Racial Disparities in Policing? An Assessment of 2009-10 Traffic Stop Data in Chittenden County, Vermont

Stephanie Seguino
Dept. of Economics
Old Mill 340
University of Vermont
Burlington, VT USA 05405
stephanie.seguino@uvm.edu

Nancy Brooks
Dept. of City and Regional Planning
212 W. Sibley Hall
Cornell University
Ithaca, NY USA 14853
nb275@cornell.edu

Kyle Mitofsky
Research Assistant
Department of Economics
University of Vermont
Burlington, VT USA 05405
kyle@kylemitofsky.com

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Racial Disparities in Policing? An Assessment of 2009-10 Traffic Stop Data in Chittenden County, Vermont

I. Introduction and Executive Summary

Racial profiling in policing has emerged as a significant social issue across the United States, with a Gallup survey finding that 67% of Blacks and 63% of Hispanics generally believe it is common in traffic stops; 50% of non-Hispanic whites concur with that view (Gallup and Newport 2004).

Concerns about unequal police treatment have spread to Chittenden County, Vermont in recent years, coinciding with significant change in the ethnic composition of the population. Concerned community members maintained that race and ethnicity unduly influence policing behavior in the jurisdictions surrounding and including Burlington, whether on foot or traffic patrols. In response, a local community action group—Uncommon Alliance—was formed. The group is comprised of members of the community of color, other concerned citizens, and police chiefs from Burlington, South Burlington, Winooski, and the University of Vermont. As a first step, the parties agreed to cooperate in the collection and analysis of traffic stop data in an attempt to move beyond anecdotal evidence, which was deemed insufficient to confirm or disprove that patterns of racial disparity exist.[1]

In preparation for the data collection effort, the cooperating police departments developed a protocol for collecting the required data on traffic stops in consultation with members of the Uncommon Alliance. Beginning in January 1, 2009, law enforcement officers in the four jurisdictions began collecting race data on every traffic stop. Because Vermont licenses do not include information on the race or ethnicity of the driver, officers rely on their own perceptions of race to categorize drivers.[2] In addition to race, officers record information on the age and gender of the driver, the time and location of the stop, reason for and outcome of stops, and data on searches.

A report analyzing 2009 traffic stop data was released in January 2011 (McDevitt &

[1] This alliance is noteworthy in that the cooperating police departments are voluntarily participating in this project. These police departments received the International Association of Chiefs of Police 2011 Multi-Agency Team Award, based on their work on the Uncommon Alliance Race Data Collection project.

[2] This can result in cases of mis-categorization of drivers' racial identity. There is anecdotal evidence that some drivers of color have been classified as white on their citations when in fact they are black or Hispanic (personal communication, Uncommon Alliance member, October 2011). The data made available for this study does not permit any assessment of the accuracy of the racial categorization of drivers. The possibility exists that officers could intentionally mis-identify drivers' ethnicity as a means to mask racial bias. We have no evidence to suggest that is systematically occurring. However, it would be useful to conduct a follow-up study whereby a random sample of stopped drivers is contacted with the goal of assessing the accuracy of racial identification in the data provided by the departments for 2009 and 2010 (see recommendations in Section VI).

Hakstian 2011). Data for 2010 from the four cooperating departments has now become available with almost 26,000 observations spanning the 2009-10 period. The size of this dataset is sufficiently large to enable statistically valid conclusions about the extent of racial disparities in traffic stops, if any, for many of the questions we list below.

The purpose of the present study is to determine whether there is evidence of racially disparate traffic enforcement practices in these four jurisdictions, based on the data collected over the two-year period 2009-2010. We analyze the data with a goal of addressing several specific questions:

- Are non-white drivers stopped more often than their representation in the population would predict? Are male non-white drivers disproportionately represented in traffic stops?

- Once stopped, do non-white drivers receive heavier penalties than white drivers? Do male non-white drivers receive heavier penalties than whites and non-white females?

- Are non-white drivers more likely to be targeted for high-discretion stops, defined as cases in which the officer has latitude in making a decision to stop or not?

- Once stopped, are non-white drivers more likely to be searched than white drivers? To what extent can racial disparities in the proportion of drivers who are searched be explained by factors other than race of the driver?

Parties are agreed that the results of the quantitative data analysis are a starting point for broader and richer discussions on racial issues in policing and that qualitative research methods should also be used to explore the relationship between policing and race. This additional qualitative research will be useful, since anecdotal evidence from the community of color also identifies the disparate monitoring and surveillance of young men of color by police on foot patrols. This traffic stop study is not designed to capture police-citizen interactions from foot patrols. Nor can we assess the quality and duration of police contact with citizens that can influence perceptions of disparate treatment. This study therefore offers a piece of a much larger racial experience in the four jurisdictions. It can, however, serve as a useful departure for community-law enforcement discussions.

Summary of findings

- *Black stop rates per 1000 black residents 18 and over are approximately double white stop rates in Burlington and South Burlington, and are 25% higher than the white rate at UVM*. Asian stop rates are substantially lower than white rates in all four jurisdictions (Table 4).

- Though males comprise roughly 49% of the population 18 and over, they are stopped at a higher rate than females. Although higher stop rates for males is not an unusual research finding, *there are statistically significant disparities between black and white male stop rates across all departments.*[3] *Black males are over 75% of all black drivers stopped in all departments. This rate is almost 20 percentage points higher than the white male share of all white drivers. Hispanic males are also a larger percentage of all stopped Hispanic drivers than are white males.* Male Asian drivers in contrast are a smaller share of all stopped Asian drivers in Burlington, but a larger percentage (than white males) in Winooski and at UVM (Table 6).

- The evaluation of high-discretion stops—stops in which the officer has latitude on whether or not to make a stop—focuses on cases where the reason for the stop is identified as "other," vehicle equipment, or investigatory stop. The minority-white difference in high-discretion stop rates is statistically significant in several cases. In particular, in Burlington, the percentage of blacks and Hispanics stopped for reasons of "other" and vehicle equipment is higher than for whites, while at UVM, the Asian stop rate for these motives is higher. *In Burlington, the share of black drivers subject to an investigatory stop is approximately 85% higher than whites. At UVM, the percentage of black drivers subject to an investigatory stop is about 60% higher than the white percentage* (Table 8).

- The weighted sum of outcomes of a stop (this comprises warnings, tickets, arrests, and searches) can be construed as the total penalties assigned to a driver, subsequent to a stop. *The penalties are between 9-14% heavier on average for black drivers than white drivers in Burlington and South Burlington, even once we control for other factors that may influence the outcome of a stop. Hispanic drivers on average receive 15% heavier penalties than whites at UVM.* There is no evidence of a statistically significant difference in penalties between whites and blacks in Winooski and at UVM, but Asian weighted outcomes are significantly lower on average than white penalties in all jurisdictions (Tables 9, 14, and A.7).

- The total penalties assigned, subsequent to a stop, are larger for men than women, but *the gender disparity is largest for blacks, especially in Burlington and South Burlington* (Table 10).

- *In Burlington and South Burlington, blacks are arrested at a significantly higher rate than whites, subsequent to a stop* (Table 11).

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[3] While the data we use is assumed to be the population of drivers stopped, the data should still be treated as a sample. That is because when the police are on patrol and making decisions on whom to stop and search they are creating a sample of the population's driving behavior.

- *The search rate of black drivers in Burlington is roughly double that of white drivers. In South Burlington, the rate at which black drivers are searched is nearly 6 times greater than the white rate* (Table 12). *Controlling for other factors that may influence the decision to search, the odds of a black driver being searched in that jurisdiction is more than 5 times greater than a white driver* (Tables 15 and A.8). While the success rate of black searches is slightly higher than whites in South Burlington, the magnitude of the difference in search rates between the two departments seems unusual and merits further investigation by the South Burlington Police Department.

To summarize, we find evidence of racial disparities in traffic stops, outcomes, and searches for each of the jurisdictions, though for Winooski, this holds only for one indicator. A statistically significant disparity is not definitive proof of racially biased policing. For example, in some cases, the disparity may be statistically significant but very small in size. Furthermore, factors other than departmental or officer bias may contribute to racial disparities. As an example, driving patterns may in fact differ by race/ethnicity, perhaps related to the different levels of driving experience of new Americans as compared to longer-term US residents. Males may comprise a larger share of stops if males drive more than females. We have used the data made available to us to control for race-neutral factors that influence outcomes, but there may be other factors that influence traffic stops and outcomes for which we do not have data. That said, it should be noted that as the size of the disparity increases, the range of plausible race-neutral explanations decreases.

II. Background and Context

The combined resident population of Burlington, South Burlington, and Winooski (in descending order of size) rose to slightly more than 57,000 in 2010 – holding roughly one-third the population of Chittenden County. These communities have experienced significant shifts in the racial/ethnic composition of their populations over the last twenty years. The demographic changes are in part due to internal migration of US born minorities to the greater Burlington area. Growth of the foreign-born population, many of whom are refugees, also accounts for some of these changes. (The latter includes both white and non-white groups with Canadians the largest share of foreign-born residents of Vermont).

A brief summary of changes in the racial/ethnic composition of the communities in the Burlington area provides context for the complex social dynamics that play a role in the policing outcomes that we are exploring. A noteworthy factor that has prompted demographic shifts is the influx of refugees over the last 20 years. The Vermont Refugee Resettlement Program (2011) compiles data on newly resettled refugees to Vermont. Beginning in the 1990s, Vietnamese refugees began to resettle in Vermont (ending by about 2000). Bosnians followed from 1994 to 2004. The 2000s witnessed the resettlement of refugees from the Congo, the Sudan, Somalia, and Togo. The newest resettled refugees (since 2008) are Iraqi, Burmese, and Bhutanese refugees. The arrival of the Burmese and Bhutanese has significantly changed the composition of the Asian population in the local area.

For a variety of reasons including availability of services and access to affordable transportation, most refugees (over 98%) resettle in Chittenden County. Further, in recent years, a growing number of Mexican migrant farmworkers (not part of the refugee program) have been employed in Vermont. These demographic shifts are particularly evident in the Burlington and Winooski schools (less so in South Burlington). By 2009, students of color made up over 22% of the student body in the Burlington school district with more than 40 languages spoken by children enrolled in Burlington High School; 30% of Winooski’s school-age children are English language learners.

Each group of new Americans arrives in Vermont with its own history and sense of vulnerabilities. The challenge to integration that new Americans face is not only due to their racial/ethnic identity that differs to varying degrees from the predominantly white local population. They must also navigate the effect of differences in religion and gender norms and relations. Thus, the dominant group – primarily whites – develop perceptions, attitudes, and stereotypes based on a complex interplay of identity differences new arrivals (US- or foreign-born) are perceived to have.

This is a crucial period of transition and adaptation for Burlington, South Burlington, and Winooski. UVM culture, too, is shifting, though the operative factors emanate from the university’s own strategic goal to diversify its faculty, staff, and student body.

Communities respond to transitional times in different ways. The influx of refugees to Lewiston, Maine in the early 2000s, and to Clarkson, Georgia a few years later, was met with anxiety and as a result, polarization. Vermont, and specifically, for example, Winooski, has a long history of labor migration and discrimination based on class, ethnicity, language and religion for many of the French Canadian and Irish immigrants who settled there.

In contrast to contentious and polarizing integration, inclusive integration of new groups requires proactive efforts on the part of institutions to be vigilant against possible racial/ethnic bias in their practices. This vigilance is required not only of law enforcement but also the school district, health system, credit system, and local government. Studies such as this one help to assess the progress of institutions in adapting to demographic and social transition.

III. Race and Policing

Historically, minorities – and in particular, blacks— have experienced higher rates of force used against them by police than their percentages in the population. Young black males are sentenced more severely than are members of other racial or ethnic groups (Steffensmeier, Ulmer, & Kramer 1998). Further, both nationally and in Vermont, minority incarceration rates are disproportionate to percentages in the population. Indeed, Vermont is among the states with the highest ratio of black to white rates of incarceration – 12.5 compared to a national average of 5.6 (Mauer & King 2007). Hispanic incarceration rates are also higher than that of whites, but less than African Americans.

Concerns that racial stereotypes influence policing in the US are reflected in a widespread perception of racial profiling by police in traffic stops, a problem euphemistically known as "driving while black (DWB)" – although the phenomenon is cited also in police treatment of Hispanics and other non-white ethnic groups. More formally, we can define racial profiling as the use of skin color and thus racial/ethnic group membership in any police-initiated action rather than the behavior of an individual.[4]

Racial stereotypes, fueled by the media, tend to associate crime with blackness. While such stereotypes have existed for some time, beginning in the 1970s and 1980s, young black men in particular began to be identified as criminal and threatening (Welch 2007). To the extent these stereotypes shape police perceptions and attitudes, policing behavior may be affected, which would manifest as racial disparities in policing outcomes.

There is broad consensus that police should not use racial or ethnic stereotypes as factors in selecting whom to stop and search. Further, there is agreement that racial profiling undermines community trust and indeed, makes the job of policing more difficult and less effective. It is therefore in the interest of the broader community and the police forces themselves to be vigilant in monitoring their stop and search practices.

A large number of studies on racial disparities in traffic stops have been conducted over the last decade. Evidence of racial disproportionality in traffic stop and/or search rates that cannot be explained by driver behavior has been found in a wide variety of states, including Florida, New Jersey, Rhode Island, and Minnesota (Cleary 2000; Council on Crime and Justice 2003; Farrell & McDevitt 2006; Mason 2007). Disproportionality refers to traffic stops and outcomes by race or ethnicity that occur at a (statistically significant) different rate than the share of the racial/ethnic group in the population. For example, if 10% of Hispanic drivers are searched in a jurisdiction in which they are only 4% of the driving population, this would be considered a disproportionate outcome. Further, racial disparities in traffic stops and searches have a gender dimension. Mason

[4] Empirical studies in recent years have found that the degree of wage discrimination is positively correlated with an individual's skin color or phenotype (Goldsmith, Hamilton, & Darity 2006). Underlying stereotypes that produce such discrimination are likely at play not only in labor markets but also in policing.

(2007), for example, finds evidence of bias against African American male and Latino drivers and no evidence of police bias against white male drivers. This is consistent with our hypothesis that in the US context, darker-skinned drivers, especially males, are the object of more negative stereotypes, leading to greater monitoring and sanctions than whites and other light-skinned residents.

There are several ongoing challenges in traffic stop studies that this paper attempts to address. The first is the benchmarking problem (also known as the “denominator problem”) [Walker 2001]. In order to assess the extent of disproportionality in traffic stops, it is necessary to know the sizes of the driving population of relevant ethnic groups. Some studies base estimates of the racial make-up of driving population on road surveys, but this method is rarely used due to cost and is fraught with its own measurement problems.[5]

We use US Census Bureau estimates of the population 18 years of age and over by demographic group as a proxy for the driving population in the four jurisdictions. This proxy measure of the driving population has some weaknesses that should be noted. The US Census data represent the driving *age* population, not the actual driving population. Researchers have found that the demographics of individuals who are observed driving in specific locations often differ from the Census population of the areas, especially on turnpikes (Greenwald 2001). Because the Vermont study focuses on four localities, the Census data may be more useful than in studies that include highway data.

The Census data suffer from other measurement problems. Low-income residents tend to be undercounted in the Census, leading to an underestimation of their representation in the population. On the other hand, low-income households, which in our study are disproportionately comprised of new Americans and/or minorities, are more likely than whites to rely on public transportation. This implies that estimates of the driving population based on Census data overestimate the representation of minorities in the population. In jurisdictions where the populations of color are small (such as Native Americans in any of our jurisdictions), there are limitations to our ability to determine whether variations in stop rates and outcomes by racial/ethnic group are statistically significant. Finally, the Census defines Hispanics as an ethnicity. Each individual, Hispanic or not, also reports a race. As we will see when we discuss our police data, the police departments used Hispanic as a racial category. Thus, the Census data on the Hispanic population are incompatible with the police data. In our recommendations, we will ask the police to make their survey consistent with the Census definitions of race versus ethnicity.

A second “benchmarking” method is to use racial population shares obtained from accident data in the relevant localities as the denominator. This is predicated on the reasonable assumption that accident rates are not correlated with ethnicity (we would not expect that the percentage of black drivers who are operators of vehicles in accidents to

[5] See Farrell & McDevitt (2006) for an analysis of Rhode Island traffic stop data that relies on a benchmark roadway study.

differ significantly than their share of the driving population, for example), thus offering a more accurate measure of ethnic shares of the driving population than Census data. We have accident data for South Burlington and compare the ethnic proportions from the accident data set to the US Census data on population 18 and over to assess the reliability of the latter.

A third method which allows us to avoid using a denominator based on underlying population data is to evaluate the extent of racial disparities once the traffic stop has occurred. For example, by weighting the outcome of traffic stops by the severity of penalties assigned, the researcher can calculate the total impact of traffic stops by race. More specifically, a weighted sum of all outcomes can be calculated, comprised of warnings, citations, searches, and arrests. It is then possible to use this weighted outcome to test for disparities in outcomes across ethnic groups.

Fourth, regression analysis can be used to determine whether once stopped, drivers of color have worse outcomes resulting from the stop and a higher probability of being searched than white drivers. Regression analysis permits the researcher to isolate the effect of a driver's race from all other possible factors (for which data is available) that might trigger an outcome of a stop, including a search.

A fifth method is to develop internal benchmarks – that is, a comparison of stop and search rates within departments and in our case, between departments in a relatively small geographic area. Statistically significant differences in traffic stop rates by ethnicity within and between departments would be evidence of disparate police treatment based on racial identity. It should be noted that even if evidence of racial disparities is found within some of the departments, the methods we use do not permit a "true" estimate of the extent of racial disparities in a department. Evidence of disparities can, however, serve as an early warning signal, and function as a useful opportunity for internal examination of police practices (Walker 2001).

This points to another set of challenges faced in race data analysis of policing which are similar to those economists face in estimating the extent of racial discrimination in labor markets. That is, there may be missing information or information that is available to the officer but not to the researcher – or relevant attributes of the officer, such as their race, gender, age, and years of experience—which may influence police behavior. We do not have data on the characteristics of the officer involved in each stop. Given all of these caveats, caution should be used in drawing firm conclusions from these results. The measurement challenges are endemic to any data-based study, and are not unique to the present study. We discuss these issues in more detail in the following section.

IV. Empirical Analysis

A. The Data and Measurement Issues

The Burlington, South Burlington, Winooski and University of Vermont police departments provided the quantitative data used in this analysis. The datasets include all traffic stops made from January 2009 to December 2010. The variables included in the datasets are: date and time of the traffic stop, location of the stop, reason for stop, outcome of stop, whether or not a search was conducted, rationale for search, search type, and outcome of the search. Data on drivers include: race/ethnicity (as identified by the officer), gender, age, (in Winooski, three age ranges only are provided: 11-20, 21-40, and over 41), and city of residence. We have limited additional data on the year and state in which the vehicle is registered (available for Burlington and UVM).

The police officers record the race of the driver based on their own perceptions. The racial categories they use are: black, whites, Asian (this includes Pacific Islanders), Hispanic, and Native American (American Indian or Alaskan). Because Native Americans comprise a small percentage of the local population and stops in this data set, we do not separately report results for that racial group in the following tables in most cases. In some instances, however, we do calculate results for all minorities, which include Native Americans. (See Table A.1 in the appendix for a list of variables made available by each department).

The four law enforcement agencies in this study employ a method for identifying race and ethnicity that differs from that used in US Census Bureau population statistics, which is one of our benchmarks. The difference is that in the police data collection, Hispanics are considered a racial group mutually exclusive from other races (white, black, or Asian).

In contrast, the US Census defines Hispanic as a separate measure of ethnicity while also allowing individuals to independently identify their race. In future data collection (discussed in more detail in the recommendations), we propose that the police change their method and remove Hispanic as a race category, and *separately* indicate whether or not the person (whatever their race) is of Hispanic ethnicity. This would allow the calculation of stop rates for people of Hispanic ethnicity, which is not possible with the current data set.

Moreover, this would also permit a disaggregation of white Hispanics from non-white Hispanics. This is important, since according to race theory and empirical analysis, skin color is a major factor influencing stereotypes, status, and treatment of individuals. Individuals of the same ethnicity may in fact have differing skin tones and as a result, face different treatment in society (as an example, Mestizo Mexicans are situated very differently socially than Mexicans of European origin). Given the differences in police and US Census racial/ethnic categorization strategies, we do not report Hispanic stop rates when using the Census population data as our benchmark. For the remaining analyses that are conditional on a stop occurring (and therefore do not require Census data), we do analyze whether an officer's perception that the driver is Hispanic is correlated with the outcome of the stop.

In a number of cases, race data were missing. As a first step in our analysis, we removed observations where the race of the driver was marked as "unknown." The total number of observations in which the race of the driver is identified as "unknown" over the two-year period is 67 out of a total of 25,868 traffic stops by all four departments or 0.26%. It is possible that the officers were unsure of the race of the driver, which is more likely to occur if the driver is non-white. It is also conceivable that the officer's failure to identify the race of the driver is correlated with the actual race of the driver and outcome of the stop. We therefore conducted some tests (not reported here) in which we grouped observations where the driver's race is unknown with "all minorities" in order to observe whether this has an identifiable effect on the results. It did not.

Another challenge in matching the Census data with the police data is that a growing number of US residents identify themselves as belonging to more than one race, creating a problem of how to allocate the racial identity of multiracial residents in order to estimate the racial composition of the four jurisdictions under study. We adopted a method used in previous studies and proposed by the Office of Management and Budget for working with Census racial categorization. Specifically, we assigned equal fractions to each non-white race checked by respondents. For example, for a person who checked Asian and African American, we added 0.5 to the Asian and 0.5 to the African American categories. If a person checked white and African American, we assigned them to the African American category. The white category we use consists only of people who identified themselves in the Census as white alone.

While it is important to be aware of measurement issues with the quantitative data we use, any dataset or indicator has strengths and weaknesses; these concerns are not unique to our dataset. To address this, the strategy we adopt for evaluating the degree of racial disparities in traffics stops and outcomes is to use more than one indicator. Our goal is to see if there is evidence of a pattern of racial disparities across seven indicators, rather than drawing conclusions from a single indicator.

In addition to the quantitative data provided by the participating law enforcement agencies, one of the authors of this study participated in patrols ("ride-alongs") in November and December of 2011 with officers in Burlington (early evening shift), Winooski (evening shift), and South Burlington (day shift). Researcher participation in patrols offered an opportunity for observation of police practices and informed the authors' understanding of the context of decision-making. These also provided extended time to interview officers about traffic policing practices as they were performing their job. In addition, during the course of data analysis, the research questions and data analysis were discussed with members of Uncommon Alliance, who provided useful perspectives on ways to view the data and interpret results.

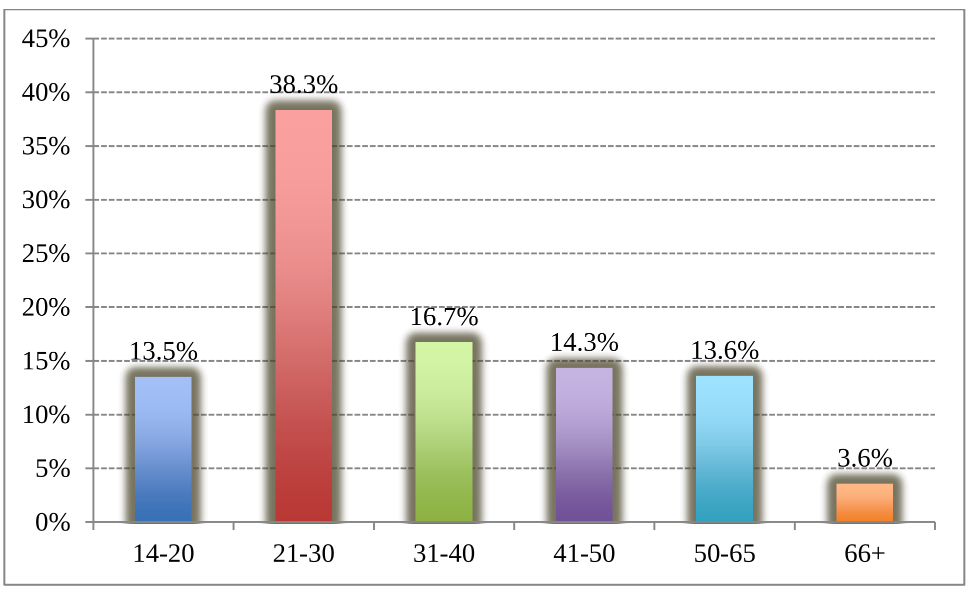
Table 1 summarizes the number of traffic stops by department in 2009-10. It will be noted that there is a significant increase in stops in Winooski from 2009 to 2010 and decrease at the University of Vermont over the same period. In three jurisdictions, drivers between the ages of 21 and 30 made up the largest number of stops (38.3%) followed by the motorists 31-40 (16.7%) [Figure 1, panel A]. In Winooski, which uses a different method of categorizing the age of the driver, over half of all drivers are between the ages of 21 and 40 (panel B).

Table 1. Total Traffic Stops by Department, 2009-10

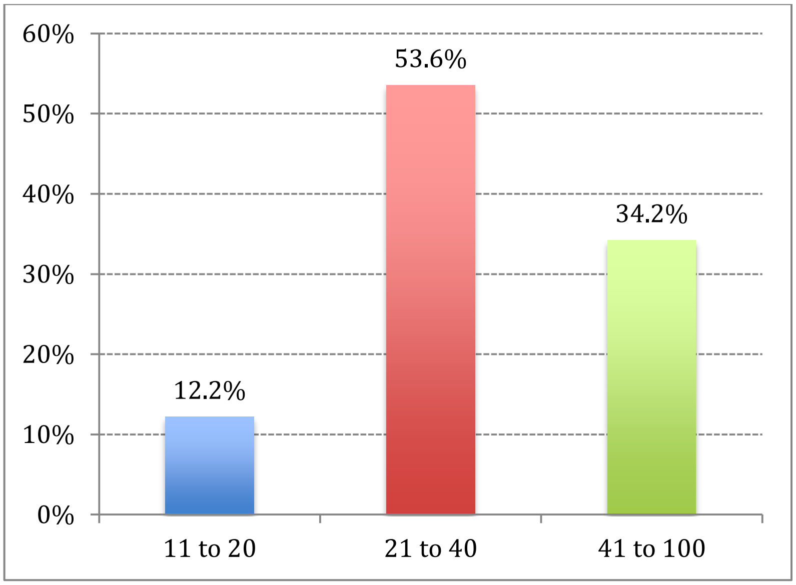
	2009	2010	Total
Burlington	5,578	5,584	11,162
South Burlington	3,789	3,748	7,537
Winooski	1,054	1,699	2,752
UVM	2,715	1,702	4,417
Total	**13,136**	**12,733**	**25,868**

Figure 1. Age Distribution of Stopped Drivers 2009-10

Panel A. *Burlington, South Burlington, and UVM*



Panel B. *Winooski*



B. Stop Rates by Race

The racial distribution of traffic stops by department for 2009-10 is given in Table 2. The minority share of all traffic stops ranges from 6.9% at UVM to 10.1% in Burlington.

Table 2. Traffic Stops by Race/Ethnicity, 2009-10

	Total	**Whites**	**Blacks**	**Hispanics**	**Asians**	**Native Americans**
Burlington	11,162	89.95%	6.49%	0.93%	2.49%	0.14%
S. Burlington	7,537	92.93%	3.79%	0.77%	2.45%	0.05%
Winooski	2,752	89.97%	6.10%	0.80%	3.05%	0.08%
UVM	4,417	93.07%	3.24%	0.72%	2.69%	0.27%
Total	25,868	91.34%	5.14%	0.84%	2.56%	0.13%

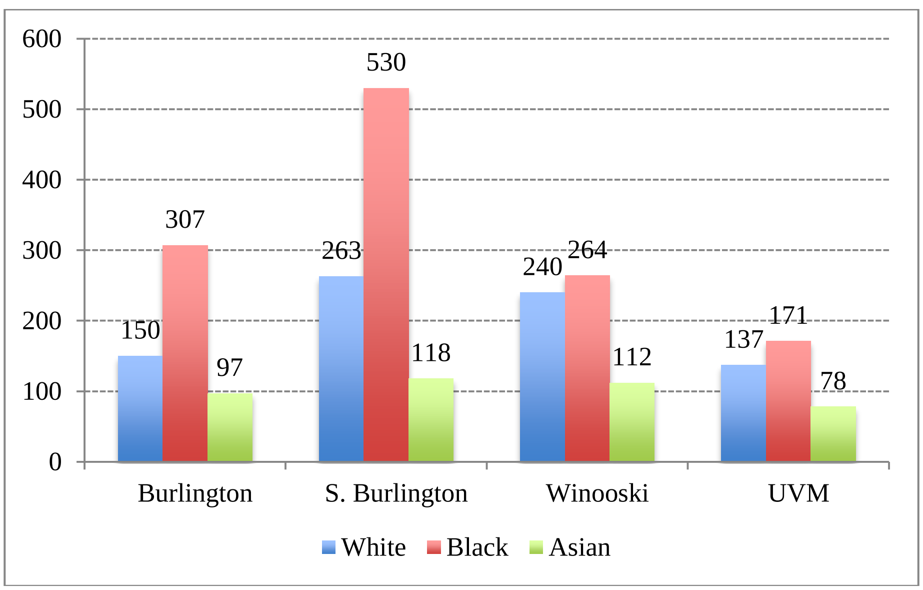
To calculate stop rates by race, we estimate the driving population using 2010 US Census data for Burlington, South Burlington, and Winooski. We use the 18 and over population rather than the total population so as to better isolate the local driving population. Since UVM campus police may stop anyone driving near campus, we assign the racial shares from the combined Burlington and South Burlington population to UVM's population.

Based on the 2010 Census estimates of the driving population, Table 3 presents data on traffic stops per 1000 residents 18 and older. (Table A.4 in the appendix presents data on traffic stops, resident population, and stop rates for all departments by race and ethnicity). While this indicator only approximates traffic stop rates by race since we do not have a true measure of the driving population, it is useful insofar as it reflects differences in probabilities of being stopped relative to the size of the local population by race. The data in Table 3 show that the stop rates of blacks are higher than for any other race in all departments. For example, in Burlington, 307 blacks are stopped per 1000 in the population in 2010 compared to 150 whites. Asian stop rates are lower than white rates in all jurisdictions. Figure 2 provides a visual representation of stop rates per 1000 residents 18 and over averaged for 2009-10.

Table 3. Stop Rates per 1000 Residents 18 and Over by Race, 2009-10

	White	Black	Asian
Burlington	150	307	97
S. Burlington	263	530	118
Winooski	240	264	112
UVM	137	171	78

Figure 2. Stop Rates per 1000 Residents 18 and Over by Race, 2009-10

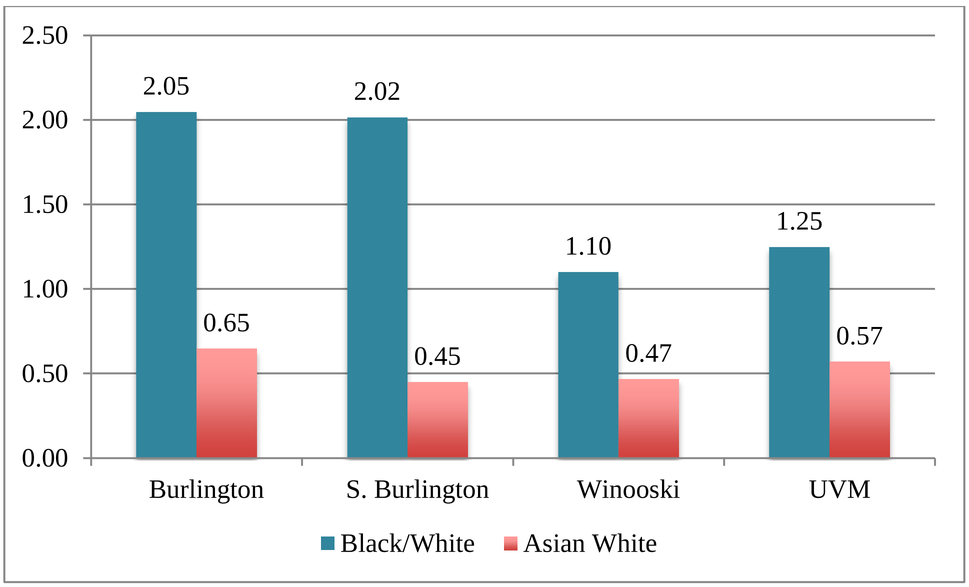


To facilitate comparison of stop rates by race, we calculate the ratio of minority to white stop rates. Those data are presented in Table 4. The data show that blacks are roughly twice as likely as whites to be stopped in Burlington and South Burlington. In Winooski and at UVM the black/white disparity is less pronounced. Blacks are 10% more likely to be stopped than whites in Winooski, and 25% more likely at UVM. Asians are substantially less likely than whites (and therefore blacks) to be stopped. See Figure 3 for a visual representation of these data.

Table 4. Ratio of Minority to White Probabilities of Traffic Stops, 2009-10

	Black/White	**Asian/White**
Burlington	2.05	0.65
South Burlington	2.02	0.44
Winooski	1.10	0.47
UVM	1.25	0.57

Figure 3. Ratio of Minority to White Probabilities of Traffic Stops, 2009-10



Given concerns about the accuracy of population as a proxy for driving population, we evaluate traffic stop data using an alternate benchmark. The racial composition of accident rates can be used in place of population estimates, assuming that accident rates are proxies for the ethnic composition of the driving population and are uncorrelated with illegal driving practices that might explain racial differences in stop rates. South Burlington is the only department with available accident data by race and ethnicity.

In Table 5, we report comparisons of South Burlington's racial/ethnic shares of: 1) stops, 2) residents 18 and over, and 3) drivers in accidents for 2009-10. Whites comprise a slightly higher share of traffic stops than they do of residents over 18, but a smaller share of stops than their representation as drivers in accidents. Assuming the accident data provide a more precise measure of the racial composition of the driving population, this implies that using residents 18 and over as a benchmark for whites *over*estimates their share of traffic stops. In contrast, the black share of the population is somewhat higher than their share of accidents, leading to an *unde*restimation of black stop rates when using the resident population as the denominator. Finally, the data on Asians indicates that using residents 18 and over as a benchmark *under*estimates the traffic stop rate of this group.

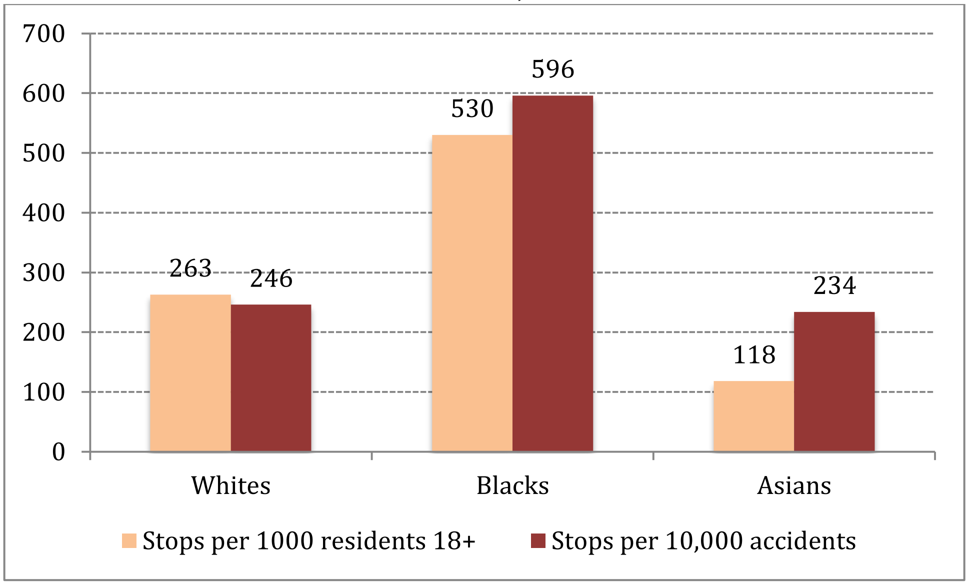
Based on the population and accident data, we calculate stop rates per 1000 residents 18 and over and stop rates per 10,000 accidents (Table 5). The black/white disparity in traffic stop rates is clearly larger when using racial shares from accident data as the denominator. Using these data to calculate the ratio of black to white stops, we can observe that the black stop rate is 242% higher than the white stop rate (596/246) as compared to 202% higher using the Census data. There is reason to rely more heavily on the accident data, given that it measures the actual driving population. Figure 4 compares stop rates based on US Census population estimates and accident data for 2009-2010.

Table 5. South Burlington Traffic Stops Relative to US Census Resident Population and Accident Population, 2009-10

	Whites	**Blacks**	**Asians**
Racial share of traffic stops	92.3%	3.8%	2.5%
Racial share of residents 18+	91.8%	1.9%	5.4%
Racial share of accidents	94.9%	1.6%	2.6%
Stops per 1000 residents 18+	*263*	*530*	*118*
Stops per 10,000 accidents	*246*	*596*	*234*

Note: Total number of accidents in 2009 is 1540 (excluding 17 accidents in which race is marked as unknown). In 2010, there were a total 1436 accidents, excluding 23 of unknown race.

Figure 4. South Burlington Stop Rates by Race: A Comparison of US Census and Accident Data, 2009-10



C. Gender and Traffic Stops

Although males are perceived as more crime-prone or as having poorer quality driving than females, negative stereotypes about black men are particularly strong. If local police officers hold similar stereotypes, we would expect to find that black males comprise a larger share of all black stops than males in other racial groups. We therefore explore the extent to which traffic stops by gender differ by racial group. Table 6 summarizes those data (Table A.5 in the appendix provides raw data by gender, race, and department).

In this section and in the remainder of the analyses, we report Hispanic outcomes because we are not comparing police data with Census data, which categorizes Hispanic ethnicity differently. We nevertheless urge caution on Hispanic results for two reasons. The number of drivers identified as Hispanic is relatively small, reducing the reliability of statistical inference. Second, the classification of Hispanics may differ substantially from driver's self-identification given that officers do not differentiate between white and non-white Hispanics.

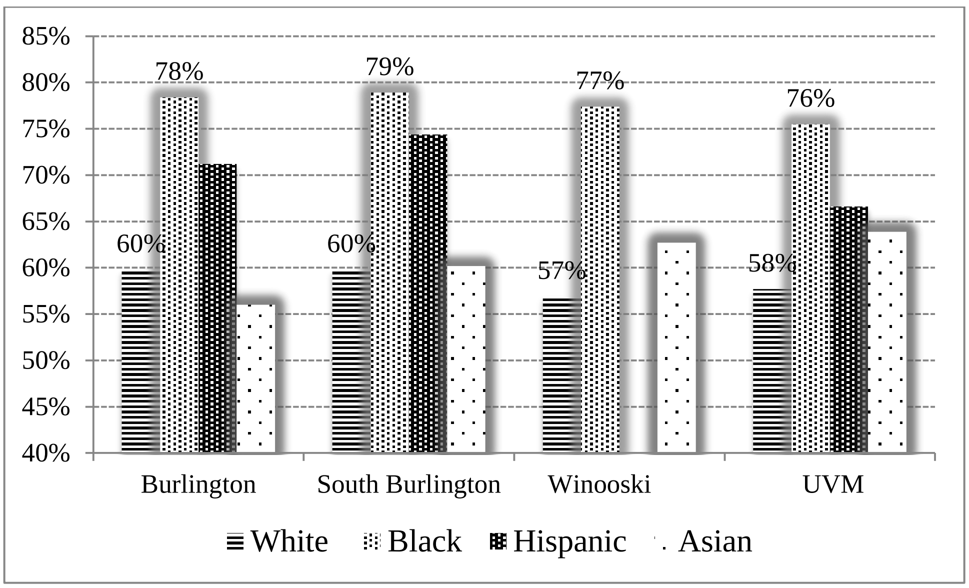
For all racial groups, males comprise more than 50% of traffic stops in all departments. However, the black male shares are significantly higher than the white male shares. For example, in South Burlington, 78.9% of all blacks stopped are male compared to 59.8% for whites. Hispanic and Asian percentages show more variability across jurisdictions. In all cases, the Hispanic male share of stops is greater than the white male share. The percentage of Asians stopped that are male is similar to that of white males in South Burlington, but is significantly lower in Burlington, and higher in Winooski and at UVM. Figure 5 gives a graphic representation of the results in Table 6.

Table 6. Males as Percentage of Drivers of All Vehicles Stopped by Racial/Ethnic Group, 2009-10

	Total	White	Black	Hispanic	Asian
Burlington	5,997	59.8%	78.4%*	71.2%*	56.0%*
South Burlington	4,566	59.8%	78.9%*	74.1%*	60.2%
Winooski	1,513	56.9%	77.4%*	*na*	62.7%*
UVM	2,547	57.7%	75.5%*	66.6%*	63.9%*

Note: We do not report the Hispanic male share of stops in Winooski due to the small sample size, making the estimate unreliable (*na* = not available). An asterisk (*) indicates the difference between the minority and white male percentages is statistically significant at the 99% level.

Figure 5. Males as Percentage of Drivers of All Vehicles Stopped by Racial/Ethnic Group, 2009-10



D. A Comparison of Policing Practices: Reasons for Stops

Departments may differ in their policing practices, as evidenced by reasons officers identify for the traffic stop. This may be due to department culture, staffing constraints, and public safety priorities in the various communities. The data in Table 7 show that the four law enforcement agencies in this study differ primarily in the probabilities of stopping for reasons of moving violations, "other", and vehicle equipment. The primary reason given by the Winooski Police Department for stopping vehicles is moving violations, with over 99% of stops so categorized. South Burlington officers rarely identify "other" as a reason for a stop. UVM has a noticeably higher rate of investigatory stops than the other agencies.

Table 7. Reason for Stop by Department, 2009-10

Department	Total	DUI	Externally generated	Invest-igatory	Moving violation	Other	Vehicle Equipment
Total stops by reason							
Burlington	11,162	95	224	91	6,209	419	4,124
S. Burlington	7,537	14	49	15	5,699	129	1,631
Winooski	2,752	0	12	3	2,715	0	2
UVM	4,417	3	4	117	3,263	168	862
Total	25,868	112	289	226	17,886	716	6,619
Reason as % of all stops							
Burlington		0.9%	2.0%	0.8%	55.6%	3.8%	36.9%
S. Burlington		0.2%	0.7%	0.2%	75.6%	1.7%	21.6%
Winooski		0.0%	0.4%	0.1%	99.4%	0.0%	0.1%
UVM		0.1%	0.1%	2.6%	73.9%	3.8%	19.5%
Total		0.4%	1.1%	0.9%	69.0%	2.8%	25.8%

E. *An Analysis of Racial Disparities in High-Discretion Stops*

Reasons for traffic stops range from a continuum of low-discretion to high-discretion circumstances. Low-discretion stops are those in which the officer's latitude *not* to make a stop is limited. Examples include stops in response to an externally generated complaint, or a driver running a red light, moving at high speed through a low-speed neighborhood, or exhibiting evidence of intoxication with erratic driving patterns. In these cases, good policing practice may oblige an officer to make the stop.

In contrast, high-discretion stops offer a greater opportunity for unconscious racial biases to play a role. Evidence of racial bias may be reflected in disparate rates of stops for lesser traffic violations such as under-inflated tires, something hanging from the mirror, failure to signal a turn, or moving at a speed less than five miles over the limit. Investigatory stops are also high-discretion stops.

We can test for evidence of racial disparities in traffic stops by assessing whether the various departments exhibit significant racial differences in high-discretion stop rates. It will be important to observe whether this analysis and the post-stop analysis discussed in the next section contradict or confirm racial patterns found in the traffic stop rates. Since we no longer need to use the Census data, we can include Hispanics in our analysis again.

For this analysis, we examine data on the reason the officer identifies for the stop which may include: 1) "other" for minor traffic or equipment violations, 2) vehicle equipment,

3) moving violation, 4) driving under the influence (DUI), 5) investigatory stop, and 6) externally generated stop. Categories 1 and 2 (other and vehicle equipment) comprise one type of high-discretion stop. These are sometimes called "pretextual" stops – stops that rely on a pretext of a vehicular infraction as a justification for stopping drivers. In these cases, the driver has violated the law but officers vary in their response, based on their own discretion of whom to stop. This affords an opportunity for discriminatory biases to influence an officer's decisions.

It should also be noted that not all stops based on "other" or vehicle equipment are in fact discretionary stops. For example, in cases of a loud muffler that violates a noise ordinance, officers have little discretion in the decision to make a stop. That said, these two categories of stops, on average, are subject to greater discretion on the officer's part than, for example, DUI or moving violations. At least some investigatory stops are also high-discretion stops. These are stops in response to the belief of criminal activity based on observation (Ramirez, McDevitt, and Farrell 2000), or are stops resulting from information developed through an investigation or in direct response to a crime report (which may be considered as non-discretionary). We explore racial differences in those rates as well.

The data in Table 8 compare rates of high-discretion stops across racial and ethnic groups by department using two measures of discretion. The first is the share of all stops by ethnic group in which the reason for the stop is identified as "other" or vehicle equipment.[6] The percentage of blacks stopped for these reasons exceeds the white percentage in Burlington and South Burlington and the difference is statistically significant. Conversely, Asian percentages are lower than those of whites in those jurisdictions. The Hispanic percentage, too, is higher than that of whites in Burlington and the difference is statistically significant, while at UVM, the Hispanic percentage is below that of whites. As can be seen, police in Winooski rarely identify "other" or vehicle equipment as the reason for the stop.

The second measure of discretionary stops in that table is investigatory stop. In both Burlington and South Burlington, the percentage of blacks undergoing investigatory stops is higher than that of whites, and the difference is statistically significant. The Hispanic rate is higher than the white rate in Burlington as well, while the Asian rate is higher than the white rate at UVM. Asian rates are otherwise lower than white rates. In the column to the far right, we combine these into the broadest measure of high-discretion stops as a percentage of all stops. In general, high-discretion stops of blacks occur at a higher rate than of whites in Burlington and South Burlington, and of Hispanics in Burlington. High-discretion stops of Asians occur at a lower rate than whites in Burlington and South Burlington, but at a higher rate at UVM.

[6] Officers may vary in how they code reasons for stops. In some cases, "other" is indicated while the same underlying event resulted in vehicle equipment being identified as the reason for the stop in other cases. This should not affect our results insofar as we are combining these two categories of high-discretion stops in our analysis.

Table 8. High-Discretion Stop Rates by Race/Ethnicity, 2009-10

	Number of vehicle equipment and "other" stops	Vehicle equipment and "other" as % of all stops	Number of investigatory stops	Investigatory stops as % of all stops	High discretion stops as % of all stops
Burlington					
White	4,083	40.7%	79	0.8%	41.5%
Black	309	42.7%*	11	1.5%*	44.2%*
Hispanic	48	46.2%*	0	0.0%	46.2%*
Asian	96	34.5%*	1	0.4%	34.9%*
South Burlington					
White	1,701	23.4%	14	0.2%	23.4%
Black	77	24.7%*	1	0.3%	25.0%*
Hispanic	13	19.0%*	0	0.0%	19.0%
Asian	36	19.3%*	0	0.0%	19.3%*
Winooski					
White	2	0.1%	1	0.4%	0.1%
Black	0	0.0%	1	0.7%	*na*
Hispanic	0	0.0%	1	4.8%	*na*
Asian	0	0.0%	0	0.0%	0.0%
UVM					
White	957	23.3%	108	2.6%	25.9%
Black	31	21.7%	6	4.2%*	25.9%
Hispanic	5	15.6%*	0	0.0%	15.6%*
Asian	35	29.4%*	3	2.5%	31.9%*

Note: An asterisk (*) indicates that the difference between minority and white rates is statistically significant at the 99% level. The small number of Hispanic drivers stopped in South Burlington, Winooski, and at UVM makes statistical inference unreliable. *Na* = not available, due to low numbers, making a test of statistical significance unreliable.

F. Estimation of Disparities in Post-Stop Activities

1. Outcome of Stops

In addition to discretion on whom to stop, officers have latitude to exercise judgment on the penalty (penalties) they impose on stopped drivers. This was confirmed in discussions with officers during ride-alongs with each of the departments. Officers noted that the penalty they assign is influenced by the driver's previous traffic record.[7] A first offense is more likely to lead to a warning than a record of repeated infractions, for example. This seems to be a reasonable practice in theory, although racial bias in the past can lead to a vicious cycle, with previous citations and arrests leading to more severe treatment in future traffic stops. In other words, if a driver stopped today has a record of repeated infractions due to past bias, upon observing that record, today's officer is more likely to issue, say, a citation than a warning. We evaluate the data to determine whether there are racial disparities in outcomes, and note that whatever disparities we observe may be the result of accumulated disparities in the treatment of drivers by race, based on their previous driving record.

The severity of outcomes is influenced by the fact that officers may assign more than one outcome to a stop. For example, a driver may get a warning for one infraction, a citation for another, and even receive multiple citations. We therefore develop a measure that fully accounts for all the consequences of the stop. This is a useful indicator since disparate treatment of drivers by police, based on the driver's race or ethnicity, may also affect the severity of the outcome of the stop.

In order to assess whether the outcomes of stops are more or less severe for minorities than whites, we weight each outcome of each driver's stop. Outcomes are weighted as follows: no citation = 0, any number of warnings = 1, each citation = 2, any number of consent searches (of the same driver) = 3, and each arrest = 4.[8] We exclude arrests based on a warrant given that such arrests are not discretionary. To give an example of how we calculate weighted outcomes, let's assume a driver receives two citations and is also arrested. The weighted outcome of that stop is 2 + 2 + 4 = 8 (two points for each citation and 4 points for the arrest). The averages of weighted outcome indicators are summarized in Table 9 by race and department for 2009-10. (Table A.6 provides data on the full range of outcomes of stops by department).

Several observations may be made about these data. Blacks experience more negative outcomes as a result of traffic stops than whites in Burlington and South Burlington but not in Winooski or at UVM. Hispanic outcomes are more negative than white outcomes at UVM. In contrast, Asian outcomes are lower than white outcomes on average, a result that is statistically significant in all departments. To give a more concrete illustration of white-minority gaps, in Burlington, the penalties assigned to blacks subsequent to a stop

[7] In one case, the fact that a driver was unemployed influenced the officer's decision to issue a warning rather than a citation.

[8] For example, a case where the driver is arrested for more than one reason (e.g., DUI and driving with a suspended license) would count as *two* arrests (8 points) in calculating the weighted outcome. This is because the impact on the driver is more serious (negative) as the number of reasons for an arrest increases. We also calculated weighted outcomes, with any number of arrests (rather than each arrest) given 4 points in the construction of our indicator. That did not change the racial disparity in racial outcomes from the method used to calculate outcomes in Tables 9 and 10.

Table 9. Average Weighted Outcomes by Race/Ethnicity and Department, 2009-10

	Whites	Blacks	Hispanics	Asians
Burlington	1.61	1.80*	1.56	1.46*
South Burlington	1.55	1.80*	1.57	1.40*
Winooski	1.31	1.33	1.26	1.21*
UVM	1.39	1.38	1.59*	1.28*
All departments	1.53	1.70*	1.54	1.38*

Note: Asterisks (*) indicate the differences between the white and minority outcomes are statistically significant at the 95% level.

are on average 12% heavier than white penalties. In South Burlington, blacks receive penalties that are 16% higher than the average white penalty. In contrast, taking Burlington as an example gain, the average penalties assigned to Asians are 9% lower than those assigned to whites and almost 20% lower than average black penalties.

Table 10 disaggregates weighted outcomes by gender. Males receive heavier penalties than females across all racial/ethnic groups, with the exception of Winooski. Black male penalties are notably heavier than those applied to black females in Burlington and South Burlington, and are much larger than gender differences for all other racial/ethnic groups. The size of the Hispanic gender gap parallels that of blacks in Burlington. For Asian females as well as males, the weighted outcome of stops is lower than whites of the same gender, a difference that is statistically significant in most cases.

Table 10. Average Weighted Outcomes by Gender and Race/Ethnicity, 2009-10

	Whites	Blacks	Hispanics	Asians
Burlington				
Female	1.52	1.58	1.33	1.38*
Male	1.68	1.87*	1.65	1.52*
South Burlington				
Female	1.49	1.43	1.47	1.34*
Male	1.58	1.91*	1.60	1.43*
Winooski				
Female	1.28	1.31	*na*	1.14*
Male	1.30	1.28	*na*	1.23
UVM				
Female	1.32	1.29	1.27	1.21
Male	1.44	1.41	1.76	1.32*

Note: Asterisks (*) indicate the differences between the white versus black, Hispanic, and Asian weighted outcomes are statistically significant at the 95% level. *Na* = not available, due to small number of observations, making a test of statistical significance unreliable.

2. Racial Disparities in Arrest Rates

In the previous section, we looked at the total penalties assigned by officers, subsequent to a stop. Here we examine the data to observe whether arrest rates due to a violation (thereby excluding arrests based on a warrant) differ significantly by race. Our results are summarized in Table 11. Combining data for all departments, we observe that the arrest rate of black drivers subsequent to a stop is 1.78 times greater than for white drivers, and this difference is statistically significant. These results are driven by racial disparities in arrest rates in Burlington and especially South Burlington where black drivers are

Table 11. Arrest Rates by Race/Ethnicity and Department, 2009-10

	Total arrests on violation	Arrest rate (% of stopped drivers arrested)	Ratio minority/white arrest rate
All Departments			
White	340	1.44%	
Black	33	2.50%*	***1.78***
Hispanic	3	*na*	
Asian	5	*na*	
Burlington			
White	135	1.42%	
Black	16	2.35%*	***1.66***
Hispanic	1	*na*	
Asian	2	*na*	
S. Burlington			
White	147	2.09%	***2.04***
Black	12	4.23%*	
Hispanic	1	*na*	
Asian	2	*na*	
Winooski			
White	16	0.65%	
Black	1	*na*	
Hispanic	0	0%	
Asian	0	0%	
UVM			
White	42	1.02%	
Black	4	2.80%	***2.74***
Hispanic	1	*na*	
Asian	1	*na*	

Note: An asterisk (*) indicates the difference between the proportions of white and minority drivers arrested subsequent to a stop is statistically significant at the 99% level. *Na* = not available due to a small number of observations, making a test of statistical significance unreliable.

arrested at double the rate of white drivers. . It is notable that here too we observe Asian rates are lower than white rates and thus substantially lower than black rates. The number of minority arrests in Winooski, and of Hispanics in all four jurisdictions is too low to be able to draw any statistically valid inferences

3. Search Rates and Success Rates in Searches

In this section, we examine search rates, once a vehicle has been stopped. The search rate is defined as the number of consent searches (thus excluding searches based on a warrant) relative to the number of drivers stopped.[9] This too is a useful means to detect evidence of racial bias insofar as it overcomes the benchmarking problem. Moreover, law enforcement officials frequently argue that they do not know the race of a driver before the stop. However, officers make motor vehicle search decisions *after* face-to-face contact has been established with the driver of a vehicle, thus offering the possibility for bias to influence the officer's decision to search.

We also provide data on the success rates of searches, alternatively called "hit" rates or productivity rates of searches. This is calculated as the percentage of searches in which contraband was found. In theory, search rates may differ by racial group for two reasons. Police may be exhibiting racial bias or they may be acting on a valid assumption that some groups have a higher probability of carrying contraband, a phenomenon labeled "statistical discrimination." Insofar as the latter assumption is accurate, then hit rates across racial groups should be similar, even if search rates are not. In contrast, lower hit rates for minorities as compared to whites would suggest inefficient policing, and offer evidence of racial bias in decisions to search drivers.

Table 12 provides data for Burlington, South Burlington, and UVM on the total number of searches by racial/ethnic group as well as the respective search rates and success rates of searches.[10] (Winooski conducted no searches during this 2-year period). Given that the numbers of discretionary searches of Hispanics and Asians are very low, as are the total

[9] The data provided by the cooperating departments for this study identify one of three types of searches: 1) search with reasonable suspicion, 2) search with probable cause, and 3) search based on a warrant. Only the first two types of searches are considered consent searches and are discretionary. We therefore confine our analysis of search rates to these two combined categories of searches.

[10] By way of comparison, Smith and Petrocelli (2001) found that in Richmond, Virginia, search rates averaged 7.9% of all stops with no statistical difference in white and minority search rates. In contrast, Anwar and Fang (2006), based on a Florida state trooper dataset, found search rates of 0.81% for whites compared to 1.34% and 1.35%, respectively for Blacks and Latinos, with success rates of white searches 25% compared to 21% for blacks and 12% for Latinos. In a 2004-05 study of Rhode Island traffic stops (Farrell and McDevitt 2006), consent search rates ranged from 0.8% to 11.3% of all vehicles stopped, with contraband found in roughly 25% of all searches. In that state, white consent search rates were 1.6% compared to 3.6% for non-whites. A 2012 study of Vermont State Police traffic stops found that the minority search rate in 2010 was 2.5% compared to 1% for whites, a difference that is statistically significant (McDevitt and Posnick 2012).

number of searches at UVM, we confine our discussion to a comparison of white and black outcomes in Burlington and South Burlington.

Table 12. Search and Success Rates by Department and Race/Ethnicity, 2009-10

	Number of discretionary searches	Search rate	Success rate
Burlington			
White	159	1.7%	65%
Black	25	3.5%*	60%
Hispanic	3	2.9%	*na*
Asian	0	0.0%	0%
South Burlington			
White	94	1.3%	72%
Black	22	7.7%*	77%
Hispanic	1	1.7%	*na*
Asian	1	0.5%	100%
UVM			
White	44	1.0%	95%
Black	1	0.7%	0%
Hispanic	0	0.0%	*na*
Asian	1	0.7%	*na*

Note: An asterisk (*) indicates the difference between the black and white search rates is statistically significant at the 99% level. *Na* = not available due to low numbers, making a test of statistical significance unreliable.

The Burlington Police Department's search rate of black stopped drivers is 3.5%, a rate that is more than double that of whites (1.7%). The success rate of black searches (the percentage of cases in which contraband is found) is 60% as compared to 65% for whites, a difference that is not statistically significant.

South Burlington's data suggest a more complex case. Black drivers stopped in South Burlington are almost six times more likely to be searched than white drivers. However, success rates of black searches are also slightly higher (although this difference is not statistically significant). While we do not see evidence of inefficient searching, the large racial difference in search rates merits review by both police departments.

G. In-State and Out-of-State Vehicles

Conversations with local law enforcement officers identified an additional factor that may influence stop and search decisions – whether a vehicle is registered in- or out-of state. Drivers of out-of-state vehicles may be suspected of a greater likelihood of involvement in drug trafficking, independent of the race of the driver. But if minorities are a larger share of drivers of out-of-state than in-state vehicles, the racial disparities we have identified may in fact be capturing the state of the vehicle's registration plate. We have information on the state of the vehicle's registration only for UVM and Burlington (Table 13). The data indicate that the black and Asian shares of all out-of-state drivers are in fact *lower*, not higher, than their in-state share of drivers in Burlington. This is the opposite of what would be expected if in fact, racial disparities in stop rates were due to a larger share of minority out-of-state drivers than in-state drivers. The Hispanic out-of-state drivers are a modestly larger share of all out-of-state drivers in Burlington but the difference is small. At UVM, there is no statistically significant difference in racial shares of out-of-state and ins-state stopped drivers.

Table 13. Racial/Ethnic Share of Stops of In-State and Out-of-State Vehicles, 2009-10

		Total stops	White	Black	Hispanic	Asian	Native American
Number of stops							
Burlington							
	Out-of-state	1,456	844	62	19	17	2
	In-state	9,020	4,494	621	89	251	13
UVM							
	Out-of-state	1,077	999	36	10	27	5
	In-state	3,161	2,939	103	22	90	7
Racial/Ethnic % of all stops							
Burlington							
	Out-of-state	100.0%	93.2%	4.3%	1.2%	1.2%	0.1%
	In-state	100.0%	89.3%*	6.9%*	0.9%*	2.8%*	0.1%
UVM							
	Out-of-state	100.0%	92.8%	3.3%	0.9%	2.5%	0.5%
	In-state	100.0%	93.0%	3.3%	0.7%	2.8%	0.7%

Note: The data on vehicle registration are incomplete for both Burlington and UVM, so traffic stop totals in this table are lower than the total number of traffic stops in each jurisdiction (shown in Tables 1 and 2). An asterisk (*) indicates that the difference between a group's share of in-state and out-of-state vehicle stops is statistically significant at the 95% level.

V. Regression Analysis

A. Weighted Outcomes of Stops

One methodology for identifying the role of race in traffic stop outcomes is multiple regression analysis. This statistical procedure allows the researcher to control for (or hold constant) other factors that may have contributed to officer decisions on what outcomes to apply to the stop, thereby isolating the role of race. Specifically, we control for the gender and age of the driver, the time of the stop (day, evening, or night), and department. Age and gender may be correlated with quality of driving, independently of the race or ethnicity of the driver. Driving patterns may also differ by shift. Finally, departmental policing practices may differ. We exclude all stops in which there is an arrest or search based on a warrant.

We use a Poisson regression since the dependent variable is discrete. The omitted race in the regression is white, and the omitted shift is night (12pm to 8am). In the case of Winooski, only data on age groups are available (11-20, 21-40, 40+) rather than age. In order to make our results comparable, we used age groups for all departments.

The results presented in Table 14 report on the degree to which race explains outcomes, after controlling for other factors that might affect the officer's decision on penalties to impose subsequent to the stop. (Full regression results on blacks are reported in Table A.7 in the appendix). We test to determine whether all non-Asian minorities (thus combining outcomes for blacks, Hispanics, and Native Americans) have more negative outcomes from a stop (a higher average weighted outcome) as compared to whites and Asians. We then test to determine whether the outcomes for blacks are more negative than for whites. We report the incidence rate ratio (IRR). The IRR compares the weighted average of a group or category to the control group. In the case of non-Asian minorities for all departments, we see that the IRR is 1.067. This implies that the penalties assigned to non-Asian minorities are 6.7% more severe compared to whites and Asians. An asterisk next to the IRR indicates that the effect of race on outcomes applied subsequent to a stop is statistically significant. The IRR for Burlington only is similar to the IRR for all departments combined, while for South Burlington, the IRR indicates penalties for non-Asian minorities are 11.4% higher than for whites and Asians. The difference between weighted outcomes of non-Asian minorities vs. whites and Asians in Winooski and UVM is not statistically significant.

Restricting our attention to blacks only, black outcomes are higher than all other racial/ethnic groups in Burlington and South Burlington (by a factor of 1.085 and 1.138, respectively). This implies, in other words, that penalties applied to blacks are 8.5% and 13.8% more severe than penalties assigned to all other racial/ethnic groups combined. In contrast, in Winooski and at UVM, differences are not statistically significant.

Table 14. Determinants of Weighted Outcomes: The Role of Race/Ethnicity

	Stops Included (N)	IRR of Non-Asian Minorities	Standard Error	IRR of Blacks	Standard Error
All departments	25,868	1.067*	0.022	1.080*	0.024
Burlington	11,162	1.068*	0.029	1.085*	0.031
S. Burlington	7,537	1.114*	0.047	1.138*	0.052
Winooski	2,752	1.025	0.067	1.030	0.072
UVM	4,417	0.996	0.031	0.979	0.072

Note: The IRR is the incidence rate ratio, and compares the outcome of a group (non-Asian minorities or blacks only) to the remainder of the racial groups. Non-Asian minorities are those identified by officers as black, Hispanic, or Native American, and the coefficient evaluates outcomes for that group as compared to those identified as white and Asian. An asterisk (*) indicates statistical significance at the 99% level.

B. Race and Search Decisions

In order to isolate the degree to which race alone is associated with search decisions, we use a statistical technique called logistic regression, which predicts the odds of a search being conducted, controlling for other factors that could also be associated with the decision to search. Specifically, we examine the relationship between race and searches while controlling for driver characteristics (gender and age) and time of day.

Logistic regression uses binary outcome variables that are coded either 0 or 1. In this case, our outcome variable is whether or not a discretionary search was conducted, coded 1 for a discretionary search and 0 for no discretionary search conducted.

The results on the race variables are shown in Table 15. (For full regression results on all variables, see Table A.8). We conduct this analysis for all departments, and then, separately only for Burlington and South Burlington since the number of searches was too few at UVM and in Winooski to be statistically meaningful. Further, we focus on blacks, given the low number of searches of Hispanic and Asian drivers.

In the full sample that uses data from all departments, the odds of a black driver being searched are more than twice a white driver's (odds ratio = 2.489). In Burlington, the odds are slightly lower at 1.863 while in South Burlington, the odds of a minority driver being searched are more than five times that of a white driver (odds ratio = 5.108).

Table 15. Relative Black/White Probabilities of Being Searched, 2009-10

	Odds Ratio	Standard Error
Full sample	2.489*	0.441
Burlington	1.863*	0.412
S. Burlington	5.108*	1.297

Note: Blacks are compared to whites only. An asterisk (*) indicates significance at the 99% level.

In sum, regression results indicate that the race of the driver influences both the outcome of a stop and the probability a driver will be searched. The most severe disparities are between blacks and the remaining racial/ethnic groups. We have controlled for other factors that may influence outcomes, although there may be missing variables that explain outcomes for which we do not have data. That said, the size of the disparities in Burlington and South Burlington suggests the need for careful exploration of the source of these disparities.

VI. Recommendations

A. Community engagement, education, and diversity training

A study such as this can uncover patterns of disparities but it does not explain the causes of behavior, whether of the driver or the officer. Further, disparities might be explained by factors not controlled for in our analysis. For example, the perceived socioeconomic status of the driver may influence the officer's response to drivers. Conversations with the law enforcement agencies in this study indicate that the age and condition of a vehicle is seen as a potential indicator of driver behavior, with an assumption that older vehicles in ill-repair are more likely to be involved in illicit activity. Insofar as minorities are lower income and therefore drive a larger share of such vehicles, we might expect higher stops rates for minorities relative to whites.

If the officer is unaware of the race of the driver, higher minority stops rates resulting from different socioeconomic status might have nothing to do with the driver's race. Alternatively, if the officer stops a driver in response to both the race of the driver as well as the indicators of the driver's socioeconomic status (such as condition of the vehicle), then this would be considered an example of *soft profiling*. That is, the use of race or ethnicity is only one factor in the decision to stop a vehicle. (In contrast, hard profiling is defined as a police initiated action only in response to the race of the driver). Soft profiling may be deemed more socially respectable than hard profiling. That said, assumptions that lead police to stop drivers at different rates should be evaluated for their validity.

Unraveling the factors behind disparities and using these findings as a bridge to community-police engagement is the next stage in this work. In fact, there is a real danger that without a committed effort to get the story behind the numbers, the results of this study will simply confirm negative stereotypes about the criminality of minority groups, in particular, blacks. Moreover, members of the affected minority communities may see their negative images of police confirmed by their view of these results.

To that end, we suggest three steps:

- First, we suggest that as a next phase, the results of this research be triangulated with qualitative studies (phone survey follow-ups as well as interviews). Appendix B gives, for example, the results of a survey we conducted of local residents to supplement the official police data relied most heavily on for this study. The target group of the sample is professionals and college-age students (we also worked to ensure the sample included a large share of minorities). This allowed us to examine driver perceptions of racial bias in traffic stops, focusing on a socioeconomic group law enforcement agencies identify as less likely to be stopped due to their more elevated socio-economic status. The survey results suggest that even among those of a higher socio-economic class, the perception of racially biased traffic stops in the local area is in evidence, with both minorities *and* whites perceiving such bias.

- Second, we recommend community involvement, such as with Uncommon Alliance, to develop an initiative that engages the public in discussions of the study's findings, and that works to educate the community and law enforcement on the sources of disparities.
- Third, it will be beneficial for the agencies to bring in skilled diversity trainers to discuss this report with their officers and together to analyze both their policing practices as well as common preconceptions and stereotypes in order to isolate those that are legitimate versus those that warrant change.

B. Data Collection

1. Additional Data

The commitment of these four agencies to continue race data analysis is laudable. To that end, several revisions to the data collection process are recommended. We suggest that all departments collect the following additional data (some already do):

- Accident data by race, gender, and age
- Age of vehicle
- Beat area
- Duration of the stop
- Data on Hispanic ethnicity, eliminating Hispanic as a race category
- State in which vehicle is licensed

The reasons for suggesting these additional categories of data be collected is as follows. Accident data is a useful benchmark and overcomes some of the measurement problems inherent in Census data. South Burlington already compiles these data. It will be useful for the other agencies to similarly report these data, not only by race, but also by age and gender of drivers. The duration of the stop has been identified in other studies as an additional aspect of racial disparities in policing, with claims that minorities face more extensive detention, subsequent to a stop. For this reason, we suggest these data also be collected, to add information on another aspect of potential racial disparities in outcomes. Data on the beat area is useful in order to identify patterns of traffic patrol that may result in racially disparate traffic stops. For example, higher minority stop rates might occur if police disproportionately patrol neighborhoods with a high percentage of residents of color.

With regard to data on Hispanic ethnicity, we suggest the data collection protocol be revised to be consistent with US Census categories. The Census, as we have noted, considers race and Hispanic origin to be two distinct categories. Hispanic is defined as an ethnicity or cultural background, and Hispanics may be of any race.[11] The categories used by the participating departments include Hispanic as a racial category, however, and it is not clear whether those so identified are white or non-white Hispanics. We also therefore

[11] "Latino" is often used interchangeably with Hispanic. The Office of Management and Budget (OMB) defines Hispanic or Latino as a person from Cuban, Mexican, Puerto Rican, South or Central American culture regardless of race.

propose that officers add an additional category to their race data collection, responding to the question "Is the driver of Hispanic ethnicity?" Just as for race, the officer's response would be based on their *perception* of the driver's ethnicity. In this way, officers will code both the race of the driver (white, black, and Asian) according to the Census methodology, and also capture the Hispanic ethnicity of drivers. We suggest that this practice be extended to accident data collection as well.

We also suggest that all racial categories be revisited to consider whether it would be useful to expand or revise the racial categories. For example, it is not clear how officers currently categorize new Americans of Bhutanese or Iraqi ethnicity.[12] For the race data to be meaningful, categories must be clarified. This of course does not change the fact that officers will be relying on their own perceptions of the driver's race. However, it does improve the consistency with which categories are used.

2. Triangulation: Follow-up Interviews

We recommend that resources be engaged to triangulate the research results with qualitative studies – specifically surveys and interviews of a sample of those who have been stopped and of community members of color. These qualitative methods can help to build a more comprehensive and nuanced portrait of driver-police interactions. It can also help to identify additional research questions to be investigated regarding the evolution of community-police relations.

Further, we recommend that a random telephone survey be conducted to check the officially recorded race and sex of the driver in the 2009-10 stops. The results of this telephone survey can be used to inform decisions on whether further training of officers in race data identification would be useful, as a way to generate more accurate data.

3. Early Warning System

Departments are also advised to develop an Early Warning System (EWS) as outlined by Walker (2001) to identify significant disparities within individual departments. In addition to officer-specific racial patterns in traffic stops, the EWS might include information on citizen complaints and excessive use of force, contributing to a fuller profile of officers' behavior. The EWS can help a department to identify individual patterns of behavior that differ from the group (department) norm. Racial disparities in traffic stops alone, in other words, would not necessarily be sufficient evidence to suggest a pattern. But if departments observe that an officer is an outlier on *several* indicators, this may suggest the benefit of discussions. To this end, it would be useful to provide data on the officer's age, job experience, gender, and race on each traffic stop, which can be used to explore whether there are patterns of traffic stop behavior that are linked to any one of these variables. For instance, officers with more years of experience may demonstrate different behavior than newer officers, perhaps due to longer exposure to

[12] In Census data, for example, white refers to Middle Easterners and North Africans while Bhutanese would be classified as Asian.

diversity training as well as simply the learning that occurs over time. Data from the EWS would be for the department’s internal use only.

VII. Conclusion

The National Organization of Black Law Enforcement (NOBLE) defines bias-based policing as “the act (intentional or unintentional) of applying or incorporating personal, societal, or organizational biases and/or stereotypes as the basis, or factors considered in decision-making in police actions, or administration of justice” (Davis 2001). Racial bias is a narrower subset of the broader concept of bias-based policing.

This report has identified statistically significant racial disparities across several indicators for Burlington, South Burlington, and UVM, and to a lesser extent, Winooski. Disparities between blacks and whites are prominent in most jurisdictions, with blacks facing a higher probability of being stopped, of receiving harsher penalties, and of being arrested and searched. The size of the disparities underscore the imperative to dig deeper into policing practices in order to identify factors that may lead to bias-based policing. Table 16 summarizes our results for blacks, the racial group with the most consistent evidence of racial disparities as compared to whites.

Table 16. Summary of Evidence of Black/White Disparities in Traffic Stops, Outcomes, and Searches

	Traffic stops per 1000 residents 18+	Male stop rates by race	High discretion stop rates: investigatory stops only	Weighted outcomes	Arrest rates	Search rates
Burlington	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
S. Burlington	**Yes**	**Yes**	No	**Yes**	**Yes**	**Yes**
Winooski	~	**Yes**	No	No	No	No
UVM	**Yes**	**Yes**	**Yes**	No	~	No

Note: “Yes” indicates the disparities are confirmed subsequent to tests of statistical significance, such that the racial disparities are unlikely to be due to random fluctuations in our data. “No” indicates that either disparities do not exist or are statistically insignificant. “~” indicates that disparities, even if statistically significant, are based on a small number of observations or the size of the disparity is small so that the significance of the disparity is inconclusive.

The findings of this study suggest that racial disparities vis-à-vis Asians and whites work in the opposite direction from that of black and whites. Asian stop rates and outcomes are less severe than for whites, according to a number of our indicators. This outcome fits with a widely held stereotype of Asians as the “model” minority, with Asians as a group seen to be hard working, respectful of authority, of higher than average intelligence, and willing to assimilate quietly into American culture. To the extent residents and police in the Burlington area hold such stereotypes, this might explain racial disparities that favor

Asians.[13] Despite such stereotypes, there is great diversity in the Asian American population in the US. This is particularly relevant in the Burlington area where the ethnic composition of Asian Americans is shifting. While the early 1990s witnessed the expansion of Vietnamese in-migration, recent immigration of South Asians, including Bhutanese, Burmese, and Nepalese, is changing the make-up of the local Asian American population. Whether this will affect norms and stereotypes of Asians and, as a result, policing practices towards this group, remains to be seen.

On a more general note, for several of the measures (more fully discussed earlier in this report), there are limitations to the precision of our estimates of traffic stop rates by race/ethnicity, given that we are only able to estimate the driving population. Care should thus be used in interpreting those results. That said, the average weighted outcomes, arrests, and search rates are determined using only the data provided by law enforcement officers and is not subject to the same concerns.

The results of this study suggest it will be useful for participating departments to examine internal practices to rule out the possibility of or reduce the incidence of bias-based policing. The two most common sources of racial bias are conscious bias and unconscious prejudice, based on stereotypes. Today, 50 years after the civil rights movement began, conscious bias is far less common, and most disparate outcomes in policing –as in employment—are a function of unconscious stereotypes that all Americans are exposed to on a daily basis. This should not be surprising, given media images that present blacks, and in particular, young black men as dangerous and prone to criminality.

Because officers are likely to be unaware of any biases they might carry, training and education with skilled diversity trainers who are able to help officers “unpack” their unconscious stereotypes is a first step at reducing and eventually eliminating racially prejudicial judgments that lead to disparate outcomes.

The cost to minority drivers of disparate treatment is significant. In the case of black drivers, using the resident population benchmark, if there were no racial disparities in traffic stops, 533 fewer blacks would have been stopped over this two-year period in all departments. Twelve fewer blacks would have been subjected to investigatory stops, were such stops occurring at the same rate as the average (across all departments) white investigatory stop rate (0.85%).

[13] Not all racial profiling studies find evidence of disparities that favor Asians. Lee (2007) finds evidence of disparate (negative) outcomes for those identified as Asians in LaCrosse, Wisconsin, where a significant portion of this group are Hmong.

APPENDIX A

Table A.1. Data Used in the Study

Gender Female Male Transgendered
Race Asian Black Hispanic Native American White
Age or Age range (Winooski) 11-20 21-40 41+
Time of Stop
State of registration (Burlington and UVM only)
Reason for Stop Other Vehicle equipment Moving violation DUI Investigatory stop Externally generated stop
Outcome of Stop No action Warning Ticket Search Arrest Arrest on warrant
Reason for Search Probable cause Reasonable suspicion Search on warrant
Contraband and search Contraband found No contraband

Table A.2. US 2010 Census Data by Race for Population 18 Years and Over

	Total	White	Black	Asian	American Indian	Some other race
Burlington	36,688	33,402	1,182	1,426	366	292
S. Burlington	14,522	13,325	270	778	91	60
Winooski	5,962	5,152	318	375	76	42

Notes: White total is white alone. We assigned equal fractions to each non-white race checked by respondents. For example, for a person who checked Asian and African American, we added 0.5 to the Asian and 0.5 to the African American categories. Asian includes Native Hawaiians and Pacific Islanders. American Indian includes Alaskan Natives.

Source: US Census, Table P10 (2010).

Table A.3. UVM's Gender and Racial/Ethnic Composition of Staff, Faculty, and Students, 2009-10

	White	Black	Hispanic	Asian/ Pacific Islander	American Indian/ Alaska Native	Two or More Races	Total
Students							
2009	11,637	190	373	353	41	268	12,863
2010	11,605	173	257	346	34	218	12,634
Faculty							
2009	3,343	85	70	220	16	0	3,734
2010	3,328	88	74	216	17	0	3,723
Total							
2009	14,980	275	443	573	57	268	16,597
2010	14,933	261	331	562	51	218	16,357

Source: University of Vermont Office of Institutional Studies, extracted upon request of the authors in October, 2011. See also www.uvm.edu/isis/.

Table A.4. Stops by Race/Ethnicity and Demographics, 2009-10

	Total	Whites	Blacks	Hispanics	Asians	Native Americans
Traffic Stops						
Burlington	11,162	89.95%	6.49%	0.93%	2.49%	0.14%
South Burlington	7,537	92.93%	3.79%	0.77%	2.45%	0.05%
Winooski	2,752	89.97%	6.10%	0.80%	3.05%	0.08%
UVM	4,417	93.07%	3.24%	0.72%	2.69%	0.27%
Total	25,868	91.34%	5.14%	0.84%	2.56%	0.13%

Residents 18 +		Whites	Blacks	Hispanics	Asians	Native Americans
Burlington	36,688	91.09%	3.22%		3.89%	1.00%
South Burlington	14,522	91.76%	1.86%		5.35%	0.62%
Winooski	5,962	86.41%	5.33%		6.28%	1.27%
UVM	16,357	91.43%	2.54%		4.62%	0.81%

Ratio stops to population		Whites	Blacks	Hispanics	Asians	Native Americans
Burlington		0.987	2.016		0.640	0.140
South Burlington		1.013	2.038		0.458	0.081
Winooski		1.041	1.144		0.486	0.063
UVM		1.022	1.066		0.692	0.270

Note: Traffic stops are for 2009-10. Residents 18 and over are from the 2010 US Census (see details in notes to Table A.2). Because we do not report “Some other race” from the US Census data, resident population 18+ does not sum to 100%. We assigned the average of Burlington’s and South Burlington’s racial population shares to UVM, given UVM’s policing area. Since Hispanic is recorded as an ethnicity, not a race, in the US Census, Hispanic stop rates cannot be calculated.

Table A.5. Traffic Stops by Race/Ethnicity, Gender, and Department, 2009-10

	White	Black	Hispanic	Asian
Burlington				
Females	4,037	156	30	120
Males	5,997	566	74	153
South Burlington				
Females	2,813	60	15	72
Males	4,186	224	43	109
Winooski				
Females	1,010	35	9	28
Males	1,333	120	13	47
UVM				
Females	1,780	35	11	43
Males	2,331	108	21	76

Note: Observations in which sex is unknown (180) or transgendered (2) are not included. Also, we do not report here Native American/Pacific Islanders due to low numbers.

Table A.6. Outcome of Stops, 2009-10

Department	Total	No Action	Warning	Ticket	Arrest	Arrest on Warrant
Total Outcomes						
Burlington	11,162	3	7,183	3,819	154	0
S. Burlington	7,537	0	4,871	2,503	162	1
Winooski	2,737	8	1,911	801	17	0
UVM	4,417	0	3,164	1,202	48	3
	25,853					
Outcome as % of all outcomes						
Burlington		0.0%	64.4%	34.2%	1.4%	0.0%
S. Burlington		0.0%	64.6%	33.2%	2.1%	0.0%
Winooski		0.3%	69.8%	29.3%	0.6%	0.0%
UVM		0.0%	71.6%	27.2%	1.1%	0.1%

Note: Totals differ from Tables 1 and 2 due to missing data on outcome of stop.

Table A.7. Poisson Regression Results on Determinants of Weighted Outcomes

	Full Sample		**Burlington**		**South Burlington**		**Winooski**		**UVM**	
Explanatory variables	IRR	z-statistic	IRR	z-statistic	IRR	z-statistic	IRR	z-statistic	IRR	z-statistic
Black	1.080*	3.49	1.085*	2.830	1.138*	2.840	1.030	0.43	0.979	-0.290
Hispanic	0.995	-0.09	0.957	-0.550	0.995	-0.040	0.961	-0.22	1.134	0.890
Asian	0.910*	-2.81	0.911	-1.860	0.894	-1.770	0.924	-0.79	0.933	-0.840
Native American	0.858	-1.01	0.870	-0.650	0.890	-0.280	1.111	0.18	0.784	-0.870
Age 21-40	0.926*	-5.20	0.929*	-3.360	1.000	0.010	0.963	-0.74	0.817*	-6.160
Age 41+	0.807*	-13.11	0.798*	-9.130	0.845*	-5.370	0.916	-1.61	0.750*	-7.590
Male	1.082*	7.60	1.112*	6.840	1.064*	3.230	0.981	-0.56	1.088*	3.210
Day	1.031	2.36	1.046	2.240	0.993	-0.310	1.187*	4.09	0.986	-0.410
Evening	0.929*	-5.62	0.949*	-2.710	0.855*	-6.110	1.006	0.13	0.951	-1.530
Burlington	1.234*	11.51								
South Burlington	1.177*	8.55								
UVM	1.054*	2.48								
Pseudo R^2	0.0080		0.0061		0.0067		0.0041		0.0069	
Log Likelihood	-35,389.6		-16,258.9		-10,271.3		-3,257.4		-5,560.5	
Prob > χ^2	0.000		0.000		0.000		0.002		0.000	
N	25,869		11,162		7,537		2,753		4,417	

Note: IRR is the incidence rate ratio, and compares the outcome of a group or category to the control group. Day is from 8am-4pm; evening spans 4pm-midnight. An asterisk (*) indicates statistical significance at the 99% level. Data are for 2009-10.

Table A.8. Logistic Regression Results on Probability of a Consent Search

	Full Sample		**Burlington**		**South Burlington**	
Explanatory variables	Odds ratio	z-statistic	Odds ratio	z-statistic	Odds ratio	z-statistic
Black	2.489*	5.650	1.863*	2.81	5.108*	6.42
Hispanic	1.356	0.590	1.863	1.05	0.994	-0.01
Age	0.951	-8.730	0.967*	-4.8	0.932*	-6.24
Male	2.796*	7.330	2.882*	5.45	2.652*	3.67
Day	0.532*	-4.190	0.648	-2.16	0.417*	-3.17
Evening	0.911	-0.750	0.803	-1.25	1.250	1.07
EGS	4.912*	6.340	3.203*	3.57	6.989*	4.18
Pseudo R^2	0.0764		0.0497		0.1347	
Log Likelihood	-1,675.1		-898.9		-525.7	
Prob > χ^2	0.000		0.000		0.000	
N	23,098		11,153		7,529	

Note: EGS is externally generated stop. Age is in years. Day is from 8am-4pm; evening spans 4pm-midnight. An asterisk (*) indicates statistical significance at the 99% level. Data are for 2009-10.

Table A.9. Traffic Police: Racial Composition of Officers by Department, 2010

	Total	White	Black	Asian/Pacific Islander	Native American
Burlington					
Number	92	85	3	1	0
% of officers		92.4%	3.3%	1.1%	0.0%
% of population		91.1%	3.2%	3.9%	1.0%
South Burlington					
Number	37	33	0	0	0
% of officers		89.2%	0.0%	0.0%	0.0%
% of population		91.8%	1.9%	5.4%	0.6%
Winooski					
Number	14	14	0	0	0
% of officers		100%	0%	0%	0%
% of population		86.4%	5.3%	6.3%	1.3%
UVM					
Number	34	32	2	0	0
% of officers		94.1%	5.9%	0.0%	0.0%
% of population		91.1%	3.2%	3.9%	1.0%

Source: Data provided by police departments to authors, December 2011.

APPENDIX B

We report on results obtained from a survey conducted between December 7 and 18, 2011, targeted at two groups in the local driving population: UVM students and professionals. The goal of this survey is twofold. First, the data reported up to this point were obtained from police officers. It is useful to compare those data with a survey that can capture the perceptions of the driving population itself. The second purpose of this survey, and the reason for which we limited its distribution to UVM students and professionals, is to test the hypothesis that stop rates of minorities, and in particular blacks, may be capturing their socioeconomic status (based on police perceptions that low-income drivers are more likely engaged in crime) rather than the race of the driver.

The survey of students covers most of UVM's colleges, and was distributed via professors to their large and small classes. The responses from professionals was obtained via a snowball sample: 30 professionals were initially identified to respond to the survey, and these respondents were asked for additional names of professionals to include in the sample. Table B.1. provides demographic information on the survey respondents. Roughly two-thirds of respondents are white and the remainder represents a variety of racial/ethnic groups. Further, approximately two-thirds of respondents are female.

Table B.1. Characteristics of Survey Respondents

Race	Females	Males	Trans-gendered	% of all respondents
Asian/Pacific Islander	8	1	0	6.1%
Black	8	13	0	14.3%
Hispanic, not white	3	3	0	4.1%
Native American	1	0	0	0.7%
Multiracial	7	6	0	8.8%
Other	1	0	0	0.7%
White	64	31	1	65.3%
Total	90	52	1	100.0%

The survey questions are shown in Table B.2. The first two questions are designed to elicit impressions of the extent of racial profiling by police in traffic stops in the US versus in the four jurisdictions in this study.

Table B.2. Survey Questionnaire

1. It has been reported that some police officers stop drivers of certain racial or ethnic groups because these officials believe that certain groups are more likely than others to commit certain types of crimes. Do you think this practice, known as racial profiling, is widespread nationally?

Responses*: Yes/No*

2. Do you think this practice occurs when motorists are stopped in Burlington, Winooski, South Burlington, and UVM?

Responses: Frequently/Occasionally/Rarely/Never

3. Please check the category below that best represents your racial or ethnic identity.

Responses: *Black/White/Asian-Pacific Islander/Native American/Hispanic/Multiracial*

4. Have you, as the operator of a vehicle, experienced an incident of what you perceive to be racial profiling in a traffic stop at any time during the last two years while living in the Burlington, UVM, Winooski, or South Burlington area?

Responses: *Yes/No/Not applicable*

5. If your response to the previous question is yes, how many times have you had this experience during the past two years (indicate the number of instances) while driving in the Burlington, Winooski, UVM, or South Burlington area?

Response: *Number of times*

6. Have you been a passenger in a vehicle stopped by the police where you believe the officer's motivations were consistent with racial profiling in the last two years in Burlington, Winooski, UVM, or South Burlington?

Responses: *Yes/No*

7. Which category best represents your gender identity?

Responses: *Female/Male/Transgendered*

8. What is your age?

Response: *Number of years*

9. Please check the box below to confirm that you have not previously responded to this survey.

10. Please let me know if you have any other thoughts or reflections on possible racial disparities in traffic stops, searches, and treatment by police officers as it relates to the local area.

Fully 98% of respondents believe that racial profiling is widespread nationally (only 3 respondents disagreed, two of whom identify as white). There is also a widely held perception that racial profiling exists in the four jurisdictions under study (Table B.3). The proportion of minorities and whites that believe that racial profiling occurs frequently is approximately 17%, with another 65% believing this is an occasional occurrence. It is notable that although whites believe racial profiling occurs less frequently than minorities do, a substantial portion perceive racial profiling to occur. The greatest divergence in attitudes is on whether racial profiling happens only rarely or never. [Although not reported here, it is noteworthy that among minorities, none believe that racial profiling never happens, and even among whites, only 3% hold that view. Results available on request].

Table B.3. Do you think (racial profiling) occurs when motorists are stopped in Burlington, Winooski, South Burlington, and UVM?

	Frequently	**Occasionally**	**Rarely or never**
Asian/Pacific Islander	33.0%	55.5%	11.1%
Black	27.8%	72.0%	0.0%
Hispanic, non-white	16.7%	66.7%	16.7%
Multi-racial	8.3%	66.7%	25.0%
All minorities	***21.3%***	***63.8%***	***14.9%***
White	14.7%	65.3%	20.0%

Note: "All minorities" includes all those identifying as non-white.

We asked respondents if they believe they have been racially profiled in traffic stops or been a passenger in a car in which they believe the driver was stopped because of his or her race rather than the driver's operation of the vehicle or other objective factors. The results are shown in Table B.4. Twelve percent of minorities responding to this survey believe they have been stopped based on their race when operating a vehicle in the greater Burlington area over the last two years. Of that 12%, all identify as black. They estimate the number of stops in which they believe police racial bias motivated the traffic stop to be between 1 and 5. The same percentage of minority respondents (but not necessarily the same respondents) believes that drivers of vehicles in which they were passengers were stopped as a result of racial bias. Interestingly, 2.3% of white drivers also perceived that at least one stop of a vehicle in which they were a passenger (with a minority driver) was motivated by racial bias. It should be underscored that respondents are referring to experiences over the last two years in one of the four jurisdictions in this study.

These responses suggest that even among those of a higher socio-economic class, there is a perception of racially biased traffic stops in the local area, with both minorities *and* whites perceiving such bias. The sample size is too small to draw firm conclusions, but responses are suggestive at a minimum of a polarization of attitudes and perceptions between law enforcement and citizens, and these results suggest that it will be important to explore that extent to which racial disparities result from factors other than the class status of the driver.

Table B.4. Community Perceptions of Racial Profiling in Traffic Stops

	Believe self racially profiled	**% of group**	**Avg. no. of times believe self profiled in two years**	**Believe passenger in car of profiled driver**	**% of group**
Blacks	7	33.3%	2.5	4	19.1%
All other minorities	0	0.0%	0.0	2	7.7%
Whites	*na*	*na*	*na*	2	2.3%

Note: *Na* = not applicable. Whites may believe they have been profiled for other reasons (see respondent comments in Table B.5). However, here we only asked if the driver believed he or she had been *racially* profiled, that is, stopped exclusively because of their race. The average number of times a person believes self to have been racially profiled is only for those who believe they *have* been racially profiled (thus excluding those who indicated they believe they have not been profiled). One respondent indicated the number of times believed to have been profiled in the last two years in the Burlington, South Burlington, Winooski, and UVM area is 15. Because this number is an outlier and we do not have a means to verify its accuracy, we do not report it in the table above.

Table B.4 provides a summary of open-ended responses to the survey. There are several observations that may be made about these comments. First, both older and younger respondents across racial/ethnic groups register concerns that racially biased policing may be occurring in this area. Second, one respondent suggests that profiling may also occur for other reasons such as whether a driver's dress suggests an association with hip-hop culture. These comments suggest the usefulness, indeed importance, of follow-up measures to this study that engage law enforcement and the community in discussions about policing practices in order to identify where improvements in policing can be made, and where perceptions of the local population may be due to faulty information (or be influenced by knowledge of disparate practices in metropolitan areas) rather than actual practice.

Table B.5. Open-ended Responses from Survey Respondents

Although I have not personally experienced being stopped by police at a traffic stop, searched, or experienced mistreatment, I frequently read in the national papers as well as in the local newspaper of racial profiling. In larger urban areas, it is probably easier to report such incidents but in our small predominantly White state I wonder about the number of racial profiling occurrences that go unreported because of fear of retribution or fear of just being publicly targeted.

I was stopped in the NY state for what seemed to be profiling. I had my hat on in a way that represents hip-hop culture. I was traveling with my son and puppy. The way he [the officer] approached the car made me feel nervous. I have experienced profiling in the past in numerous areas of the country (White male respondent, age 33).

Re the So. Burlington police officer…who is accused of mistreating a black woman sometime in the past year: I have not been following this case in the news but I hope some charges will be made against him. From what I have heard from community members, the charges are quite true and this man should not get away with what he has done. Thank you for looking into this (White female, age 65).

As the parent of two young people of color, I have experienced numerous incidents where police have treated them in a way I suspect they would not be treated if they were white. This includes numerous stops by police, charges when white kids were not charged, assumptions about who they are, being tazed by UVM police, etc. Very tired of it! (White female, age 55).

I know the BPD has bias-free policing policies, which is a good start. There's always need for re-visiting and improving policies, more education and training in the policies that exist, and monitoring and enforcing policies (White female, age 57).

I am not sure what were the reasons behind the officer's decision of stopping a car on I89 early this fall. The officer then found two (undocumented) persons that were apprehended. I thought it was interesting that the officer was found "not guilty" for his actions. It seems that this happens rather often in Vermont: The police (are) always right (Hispanic female, age 49).

I was stopped in Essex for having a tinted frame/cover on my license plate. I am sure I was stopped because I identify as African American (Black male, age 43).

Police racially profile farm workers (Hispanic male, age 31).

Most officers are polite and professional. Occasionally there are vile individuals who believe they are doing their job by scapegoating people of dark skin who are going about their daily life (Black male, age 25).

A friend of mine, who is black, told me that he feels like racial profiling occurs to him and his other friends often. In addition, a friend of mine even wrote their college essay on racism in Vermont, and how prevalent it was. Based off these two notions, as well as a few others, I am practically certain that racial profiling not only occurs in Vermont, but everywhere (White male, age 25).

Once I was stopped while walking home after a night out on Church Street. I suppose I may have appeared slightly intoxicated, but I was surprised to have been stopped by a UVM police officer in a motor vehicle as someone just walking on the sidewalk (Asian/Pacific Islander male, age 24).

It definitely happens most with mall cops, in my experience. Nothing traffic related yet, but I have not a doubt in my mind that it happens from time to time (Multiracial female, age 22).

I think Burlington is probably better than other VT areas because of its trying to stop racial profiling like Middlebury with the matricula consultar and because Burlington is known as a very progressive city (Asian/Pacific Islander female, age 19).

I think it happens all over the country and world, not just in certain areas. Most of the police force is white (I'm assuming), so this may have an effect on who they perceive is causing crime, and therefore whom they pull over (White male, age 27).

Most of all my black male friends told me police officers are very biased against African American population. No evidence, but it is a widespread idea (Asian/Pacific Islander female, age 22).

I am aware that racial profiling, whether consciously intentional or not, does exist in law enforcement. I am a white female but one thing I've noticed is that often when I drive past someone who has been pulled over, often at least one person in the car, whether the driver or not, is a person of color. Thanks for doing this research and working with local law enforcement on this (White female, age 29).

The fact that persons of color brought this matter to the attention of police departments indicates that racial profiling is a problem in this area. Persons of the dominant race in VT (white) need to be educated on what it's like to be a minority in this state. Only when the mostly white police acknowledge their prejudices and attempt to change them will everyone feel like they can be "served and protected" by law enforcement (White, no data on age or gender).

One of my coworkers is African American and has run into numerous issues after being stopped by the police. For example, he claimed he was stopped for having muffler issues and had his car impounded. Perhaps he was not telling the whole truth. Perhaps the cop was acting in accordance with the law, but that strikes me as extreme and potentially racially instigated (White male, age 20).

Police should only pull people over if they run red lights and stop signs. They also should (not) look for reasons to search your car if they can't find an immediate reason like a visual of drugs and guns during the stop (Black male, age 21).

I believe there is a strong ageist bias, against college age students (White male, age 19).

A friend of mine told me a story about how his Arabic professor (who I believe is from Sudan) claims to have been stopped many times in Vermont as a result of racial profiling. I believe it’s very possible that racial profiling occurs occasionally if not often in Vermont (White male, age 19).

I don't think the police officers do it purposefully. I think if it is happening, it is subconscious (White female, age 20).

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