Traffic Stops & Race in Vermont
Part Two
A Study of Six Jurisdictions

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Executive Summary

Act 193 mandates that law enforcement agencies collect data on roadside stops for the purpose of evaluating racial disparities. The Act dictates agency data collection and any related conversation centers on agency behavior. The Act and the data collected do not focus on or reflect the stories told by Black, Indigenous and People of Color (BIPOC) as related to their contacts with law enforcement agencies. Because of Vermont's rural nature, small populations, and policing strategies, we conclude that traffic stop and race data are not sufficient to inform policy makers and stakeholders. Rigorous qualitative research focused on the experiences of the BIPOC community which detects patterns and trends can distinguish structural issues within the criminal justice system. Agency data should be used as a supplement to that research.

The purpose of the study was to test different methods of assessing racial disparities in traffic stops for their applicability for all Vermont law enforcement agencies. In short, we found that this was not possible. This report reviews the methodologies tested and the findings.

On Measuring Disparities

1. We tested three peer reviewed methods for benchmarking the driving population: Commuting Hour populations, Resident Driver populations, and Crash Data benchmarking. All three failed in Vermont because of the state's rural nature and small populations. The low volume of people of color makes it difficult for consistent analysis. It is not possible for one benchmarking standard to be applied to all law enforcement agencies in the state.

2. We can recommend the "Veil of Darkness" analysis as an effort to examine racial disparities. However, that analysis essentially measures one work shift in a police department. In some departments that may just be a single officer.

3. Post-stop outcome measures may be useful, however, without more information on the stop (such as the violation for which the person was ticketed/arrested and other circumstances surrounding the stop) it is of limited value. Further, because so few people are searched or arrested it is hard to draw a conclusion from the data.

4. Stop data will now include information as to how often the same person is stopped by a department. Specifically, the year, make, model, and color of the car and the town/state of residence and the state of the plate will be available. This will help illustrate the stories community members have spoken about in protests, legislative hearings, and news articles – stories of people who feel they are being continuously targeted. For example, using these additional data fields, researchers can identify a 30-year-old Asian female from Montpelier driving a 2008 White Honda CRV who has been stopped four times in one month for various reasons.

On Data Quality, Completeness, and Accessibility

In any study, quality data is essential for producing reliable and valid results. It is important to acknowledge that no data set is without limitations. Knowing the limitations of the data is key for understanding which issues analysis of the data can and cannot inform. This is especially important when the analysis has the potential to shape policy decisions. As such, CRG has outlined crucial points concerning the quality of traffic stops and race data analyzed in this report.

1. We worked with law enforcement to facilitate the release of more data elements than required by law. Unfortunately, in one CAD-RMS that covers about half the law enforcement agencies, identifying the specific reason for a stop (5 mph over vs. 20 mph) can only be done manually.

2. The statute requires that roadside stop data shall be collected. The data are then exported into a one line per event (tickets or warnings) that happened at the stop. Therefore, if a 50-year-old White woman was stopped and issued a ticket and a warning, this is entered on two lines. The two CAD-RMS systems handle this duplication differently. The Vermont Criminal Justice Council (VCJC) should work with researchers to develop a protocol for these cases.

3. Departments do not record search and contraband data consistently. For example, some departments do not record contraband as having been found if it belongs to a passenger. The VCJC should work with researchers and CAD-RMS system experts to develop a protocol for these cases.

4. Driving Under the Influence (DUI) is a very common crime in Vermont. The criminal courts routinely process about 4,000 DUI charges a year. However, DUI stops are infrequently entered in the traffic stop data. Some departments have not filled out the traffic stop paperwork (to give a warning or ticket) when making an arrest for DUI. The VCJC should work with researchers to develop a protocol for these cases.

On the Future

1. Listen to people's experiences with the police. In the course of this study, we were able to identify data elements that will help tell the story of people who feel discriminated against because of their skin color. People's stories are data, and more nuanced than aggregate quantitative data. Good policy can come from a rigorous analysis of the qualitative data within those stories.

2. Police departments should run monthly reports to identify whether their departments are frequently pulling over the same person. For example, we found in the data that often an officer would pull a person over for an equipment violation. A few days later, another officer would pull the person over for the same violation, and so on, until the equipment was fixed. A monthly report would help identify these patterns. Additionally, these reports would be helpful for early identification of data quality issues.

3. There should be a thoughtful and coordinated effort by law enforcement, community members, researchers, and the VCJC to help define data elements.

Methodologies for Measuring Disparities- History

Benchmarking History

Interest in using traffic stop data to measure racial disparities began in the mid-1990s. The earliest studies used census data to estimate driving populations in jurisdictions. Those estimates were then used as a benchmark against which stops were measured. As the United States Court of Appeals for the 7th Circuit noted in *Chavez vs. Illinois State Police,* "Census data can tell us very little about the numbers of Hispanics and African Americans driving on Illinois interstate highways, which is crucial to determining the population of motorists encountered by the [ISP] officers."[1]

The "Gold Standard" for benchmarking is field observation study, where researchers observe the race of drivers in a jurisdiction over seasons and varying times of day. From these observations, an estimated driving population is constructed for the benchmark. These studies are often cost-prohibitive for small departments. They also need to be repeated over periods of time as demographics change.

In the early 2000s, Northeastern University's Institute on Race and Justice (IRJ) created an estimated driving population using a very sophisticated analysis of census data. IRJ first identified communities within a 30-minute driving time radius and assumed that those communities would contribute to the driving population of the community. Then, it accounted for vehicle ownership, commute times, retail, and entertainment destinations. Using these factors, IRJ created an estimated driving population.

This methodology is a significant improvement over the use of census data. However, it, too, is often cost-prohibitive for agencies to undertake. Since Northeastern University's advancement, two other benchmarking techniques have been developed that are explored in this report. The first is the use of data from the Uniform Crash Report generated when police respond to a motor vehicle crash. These data include the race of the drivers involved in a crash and from this information, the benchmark is constructed.

The second innovation in determining the estimated driving population is from Connecticut's Institute for Regional and Municipal Policy Planning at Connecticut State University. The commuting hours analysis estimates the worker population in a jurisdiction and then looks only at stops made during commuting hours. Connecticut performs an additional analysis on stops in the jurisdiction of residents only.

These are the methodologies CRG used to attempt to create a benchmark driving population for jurisdictions in Vermont.

[1] http://caselaw.findlaw.com/us-7th-circuit/1054143.html.

Methodologies for Measuring Disparities - Vermont

There are three generally accepted ways to measure racial disparities: 1) Benchmarking stops to an Estimated Driving Population (EDP);[2] 2) Veil of Darkness Analysis;[3] and 3) Disparities in Post-Stop Outcomes to determine if minority drivers are treated differently than white drivers.[4]

For this project, CRG used all three methods to test for their viability for use in Vermont and to provide a more holistic approach to understand how law enforcement agencies interact with the motorists that are stopped.

CRG first applied Connecticut's methodology for the analysis of traffic stops and race data in Vermont. The purpose was to test the methods and make recommendations on those suited for statewide analysis and to determine a method for analyzing traffic stop and race data that would work for all law enforcement agencies in Vermont going forward. The three analyses completed used the Commuting Population analysis (benchmarking), Resident Driver analysis (benchmarking), and the Veil of Darkness, in addition to analyzing disparities in post stop outcomes. Those jurisdictions were funded under BJS grant #2016-BJ-CX-K016 and the analysis was completed for 2016. We then received a grant from GHSP EDUC-2020-CRG-00027-GR1418 to test crash data benchmarking and to conduct additional analysis. Three new jurisdictions were added to the study.

Jurisdiction 1 is a local police department in a city that contains a hospital and a college.
Jurisdiction 2 is a statewide agency.
Jurisdiction 3 is a local police department in a city that contains a hospital and a small college.
Jurisdiction 4 is a local police department in a city next to a much larger metropolitan area which contains a research hospital and a prestigious college.
Jurisdiction 5 is a county-wide agency.
Jurisdiction 6 is a local police department in a small town with a well-traveled surface route between major parts of the state.

Data Quality and Caveats

On June 17, 2014, an amendment to 20 VSA § 2366, Act 193, went into effect and required that all law enforcement agencies (LEAs) in Vermont collect traffic stop data. Specifically, section (e)(1) states as follows (in part):

> On or before September 1, 2014, every State, local, county, and municipal law enforcement agency shall collect roadside stop data consisting of the following:
> (A) the age, gender, and race of the driver;
> (B) the reason for the stop;

[2] http://ctrp3viz.s3.amazonaws.com/data/April2015ConnecticutRacialProfilingReport.pdf.
[3] Grogger, Jeffrey and Greg Ridgeway, Testing for Racial Profiling in Traffic Stops From Behind a Veil of Darkness. American Statistical Association, 2006. https://www.rand.org/pubs/reprints/RP1253.html.
[4] http://ctrp3viz.s3.amazonaws.com/data/April2015ConnecticutRacialProfilingReport.pdf.

(C) the type of search conducted, if any;
(D) the evidence located, if any; and
(E) the outcome of the stop, including whether:
(i) a written warning was issued;
(ii) a citation for a civil violation was issued;
(iii) a citation or arrest for a misdemeanor or a felony occurred; or
(iv) no subsequent action was taken.

The statute further states that law enforcement agencies shall work to collect uniform data, adopt uniform storage methods, and ensure that the data can be analyzed. Further, this roadside stop data, reports, and any analysis are to be made public.[5]

There are three computer aided dispatch - record management systems (CAD-RMS) in the state: Spillman, Little Spillman, and Valcour. All three CAD-RMS systems are represented in our jurisdictional sample. When a stop is made, the officer fills out a piece of paper that records the demographics of the driver, the reason for the stop, location of the stop, whether a search was conducted, whether contraband was found, the outcome of the stop, and various other pieces of information. A piece of paper is filled out for every action taken at the stop. (see Appendix A) If an officer issues a ticket and a warning at a stop, there are two pieces of paper for that stop. What happens to that piece(s) of paper varies from department to department. In most jurisdictions, the officer turns that paper over to a clerk or clerks having the responsibility of entering it into the CAD-RMS system.

Stops with Multiple Outcomes

Because a piece of paper is created for each outcome of the stop, in all the CAD-RMS systems those outcomes are reported out in the data on multiple lines. This example from Spillman/Little Spillman illustrates how the data are presented:

Table 1: Spillman Multiple Outcomes

Date and Time of the Stop	Race	Sex	Ethnicity	Age	Location of Stop	Reason for Stop	Search?	Outcome
1/17/2019 3:50:00 PM	W	F	NHIS	45	NORTH ST & PLANK RD	M	NS	T
1/17/2019 3:50:00 PM	W	F	NHIS	45	NORTH ST & PLANK RD	M	NS	T

This stop involved a 45-year-old white female. She was stopped at 3:50 PM at North and Plank for a Motor Vehicle Violation (M), was not searched (NS), and was issued two tickets (T).

[5] 20 VSA § 2366(e)(1).

The same stop would appear in Valcour as follows:

Table 2: Valcour Multiple Outcomes

Date and Time of the Stop	Race	Sex	Ethnicity	Age	Location of Stop	Reason for Stop	Search?	Outcome
1/17/2019 3:50:00 PM	W	F	NHIS	45	NORTH ST & PLANK RD	M	NS	T
1/17/2019 3:50:00 PM				45	NORTH ST & PLANK RD			T

Note that on the second line in Valcour, race, sex, ethnicity, reason for stop and search are not recorded.

The disparate ways the CAD-RMS systems handle the multiple outcomes makes consistent identification of the multiple outcomes in a unique stop difficult. In the Spillman/Little Spillman systems we were identifying duplicates as: the same date and time, same location, and same demographics of the driver. This was on the assumption that an officer from the same department would not pull over the two or more people with the exact same demographics at the exact same time in the exact same place. This worked for Jurisdictions 1-3, but not Jurisdiction 4. Jurisdiction 4's workflow involved those pieces of paper going to several clerks for data entry. One clerk may enter the location of the stop as State and Main, and another as Main and State. For Spillman/Little Spillman agencies, we recommend analysts identify multiple outcomes by the time/date of the stop and the demographics of the driver.

Identifying multiple outcomes versus missing data becomes more complicated in Valcour. In stops with multiple outcomes, the demographic data is missing in the second line of data. We recommend that analysts work with the departments to explore the best way to identify multiple outcomes in traffic stops.[6]

Missing Stops

The legislation requires all roadside stops to be recorded in the manner described above. However, in working with departments we noticed that there were very few stops for DUI. In further conversations and investigations with the departments, many realized that officers were not filling out the roadside stop paperwork in addition to the DUI arrest paperwork. We illustrate on p. 19-20 the effect this has on post-stop outcomes.

[6] Valcour agencies report out the incident number in their data. We do not recommend analysts use the incident number to identify stops with multiple outcomes unless they talk with the individual departments. In some departments the incident number represents a speed trap. For example, an officer may sit by a school waiting for violators. Each violator in the school zone is a unique stop, but everyone might have the same incident number to reflect the officer spending the time at the school.

Searches and Search Outcomes

When the Legislature mandated traffic stop data collection in 2014, there were no definitions for the terms included in the legislation, for example, what is meant by "contraband was found." One large agency only records contraband found if it was located on the driver or attributable to the driver. If there was probable cause to search the car and contraband was found on the passenger, that agency marked the search as "contraband not found." Other agencies record that same scenario as "contraband found."

There are also data quality issues with the information on searches and contraband. Every jurisdiction we studied had some stops with contradictory answers for whether a search was conducted, or contraband was found. These data from Jurisdiction 6 illustrate the issue (data are for 3 years):

Table 3: Search Inconsistencies

	Contraband Found	No Contraband found	No Search Conducted
No Search	5	4	2,608
Consent Search	14	11	1
Search Reasonable Suspicion	3	2	
Search Warrant	1		

For five stops there was an indication that contraband was found but there was no search. In one search it was indicated that there was consent to search but also no search. The errors are not unique to Jurisdiction 6. All jurisdictions studied made these errors. We removed the inconsistencies from our analysis of post stop outcomes. However, we illustrate these inconsistencies because the search rate is so low that even small errors will affect post stop analysis. Jurisdiction 6 reported 31 searches correctly. It had a hit rate of 58%. If the five "No Search/Contraband Found" were coded as searches their hit rate would have been 63%.

Recommendation: The VCJC is responsible for all police training n the state. It should work with police, researchers, and CAD-RMS experts to determine a common set of definitions, protocols, and data quality audits.

Benchmarking Stops to an Estimated Driving Population (EDP)

LEHD Origin-Destination Employer Statistics (LODES) (Commuting Population)

Connecticut pioneered the use of a database known as the LEHD Origin-Destination Employer Statistics (LODES). LEHD is an acronym for "Local Employer Household Dynamics." This is a database of unemployment insurance data supplied by the states. Every employee who is covered by unemployment insurance is captured, along with work and home addresses. The database also contains the number of jobs by race and other demographics in a jurisdiction. The data come from a variety of sources including census data but are also supplemented with social security records and federal tax returns.[7]

[7] https://lehd.ces.census.gov/doc/QWI_101.pdf.

CRG downloaded the Estimated Driving Population (EDP) for each Vermont town - using census data and LODES (Local Employer Household Dynamics (LEHD)[8] Origin - Destination Employer Statistics). The commuting population analysis was completed for three jurisdictions that volunteered and had enough commuters to conduct this analysis. For each, the LODES data was used to identify all those employed in the town but residing in some other location regardless of how far away they live from the target community. The numbers of all commuters from the contributing towns were totaled and represent the nonresident portion of the given town's EDP. This was combined with the town's resident driving population. The combined nonresident and resident numbers from the towns complete the EDP. To avoid double counting, those both living and working in the target town were counted as part of the town's resident population and not its commuting population. The EDP is used to analyze traffic stops during commuting hours only.

The steps for conducting this analysis are:

Step 1	For each town, use LODES data to identify all those employed in the town, but residing in some other location regardless of how far away they live from the target community.
Step 2	Use ACS five-year average estimated data to adjust for individuals commuting by some means other than driving, such as those using public transportation.
Step 3	For all Vermont towns contributing commuters, racial and ethnic characteristics of the commuting population to be determined by using the jurisdictions' 2010 census demographics.
Step 4	For communities contributing more than 10 commuters who live outside of Vermont, racial and ethnic characteristics of the commuting population to be determined using the jurisdictions' 2010 census demographics.
Step 5	For communities contributing fewer than 10 commuters who live outside of Vermont, racial and ethnic characteristics of the commuting population to be determined using the demographic data for the county in which they live.
Step 6	The numbers for all commuters from the contributing towns are totaled and represent the nonresident portion of the given town's EDP. This will be combined with the town's resident driving age population. The combined nonresident and resident numbers form the town's complete EDP.
Step 7	To avoid double counting, those both living and working in the target town will be counted as part of the town's resident population and not its commuting population.

[8] LEHD is a partnership between the U.S. Census Bureau and its partner states. LODES data is available through an on-line application called OnTheMap operated by the Census Bureau and the American Community Survey (ACS).

Examples: Jurisdictions 1 and 2

Jurisdiction 1

To construct the estimated commuting population, CRG modified Connecticut's approach slightly. Like Connecticut, the analysis started with the number of jobs reported by the LODES data. These data are not an estimate but are all jobs where the employee is covered by unemployment insurance. Connecticut then pulls the demographic data from the census for those 16 years old and older from the hometowns that provided workers to a jurisdiction and begins to construct the population. Since Connecticut pioneered this, the number of jobs by race in a jurisdiction were added to the LODES data.

The assumption is made that residents of driving age are all equally likely to be driving during commuting hours, not just to work, but for school, errands, and daily life. To avoid double counting residents, the analysis attempts to back out local residents from the workforce. It is assumed that their demographics in the workforce are the same as the demographics of the community. It turns out this assumption is false. The work is shown here only to demonstrate why this method of benchmarking fails for these jurisdictions.

Because the LODES data uses census designated categories for race and treats Latinx as an ethnicity, this analysis is only applied to race and not ethnicity. Vermont LEAs treat Latinx origin as a race category.

Workers in Jurisdiction 1

Using the LODES data, employers in Jurisdiction 1 employed 9,621 workers in 2015, the latest year of data available. Of those workers, 3,304 resided in the jurisdiction. The remaining 6,317 workers live outside of the jurisdiction. Table 1 shows the top 10 towns outside of the jurisdiction that contribute to the workforce.

Table 4: Top Ten Towns Outside Jurisdiction 1 That Contribute to the Workforce

Town, State	Number of Workers	Share of Work Force
Hoosick Falls Village, NY	367	3.8%
Cambridge Village, NY	132	1.4%
South Shaftsbury, VT	123	1.3%
Rutland City, VT	116	1.2%
Pittsfield City, MA	112	1.2%
Arlington, VT	87	0.9%
Burlington City, VT	55	0.6%
Manchester Center, VT	49	0.5%
New York City, NY	42	0.4%
Troy City, NY	39	0.4%

Jurisdiction 1 businesses employ people who reside as far away as California[9] and as near as Shaftsbury. Because of the geographic diversity of workers, the perils of using town or even county census data as a benchmark alone for all stops becomes clear.

Table 5 illustrates the number and percent of jobs by race.

Table 5: Number and Percent of Jobs by Race in Jurisdiction 1

Race	Number of Jobs	Percent
White Alone	9,325	96.9%
Black or African American Alone	135	1.4%
Native American or Alaskan Native Alone	23	0.2%
Asian Alone	70	0.7%
Native Hawaiian or Pacific Islander Alone	6	0.1%
Two or More Races	62	0.6%
Total	9,621	99.5%[10]

Drivers in Jurisdiction 1

The data used to construct the estimated driving population of Jurisdiction 1 residents comes from the American Community Survey 2011-2015 5-year Estimates. Only those residents who are eligible to receive a learner's or driver's permit are used. Therefore, only those 15 and older are counted.

Table 6: Estimated Resident Driving Population in Jurisdiction 1

Race	Number	Percent
White Alone	12,475	94.55%
Black Alone	151	1.14%
Native American or Alaskan Native	22	0.17%
Asian Alone	122	.92%
Hawaiian or Pacific Islander	0	0
Some Other Race	70	.53%
Two or More Races	354	2.68%
Total	13,194	99.99%[11]

Construction of the Commuting Hour Population in Jurisdiction 1

As stated above, we assumed that Jurisdiction 1 residents work in the workforce at the same racial proportion. There were 3,304 residents working within Jurisdiction 1. Accordingly, the assumed breakdown of workers is presented in Table 7.

[9] This jurisdiction town has a hospital and college. Hospitals often employ traveling nurses or other medical staff who may consider another state home. Likewise, the college attracts students from all over the country, and their residence on a paycheck would likely reflect their home and not their college address.
[10] Numbers do not add to 100% due to rounding.
[11] Numbers do not add to 100% due to rounding.

Table 7: Assumed Breakdown Residents Who Work in Jurisdiction 1

Race	Number	Percent
White Alone	3,124	94.55%
Black Alone	38	1.14%
Native American or Alaskan Native	6	.17%
Asian Alone	30	.92%
Two or More/Some other Race[12]	106	3.21%
Total	3,304	99.99%[13]

Table 8 shows where the assumption that Jurisdiction 1 residents contribute to the workforce in equal proportions fails. The LODES data reports 62 jobs held by people who identify as Two or More Races, but calculations show that Jurisdiction 1 would supply 106 workers who identify as Two or More Races.

Table 8: Race by Worker Residence in Jurisdiction 1

Race	Total Number of Jobs	Jobs Held by Bennington Residents	Jobs Held by Non-Residents	% of Jobs by Race for Non-Residents
White Alone	9,325	3,124	6,201	98.16%
Black or African American Alone	135	38	97	1.54%
Native American or Alaskan Alone	23	6	17	.27%
Asian Alone	70	30	40	.63%
Native Hawaiian or Pacific Islander Alone	6	0	6	.09%
Two or More Races	62	106	-44	-.69%
Total	9,621	3,304	6,317	100%

Although this will not be a useful benchmarking tool for Jurisdiction 1, the discussion provides some insight on who is coming into the town for work, and where they come from. This should be kept in mind with any other benchmarking attempts to measure racial disparities in policing.

Jurisdiction 2

Unfortunately, this methodology did not work for Jurisdiction 2. This department covers a large area, and the LODES data did not have employee data for some towns, despite there being a school, post office, and other employers in the jurisdiction.

Using the LODES data for available towns, businesses in Jurisdiction 2 employed 96,705 workers in 2015, the latest year of data available. Of these workers, 78,258 are residents. The remaining 18,447 workers are non-residents. Table 9 shows the top 10 towns outside of Jurisdiction 2 that contribute to the workforce.

[12] We combine the categories of "Two or More" and "Some Other Race" for comparison into the LODES data.
[13] Numbers do not add to 100% due to rounding.

Table 9: Top Ten Towns Outside of Jurisdiction 2 That Contribute to the Workforce

City/Town, State	Number of Workers	Share of work force
St. Albans, Vermont	1308	1.4%
Rutland City, Vermont	572	0.6%
Montpelier, Vermont	544	0.6%
Barre City, Vermont	527	0.6%
Vergennes, Vermont	487	0.5%
Swanton, Vermont	355	0.4%
Waterbury, Vermont	297	0.3%
Middlebury, Vermont	238	0.3%
Plattsburgh, New York	211	0.1%
St. Johnsbury, Vermont	126	0.1%

Employers in Jurisdiction 2 employ people who reside as far away as California.[14]

Recommendation**:** Because of the geographic diversity and mobility of workers, the perils of using county census data as the sole benchmark for all stops becomes clear, therefore, it is not recommended that the commuting population analysis be used in Vermont.

Resident Driver Analysis

The resident driver analysis provides information on who is driving in the community and where they are from. This provides useful information for comparing stop outcomes for residents versus nonresidents. If citizens are experiencing or even perceiving more negative contact with the police, fundamentals of trust begin to erode. This can lead to a more dangerous policing environment for everyone. The resident driver analysis attempts to provide community members information on how the police treat members of their own community.

A few caveats about this estimate. First, it assumes that all residents 15 or older have a learner's permit or a license, which is likely untrue, but to what extent is unknown. Second, this estimate is based on the ACS 2011-2015 5-year survey, which has high margins of error for the Non-White populations. In Jurisdiction 1, the ACS estimates the total Black Alone population as 154 with a margin of error of +/- 57 meaning that the true population could be anywhere from 97 to 211. In Jurisdiction 2, one town had an ACS estimate of five Black Alone residents, with a margin of error of +/-10, meaning that the true population is anywhere from 0 to 15 residents. In Jurisdiction 3, the Black Alone population is estimated at 206, with a margin of error of +/- 121, placing the true population between 48 and 327. All jurisdictions in our study suffer from the same low population numbers and margins of error that either greatly increase or reduce to 0 the Non-White population. Finally, the census categories for race and ethnicity do not correspond with Vermont's traffic stop data collection. Latinx is considered an ethnicity in census data and race in Vermont traffic data. There are no multi-race categories in Vermont traffic data but there are in census data.

[14] As in Jurisdiction 1, Jurisdiction 2 also includes a hospital which often employs nurses and medical staff from out of state. And several colleges which attract students from all over the country.

Despite the caveats, resident driver analysis can be useful for local jurisdictions, provided the limitations are understood. The resident driver analysis for Jurisdiction 1 is presented in Table 10 for illustration:

Table 10: Race of Resident Driver and Reason for the Stop for Jurisdiction 1

	Reason for Stop				
Race of Operator (Residents)	DUI	Equipment Violation	Investigatory	Moving Violation	Grand Total
Latinx		4		8	12
Missing		10	1	18	29
Non-White Not-Latinx		17		34	51
White	1	417	27	885	1330
Grand Total	1	448	28	945	1422

In Table 10, the percent of Non-White Not-Latinx resident drivers who are stopped in Jurisdiction 1 is 3.59%. Below in Table 11 is the estimated driving population for Jurisdiction 1.

Table 11: Estimated Driving Population for Jurisdiction 1

Race	**Number**	**Percent**
White Alone	12,475	94.55%
Black Alone	151	1.14%
Native American or Alaskan Native	22	0.17%
Asian Alone	122	.92%
Hawaiian or Pacific Islander	0	0
Some Other Race	70	.53%
Two or More Races	354	2.68%
Total	13,194	99.99%[15]

The estimated driving population for Non-Whites is 5.44%, but accounts for 3.59% of the stopped resident drivers. Whites are estimated to make 94.55% of the driving population and account for 93.53% of the stopped resident drivers. From this benchmark, it does not appear that Non-Whites are stopped at a disproportionate rate to their estimated driving population. However, the driving population estimate is just that, an estimate. Some of the assumptions made in creating it may not be true. This benchmark is illustrative, but not dispositive.

Recommendation: It is useful for law enforcement agencies in Vermont to conduct the resident driver analysis for jurisdictions that serve one town or city. To accomplish this, police departments would have to report out the town/state of the driver. We also encourage police departments to run monthly reports of their stops to identify drivers who are being pulled over multiple times for equipment violations.

[15] Numbers do not add to 100% due to rounding.

Crash Data Benchmarking

The use of crash data to benchmark a driving population was pioneered in Miami. Using observations of drivers at intersections and then comparing the observed race to the race of the not at fault driver in two car crashes, the researchers found that the crash data were a reasonable benchmark for the estimated driving population. Other researchers suggest that if an agency is biased in traffic stops that bias may be present when assigning fault at an accident and therefore the race of all drivers should be used. We present both.

The benchmarking method has been tested in major metropolitan areas. It has not been tested in small towns and rural counties. Vermont is largely rural, so this method does not work for benchmarking in Vermont. Vermont Agency of Transportation provided the 2016-2019 crash data information for all crashes that occurred in the three jurisdictions we studied, regardless of responding agency.

One jurisdiction that participated has two major interstates (Jurisdiction 5). Crashes that occurred on the interstate were eliminated from the study. Other researchers have found surface roads are a better indication of the driving population in the jurisdiction.[16] Not everyone who uses the interstate stops within the actual town. The accidents within the town are a better benchmark of the people the jurisdiction was likely to stop. Table 12 shows Jurisdiction 5's perceived race for not at fault drivers:

Table 12: Jurisdiction 5 - Perceived Race for Not at Fault Drivers

Year of Crash	Asian		Black		Latinx		Native American		White		Missing	
	N	%	N	%	N	%	N	%	N	%	N	%
2017	1	.69	3	2.0	1	.69	4	2.76	127	87.59	9	6.2
2018	3	2.4	1	.8	2	1.6	1	.8	114	91.2	4	3.2
2019	4	2.9	2	1.46	1	.73	0	0	125	91.2	5	3.6

The percentage of Non-White drivers who are not-at fault drivers varies widely over the study period. In 2019, Asian drivers made up either almost 3% or less than 1% of the not at fault drivers. Every year the percentages of a particular race varied. In 2019, following this benchmarking method, the jurisdiction would not be able stop any Native American drivers, because they made up 0% of the estimated driving population.

[16] http://www.sjpd.org/records/utep-sjpd_traffic-pedestrian_stop_study_2017.pdf

Table 13: Jurisdiction 5 - Perceived Race for All Drivers

Year of Crash	Asian		Black		Latinx		Native American		White		Missing	
	N	%	N	%	N	%	N	%	N	%	N	%
2017	7	2.15	3	.92	3	.92	7	2.1	295	90.5	11	3.37
2018	6	1.98	4	1.32	2	.66	4	1.3	281	92.7	6	1.98
2019	9	2.98	7	2.32	2	.66	0	0	278	92.0	6	1.99

Using all drivers in all crashes during the study years did not help the variability of the Non-White drivers as a percentage of the driving population. Black drivers are less than 1% of the population in one year and over 2% in another year. This benchmarking strategy does not provide consistent enough results for this jurisdiction.

Jurisdiction 6, the county-wide jurisdiction, presented different challenges in benchmarking. AOT provided county-wide data for this agency, regardless of the responding agency. This agency responded to very few crashes during the study period (Avg. 42 per year). Mapping the towns where the crashes occurred to the towns where the stops occurred produced results that indicated that the department is stopping people in locations where there are no reported crashes or where they do not respond to crashes. There are towns in the county where the department conducted numerous stops, yet no crashes were reported, or single digit numbers were reported. For example, in one town approximately 100 stops were conducted over the three years. That town reported 2, 3, and 7 crashes for the relevant years. We could determine no consistent way to benchmark this department using the crash data.

Jurisdiction 7 lies between two population hubs of the state and is a destination for tourists and some employment. There is a two-lane U.S. highway that runs through the town connecting the northern and southern parts of the western half of the state. All the crashes responded to were in the jurisdiction.

Table 14: Jurisdiction 7 - Perceived Race for Not at Fault Drivers

Year of Crash	Asian		Black		Latinx		Native American		White		Missing	
	N	%	N	%	N	%	N	%	N	%	N	%
2017	0	0	1	2.38	1	2.38	0	0	32	76.19	8	19.05
2018	0	0	1	2.27	0	0	0	0	35	79.55	8	18.18
2019	0	0	4	8.00	0	0	1	2	40	80.00	5	10.00

Jurisdiction 7, similar to Jurisdiction 5, had great variability in not at fault drivers, making benchmarking difficult. Jurisdiction 7 also had a high percentage of missing race for not at fault drivers.

Table 15: Jurisdiction 7 Perceived Race All Drivers

Year of Crash	Asian		Black		Latinx		Native American		White		Missing	
	N	%	N	%	N	%	N	%	N	%	N	%
2017	3	3.9	1	1.3	2	2.63	0	0	61	80.26	9	11.84
2018	0	0	2	2.67	0	0	0	0	64	85.33	9	12.00
2019	1	1.09	4	4.35	0	0	1	1.09	81	88.04	5	5.43

Even with all of drivers, the proportion of Non-White drivers varies from year to year. We cannot consistently benchmark the driving population of this jurisdiction.

Recommendation**:** Because of the fluctuations in the race data from year to year, there is no consistency to the crash data that would allow its use for benchmarking the driving population in Vermont**.** We do not recommend that the Crash Data be used to benchmark driving populations in Vermont.

Veil of Darkness Analysis

The Veil of Darkness analysis was developed in 2002 by researchers in Oakland, California and it does not attempt to benchmark a driving population but is used to identify bias. The Veil of Darkness method is conducted on a subset of stops before and after the sun rises or sets on a given day during the inter-twilight of dawn and dusk. It assumes that the driving population at 5p.m. in January is the same population driving at 5 p.m. in June. Therefore, if there is racial bias by a police department, whether explicit or implicit, one would expect more Non-Whites to be stopped during daylight hours (in June), when officers can see into the vehicle than in the dark during January when officers may not be able to perceive the race of the driver. The steps taken to conduct this analysis were:

Step 1	Download the US Naval Observatory Data for Vermont and construct variables for dawn and dusk inter-twilight periods.
Step 2	Conduct appropriate analysis for the inter-twilight periods

The analysis focused on the 30 days before and after a time switch. This helps eliminate some of the differences that may be observed because of seasonal driving differences. For example, an area may see more traffic during the winter months than in the summer. Limiting the analysis to a sixty-day period helps strengthen the analysis as it acts as pre/post experiment. Below, in Table 16, is the Fall time switch analysis, for the afternoon hours, for Jurisdiction 1.

Table 16: Fall Switch to Standard Time for Jurisdiction 1

	Race of Operator				
	Missing	Asian	Black	Unknown	White
Light	2	1	2	0	28
Dark	13	1	6	2	128

Table 16 reveals that more people were pulled over in the dark hours than daylight hours. If racial bias influenced the decision to pull over, the theory argues that more minorities would be pulled over during daylight hours.

Testing for racial bias is done through regression modeling. Regression models control for variables that may affect the stop, such as gender, vehicle make and model, state of the plate, and race. Jurisdiction 1 did not have the age of the operator in its data, so a regression analysis was not possible. Jurisdictions 2 and 3 had all variables necessary to conduct the regression and below are findings. The full regression models are available from the author by request.[17]

Regression modeling assigns a probability that something happened more than by chance. The process of conducting a regression analysis allows a determination of which factors matter most, which factors can be ignored, and how these factors influence each other. Regression also "controls" for other factors, for example, regression can determine whether females are more likely to be pulled over, controlling for age. Although every jurisdiction had enough traffic stops during the evening hours of the 60-day period in the fall and spring, the regression modeling did not produce any relevant factors. That is, none of the variables tested predicted whether one would be stopped during the day or night. The variables tested were: state of the vehicle, race, gender, and age.

There are several possible reasons why the regression models did not produce any relevant factors. First, it could be that the variables do not, in fact, predict whether one is stopped during the day or night. However, the models returned some numbers that indicate that the data subset is too small, with little or no variance, to obtain an accurate picture. For example, one jurisdiction pulled over Latinx men and no Latinx women during the time period. This means that no test could be completed to see if gender made a difference in treatment by police because there were no women in the sample. Every jurisdiction tested had similar issues - too few people with disparate traits in the sample.

Recommendation: The Veil of Darkness analysis is useful, even if in these jurisdictions the regression modeling failed to produce relevant factors. The analysis can be performed on any jurisdiction and the raw numbers might warrant a closer look at a particular law enforcement agency. However, it should be noted that it is essentially looking at one shift of a law enforcement agency, the nighttime commuting hours shift. In some departments that might be one officer. The caveat with this method is that it is not a measure of the actions of all officers in the department.

[17] They will be shared in a Juptyr Notebook for R, with the underlying data. Knowledge of R is not necessary to understand the Notebook.

Post-Stop Outcomes

Post-Stop Outcomes are an indication of the difference in treatment by police after the stop has occurred for Non-White drivers who are stopped versus White drivers who are stopped. Post-Stop Outcomes include issuing tickets and/or warnings, arrests, and searches. These measures do not rely on benchmarking to driving populations. The race of the driver is perceived after the stop when the decision to issue a ticket or the decision to search is made. A weakness in looking at Post-Stop Outcomes is that this analysis does not account for the full range of variables that an officer uses when exercising discretion. Several analyses are presented here for descriptive purposes, with suggestions to improve the measures.

Arrests

Table 17 below shows the Post-Stop Outcomes for Jurisdiction 2. There were 20 discretionary arrests in the Jurisdiction, of which two were Non-White operators, or 10% of the arrests. Jurisdiction 2 also arrested two people for DUI in a traffic stop. In working with Jurisdiction 2, CRG learned that officers are not issuing tickets when they are arresting people for DUI or other serious motor vehicle offenses.

By obtaining data from DPS on DUI arrests for Jurisdiction 2, the number of DUI arrests during the study period was 94.[18] There were 89 arrests for White drivers, yet only 18 White driver arrests appear in the traffic stop data. There were additionally three arrests for Black drivers and two for Hispanic drivers. Omitting stop and arrest data for DUI[19] stops creates data issues for the analysis of post-stop outcomes.

Considering the additional data on arrests in the DUI traffic stops resulted in arrests for Black drivers dropping from 5.0% to 3.5%, arrests for Latinx/Hispanic drivers dropping from 5.0% to 2.6% and for White drivers increasing from 90% to 93.86%. This illustrates the point that small numbers make a big difference when moving from raw numbers to percentages. And to emphasize that any discussion of traffic stop data on Post-Stop Outcomes in Vermont should include a discussion of the omission of DUI stops and arrests from the traffic stop data.

Jurisdiction 2 is working with officers to fill out the ticket for DUI stops even when the driver is arrested, this agency may have more officers than other departments which gives it the ability to change its practices.

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[18] These arrests that are not in the traffic stop data are noted in red font in Table 14.

[19] We recognize that not all DUI arrests will be as the result of a traffic stop. However, all agencies we worked confirmed that they were not entering in DUI arrests as a result of a traffic stop.

Table 17: Post-stop Outcome by Race for Jurisdiction 2

		Outcome of Stop					
Race of Operator	Reason for Stop	Missing	Arrest	Arrest on Warrant	Ticket	Warning	Grand Total
Missing	Missing	1					1
Asian	Equipment Violation					2	2
	Moving Violation	1			45	65	111
Black	DUI		3				3
	Equipment Violation				2	13	15
	Investigatory	1				2	3
	Moving Violation		1		46	76	123
Latinx	DUI		2			1	3
	Equipment Violation					3	3
	Investigatory					1	1
	Moving Violation		1		29	33	63
Native American	Moving Violation					3	3
Unknown	Moving Violation					1	1
White	Missing	7			2		9
	DUI		2+89			1	92
	Equipment Violation		4		47	568	619
	Investigatory	1	2		31	49	83
	Moving Violation		10	2	1,243	2,649	3,904
Grand Total		11	20/114	2	1,445	3,467	5,059

Overall, in all the jurisdictions we studied, arrests rates and actual numbers are very small. Jurisdiction 4 arrested 132 people in three years of traffic stops (N= 6,003), accounting for 1.32% of all stops, five Black drivers were arrested over those three years. Jurisdiction 5 arrested 61 people in three years out of over 7,000 stops, two of whom were Black.

Search and Hit Rates

Researchers have tried to use search and hit rates to measure bias. There are two main methods of doing so, both with flaws. The first is called the KPT Hit Rate. Developed in a series of papers by Knowles, Pearson, and Todd,[20] this test looks at the success rates of searches of White drivers and compares them to success rates of Non-White drivers. The second method applies the Veil of Darkness analysis to post-stop behavior. Both methods are presented here for descriptive analysis only.

[20] Knowles, John, Nicola Persico, and Petra Todd. "Racial Bias in Motor Vehicle Searches: Theory and Evidence." Journal of Political Economy, 2001.

KPT Hit Rate Analysis

This model is based on economic Game Theory. Game Theory posits that we all act to maximize our desired outcomes. In the case of police officers, they would act to successfully discover contraband. In the case of criminals, they would act to minimize the risk of being detected. The KPT hit rate argues that if an officer wants to find illicit drugs, and the officer is intentionally biased against Blacks, then he will search Black drivers more frequently, but find more contraband on White drivers. Eventually, the theory argues, there will be equilibrium because Black drivers will begin to carry less contraband and the officer - still wanting to maximize the outcome - will search White drivers more frequently.

The theory is not without its critics. First, it assumes rationality on everyone's part. Given the amount of crime driven by mental illness and addiction, rationality of the defendants may not be the best assumption. Second, it assumes that the types of crimes for which people will be searched and contraband will be found is equal among all crime categories and that all races participate in all crimes equally. It is important to understand the assumptions in the model and know that the data do not allow us to test for these assumptions.[21]

Some searches were eliminated due to inconsistencies in the Search Reason and Search Outcome fields. In some cases, an officer indicated a search in the Type of Search field, but No Search Conducted in the Search Outcome field. In other cases, the Search Outcome field indicated a search was conducted, but the Search field indicated No Search.

Search Outcomes in Jurisdiction 2

In Jurisdiction 2, of the 4,935 stops, a total of 27 searches were conducted without a warrant. One Latinx driver was searched and contraband was found. White drivers were searched in 26 stops, 23 yielded contraband and three did not. One Black driver was searched under a search warrant and contraband was found. No probable cause searches were conducted on Black drivers.

[21] Two advancements in this area have occurred since our original analysis, neither of which we believe will work in Vermont given its low numbers. Oregon published its analysis including propensity score matching for post-stop outcomes. Researchers at Stanford published on Infra-Marginality in discrimination tests.
https://www.oregon.gov/cjc/stop/Documents/Traffic_Stop_Research_Memo_Final_Draft-10-16-18.pdf;
https://projecteuclid.org/download/pdfview_1/euclid.aoas/1507168827. Because of Vermont's small numbers such statistical tests usually fail. Oregon has not yet published regarding its smaller agencies, but we look forward to learning whether their methods work on smaller agencies.

Table 18: Search Outcomes for Jurisdiction 2

		Search					
Race of Operator	Search Outcome	Missing	No Search	Search Reasonable Suspicion	Search Warrant	Search Probable Cause	Grand Total
Missing		1					1
Asian	Missing		1				1
	No Search Conducted		112				112
Black	Contraband Found				1		1
	No Search Conducted		140				140
Latinx	Contraband Found					1	1
	No Search Conducted		65				65
Native American	No Search Conducted		3				3
Unknown	No Search Conducted		1				1
White	Missing	9					9
	Contraband Found			2		21	23
	No Contraband Found			1		2	3
	No Search Conducted		4,575				4,575
Grand Total		10	4,897	3	1	24	4,935

Solar Powered Searches

In 2013, Ritter[22] argued that applying the Veil of Darkness analysis to searches would eliminate some of the problems with the assumptions in the KPT Hit Rate Analysis. He calls his theory Solar Powered Searches. The theory argues that if there are fewer searches of minority drivers in darkness, shown by using regression analysis, then officers may be pulling over minority drivers when race is visible with the intention of searching them. The analysis is conducted the same as the Veil of Darkness analysis for stops. Only those stops occurring between the inter-twilight period are considered. In Jurisdiction 1 there were no searches conducted during this time period. Jurisdiction 2, presented below, had six searches during this time period, all of White drivers.

[22] Ritter, Joseph A. "Racial Bias in Traffic Stops: Tests of a Unified Model of Stops and Searches." University of Minnesota: Minnesota Population Center Working Paper 2013-05. June 2013.

Table 19: Jurisdiction 2 – Solar Powered Searches

		Search				
Dark	Race of Operator	Missing	No Search	Search Reasonable Suspicion	Search Probable Cause	Grand Total
Light	Asian		23			23
	Black		31			31
	Latinx		25			25
	Native American		2			2
	White	1	1,057		3	1,061
Dark	Asian		20			20
	Black		18			18
	Latinx		9			9
	White	2	676	1	2	681
Grand Total		3	1,861	1	5	1,870

Recommendation: Police should continue to report on Post-Stop Outcomes, but for testing of racial disparities the data and current methods of assessing disparity are not particularly helpful. Searches and Arrests are rare events in the data. There are some years no members of a race are arrested and/or searched. Just recently our largest city reported that no Black drivers were searched in 2019.[23] Without the reason for the arrest it is difficult to draw conclusions about any disparities that may appear in the data.

Conclusion

The purpose of the study was to test different methods of assessing racial disparities in traffic stops for their applicability for Vermont law enforcement agencies. The Commuting Hour analysis pioneered by Connecticut fails when applied to Vermont agencies. Crash data analysis as benchmarking failed. Resident Driver analysis is useful for understanding how residents of a town are being treated by the police. It should be included in future analysis of the individual law enforcement agencies. The Veil of Darkness analysis is the easiest to perform consistently over time, but in Vermont is likely to measure just one shift and possibly just one officer's behavior. Post- Stop Outcomes are likewise easy to perform, but of limited value in assessing disparities in Vermont. However, a continued emphasis on data quality and completeness should be supported.

The failure of statistical tests to reflect the experiences of people does not mean that data cannot be used to help illustrate their stories. Communities of color have spoken with honesty and pain about their collective and individual experiences and it was not reflected in the data as currently released. With new data fields and some sorting, people will be able to find themselves in the data that will help illustrate their experiences. Here is an example from Jurisdiction 4:

[23] https://vtdigger.org/2020/07/20/burlington-police-make-fewer-traffic-stops-but-racial-disparity-remains/.

Figure 1: One Black Female Driver's Experience in Jurisdiction 4

This woman was pulled over 5 times in 2017, four times within one month.

Age	Color of Car	Make	Model	Year of Vehicle	Driver race	Type of Violation	Date of Stop	Sex	Driver Residence
22	White	Jeep	Liberty	2003	Black	Equipment	1/3/2017	F	Jurisdiction 4
22	White	Jeep	Liberty	2003	Black	Moving	5/16/2017	F	Jurisdiction 4
22	White	Jeep	Liberty	2003	Black	Moving	5/27/2017	F	Jurisdiction 4
22	White	Jeep	Liberty	2003	Black	Equipment	5/30/2017	F	Jurisdiction 4
22	White	Jeep	Liberty	2003	Black	Equipment	6/12/2017	F	Jurisdiction 4

By sorting the data by the vehicle descriptions and the driver descriptions, we were able to see how many stops may have involved the same driver. Jurisdiction 4 confirmed that by using this method of sorting, we were able to pinpoint people who had been pulled over more than once. Community members will be able to perform their own analysis on this data and identify themselves and their experiences in the data.

This type of experience, being repeatedly pulled over during the study period, was found in every jurisdiction reviewed. Many people experience multiple stops during a short period of time across the state. Agencies should run reports on this activity to make sure these stops are necessary.

This is the second major report we have released on statistical analysis of racial disparities in the criminal justice system.[24] Vermont's small populations, low crime rate, and other factors make the statistical procedures used in larger jurisdictions difficult. Another way to analyze racial disparities in Vermont's criminal justice system is to focus more on rigorous qualitative analyses of people who have interacted with the system. People's experiences told from their perspective are data, and those stories can be analyzed to help policymakers focus their efforts.

[24] http://www.crgvt.org/uploads/5/2/2/2/52222091/race_and_sentencing_final_report_rev.2015.pdf.

APPENDIX A

Vermont’s Race Data Collection Ticket