.0%	0.0%	0.9%
2012-14 (% of stops)	1.2%	2.7%	0.0%	9.1%	0.0%	0.0%	1.2%
2013-15 (% of stops)	1.6%	4.0%	0.0%	7.1%	0.0%	0.0%	1.7%
2014-16 (% of stops)	1.9%	3.4%	0.0%	7.9%	0.0%	0.0%	1.9%
2015-17 (% of stops)	2.3%	3.9%	1.2%	7.5%	0.0%	0.0%	2.4%
2016-18 (% of stops)	2.7%	3.8%	2.9%	4.7%	0.0%	0.0%	2.7%
2017-19 (% of stops)	2.9%	5.5%	2.9%	4.0%	0.0%	0.0%	3.0%
Searches (excl. externally generated stops)							
Searches (PC, RS or Warrant)							
2012-14	51	13	0	0	0	0	64
2013-15	70	11	0	1	0	0	82
2014-16	79	10	0	1	0	0	90
2015-17	112	14	1	1	0	0	128
2016-18	120	14	1	2	0	1	138
2017-19	113	12	1	2	0	1	129
2011-13 (% of Stops)	0.9%	11.8%	0.0%	0.0%	0.0%	0.0%	1.1%
2012-14 (% of Stops)	0.8%	6.9%	0.0%	0.0%	0.0%	0.0%	1.0%
2013-15 (% of Stops)	0.8%	4.4%	0.0%	1.4%	0.0%	0.0%	0.9%
2014-16 (% of Stops)	0.9%	3.7%	0.0%	1.3%	0.0%	0.0%	1.0%
2015-17 (% of Stops)	1.2%	5.0%	1.2%	1.1%	0.0%	0.0%	1.3%
2016-18 (% of Stops)	1.6%	5.3%	1.5%	2.4%	0.0%	1.2%	1.7%
2017-19 (% of Stops)	1.7%	4.7%	1.5%	2.0%	0.0%	0.9%	1.7%
Contraband (All Outcomes)							
2012-14	39	4	0	0	0	0	43
2013-15	54	4	0	1	0	0	59
2014-16	62	6	0	1	0	0	69
2015-17	84	12	1	1	0	0	98
2016-18	92	11	1	1	0	1	106
2017-19	88	9	1	1	0	1	100
2011-13 (% of Searches)	73.5%	25.0%	0.0%	0.0%	0.0%	0.0%	60.9%

Table A.2a. continued

All Years	White	Black	Asian	Hispanic	Native American	Unknown	Total
2012-14 (% of Searches)	76.5%	30.8%	0.0%	0.0%	0.0%	0.0%	67.2%
2013-15 (% of Searches)	77.1%	36.4%	0.0%	100.0%	0.0%	0.0%	72.0%
2014-16 (% of Searches)	78.5%	60.0%	0.0%	100.0%	0.0%	0.0%	76.7%
2015-17 (% of Searches)	75.0%	85.7%	100.0%	100.0%	0.0%	0.0%	76.6%
2016-18 (% of Searches)	76.7%	78.6%	100.0%	50.0%	0.0%	100.0%	76.8%
2017-19 (% of Searches)	77.9%	75.0%	100.0%	50.0%	0.0%	100.0%	77.5%
Contraband (Tickets + Arrests)							
2012-14	37	4	0	0	0	0	1
2013-15	52	4	0	1	0	0	2
2014-16	60	6	0	1	0	0	2
2015-17	81	11	1	1	0	0	4
2016-18	89	10	1	1	0	1	4
2017-19	83	8	1	1	0	1	4
2011-13 (% of Searches)	67.7%	25.0%	0.0%	0.0%	0.0%	0.0%	2.0%
2012-14 (% of Searches)	72.6%	30.8%	0.0%	0.0%	0.0%	0.0%	1.6%
2013-15 (% of Searches)	74.3%	36.4%	0.0%	100.0%	0.0%	0.0%	2.6%
2014-16 (% of Searches)	76.0%	60.0%	0.0%	100.0%	0.0%	0.0%	2.6%
2015-17 (% of Searches)	72.3%	78.6%	100.0%	100.0%	0.0%	0.0%	2.7%
2016-18 (% of Searches)	74.2%	71.4%	100.0%	50.0%	0.0%	100.0%	2.9%
2017-19 (% of Searches)	73.5%	66.7%	100.0%	50.0%	0.0%	100.0%	3.0%
Contraband (Arrests only)							
2012-14	9	0	0	0	0	0	9
2013-15	8	0	0	0	0	0	8
2014-16	8	0	0	0	0	0	8
2015-17	20	4	1	0	0	0	25
2016-18	25	4	1	0	0	0	30
2017-19	28	5	1	0	0	0	34
2011-13 (% of Searches)	29.4%	0.0%	0.0%	0.0%	0.0%	0.0%	21.7%
2012-14 (% of Searches)	17.7%	0.0%	0.0%	0.0%	0.0%	0.0%	14.1%
2013-15 (% of Searches)	11.4%	0.0%	0.0%	0.0%	0.0%	0.0%	9.8%
2014-16 (% of Searches)	10.1%	0.0%	0.0%	0.0%	0.0%	0.0%	8.9%
2015-17 (% of Searches)	17.9%	28.6%	100.0%	0.0%	0.0%	0.0%	19.5%
2016-18 (% of Searches)	20.8%	28.6%	100.0%	0.0%	0.0%	0.0%	21.7%
2017-19 (% of Searches)	24.8%	41.7%	100.0%	0.0%	0.0%	0.0%	26.4%

Note. All data exclude externally generated stops.

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							
2011	264	2	2	1	0	97	366
2012	1,675	47	10	8	1	124	1,865
2013	2,208	60	16	14	1	112	2,411
2014	2,787	99	27	18	1	14	2,946
2015	4,748	114	43	46	1	3	4,955
2016	2,388	77	22	20	0	9	2,516
2017	2,976	113	28	32	3	9	3,161
2018	2,513	96	23	39	3	71	2,745
2019	1,742	67	21	36	6	37	1,909
Excluding externally generated stops							
2011	255	2	1	1	0	96	355
2012	1,592	42	10	7	1	119	1,771
2013	2,049	58	13	12	1	105	2,238
2014	2,474	88	27	14	1	14	2,618
2015	4,324	107	37	44	1	2	4,515
2016	2,179	73	20	18	0	8	2,298
2017	2,804	99	27	31	3	8	2,972
2018	2,412	92	22	36	3	70	2,635
2019	1,622	62	20	34	5	35	1,778
Annual Percentage Change							
2011 to 2012	524.3%	2000.0%	900.0%	600.0%	100%%	24.0%	398.9%
2012 to 2013	28.7%	38.1%	30.0%	71.4%	0.0%	-11.8%	26.4%
2013 to 2014	20.7%	51.7%	107.7%	16.7%	0.0%	-86.7%	17.0%
2014 to 2015	74.8%	21.6%	37.0%	214.3%	0.0%	-85.7%	72.5%
2015 to 2016	-49.6%	-31.8%	-46.0%	-59.1%	-100.0%	300.0%	-49.1%
2016 to 2017	28.7%	35.6%	35.0%	72.2%	300.0%	0.0%	29.3%
2017 to 2018	-14.0%	-7.1%	-18.5%	16.1%	0.0%	775.0%	-11.3%
2018 to 2019	-32.8%	-32.6%	-9.1%	-5.6%	66.7%	-50.0%	-32.5%
Stops per 10,000 residents							
2011	199	90	38				
2012	1,243	1,892	385				
2013	1,600	2,613	500				
2014	1,931	3,964	1,038				
2015	3,375	4,820	1,423				
2016	1,701	3,288	769				
2017	2,189	4,459	1,038				
2018	1,883	4,144	846				
2019	1,266	2,793	769				

Appendix A.3. Data Quality and Methodology

The Rutland Police Department (RPD) traffic stop data used in this study consists of 25,025 rows, spanning nine years (2011-2019). Each row corresponds to a single outcome resulting from a traffic stop (there may be multiple outcomes of a stop). Date and time of stops are not required by legislation, although some agencies have chosen to provide date and time. Because date and time are useful for many types of analysis, the existence and quality of that field of data is reported in this section as well.

A. Missing or Unknown Data Values by Field

Table A.3a shows the counts and percentages of missing or unknown data values. Missing data is when the officer fails to record data on a particular field. Unknown is where the officer records "unknown" as a value in a field. In either case, we lack data on that variable and thus we group missing and unknown together in assessing the quality of the data RPD 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												
2011	355	8	0	7	96	2	0	0	0	0	0	0
2012	1,771	72	0	147	119	8	0	0	0	0	0	0
2013	2,238	131	0	156	105	8	0	0	0	0	713	16
2014	2,618	181	0	115	14	10	0	0	0	0	640	23
2015	4,515	304	0	59	2	30	0	0	0	0	360	30
2016	2,298	2,298	0	1,475	8	6	20	14	14	17	308	15
2017	2,972	2,972	0	16	8	6	15	5	5	5	240	2
2018	2,635	2,635	0	5	70	6	50	4	4	7	280	2
2019	1,778	1,778	0	5	35	10	58	3	3	2	265	6
All Years	21,180	10,379	0	1,985	457	86	143	26	26	31	2,806	94
Percentage of Blank or Unknown Rows												
2011	355	2.3%	0.0%	2.0%	27.0%	0.6%	0.0%	0.0%	0.0%	0.0%	0	0.0%
2012	1,771	4.1%	0.0%	8.3%	6.7%	0.5%	0.0%	0.0%	0.0%	0.0%	0	0.0%
2013	2,238	5.9%	0.0%	7.0%	4.7%	0.4%	0.0%	0.0%	0.0%	0.0%	713	2.2%
2014	2,618	6.9%	0.0%	4.4%	0.5%	0.4%	0.0%	0.0%	0.0%	0.0%	640	3.6%
2015	4,515	6.7%	0.0%	1.3%	0.0%	0.7%	0.0%	0.0%	0.0%	0.0%	360	8.3%
2016	2,298	100.0%	0.0%	64.2%	0.4%	0.3%	0.8%	0.6%	0.6%	0.7%	308	4.9%
2017	2,972	100.0%	0.0%	0.5%	0.3%	0.2%	0.5%	0.2%	0.2%	0.2%	240	0.8%
2018	2,635	100.0%	0.0%	0.2%	2.7%	0.2%	1.8%	0.2%	0.2%	0.2%	280	0.7%
2019	1,778	100.0%	0.0%	0.3%	2.0%	0.6%	3.0%	0.2%	0.2%	0.1%	265	2.3%
All Years	21,180	49.0%	0.0%	9.4%	2.2%	0.4%	0.6%	0.1%	0.1%	0.1%	2,806	3.4%

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 RPD data shows that required field values are sometimes missing or incorrect. However, the inclusion and quality of the data has improved since 2011. That said, there is still work to do to improve the quality of these data, including ensuring that the race of the driver is identified in all incident reports as well as the reason for the stop. Even by 2019, race of driver is missing in 2.2% of all traffic stops. Further, and 3.4% of accident reports had missing race data. 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 RPD 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)
2011	355	103	29.0%
2012	1,771	262	14.8%
2013	2,238	258	11.5%
2014	2,618	128	4.9%
2015	4,515	75	1.7%
2016	2,298	1,483	64.5%
2017	2,972	36	1.2%
2018	2,635	126	4.8%
2019	1,778	103	5.8%
All Years	21,180	2,574	12.2%

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

Table A.3c shows the relationship between missing data and race of driver. We would expect that, absent any anomalies in data reporting, the percentage of missing data by race would be roughly equal. (There would be no reason to expect that the percentage of stops that are missing the reason for the stop would be higher or lower for any one racial group than another). Further, we would expect that for those stops for which the race of the driver is unknown, the percentage with missing data on say, stop reason, should be similar to that for each racial group. This is in fact what we found for Rutland, with the exception of a higher than expected rate of Hispanic missing data for stop reason (it is 4 times higher than missing stop reason for white drivers, although that is based on only 5 stops with missing data for Hispanics).

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

	White	Black	Asian	Hispanic	Unknown
Count of Blank or Unknown Rows					
Total Stops (excl. EGS)	19,711	623	177	197	457
Unknown Stop Reason	126	6	2	5	4
Unknown Stop Outcome	26	1	0	0	4
Unknown if Search occurred	22	0	0	0	4
Unknown if Contraband found subsequent to a search	0	0	0	0	0
Unknown Outcome if contraband found	0	0	0	0	0
Percentage of Blank or Unknown Rows					
Unknown Stop Reason as % of all stops	0.6%	0.9%	1.0%	2.3%	0.8%
Unknown Stop Outcome as % of all outcomes	0.1%	0.1%	0.0%	0.0%	0.9%
Unknown if Search occurred as % of all stops	0.1%	0.0%	0.0%	0.0%	0.9%
Unknown if Contraband found as % of all searches	0.0%	0.0%	0.0%	0.0%	0.0%
Unknown Outcome if contraband found as % of all searches	0.0%	0.0%	0.0%	0.0%	0.0%

B. Stop IDs

Most Vermont traffic stop data files contain only one stop outcome per row (where an outcome can be one arrest, one ticket, one warning, etc.). However, a single traffic stop can have multiple outcomes. For example, it is possible for a single stop to result in multiple tickets being issued, or other combinations such as a ticket and a warning, and so forth. It is important to be able to collect multiple outcomes into stops to avoid overcounting as well as to recognize stops where more than one ticket is issued. 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 nine years of data available from Rutland, 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. Stop IDs for Rutland

Year	Usable Stop ID	Could Derive Stop IDs	Stop Count	Row Count
2011	No	Yes	366	374
2012	No	Yes	1865	1950
2013	No	Yes	2411	2594
2014	No	Yes	2946	3211
2015	No	Yes	4955	5394
2016	No	Yes	2516	2768
2017	No	Yes	3161	3571
2018	No	Yes	2745	3043
2019	No	Yes	1909	2118

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