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

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

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

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

July 2020

Table of Contents

List of Tables

List of Figures

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

EXECUTIVE SUMMARY

This study of Colchester traffic stops forms part of a statewide report of Vermont traffic stop data by the authors that includes additional years of data since the Seguino and Brooks (2017) study was issued. In each study of individual law enforcement agencies, we examine the data for racial disparities in several areas: racial share of stops, tickets vs. warnings, reasons for stops, arrest rates, search rates, and contraband "hit" rates. We also examine trends to determine whether racial disparities fall over time. Finally, we comment on the completeness and quality of the data collected by the Colchester Police Department (CPD).

Our main findings are that in Colchester:

- Black and Hispanic shares of stopped drivers exceed their shares of the estimated driving population. The data indicate Black drivers were overstopped by 40% to 225%, depending on the measure of the driving population used. Hispanics were overstopped by 38% relative to their estimated share of the driving population.
- Black drivers are slightly less likely than white drivers to be stopped for safety reasons, and Black drivers are more likely to experience pretextual stops—stops that may be used to investigate "suspicious" behavior and are therefore more prone to racial bias.
- The arrest rate of Black drivers is almost three times that of white drivers.
- Black drivers are about 2.3 times more likely to be searched subsequent to a stop than white drivers. Asian and Hispanic drivers are less likely to be searched than white drivers.
- Black drivers are less likely to be found with contraband than white drivers, despite their higher search rate.

Regarding trends over time:

- Over time, racial disparities in pretextual stops, arrest rates, search rates, and contraband hit rates have worsened.
- The total number of stops per year rose by 21% from 2017 to 2019. For Blacks, the 2019 per capita stop rate was double that of 2017, resulting in more than one stop per estimated Black resident. The Black stop rate in 2019 was more than 5 times that per estimated white resident.

Regarding data quality, our main findings are:

- Data was provided for five years (2014-2019) with 34.1% of traffic stop reports having missing or unknown values for at least one variable. Race data was missing in 1.2% of all stops. The quantity of missing data has declined substantially since 2014.

We note that disparities do not automatically infer bias. A typical measure of racial bias in policing is the hit rate test (Persico and Todd 2008), whereby lower hit rates for an oversearched group is suggestive of implicit (unconscious) or explicit bias. The evidence for Colchester indicates a higher search rate but lower hit rate for Black drivers, a finding consistent with racial bias in officer decision-making in traffic stops. Of further note in Colchester is the racially consistent pattern of results, with more negative outcomes for Black drivers than white drivers across all of the indicators examined.

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

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.

Our study aims to identify whether there are racial disparities in traffic stops and outcomes of stops in Vermont law enforcement agencies. 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 additional agencies. We can now also evaluate trends over time in racial disparities.

This report, which forms a component of a statewide report, analyzes data for Colchester, Vermont for 2014-2019. Colchester Police Department (CPD) collected data on 19,736 traffic stops during this time period. Our focus is primarily on actions that require officer discretion on whom to stop, arrest, and search. For this reason, we exclude externally generated stops in much of the analysis that follows. That said, officer behavior is influenced by agency leadership and culture, the extent of trainings on implicit bias related to race, as well as agency policies that shape officer decisions.[2] Not all disparities, where they are found then should be solely attributed to officer discretion.

The law requires that the following traffic stop data be collected and made available to the public: race, age, and gender of driver; reason for stop; type of search, if any; evidence found during the search, if any; and the outcome of stop. In Vermont, driver's licenses do not include race/ethnicity of the driver. The race of driver indicated in officer reports on traffic stops is based on officer perception. In analyzing each agency's data, we identify racial shares of stops as compared to racial shares of the driving population, and racial disparities, if any, in reasons for a stop, arrest rates, search rates, and contraband "hit" rates.[3]

In the next section, we provide an overview of the Colchester data, identify methodological issues of relevance to our analysis, and report on the quality of the data. In Section III, we report descriptive data on key indicators and discuss results of the hit rate test. In Section IV, we assess trends over time in racial disparities, using 3-year rolling trends (2014-16, 2015-

[1] The bill is 20 V.S.A. § 2366.

[2] For example, some agencies have a policy that a stopped driver found to be driving with a suspended license is automatically given a citation. Thus, not all officer decisions are the result of discretion. To some extent, the results reflect the role of leadership, training, agency culture, and policies.

[3] Additional data would have been helpful to include in our analysis, but this would require a change to the legislation that has not yet been forthcoming. For example, the type of contraband found, the state the vehicle is registered in, the duration of the stop, officer-level data, and stop IDs would improve the ability to assess the degree, if any, of racial disparities in traffic policing.

17, etc.) instead of year by year, to expand the sample size. In Section V, we conduct a logit analysis to estimate the probability of a search and of finding contraband, based on a variety of factors (such as age, gender, and reason for the stop) in addition to the race of the driver. This methodology, by controlling for the context of the stop, better isolates the role of the driver's race in the officer's decision to search a vehicle and in finding 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 more reason for concern. We conduct a similar analysis of the probability of contraband being found in a search (Section V).

---

[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

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 the 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 CPD from 2014-19. As can be seen, a total of 19,736 stops were made from 2014 through 2019. Approximately one third of these stops resulted in the issuance of a citation. The percentage of stops that resulted in an arrest was 0.6%, while 1.2% of stopped vehicles were searched. And contraband was found in 1.0% of all stops. The overall contraband hit rate (the number of contraband finds divided by the number of searches) is 80.2%.

Our focus is primarily policing decisions based on officer discretion although it is impossible to entirely disentangle the role of agency culture and leadership from individual officer decisions. In order to restrict our attention to discretionary decisions and actions, in the following analysis we exclude stops that are externally generated. Externally generated stops are those that rely on external information to initiate a stop. An officer may be directed to stop a vehicle, for instance, in response to a be-on-the-lookout (BOLO) alert. In this case, the officer did not initiate the stop. In the case of Colchester, 2.1% or 414 of all stops were externally generated. These exclusions reduce our sample size to 19,322 traffic stops.

---

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

Table 1. Overview of the Data, 2014-19

	Observations	**Rates**
Total Stops		
incl. EGS	19,736	
excl. EGS	19,322	
2014	3,371	
2015	3,687	
2016	2,787	
2017	2,480	
2018	3,939	
2019	3,058	
Citations	5,993	31.0%
Arrests	123	0.6%
Searches	237	1.2%
Contraband	190	1.0%
Contraband as % of searches	190	80.2%

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

A challenging problem in the data, not only for Colchester but other agencies as well, is that more than one row in the raw data appear to refer to the same stop in a number of cases. This typically occurs if there is more than one outcome to a stop. For example, the officer may issue the driver a citation as well as a warning. This scenario would result in 2 lines of data—one for each outcome—and would lead to over-counting of stops, absent efforts to identify stops with multiple outcomes. We therefore developed a method for detecting and reconciling multiple row stops by matching age, race, gender, and date/time of stop. We retained all information in the multiple rows with regards to tabulating the outcomes of stops while counting each stop only once.

A summary of the raw data for all racial/ethnic groups is provided in Appendix Table A.1. In the analysis that follows, we report data only for white, Black, Hispanic, and Asian drivers, omitting Native Americans due to the small sample size that limits our ability to make sound inferences about the results. In the case of Colchester, over the time period of this study, 2014-19, only 7 drivers were identified as Native American.

Appendix Tables A.1 and A.3a-A.3c detail information on missing or contradictory data reported by CPD. The race of the driver was omitted in 234 rows of data or in 1.2% of all rows from 2014 to 2019. Further, in two areas (investigatory/pretextual stops and warnings as outcomes of stops), the amount of missing/unknown data by race is concerning. The accuracy of data analysis depends on unbiased reporting on traffic stops, and disproportionate amounts of missing data by race can undermine confidence in the quality of the 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 compare 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).[6] Thus, there may be reason to question whether the racial composition of the population in an area is the same as the racial composition of drivers on the road. That said, this benchmark could be enlightening, especially when coupled with alternative benchmarks.

The second benchmark we use is the racial composition of drivers involved in accidents in Vermont. Officers collect data on the race of drivers in accidents, and these data are reported to the Department of Motor Vehicles (DMV). This approach has emerged as an alternative method to determine 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 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 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

---

[6] Baumgartner, *et al* (2018) report, for example, that 83% of whites own a car, compared to 53% of Blacks, and 49% of Hispanics. Whites also drive approximately 20% more miles per year than Blacks and Hispanics. In Vermont, we find similar racial differences with 19.3% of Blacks using public transportation or walking to work, compared to 6.9% of whites, according to ACS 2013-19 estimates.

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. [7]

Data on racial shares of stopped drivers and the driving population are shown in Table 2. The share of stops relative to share of population based on U.S. Census data is calculated only for Blacks, Asians, and whites. This is because the U.S. Census Bureau categorizes Hispanic as an ethnicity rather than race—and, thus, Hispanics may be white or non-white. In contrast, in numerous law enforcement agencies, police officers collecting data on traffic stops in Vermont do not distinguish between white and non-white Hispanics, and simply categorize Hispanics as a separate group. (Other agencies collect data on both race and ethnicity of the driver, but with ethnicity often left blank). The DMV accident data, however, use the same racial/ethnic categories as Vermont law enforcement agencies for traffic stops and so we can calculate the Hispanic share of drivers using that metric. It should be noted that a factor undermining the accuracy of Colchester's accident data is that officers did not report race of driver in 6% of all accidents. Although the percentage of accidents missing race of driver has declined over time to 2.6% in 2019, given that Blacks are 4.3% of stopped drivers, missing race in accident data is almost 2/3 the Black share of stops.

White drivers in Colchester comprised 93.2% of all stopped drivers from 2014 through 2019, with Blacks 4.2%, Asians 2.0% and Hispanics 0.5% of all drivers stopped. Inclusion of externally generated stops does not markedly change these percentages. Black and Hispanic shares of stops are higher than their share of the driving population, whether using the ACS or DMV accident data. For example, the estimates of Black drivers' share of the driving population range from 1.3% to 3.0%, lower than their share of stopped drivers (4.2%).

[7] The original study that uses accident data to measure racial shares of the driving population (Albert, *et al* 2004) was based on accidents in a location with a much larger population.

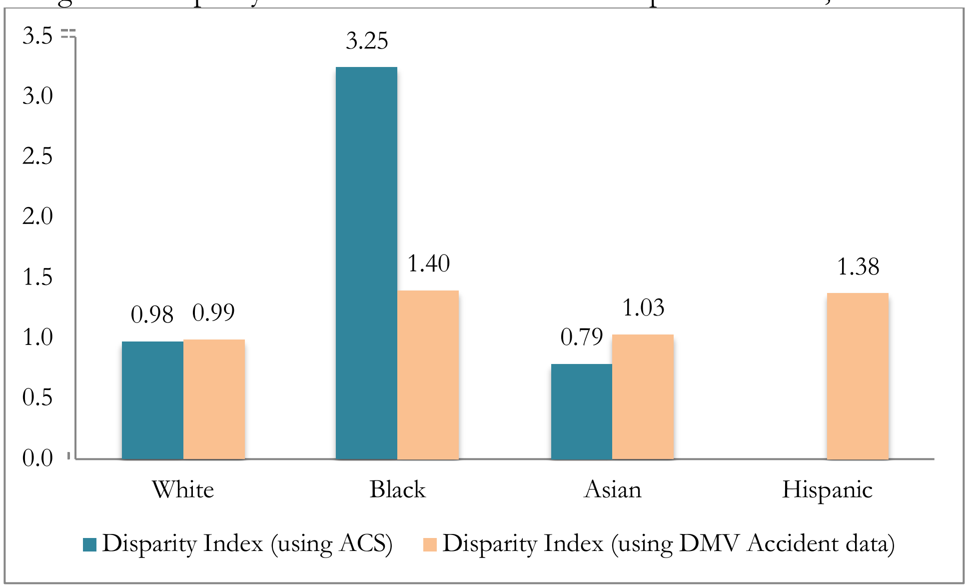
Table 2. Racial Shares of Stops, Reasons for Stops, and Post-Stop Outcomes

	White	Black	Asian	Hispanic
Racial Shares of Stops				
Including externally generated stops	93.2%	4.3%	2.0%	0.5%
Excluding externally generated stops	93.3%	4.2%	2.0%	0.6%
Driver Percentage (ACS)	96.2%	1.3%	2.5%	
Driver Percentage (DMV Accident data)	94.2%	3.0%	1.9%	0.4%
Disparity Index (using ACS)	0.98	3.25	0.79	
Disparity Index (using DMV Accident data)	0.99	1.40	1.03	1.38
Stop Reason as % of All Stops				
Safety Stops	83.7%	78.5%	83.9%	85.9%
Moving Violation	83.5%	78.3%	83.9%	85.9%
Suspicion of DWI	0.2%	0.2%	0.0%	0.0%
Investigatory/Pretextual Stops	13.2%	17.4%	12.7%	13.2%
Investigatory Stops	0.4%	0.8%	0.3%	0.0%
Vehicle Equipment	12.8%	16.5%	12.5%	13.2%
Externally Generated Stops	2.0%	3.4%	2.6%	0.9%
Multiple Reasons	0.1%	0.0%	0.0%	0.0%
Unknown Reason	1.1%	0.7%	0.8%	0.0%
Outcome Rates as a % of All Stops (excl. externally generated stops)				
Warning Rate	70.1%	67.9%	72.0%	71.4%
Ticket Rate	31.1%	33.3%	28.5%	31.4%
Arrest for Violation Rate	0.6%	1.8%	0.0%	0.0%
Arrest for Warrant Rate	0.0%	0.4%	0.3%	0.0%
No Action Rate	0.1%	0.0%	0.0%	0.0%
Search Rates				
Search rate (excl. searches on warrant)	1.1%	2.6%	0.8%	1.0%
Search rate (incl. searches on warrant)	1.2%	2.6%	0.8%	1.0%
Hit rates (as a % of PC, RS & Warrant Searches)				
Hit rates (incl. all outcomes)	81.1%	66.7%	100.0%	100.0%
Hit rates (excl. warnings as outcomes)	65.6%	52.4%	66.7%	100.0%
Hit rates (outcome = arrest)	3.8%	9.5%	33.3%	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. The ASC 2-13-17 estimates of racial shares of the driving population for Colchester are based on "Chittenden county-subdivision" data rather than "place." 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 their share of the driving population and a ratio of less than 1 indicates a group is understopped. For Blacks in Colchester during this time period, that ratio ranges from 1.40 (that is, 4.2%/3.0%) using the DMV data to 3.25 using ACS data. Put another way, Black drivers are stopped at a rate that is from 40% to 225% greater than their share of the driving population. Hispanics, too, are overstopped relative to their share of the driving population, with a DI of 1.38, indicating they are stopped at a rate that is about 38% greater than their share of the driving population. In contrast, whether we use the ACS or DMV data, white drivers are understopped as compared to what would be expected while the Asian DI ranges from 0.79 (signifying understopping) to 1.03, approximately the same DI for white drivers.

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



For comparison, at the national level, Pierson, *et al* (2020), using data on almost 100 million traffic stops, find that Black drivers were roughly 50% more likely to be stopped than white drivers in stops conducted by municipal police departments. They also found that Hispanics are less likely to be stopped. The authors 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 Colchester traffic stops using ACS data are much wider than the estimated differential at the national level.

A final note on racial disparities in stops is necessary. The racial share of stops is one of the most contested metrics of racial disparities in traffic policing because of the weaknesses of the two available measure of the driving population (U.S. Census data and accident data). While the U.S Census data may underestimate the minority shares of the driving population, given that it measures residents and not drivers, and the accident data may overestimate minority shares of the driving population, given the possibility that not all accidents involve police reports, most critical to our analysis 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. (In rare cases, officers indicate multiple reasons). Investigatory stops are those in which officers stop a vehicle to investigate further whether a crime has been committed or not. The law requires that the officer have reasonable suspicion to conduct such as stop, based on specific and articulable facts. (As noted above, externally generated stops are not officer-initiated, but instead result from information from a person other than the officer). Table 2 shows the distribution of reasons for stops by race. By far the most common reason motorists in Colchester are pulled over is for moving violations (such as speeding). The second most common reason is vehicle equipment (such as a faulty taillight). Other reasons for stops are far less common.

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

If negative stereotypes were operative in Vermont (and there is no reason to think they would not be), we would expect Black and Hispanic drivers to have higher shares of investigatory/pretextual stops as compared to white and Asian drivers. The percentage of these stops is in fact higher for Black drivers (18% compared to 13.4% for whites) and this difference is statistically significant (z=3.68). The share of stops of Hispanic drivers that are pretextual, however, is the same as the white share.

C. Post Stop Outcomes

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

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

Table 2 reports Colchester 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 relative to those of white drivers. Table 3 reports minority/white ratios of outcomes, 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
Warning Rate	0.97	1.03	1.02
Ticket Rate	1.07	0.92	1.01
Arrest Rate	2.87	NA	NA
Search Rate	2.32	0.71	0.84

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

Black drivers are less likely to be given a warning than white drivers, and Asian and Hispanic drivers are slightly more likely to receive a warning, although none of these differences are statistically significant. Black drivers are 7% more likely to be ticketed than white drivers, but the difference in ticketing rates is not statistically significant. Asian drivers are less likely to be ticketed than white drivers and the rate of Hispanic stops resulting in a ticket are on par with the white rate. That said, these differences for both Asians and Hispanics as compared to whites are not statistically significant, either.

There were no arrests of Asian or Hispanic drivers and therefore we only report the ratio of the Black to white arrest rates. Blacks are almost 3 times more likely to be arrested subsequent to a stop than white drivers. Due to the small sample size for Black arrests (14 over the 5-year period), these numbers should be interpreted with caution although the difference is statistically significant (z=3.88).

Search rate data used for Table 3 exclude searches based on a warrant.[8] Black drivers are searched at a rate that is about 2.3 times greater than that of white drivers, a difference that is statistically significant (z=3.48). In contrast, Asian drivers are about one third as likely to be searched as white drivers, with only 3 Asian drivers searched during the 6-year period. The Hispanic/white ratio is 1.19, although this is based on only one search of a Hispanic driver and thus this statistic is not reliable because of the small sample size.

[8] Searches resulting from a warrant could reasonably be described as discretionary because they are the result of a driver refusing to consent to a search. In those cases, the officer impounds the vehicle and seeks a warrant 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.

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 U.S. traffic stops, finding that Black and Hispanic drivers are searched at more than twice the rate of white drivers.[9] In a study of 20 million car stops in North Carolina from 2002-2016, Baumgartner, *et al* (2018) also find evidence of higher arrest and search rates of Black and Hispanic drivers. The ratio of Black to white search rates in North Carolina was roughly 2 to 1, similar to Pierson, *et al* (2020), indicating search rate disparities between Black and white drivers that are lower than in Colchester.

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 Black and Hispanic drivers on the basis of racial stereotypes about who drug users and couriers are. Implicit bias based on faulty stereotypes may also play a role. For example, evidence shows that Black and white Americans sell and use drugs at similar rates (U.S. Department of Health and Human Services 2012, 2013).

Whether or not there is racial bias (implicit or explicit) in search racial disparities is a question that can be assessed by examining the productivity of searches, that is, the percentage of searches that result in contraband being found, often called the hit rate. Contraband in Vermont ranges from underage cigarette possession to stolen goods to illegal drugs.[10] Absent racial bias (as compared to racial disparities), we would expect that officers should find contraband on searched minorities at the same rate as on searched white drivers. If searches of minorities turn up contraband at lower rates than searches of white drivers, the hit rate test suggests officers base their decision to search minority drivers on less evidence than they require as a basis for initiating searches of white drivers. Put another way, minority hit rates that are lower than white hit rates are an indication that police may be oversearching minorities (or under-searching white drivers) and that racial bias has influenced the officer's decision on whom to search.

Vermont law enforcement agencies are only required to report on whether or not contraband is found and are not required to report the type of contraband. As a way to get at the severity of contraband found, we adopt a method to differentiate the type of contraband by the severity of the outcome as follows: 1) hit rates for all outcomes (warning, ticket, arrest), 2) hit rates in which contraband leads to a ticket(s) and/or an arrest, and 3) the arrest-worthy contraband hit rate.

In conducting the hit rate test, we focus on white and Black drivers. The number of searches of Asian and Hispanic drivers is small, preventing hit rate comparisons of these groups to whites. In the case of the overall hit rate and the hit rate that leads to a ticket or arrest, the

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

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

productivity of searches of Black drivers is lower than that of white drivers. For example, in all searches in which contraband is found, the hit rate for white drivers is 81.1% compared to 66.7% for Black drivers, and the difference is borderline statistically significant (z=1.57, p-value = 0.06). When the outcome of the search is at least a citation and/or an arrest, the Black hit rate is still lower than that of white drivers, 52.4% compared to 65.6%. When the outcome of a search is an arrest (signifying more serious contraband found), the Black hit rate exceeds the white hit rate, but given that there were only 2 such Black searches, the Black-white comparison is unreliable in this case. Overall, the results of the hit rate test are indicative not only of Black-white disparities in policing, but also of racial bias, whereby the race of the driver influences traffic policing decisions.

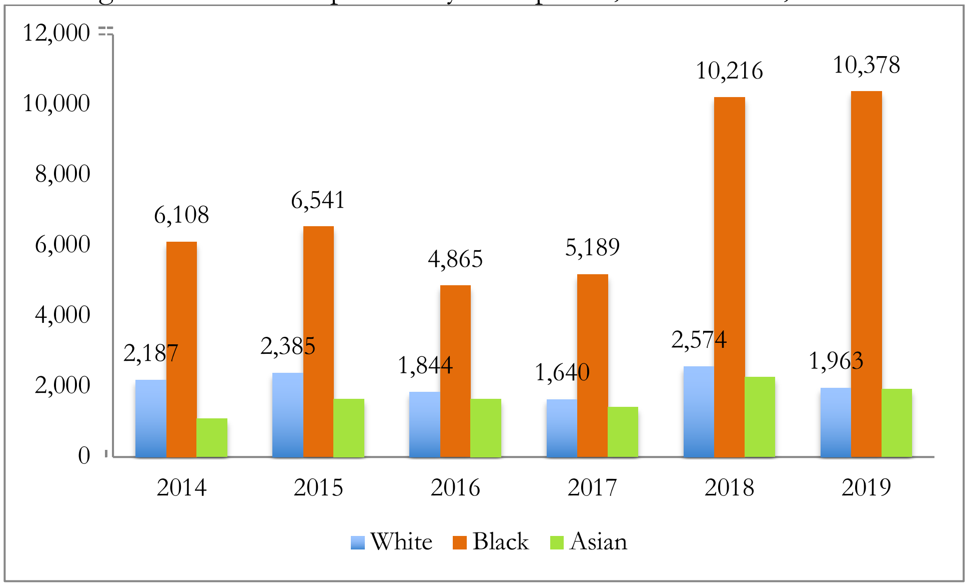
IV. Trends Over Time

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). The total number of stops varies each year for all groups, but the largest single year increase is for Blacks from 2017 to 2018, with an annual increase in stops of 96.7%. This compares to an overall increase in stops during that time period of 56.7%. For 2017, we estimate that white drivers were stopped at a rate of 1,640 per 10,000 residents[11] rising to 2,574 per 10,000 in 2018. For Black drivers, the rate in 2017 was 5,189 per 10,000, increasing to 10,216 in 2018 (Figure 2).

[11] 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 Colchester 15 and older, all multiplied by 10,000.

Figure 2. Annual Stop Rates by Race per 10,000 residents, 2014-19

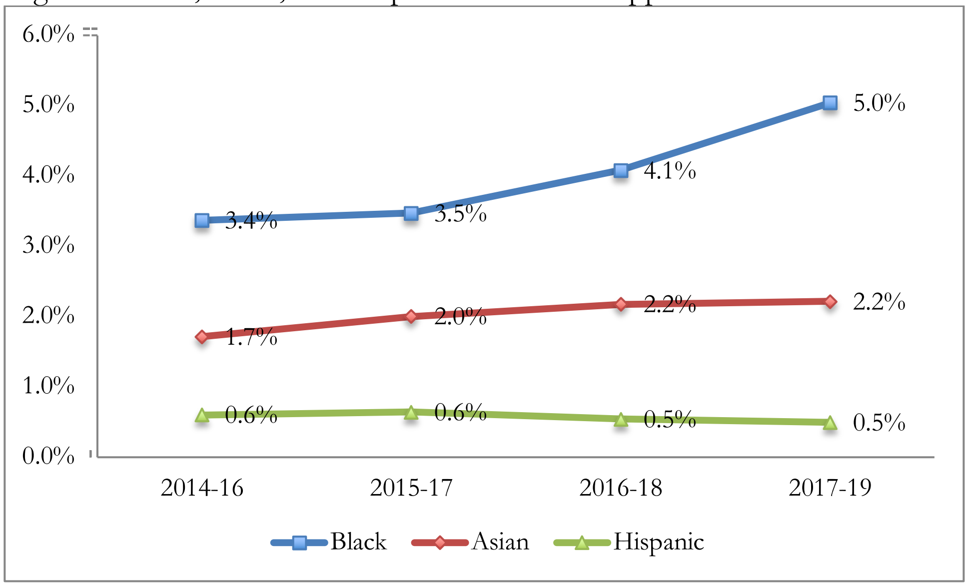


Between 2018-2019 the total number of stops declined roughly 23% but decreases for white, Asian, and Hispanic drivers mask a 1.6% increase in the number of stops of Black drivers. For 2019, we estimate that there were 1,963 stops per 10,000 white drivers but 10,378 stops per 10,000 Black drivers. In other words, in both 2018 and 2019, more Black drivers were stopped in Colchester than are estimated to be in the local population. It would be useful for the Colchester Police Department to identify the factors that influence the total volume of traffic stops. Did the decrease in number of stops from 2014-2017 lead to a decrease in public safety? What caused the increase in stops in 2018 and 2019?

Secondly, we present results here for Colchester on trends in stop shares, investigatory/pretextual stops, 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 2014-16, 2015-17, etc. (See Table A.2a. for the raw numbers on which the following figures are based).

Figure 3 portrays trends in the shares of stops of Black, Asian and Hispanic drivers. It is noteworthy that the Black share of stopped drivers has risen by 32% over this time period, with the Asian share also rising and the Hispanic share relatively constant.

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



Of interest, as noted, is the percentage of stops that are pretextual. This type of stop is one that is more susceptible to bias than are safety stops, the latter being based on discernible driver behavior. The ratio of minority to white pretextual stops as a share of all stops rose in each 3-year period up to 2016-18. In 2017-19, the Black/white ratio of the share of stops that are pretextual rose substantially from 1.30 to 1.74. That is, by 2017-19, Black drivers were roughly 75% more likely to be stopped for investigatory/pretextual reasons than white drivers (Figure 4). In fact, from 2016-18 to 2017-19, the share of stops of Black drivers for which the recorded reason for the stop is investigatory/pretextual rose by 109.5% compared to 25.2% for white drivers. Asian/white pretextual stop ratios are relatively constant over time, with Asian drivers stopped for pretextual reasons at roughly the same rate as white drivers.

Figure 4. Ratio of Minority/White Investigatory/Pretextual Stops as % of All Stops

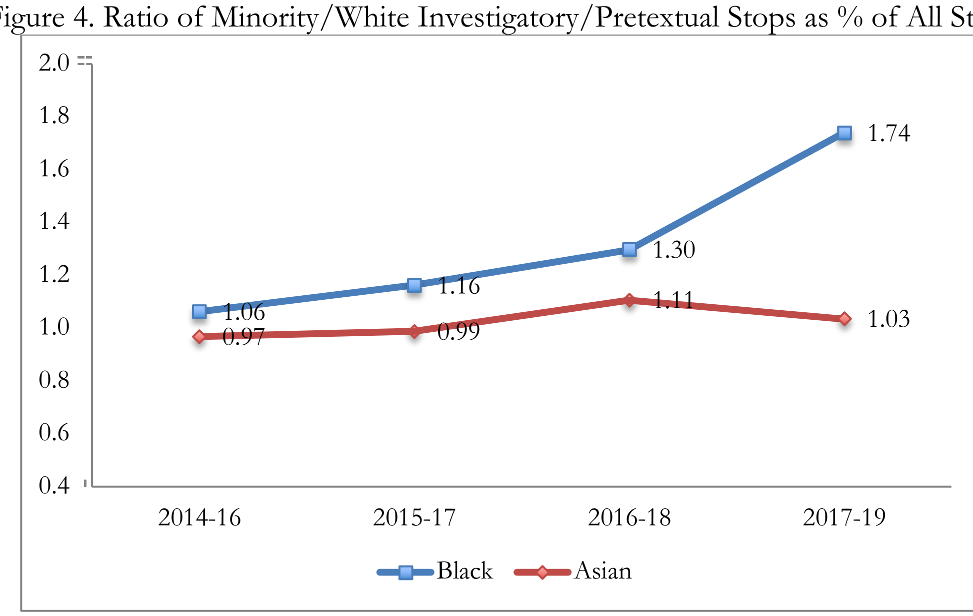
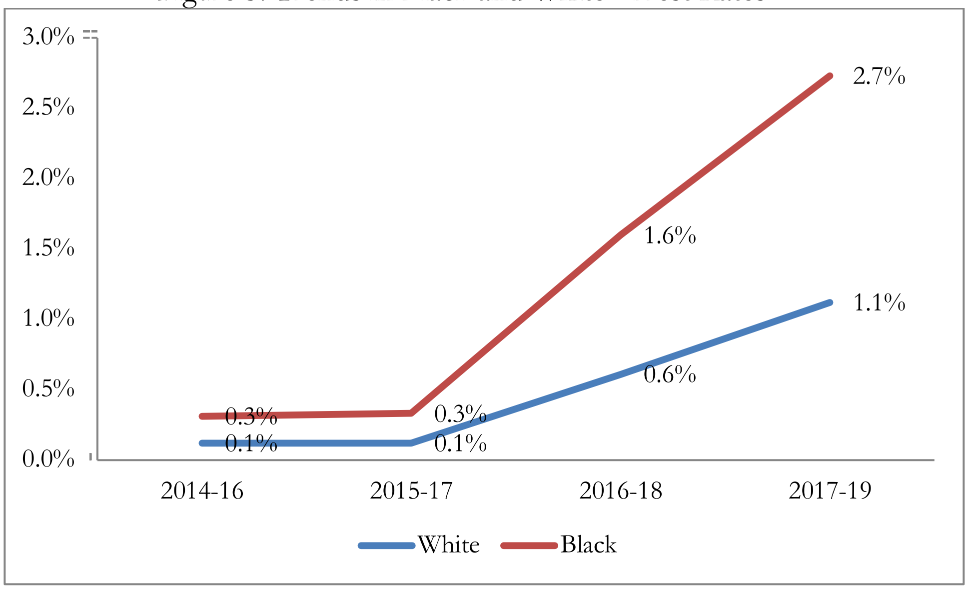


Figure 5 shows trends in Black and white arrest rates. (There were just 4 and 7 arrests of Asian and Hispanic drivers over this period of time, respectively, making trend analysis for these groups unreliable). For both Black and white drivers, arrest rates were very low in 2014-16 and 2015-17, but rose substantially thereafter. Moreover, the Black-white gap has substantially increased with 2.7% of Black drivers arrested in 2017-19, compared to 1.1% of white drivers. That is, by 2017-19, Black drivers were arrested at a rate that was about 2 and a half times greater than the white rate.

Figure 5. Trends in Black and White Arrest Rates



White and Black search rates are shown in Figure 6. The Black search rate has risen over time with Black drivers 2.2 times more likely to be searched than white drivers in Colchester in 2017-19. (The number of annual searches of Asian and Hispanic drivers is very small and so we do not include those in Figure 6).

Figure 6. Trends in Black and White and Black Search Rates

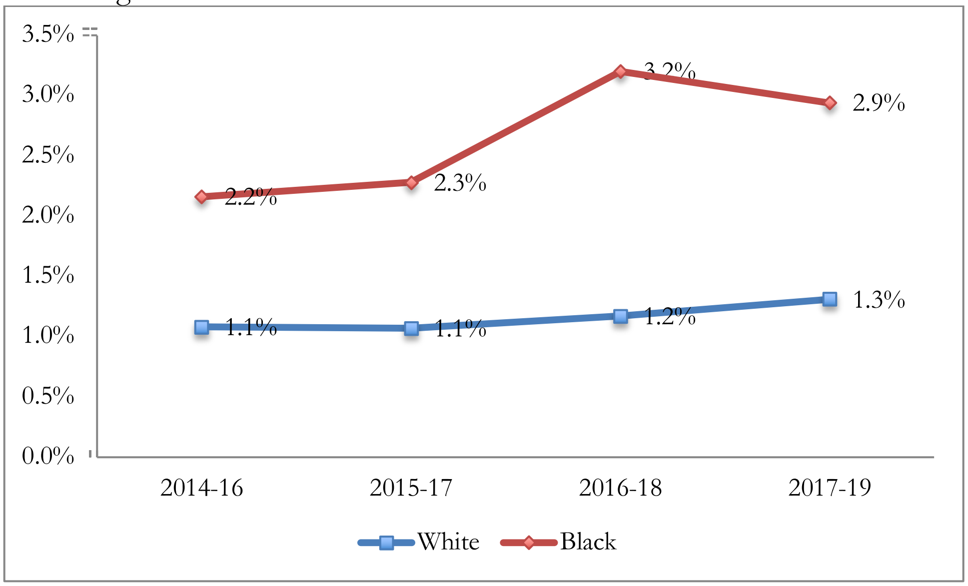
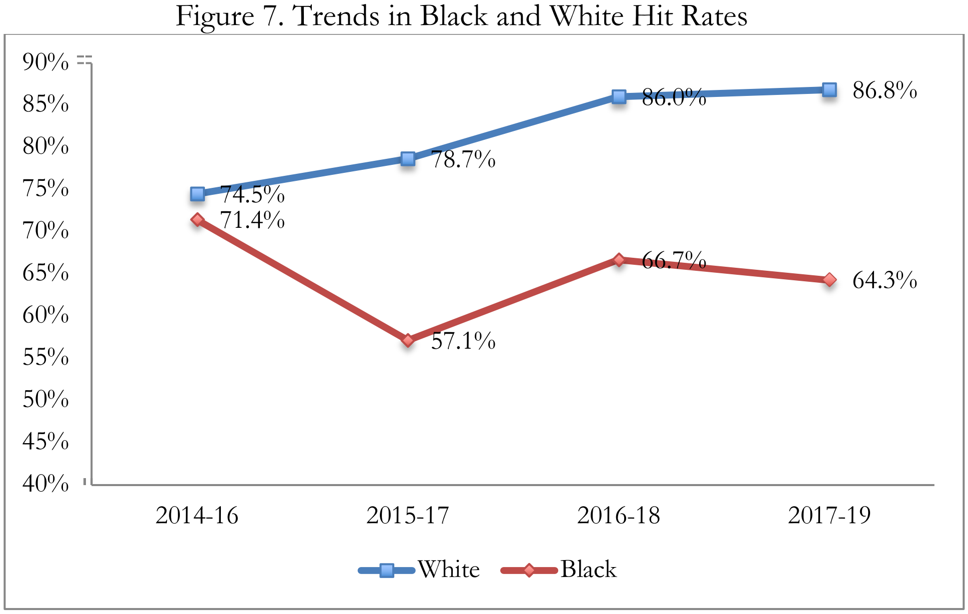


Figure 7 shows trends in white and Black contraband hit rates for all outcomes. The Black hit rate is consistently below the white hit rate over this time period. The gap is much wider in 2017-19 than in 2014-16. (Asian and Hispanic hit rates are not shown due to small sample sizes). In particular, the white hit rate exceeds the Black hit rate in 2017-19 by 35%. This result demonstrates that searches of Black drivers are less efficient (or productive) than searches of white drivers. This may result from officers having a lower bar of evidence on which to initiate searches of Black drivers and is consistent with the hypothesis that the race of the driver influences officer decisions to search vehicles in Colchester.

Figure 7. Trends in Black and White Hit Rates



V. Logit Analysis

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

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 of 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 racial probabilities of being searched. A ratio that is greater than one indicates a racial 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. Unfortunately, the data on age of driver was not provided for 2014-15 so the regressions that include that age variable (columns 4-5) are for the years 2016-2019 only. We also control for day of week and time of day of the search.

We also control for the reason for the stop in two ways. First, we include all reasons for a stop as explanatory variables. The excluded category for this set of variables is moving violation. The coefficients on the *Reason for Stop* variables indicate the odds of being searched for each reason given for a stop divided by the odds of being searched due to moving violation, where the reason is one of the following: suspicion of DWI, investigatory stop, multiple reasons for a stop (where the officer indicated more than one reason for the stop), and for reasons unknown (that is, the reason was not stipulated in the incident report), 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 the factors we control for that may lead to an officer's decision to search a vehicle, race influences the officer's decision to search (net of those factors).

We report results on five variations of our basic model. One of the reasons we need to run the regression with multiple specifications is due missing data on age of driver in some of the Colchester dataset. We lose those observations when we include age as an independent variable in our regression.

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, the odds a Black driver will be searched are 2.23 times greater than the odds for a white driver. That is, officers in Colchester are more than twice as likely to search a Black driver as they are a white driver. In contrast, the odds for Asian drivers are a little more than half the odds for white drivers. Hispanic drivers have the same likelihood of being searched as white drivers. 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 very small and so that category was omitted.

In Model 2, adding controls for gender, time, and reason for stop, we find that the odds of a male driver being searched are 2.7 times the odds of a female driver being searched. The odds of a search in the morning are lower than in the afternoon, and the odds of a search at night are more than double those in the afternoon. None of the coefficients on days of the week are significant. That is, there are equal odds of being searched, regardless of day of week.

The odds that a driver in an investigatory stop is searched are 28.3 times greater than the odds for a stop initiated due to a moving violation. The odds of a search when the stop reason is missing or unknown are 8.35 times more likely to lead to a search than the odds for moving violations. If there are multiple reasons for the stop, the odds the driver is searched are 9.3 times larger, and if the reason is suspicion of DWI, the odds are more than double the odds for stops due to a moving violation, but this difference is not statistically significant. If the reason for the stop is vehicle equipment, drivers are also slightly more likely to be searched than if the reason is moving violation, but this is not statistically significant. The Black/white odds ratio is a little smaller at 1.724 in Model 2. (We will note, though, that because Black drivers in Colchester are more likely to be subject to investigatory stops/pretextual stops than white drivers, we should be careful interpreting the smaller coefficient as being a more accurate measure of disparity compared to the model without controls for type of stop). The Black-white odds ratio coefficient continues to be statistically significant at the one percent level. That is, we can reject the null hypothesis that there is no difference in search rates between Black and white drivers with a high degree of certainty.

In Model 3, we include two categories of *Reason for Stop*—safety stops (the omitted variable) and pretextual stops. The results indicate that when the reason for the stop is pretextual, the odds of a driver being searched are more than twice the odds if it is a safety stop.

In Models 4-5, we add age of driver as an independent variable. The missing 2014 and 2015 data on age reduces the sample size. In Model 4, the odds ratio on age is below 1.0, meaning that the older the driver, the lower the probability of being searched, as would be expected. The addition of this control reduces the odds ratio of Black drivers being searched compared to white drivers to 1.599, suggesting that Black drivers in Colchester are younger than white drivers. Model 5, which uses safety and pretextual stops as reasons for the stop, yields very similar coefficient results on all of our variables to those in Model 4.

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

	(1)	(2)	(3)	(4)	(5)
	2014-19	2014-19	2014-19	2016-19	2016-19
VARIABLES	Race only	With gender, time, and stop reason	With gender, time and pretextual stop control	With all controls and stop reason	With all controls and pretextual stop control
Black	2.233***	1.724**	1.722**	1.599*	1.551*
	(0.517)	(0.414)	(0.403)	(0.430)	(0.409)
Asian	0.669	0.626	0.609	0.466	0.454
	(0.390)	(0.369)	(0.356)	(0.337)	(0.326)
Hispanic	0.797	0.871	0.763	1.173	1.083
	(0.803)	(0.879)	(0.770)	(1.190)	(1.098)
Male		2.703***	2.770***	2.855***	2.829***
		(0.458)	(0.465)	(0.585)	(0.572)
DefAgeInt				0.948***	0.948***
				(0.00695)	(0.00691)
Morning		0.533	0.512	1.147	1.146
		(0.247)	(0.236)	(1.701)	(1.638)
Night		2.342***	2.158***	5.660	3.965
		(0.657)	(0.600)	(6.098)	(4.153)
Saturday		1.458	1.392	1.752	1.499
		(0.529)	(0.500)	(1.913)	(1.583)
Sunday		0.944	1.026	0.919	0.991
		(0.222)	(0.238)	(0.241)	(0.255)
Monday		1.030	1.193	1.180	1.322
		(0.213)	(0.243)	(0.267)	(0.294)
Tuesday		1.208	1.162	1.210	1.091
		(0.252)	(0.239)	(0.283)	(0.251)
Wednesday		1.292	1.318	1.944	1.519
		(0.332)	(0.333)	(2.103)	(1.617)
Thursday		1.567	1.524	3.464*	3.433*
		(0.601)	(0.582)	(2.263)	(2.217)
Investigatory Stop		28.30***		31.86***	
		(8.006)		(9.856)	
Multiple stop reasons		9.305**		15.76**	
		(9.897)		(18.28)	
Suspicion of DWI		2.392		3.719	
		(2.450)		(3.893)	
Unknown stop reason		8.350***		5.192***	
		(2.260)		(2.136)	
Vehicle Equipment		1.047		1.284	
		(0.213)		(0.301)	
Pretextual stop			2.197***		2.551***
			(0.331)		(0.458)
Constant	0.012***	0.001***	0.001***	0.002***	0.003***
	(0.001)	(0.0003)	(0.0004)	(0.002)	(0.003)
Observations	19,075	19,070	19,070	12,865	12,865

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

Taken together, these results suggest that Black/white disparities in search rates are extremely robust, regardless of the contextual factors controlled for. Moreover, the levels of disparity indicated by the logistic regressions are very similar to the Black/white search rate ratio in Figure 6. The use of more rigorous statistical techniques does not in any meaningful way change the nature of the descriptive data findings.

B. The Probability of Finding Contraband

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

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

Table 5 reports the results of the probability of contraband found for searches for any outcome of the stop and search (that is, in which the result was a warning, a citation, and/or an arrest) for all years for which we have data. The results shown for Model 1, where the only explanatory variable is race of the driver, indicate that the odds of a search of a Black driver yielding contraband are less than half the odds a white driver will be found with contraband subsequent to a search. The difference, although seemingly large, is not statistically significant. There were too few searches that yielded contraband of other racial groups so only white and Black drivers are included in this set of regressions.

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 81.1% of searched white drivers are found with contraband and thus, 18.9% are not found with contraband. This implies an odds ratio for white drivers of 81.1/18.9= 4.3. In other words, the odds are more than 4 to 1 that a search of a white driver will yield contraband. For Black drivers, we find in Table 2 that 66.7% of them are found with contraband so their odds ratio is 66.7/33.3=2.00. The Black/white ratio of these two odds is the coefficient in our regression (2.0/4.3 =0.47), very close to the coefficient estimate on race when we formally run the logit regression.

The addition of controls in Models 2-3 lowers the odds ratio of finding contraband in searches of Black as compared to white drivers to about one third of the white odds. In Model 2, where we control for gender and reason for stop, we continue to observe lower odds of finding contraband in a search of a Black driver as compared to white, and this difference is statistically significant. In Model 3, we obtain similar results on the Black to white odds of contraband being found, 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, although this is not statistically significant.

In Models 4-5, we add age of driver, reducing our sample size to just the data reported for the later years, 2016-2019. These results show that the odds of a Black driver being found with contraband relative to the odds for a white driver are substantially lower than in Models 1-3, ranging from 0.264 to 0.314 (that is, the odds of Blacks being found with contraband are between a quarter and a third the odds white drivers will be found with contraband.).

These coefficients are statistically significant.[12] This is consistent with the results in Figure 7 where we show that the Black/white disparity in the hit rate has increased. It is also relevant to point out that this time period corresponds with an increase in the number of stops per capita compared to the earlier period. Regarding searching, the additional policing has not increased efficiency.

To sum up the results of the logistic regressions, adding controls for a variety of contextual factors has little effect on racial disparities in the probability of being searched and of contraband being found during a search. This is not to say that the controls were not meaningful or significant. Searches and the likelihood of finding contraband are more likely to happen under some conditions as compared to others (e.g., during investigatory stops as compared to motor vehicle stops). But even controlling for these factors, race continues to be a statistically significant factor in an officer's decision to search a vehicle. Moreover, and with regard to the question of racial bias as an explanation for such disparities, the analysis shows that Black drivers are less likely to be found with contraband, a finding that is consistent with oversearching of that group of drivers—a trend that is getting worse in recent years.

[12] In results not reported here (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 compared to white drivers.

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

VARIABLES	(1) 2014-19 Race only	(2) 2014-19 With gender, time, and stop reason	(3) 2014-19 With gender, time and pretextual stop control	(4) 2016-19 With all controls and stop reason	(5) 2016-19 With all controls and pretextual stop control
Black	0.465	0.324**	0.324**	0.264**	0.314*
	(0.230)	(0.182)	(0.172)	(0.179)	(0.189)
Male		1.503	1.306	1.183	1.158
		(0.716)	(0.588)	(0.728)	(0.666)
Age				1.008	1.007
				(0.0247)	(0.0230)
Morning		0.241	0.153*		
		(0.274)	(0.166)		
Night		3.028	2.259		
		(2.360)	(1.528)		
Saturday		0.609	0.466		
		(0.473)	(0.356)		
Sunday		5.843**	5.093**	8.841**	5.465**
		(4.328)	(3.708)	(7.840)	(4.596)
Monday		2.989**	2.816*	3.763**	2.617*
		(1.656)	(1.503)	(2.260)	(1.481)
Tuesday		1.994	1.448	3.350*	1.408
		(1.102)	(0.716)	(2.267)	(0.801)
Wednesday		2.981	2.751		
		(2.139)	(1.863)		
Thursday		2.585	2.339		
		(2.564)	(2.278)		
Vehicle equipment		0.472		0.274**	
		(0.231)		(0.161)	
Pretextual stop			1.491		1.139
			(0.623)		(0.539)
Constant	4.300***	0.372	0.724	1.119	1.685
	(0.755)	(0.460)	(0.799)	(1.523)	(2.134)
Observations	233	195	233	135	162

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. In this report, we have discussed some concerns with Colchester's traffic stop data quality. While there are some areas for improvement in the quality of the data, which could be achieved by greater efforts to eliminate missing data, the data we do have from Colchester are useful for gauging racial disparities in policing and give no evidence of being so systematically flawed that they are unusable.

In this report, we provide descriptive data on racial disparities in traffic stops and we also report on a statistical analysis that controls for other factors that may influence the probability of being searched or of contraband being found during a search. 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. We also find that since 2015, racial disparities in pretextual stops, arrest rates, search rates, and contraband hit rates have worsened, and Black stop rates have risen more than stop rates of any other racial group.

REFERENCES

Alpert, G., M. Smith, and R. Dunham. 2004. "Toward a Better Benchmark: Assessing the Utility of Not-at-fault Traffic Crash Data in Racial Profiling Research." *Justice Research and Policy* 6(1): 43-69.

Banaji, M. and A. Greenwald. 2013. *Blind Spot: Hidden Biases of Good People.* Delacorte Press.

Baumgartner, F., D. Epp, and K. Shoub. 2018. *Suspect Citizens: What 20 Million Stops Tell Us About Policing and Race.* Cambridge University Press.

Eberhardt, J. 2019. *Biased: Uncovering the Hidden Prejudice That Shapes What We See, Think, and Do.* Penguin Books.
Ivers, R., T. Senserrick, S. Boufous, M. Stevenson, H.-Y. Chen, M. Woodward, and R. Norton. 2009. "Novice Drivers' Risky Driving Behavior, Risk Perception, and Crash Risk: Findings from a DRIVE Study." *American Journal of Public Health* 99(9): 1638-1644.

Ivers, R., T. Senserrick, S. Boufous, M. Stevenson, H.-Y. Chen, M. Woodward, and R. Norton. 2009. "Novice Drivers' Risky Driving Behavior, Risk Perception, and Crash Risk." *American Journal of Public Health* 99(9): 1638-1644.

Persico, N. and P. Todd. 2008. "The Hit Rates Test for Racial Bias in Motor Vehicle Searches." *Justice Quarterly* 25: 37-53.

Pierson, E., C. Simoiu, J. Overgoor, *et al.* 2020. "A Large-scale Analysis of Racial Disparities in Police Stops Across the United States. *Nature Human Behavior.* https://doi.org/10.1038/s41562-020-0858-1

Seguino, S. and N. Brooks 2017. *Driving While Black and Brown in Vermont.* https://www.uvm.edu/giee/pdfs/SeguinoBrooks_PoliceRace_2017.pdf

Tal, G. and S. Handy. 2005 "The Travel Behavior of Immigrants and Race/Ethnicity Groups: An Analysis of the 2001 National Household Travel Survey." Report No. UCD-ITS-RR-05-24. Institute of Transportation Studies, University of California Davis.

U.S. Department of Health and Human Services. 2012. "Results from the 2012 National Survey on Drug Use and Health: Summary of National Findings." https://www.samhsa.gov/data/sites/default/files/NSDUHresults2012/NSDUHresults2012.pdf

U.S. Department of Health and Human Services. 2013. "Results from the 2013 Survey on Drug Use and Health: Summary of National Findings." https://www.samhsa.gov/data/sites/default/files/NSDUHresultsPDFWHTML2013/Web/NSDUHresults2013.pdf

U.S. Department of Justice. 2003. "Guidance Regarding the Use of Race by Federal Law Enforcement Agencies." https://www.justice.gov/crt/guidance-regarding-use-race-federal-law-enforcement-agencies

APPENDIX

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

All Years	White	Black	Asian	Hispanic	Native American	Unknown	Total
Total Traffic Stops							
Including externally generated stops	18,171	829	385	106	7	238	19,736
Excluding externally generated stops	17,800	801	375	105	7	234	19,322
Reasons For Stops							
Safety Stops	15,203	651	323	91	7	184	16,459
Moving Violation	15,173	649	323	91	7	184	16,427
Suspicion of DWI	30	2	0	0	0	0	32
Investigatory/Pretextual Stops	2,389	144	49	14	0	43	2,639
Investigatory Stop	69	7	1	0	0	0	77
Vehicle Equipment	2,320	137	48	14	0	43	2,562
Externally Generated Stop	371	28	10	1	0	4	414
Multiple Reasons - Moving Violation & Suspicion of DWI	0	0	0	0	0	0	0
Multiple Reasons - Moving Violation & Vehicle Equipment	12	0	0	0	0	1	13
Multiple Reasons - Suspicion of DWI & Vehicle Equipment	0	0	0	0	0	0	0
Unknown Stop Reason	196	6	3	0	0	6	211
Outcomes							
Ticket	5,531	267	107	33	2	53	5,993
Warning	12,481	544	270	75	4	179	13,553
No Action Taken	13	0	0	0	0	2	15
Arrest for violation	109	14	0	0	0	0	123
Arrest for warrant	7	3	1	0	0	0	11
Searches							
Total Stops with No Search	17,582	780	372	104	7	232	19,077
No Search & Contraband & Arrest for violation	1	0	0	0	0	0	1
No Search & Contraband & No arrest	16	1	1	0	0	0	18
No Search (all others)	17,565	779	371	104	7	232	19,058
Total Stops with Unknown Search	6	0	0	0	0	2	8
Total Stops with Search	212	21	3	1	0	0	237
Search with Probable Cause (PC)	155	18	2	1	0	0	176
Stops with PC Searches, No contraband	19	5	0	0	0	0	24
Stops with PC Searches, Unknown contraband	1	0	0	0	0	0	1
Stops with PC Searches, Contraband	135	13	2	1	0	0	151
Outcomes of PC Search							
Stops with PC Searches, Contraband & Warning, No Action or Unknown	24	3	0	0	0	0	27
Stops with PC Searches, Contraband and Ticket	105	9	1	1	0	0	116
Stops with PC Searches, Contraband and Arrest	6	1	1	0	0	0	8
Search with Reasonable Suspicion (RS)	47	3	1	0	0	0	51
Stops with RS Searches, No contraband	17	2	0	0	0	0	19
Stops with RS Searches, Unknown contraband	0	0	0	0	0	0	0
Stops with RS Searches, Contraband	30	1	1	0	0	0	32
Outcomes of RS Search							
Stops with RS Searches, Contraband & Warning, No Action or Unknown	6	0	1	0	0	0	7
Stops with RS Searches, Contraband & Ticket	24	0	0	0	0	0	24
Stops with RS Searches, Contraband & Arrest	0	1	0	0	0	0	1
Search with Warrant	10	0	0	0	0	0	10
Stops with Warrant Searches, No contraband	3	0	0	0	0	0	3
Stops with Warrant Searches, Unknown contraband	0	0	0	0	0	0	0
Stops with Warrant Searches, Contraband	7	0	0	0	0	0	7
Outcomes of Warrant Search							
Stops with Warrant Searches, Contraband & Warning, No Action or Unknown	3	0	0	0	0	0	3
Stops with Warrant Searches, Contraband & Ticket	2	0	0	0	0	0	2
Stops with Warrant Searches, Contraband & Arrest	2	0	0	0	0	0	2

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

Table A.2a. Colchester 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							
2014-16	9,069	324	165	58	4	225	9,845
2015-17	8,296	307	177	57	3	114	8,954
2016-18	8,563	375	200	50	3	15	9,206
2017-19	8,731	477	210	47	3	9	9,477
Reasons For Stops (excl. externally generated stops and unknown reasons)							
Safety Stops							
2014-16	7,489	266	138	49	4	179	8,125
2015-17	7,192	261	154	47	3	88	7,745
2016-18	7,755	331	179	43	3	10	8,321
2017-19	7,714	385	185	42	3	5	8,334
2014-16 (% of stops)	83.6%	82.6%	84.2%	84.5%	100.0%	81.0%	83.6%
2015-17 (% of stops)	87.4%	85.3%	87.5%	82.5%	100.0%	79.3%	87.2%
2016-18 (% of stops)	91.3%	88.7%	90.4%	86.0%	100.0%	83.3%	91.2%
2017-19 (% of stops)	89.3%	81.4%	88.9%	89.4%	100.0%	83.3%	88.9%
Pretextual Stops							
2014-16	1,466	56	26	9	0	42	1,599
2015-17	1,042	45	22	10	0	23	1,142
2016-18	737	42	19	7	0	2	807
2017-19	923	88	23	5	0	1	1,040
2014-16 (% of stops)	16.4%	17.4%	15.9%	15.5%	0.0%	19.0%	16.4%
2015-17 (% of stops)	12.7%	14.7%	12.5%	17.5%	0.0%	20.7%	12.9%
2016-18 (% of stops)	8.7%	11.3%	9.6%	14.0%	0.0%	16.7%	8.8%
2017-19 (% of stops)	10.7%	18.6%	11.1%	10.6%	0.0%	16.7%	11.1%
Outcomes (excl. externally generated stops)							
Tickets (one or more)							
2014-16	3,025	100	61	17	1	49	3,253
2015-17	2,620	98	53	18	1	24	2,814
2016-18	2,602	132	52	17	2	5	2,810
2017-19	2,506	167	46	16	1	4	2,740
2014-16 (% of stops)	33.4%	30.9%	37.0%	29.3%	25.0%	21.8%	33.0%
2015-17 (% of stops)	31.6%	31.9%	29.9%	31.6%	33.3%	21.1%	31.4%
2016-18 (% of stops)	30.4%	35.2%	26.0%	34.0%	66.7%	33.3%	30.5%
2017-19 (% of stops)	28.7%	35.0%	21.9%	34.0%	33.3%	44.4%	28.9%
Arrests for Violation							
2014-16	11	1	0	0	0	0	12
2015-17	10	1	0	0	0	0	11
2016-18	52	6	0	0	0	0	58
2017-19	98	13	0	0	0	0	111
2014-16 (% of stops)	0.1%	0.3%	0.0%	0.0%	0.0%	0.0%	0.1%
2015-17 (% of stops)	0.1%	0.3%	0.0%	0.0%	0.0%	0.0%	0.1%
2016-18 (% of stops)	0.6%	1.6%	0.0%	0.0%	0.0%	0.0%	0.6%
2017-19 (% of stops)	1.1%	2.7%	0.0%	0.0%	0.0%	0.0%	1.2%

Table A.2a. continued

All Years	White	Black	Asian	Hispanic	Native American	Unknown	Total
Searches (excl. externally generated stops)							
Searches (PC, RS or Warrant)							
2014-16	98	7	1	1	0	0	107
2015-17	89	7	0	1	0	0	97
2016-18	100	12	1	1	0	0	114
2017-19	114	14	2	0	0	0	130
2014-16 (% of Stops)	1.1%	2.2%	0.6%	1.7%	0.0%	0.0%	1.1%
2015-17 (% of Stops)	1.1%	2.3%	0.0%	1.8%	0.0%	0.0%	1.1%
2016-18 (% of Stops)	1.2%	3.2%	0.5%	2.0%	0.0%	0.0%	1.2%
2017-19 (% of Stops)	1.3%	2.9%	1.0%	0.0%	0.0%	0.0%	1.4%
Contraband (All Outcomes)							
2014-16	73	5	1	1	0	0	80
2015-17	70	4	0	1	0	0	75
2016-18	86	8	1	1	0	0	96
2017-19	99	9	2	0	0	0	110
2014-16 (% of Searches)	74.5%	71.4%	100.0%	100.0%	0.0%	0.0%	74.8%
2015-17 (% of Searches)	78.7%	57.1%	0.0%	100.0%	0.0%	0.0%	77.3%
2016-18 (% of Searches)	86.0%	66.7%	100.0%	100.0%	0.0%	0.0%	84.2%
2017-19 (% of Searches)	86.8%	64.3%	100.0%	0.0%	0.0%	0.0%	84.6%
Contraband (Tickets + Arrests)							
2014-16	60	4	1	1	0	0	3
2015-17	61	3	0	1	0	0	2
2016-18	74	6	1	1	0	0	3
2017-19	79	7	1	0	0	0	2
2014-16 (% of Searches)	61.2%	57.1%	100.0%	100.0%	0.0%	0.0%	3.0%
2015-17 (% of Searches)	68.5%	42.9%	0.0%	100.0%	0.0%	0.0%	2.2%
2016-18 (% of Searches)	74.0%	50.0%	100.0%	100.0%	0.0%	0.0%	2.8%
2017-19 (% of Searches)	69.3%	50.0%	50.0%	0.0%	0.0%	0.0%	1.3%
Contraband (Arrests only)							
2014-16	0	1	0	0	0	0	1
2015-17	0	1	0	0	0	0	1
2016-18	3	1	1	0	0	0	5
2017-19	8	1	1	0	0	0	10
2014-16 (% of Searches)	0.0%	14.3%	0.0%	0.0%	0.0%	0.0%	0.9%
2015-17 (% of Searches)	0.0%	14.3%	0.0%	0.0%	0.0%	0.0%	1.0%
2016-18 (% of Searches)	3.0%	8.3%	100.0%	0.0%	0.0%	0.0%	4.4%
2017-19 (% of Searches)	7.0%	7.1%	50.0%	0.0%	0.0%	0.0%	7.7%

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

All Years	White	Black	Asian	Hispanic	Native American	Unknown	Total
Total Traffics Stops							
Including externally generated stops							
For year 2014	3,114	114	41	12	1	115	3,397
For year 2015	3,447	126	65	26	1	108	3,773
For year 2016	2,706	104	65	20	2	6	2,903
For year 2017	2,389	102	55	11	0	2	2,559
For year 2018	3,707	190	86	20	1	7	4,011
For year 2019	2,808	193	73	17	2	0	3,093
Excluding externally generated stops							
For year 2014	3,091	113	41	12	1	113	3,371
For year 2015	3,371	121	62	26	1	106	3,687
For year 2016	2,607	90	62	20	2	6	2,787
For year 2017	2,318	96	53	11	0	2	2,480
For year 2018	3,638	189	85	19	1	7	3,939
For year 2019	2,775	192	72	17	2	0	3,058
Percentage Change YoY							
2014 vs 2015	9.1%	7.1%	51.2%	116.7%	0.0%	-6.2%	9.4%
2015 vs 2016	-22.7%	-25.6%	0.0%	-23.1%	100.0%	-94.3%	-24.4%
2016 vs 2017	-11.1%	6.7%	-14.5%	-45.0%	-100.0%	-66.7%	-11.0%
2017 vs 2018	57.0%	96.9%	60.4%	72.7%	100.0%	250.0%	58.8%
2018 vs 2019	-23.7%	1.6%	-15.3%	-10.5%	100.0%	-100.0%	-22.4%
Stops per 10,000 residents							
2014	2,187	6,108	1,099				
2015	2,385	6,541	1,662				
2016	1,844	4,865	1,662				
2017	1,640	5,189	1,421				
2018	2,574	10,216	2,279				
2019	1,963	10,378	1,930				

Appendix A.3. Data Quality and Methodology

The Colchester Police Department (CPD) traffic stop data used in this study consists of 17,425 rows, spanning five years (2014-2018). 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.[13]

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 CPD 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												
2014	3,371	3,371	1,027	3,371	113	6	56	3	4	22	433	18
2015	3,687	3,687	0	3,051	106	0	44	1	1	12	523	33
2016	2,787	2,787	2,787	1	6	0	13	0	0	2	447	21
2017	2,480	0	2,480	2	2	3	4	0	0	0	328	10
2018	3,939	0	3,939	5	7	7	58	4	4	5	327	12
2019	3,058	0	3,058	1	0	0	36	0	0	0	306	8
All Years	19,322	9,845	13,291	6,431	234	16	211	8	9	41	3,175	190
Percentage of Blank or Unknown Rows												
2014	3,371	100.0%	30.5%	100.0%	3.4%	0.2%	1.7%	0.1%	0.1%	0.6%	433	4.2%
2015	3,687	100.0%	0.0%	82.8%	2.9%	0.0%	1.2%	0.0%	0.0%	0.3%	523	6.3%
2016	2,787	100.0%	100.0%	0.0%	0.2%	0.0%	0.5%	0.0%	0.0%	0.1%	447	4.7%
2017	2,480	0.0%	100.0%	0.1%	0.1%	0.1%	0.2%	0.0%	0.0%	0.0%	328	3.1%
2018	3,939	0.0%	100.0%	0.1%	0.2%	0.2%	1.5%	0.1%	0.1%	0.1%	327	3.7%
2019	3,058	0.0%	100.0%	0.0%	0.0%	0.0%	1.2%	0.0%	0.0%	0.0%	306	2.6%
All Years	19,322	51.0%	68.8%	33.3%	1.2%	0.1%	1.1%	0.0%	0.1%	0.2%	3,175	6.0%

Note: These data exclude externally generated stops. Stop date/time is not required by law.

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"[14]

[13] For full details for the methodology used in all our 2020 analyses of Vermont traffic stop data, https://www.uvm.edu/sites/default/files/Department-of-Economics/faculty/Data_Quality_and_Methodology_for_Traffic_Stop_Data_Analysis.pdf.

[14] In the CPD data, three rows had the value "Transgendered – T."

- Stop Reason – Blank or "O = Other violation"
- Search Reason – Blank
- Search Outcome – Blank
- Stop Result – Blank.

Analysis of the CPD 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 dramatically reduced starting in 2016. In 2014 and 2015, most rows were missing age of driver (100% and 82.3% respectively). Missing or unknown values for driver race were the second most common in those years (3.3% and 2.8% respectively). About 6% 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 CPD data rows 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	3,371	3,371	100.0%
2015	3,687	3,069	83.2%
2016	2,787	22	0.8%
2017	2,480	7	0.3%
2018	3,939	73	1.9%
2019	3,058	37	1.2%
All Years	19,322	6,579	34.1%

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

As noted above, much of the 2014 and 2015 data was missing driver age. This is the primary reason the missing row counts appear so high for those years.

Table A.3c shows missing data by 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 Colchester.

Table A.3c. Unknowns and Race of Driver

	White	Black	Asian	Hispanic	Unknown
Count of Blank or Unknown Rows					
Total Stop Rows	19,671	931	400	117	243
Unknown Stop reason	217	10	3	0	7
Unknown Stop outcome	35	3	1	0	1
Unknown if Search occured	9	0	0	0	2
Unknown if contraband found subsequent to a search	1	0	0	0	0
Unknown outcome if contraband found	1	0	0	0	0
Percentage of Blank or Unknown Rows					
Unknown Stop reason as % of all rows	1.1%	1.1%	0.8%	0.0%	2.9%
Unknown Stop outcome as % of all rows	0.2%	0.3%	0.3%	0.0%	0.4%
Unknown if search occurred as % of all rows	0.1%	0.0%	0.0%	0.0%	0.8%
Unknown if contraband found as % of all searches	0.3%	0.0%	0.0%	0.0%	0.0%
Unknown outcome if contraband found as % of all searches	0.3%	0.0%	0.0%	0.0%	0.0%

B. Missing Months of Data

Since dates are missing from most of the CPD data, it is difficult to determine if stops are omitted for any significant time periods. However, it is clear that no data has been provided for April through June of 2014.

C. Duplicate Blocks of Data

A review of the 2014 CPD data revealed that all rows from July through December were duplicated because each row in this time span appeared twice with all field values matching exactly. The duplicate rows were removed prior to further analysis.

D. Stop IDs and Stops with Multiple Outcomes

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 six years of data available from Colchester, only 2017, 18 and 19 have Stop IDs that can be used to tie together multiple outcomes. For 2015 and some of 2014, date and time were available to derive usable Stop IDs. For 2016 and the remainder of 2014, no date and time were provided so each row was treated as a separate stop.

When stop IDs are absent, a heuristic approach is used to attempt to group together outcomes for the same stop. The technique associates outcomes using a combination of fields with matching values. Typically, the following set of fields is used to identify stops: Agency, Stop Date/Time, Age, Gender, and Race. This approach was successfully applied to the Colchester 2014 (Q3 and Q4) and 2015 data.

If any of the above fields is missing from the data, the heuristic approach cannot work. In this case, each row must be assumed to be a separate stop, i.e., each stop has only one outcome. Due to missing stop IDs and dates, this approach was required for the Colchester 2014(Q1) and 2016 data (Table A.3d).

Table A.3d Colchester Stop IDs

Year	Usable Stop IDs	Could Derive Stop IDs	Stop Count	Row Count
2014	No	Partial	4189	4252
2015	No	Yes	3773	3870
2016	No	No	2903	2903
2017	Yes		2559	3136
2018	Yes		4011	4864
2019	Yes		3093	3136

Table A.4. Variable Definitions

Variable	Formula
Total Traffic Stops	
Including externally generated stops	Count of all stops
Excluding externally generated stops	Count of all stops except where stop reason is "externally generated stop"
Reasons For Stops	
Safety Stops	Count of all stops where stop reason is "moving violation" or "suspicion of DWI"
Moving Violation	Count of all stops where stop reason is "moving violation"
Suspicion of DWI	Count of all stops where stop reason is "suspicion of DWI"
Investigatory/Pretextual Stops	Count of all stops where stop reason is "investigatory stop" or "vehicle equipment"
Investigatory Stop	Count of all stops where stop reason is "investigatory stop"
Vehicle Equipment	Count of all stops where stop reason is "vehicle equipment"
Externally Generated Stop	Count of all stops where stop reason is "externally generated stop"
Multiple Reasons - Moving Violation & Suspicion of DWI	Count of all stops where stop reasons include both "moving violation" and "suspicion of DWI"
Multiple Reasons - Moving Violation & Vehicle Equipment	Count of all stops where stop reasons include both "moving violation" and "vehicle equipment"
Multiple Reasons - Suspicion of DWI & Vehicle Equipment	Count of all stops where stop reasons include both "suspicion of DWI" and "vehicle equipment"
Unknown Stop Reason	Count of all stops where stop reason is "unknown"
Outcomes (excl. EGS)	
Ticket	Count of all stops where at least one ticket was issued.
Warning	Count of all stops where at least one warning was issued.
No action taken	Count of all stops where no action was taken was issued.
Arrest for violation	Count of all stops where there was an arrest for violation.
Arrest for warrant	Count of all stops where there was an arrest for warrant.
Searches	
Total stops with no search	Count of all stops where search reason was "no search"
No Search & Contraband & Arrest for violation	Count of all stops where search reason was "no search" and stop search outcome was "contraband" and there was an arrest for violation
No Search & Contraband & No Arrest	Count of all stops where search reason was "no search" and stop search outcome was "contraband" and there was not an arrest for violation
No Search (all others)	Count of all stops where search reason was "no search" and stop search outcome was not "contraband"
Total Stops with Unknown Search	Count of all stops where search reason was "unknown"
Total Stops with Search	Count of all stops where search reason was one of "probable cause," "reasonable suspicion," or "warrant"
Search with Probable Cause (PC)	Count of all stops where search reason was "probable cause"
Stops with PC Searches, No contraband	Count of all stops where search reason was "probable cause" and search outcome was "no contraband" or "no search"

Variable	Formula
Stops with PC Searches, Unknown contraband	Count of all stops where search reason was “probable cause” and search outcome was “unknown”
Stops with PC Searches, Contraband	Count of all stops where search reason was “probable cause” and search outcome was “contraband”
*Outcomes of PC Search**	
Stops with PC Searches, Contraband & Warning, No Action or Unknown*	Count of all stops where search reason was “probable cause” and search outcome was “contraband” and one or more of the following outcomes were recorded: “warning,” “no action,” or “unknown” but no tickets or arrests
Stops with PC Searches, Contraband and Ticket*	Count of all stops where search reason was “probable cause” and search outcome was “contraband” and one or more tickets were issued but no arrest
Stops with PC Searches, Contraband and Arrest*	Count of all stops where search reason was “probable cause” and search outcome was “contraband” and one or more arrests were made (for Violation or Warrant)
Search with Reasonable Suspicion (RS)	Count of all stops where search reason was “reasonable suspicion”
Stops with RS Searches, No contraband	Count of all stops where search reason was “reasonable suspicion” and search outcome was “no contraband” or “no search”
Stops with RS Searches, Unknown contraband	Count of all stops where search reason was “reasonable suspicion” and search outcome was “unknown”
Stops with RS Searches, Contraband	Count of all stops where search reason was “reasonable suspicion” and search outcome was “contraband”
*Outcomes of RS Search**	
Stops with RS Searches, Contraband & Warning, No Action or Unknown*	Count of all stops where search reason was “reasonable suspicion” and search outcome was “contraband” and one or more of the following outcomes were recorded: “warning,” “no action,” or “unknown” but no tickets or arrests
Stops with RS Searches, Contraband & Ticket*	Count of all stops where search reason was “reasonable suspicion” and search outcome was “contraband” and one or more tickets were issued but no arrest
Stops with RS Searches, Contraband & Arrest*	Count of all stops where search reason was “reasonable suspicion” and search outcome was “contraband” and one or more arrests were made (for Violation or Warrant)
Search with Warrant	Count of all stops where search reason was “warrant”.
Stops with Warrant Searches, No contraband	Count of all stops where search reason was “warrant” and search outcome was “no contraband” or “no search”
Stops with Warrant Searches, Unknown contraband	Count of all stops where search reason was “warrant” and search outcome was “unknown”
Stops with Warrant Searches, Contraband	Count of all stops where search reason was “warrant” and search outcome was “contraband”
*Outcomes of Warrant Search**	
*Stops with Warrant Searches, Contraband & Warning, No Action or Unknown**	Count of all stops where search reason was “warrant” and search outcome was “contraband” and one or more of the following outcomes were recorded: “warning,” “no action,” or “unknown” but no tickets or arrests
Stops with Warrant Searches, Contraband & Ticket*	Count of all stops where search reason was “warrant” and search outcome was “contraband” and one or more tickets were issued but no arrest

Variable	Formula
Stops with Warrant Searches, Contraband & Arrest*	Count of all stops where search reason was "warrant" and search outcome was "contraband" and one or more arrests were made
Racial Shares of Stops	
Including externally generated stops	Number of stops for a race divided by number of stops for all races
Excluding externally generated stops	Number of non-EGS for a race divided by number of non-EGS for all races
Racial share of stops (ACS)	Percentage of area residents of a particular race as determined by the American Community Survey (ACS) five-year estimates for 2013-2017 (See https://www.census.gov/programs-surveys/acs)
Racial share of stops (DMV accident data)	Percentage of area drivers of a particular race as determined by Vermont DMV Accident data for 2013-18.
Disparity Index (using ACS)	For a particular race, the Disparity Index (ACS) is the % of non-EGS for that race divided by the % of area residents for that race based on the ACS 5-year estimates from 2013-2017.
Disparity Index (using DMV Accident data)	For a particular race, the Disparity Index (DMV) is the % of non-EGS stops for that race by the % of area drivers for that race based on Vermont DMV accident data for 2013-2018.
Stop Reason as % of All Stops	
Safety Stops	% of all stops where stop reason is "moving violation" or "suspicion of DWI"
Moving Violation	% of all stops where stop reason is "moving violation"
Suspicion of DWI	% of all stops where stop reason is "suspicion of DWI"
Investigatory/Pretextual Stops	% of all stops where stop reason is "investigatory stop" or "vehicle equipment"
Investigatory Stops	% of all stops where stop reason is "investigatory stop"
Vehicle Equipment	% of all stops where stop reason is "vehicle equipment"
Externally Generated Stops	% of all stops where stop reason is "externally generated stop"
Multiple Reasons	% of all stops where there are multiple stop reasons in the following combinations: "moving violation" and "suspicion of DWI" or "moving violation" and "vehicle equipment" or "suspicion of DWI" and "vehicle equipment"
Unknown Reason	% of all stops where stop reason is "unknown"
Outcome Rates as a % of All Stops	
Warning Rate	% of non-EGS stops where at least one warning was issued
Ticket Rate	% of non-EGS stops where at least one ticket was issued
Arrest for Violation Rate	% of non-EGS stops where there was an arrest for violation
Arrest for Warrant Rate	% of non-EGS stops where there was an arrest for warrant
No Action Rate	% of non-EGS stops where there was no action taken
Search Rates	
Search rate (excl. searches on warrant)	% of non-EGS stops where the search reason was "probable cause" or "reasonable suspicion"

Variable	Formula
Search rate (incl. searches on warrant)	% of non-EGS stops where the search reason was "probable cause," "reasonable suspicion," or "warrant search"
Hit rates (as a % of PC, RS, & Warrant Searches)	
Hit rates (incl. all outcomes)	% of non-EGS stops where the search reason was "probable cause," "reasonable suspicion," or "warrant" and contraband was found
Hit rates (excl. warnings as outcomes)	% of non-EGS where the search reason was "probable cause," "reasonable suspicion," or "warrant" and contraband was found, and the stop resulted in at least one ticket or arrest
Hit rates (outcome = arrest)	% of non-EGS stops where the search reason was "probable cause," "reasonable suspicion." or "warrant" and contraband was found, and the stop resulted in an arrest for violation or warrant

* Does not appear in all reports