Comments on Crime Research Group Study of Bennington Police Department Traffic Stop Data

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February 20, 2019

SUMMARY OF COMMENTS

1. **The 2019 Crime Research Group (CRG) report, authored by Robin Joy, does not use all available data.** The CRG report relies only on 2016 data, despite the availability of a much larger sample (running from September 2014 through at least 2017. (Data for 2018 data should now also be available). It is unclear why CRG only chose to analysis calendar year 2016 data, given that sample sizes need to be large enough to make statistical inferences.
2. **In their resident data analysis, the CRG lumps all non-White drivers into one category.** This is problematic since Asian drivers typically experience more favorable outcomes than Black and Hispanic drivers (using the terminology of the law enforcement data) compared to White drivers. By combining all non-White drivers into one category, the CRG dilutes and obscures the Black-White disparity (and also the Hispanic-White disparity).
3. The CRG critiques our methodology for estimating the driving population (which is necessary in order to assess whether racial groups are stopped at a rate equal to, greater than, or less than their share of the driving population). **And yet, their methodology (using commuter data for those who work) yields an almost identical estimate of the Black driving population that we arrive at, although the CRG fails to note this in their report.**
4. **Both our study and the CRG's reach similar conclusions on stop rate disparities for Blacks as well as search rate disparities.** Blacks are stopped at a rate that is 2.5 times their share of the driving population (using the CRG's estimate of the Black driving population of 1.14% and our very similar estimate based on accident data of 1.1%) and are searched at a rate that is almost 5 times the rate at which White drivers are searched. That our results are consistent is not noted in the CRG report. More generally, the CRG's own data conflict with their assertion that there are no racial disparities in Bennington traffic stop data.
5. **The CRG conducts a separate analysis of traffic stops for residents of Bennington vs. non-residents. It is unclear what relevance this has.** Drivers should be fairly treated, regardless of where they are from, and surely, Black and Hispanic drivers, regardless of their town of residence, will be dismayed at disparate treatment.
6. **The larger question raised by both our and the CRG report is what does Vermont need to do to ensure that data is of high quality data and is received on a timely basis?** The current legislation requires a limited number of categories of data to be collected, and not all agencies are reporting even these categories while others have a large number of missing data. A system of quarterly reports that are

standardized would help Vermont to better track trends in racial disparities in traffic policing. A mechanism also needs to found to improve the quality of data submitted.

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I. INTRODUCTION

This brief comments on Joy's (2019) study on Bennington traffic stops for 2016, released on behalf of the Crime Research Group (CRG). We also respond to their critiques of the methodology used by Seguino and Brooks (2017). Discussions about methodology are important and we hope that in this brief, we can help to clarify what we believe are sound approaches to traffic stop data analysis.

II. COMMENTS ON THE CRG STUDY

A. Incomplete Data Used in CRG Report

Bennington Police Department began collecting traffic stop data by race in September of 2014. Our study used all available Bennington data from that time through March 2016 for a total of 5,208 stops.[1] It is not clear why the CRG study limited itself to the much smaller data set (that is, calendar year 2016 data) that, according to their report, is based on 3,255 stops (it is also puzzling why this number differs from the data on their website that includes only 2,382 incidents). This is especially perplexing because small sample sizes limit the ability to make statistical inferences, as the CRG notes repeatedly in its report and we do in ours. Use of 2014 through 2017 data would result in a sample size that is 3 to 4 times larger than the single year of data CRG chose to analyze, decreasing the small sample size problem.

B. Failure to Disaggregate Non-White Driver Data

In the resident driver analysis, Joy (2019) uses non-White vs. White comparisons instead of disaggregating by race (e.g., White vs. Black, White vs. Asian, White vs. Hispanic). This is a major flaw in any kind of race analysis. That is because the data both for Vermont as well in other parts of the country show that Black-White disparities tend to be the largest of any racial group relative to Whites, while in many cases, police treatment of Asian drivers is more favorable than even of Whites (See Figure 1 below as an example which shows that Blacks and Hispanics are searched at a much higher rate than Whites, while Asian drivers are about half as likely to be searched as White drivers). By combining all non-White racial groups, then, racial disparities are diluted. CRG's failure to disaggregate non-Whites by race leads therefore to misleading interpretations of the degree of racial disparities in Bennington traffic stops.

[1] Our subsequent efforts to receive additional data for 2016, as well as 2017 from the Bennington Police Department have proven unsuccessful. The CRG communicated to us via email that it has 2017 Bennington data but it has not yet been posted, and we assume that 2018 data should now also be available.

C. The Diminishing Returns of Stop Rate Analysis

Much of the CRG study focuses on stop rate disparities by race. Analysts working with traffic stop data recognize that while stop rate data are one piece of evidence in assessing racial disparities, it is one of the weakest indicators because of the difficulty in determining the racial composition of the driving population with any certainty. In our study, we produce data on seven indicators of racial disparities, of which stop rates are only one. This approach permits us to identify patterns across indicators, which is a more robust method for detecting racial disparities. It also avoids the temptation to "cherry pick" the data for just one indicator that yields the hoped-for result. The CRG study mainly focuses on a detailed analysis of stop data, and this may in part be due to the fact that they used a small sample of 2016 data only, making it difficult to investigate other indicators. It remains a puzzle as to why CRG did not use all available data for their analysis, especially since data for 2017 and 2018 are now also available (and data for 2015 and one quarter of 2014 are also available). Use of all available data would have allowed them to focus greater attention on post-stop outcomes, which are not subject to the problem of having to estimate the driving population by race.

D. Resident vs. Non-Resident Data

The CRG report goes on to make estimates of the share of stops of residents vs. non-residents of Bennington. It is not clear why this is relevant. Surely, drivers should be stopped based on their driving behavior, not the state their vehicle is registered in or their town of residence. Moreover, if there are racial disparities in stop rates and post-stop outcomes, it is likely to be equally egregious in the eyes of residents of color of Bennington and those who are non-residents.

E. Veil of Darkness Analysis

It is sometimes claimed that law enforcement officers cannot identify the race of the driver prior to a stop. The view is that this will be especially the case in nighttime stops. Therefore, a "veil of darkness" analysis—that is, a comparison of night and day time stop rates by race, can be used to identify disparities (and potential bias) in stops of drivers of color. The CRG study attempts to use this approach on Bennington data.

We have two concerns about their analysis. The first concerns the assumption that law enforcement officers are unable to detect the race of the driver at night, prior to the stop. Law enforcement officers have reported to us in conversations during our study (including in ride-alongs) that they can sometimes identify the race of the driver at night by parking their vehicles at a stop sign under a street light, for example, or because some cruisers have computers which allow them to contact dispatchers to identify the name the car is registered to. Law enforcement officers have also stated that they may be familiar with the vehicles in their town, knowing who the drivers are, because those drivers had been previously stopped by the police. This test, then, is imperfect. This may not rule out using the test because, as we have noted, all data have their weaknesses. It is, however, important for researchers to identify and report the limitations of their data and to compare the results from different approaches to measurement to see if consistent patterns emerge.

The second critique is more serious in regards to the Bennington analysis. The CRG study asserts that the "Veil of Darkness" analysis shows no racial disparities in stop rates during the day as compared to at night. That assertion cannot be made due to the small sample size (e.g., only 2 or 3 Blacks stopped in the daytime in Tables 11, 12 and 13) which limits the ability to draw firm conclusions. Again, we are puzzled as to why the CRG did not use the readily available larger data set, which would have overcome this problem of sample size.

F. Disparities in Post-Stop Outcomes

Post-stop outcomes offer the most reliable data on which to base assessments of racial disparities in traffic policing because once the driver has been stopped, officers have had an opportunity to form a perception of the driver's race. There are four post-stop outcomes considered in our study: tickets vs. warnings, arrest rates, search rates, and hit rates. The CRG also looks at these indicators. Both they and we find no difference in ticket vs. warning rates between White and Black drivers. Other results on post-stop outcomes, however, merit further discussion.

1. Arrest rates

The CRG report finds that Blacks are much more likely to be arrested than White drivers. The share of Black drivers arrested in Bennington in 2016 is 3.74% as compared to 0.78% of White drivers. Thus, according to CRG data, Blacks are arrested at a rate that is 4.7 times greater than White drivers (3.74%/0.78%). Clearly, the small sample size limits the ability to make statistical inferences, but we note that the CRG study, in concluding no evidence of racial disparities in traffic policing in Bennington, ignores a result that contradicts their conclusion. (Our study for a different time period showed a slightly higher arrest rate of White drivers as compared to Black drivers, 2.0% for Whites compared to 1.5% for Blacks).

2. Search Rates

In our study, we found the search rate of Black drivers in Bennington to be 10.5% and of Whites, 1.9%. Our data exclude searches based on a warrant. Recalling that the time period covered by our samples differs, CRG found that the Black search rate was 5.04% in 2016 and 0.68% for White drivers. Again, with the caveat that these are small sample sizes, the racial disparity in search rates is calculated by dividing the Black search rate by the White search rate. That disparity in our study is 5.6 compared to 4.7 in the CRG study. In other words, we found that Black drivers were 5.6 times more likely to be searched than White drivers from September 2014 through March 2016, while the CRG study finds that Black drivers are 4.7 times likely to be searched than White drivers in Bennington in 2016. Our results then are very similar, even though the time periods differ. This racial disparity in search rates is very wide in both of our studies, but the CRG study does not acknowledge this and instead concludes there are no racial disparities in traffic policing in Bennington.

3. Contraband (Hit Rate) Data

Researchers have sought to find a method to test for bias in racial disparities in traffic stops. One method is to compare the percentage of searches by race that result in contraband being found. The argument is that law enforcement officers are rational: they want to minimize fruitless searches. As a result, if police are over-searching drivers of one race, as evidenced by searches that do not result in contraband being found, they will recalibrate their search criteria so that the rate at which contraband is found is the same across all racial groups. As the CRG study notes, there are criticisms of this approach and so results should be viewed with caution.

We have two comments on the hit rate data in the CRG report. First, while this is no reflection on CRG, the issue of contraband data in and of itself is a problematic area in Vermont data collection. That is because the legislation does not require law enforcement to identify the type of contraband found. Other states do report the category of contraband found, and we strongly recommend that Vermont adopt this practice. The reason is as follows. In Vermont, contraband may be anything from a 16-year old driving with a pack of cigarettes, to an open container, to marijuana, to stolen goods, to heroin, cocaine and opioids. In the cases of less serious contraband, officers will issue a warning. In the most egregious cases, the driver is arrested.

In our analysis, we attempted to deal with the lack of specifics on the type of contraband found by calculating 3 separate hit rates: 1) for all searches by race, 2) for searches by race that resulted in a ticket or an arrest (thereby dropping searches that resulted in a warning), and 3) for searches by race that resulted in an arrest. Law enforcement officers (in personal conversation) frequently make the argument that racial disparities in search rates is based on their belief that drivers of color are transporting drugs to Vermont and they are thus likely to be searched more frequently. Were this the case, we would expect that the hit rate for drivers arrested subsequent to a search would be at least equal across racial groups if not higher for Blacks and Hispanics. The current reporting requirements of law enforcement agencies in Vermont do not allow us to test this hypothesis. In an effort to get at this issue, we asked the Vermont State Police (VSP) to provide us their data on types of contraband found in 2016 searches. We found that the searches that yielded contraband of heroin, cocaine and opioids, were all of White drivers (Seguino and Brooks 2018). No drivers of color were found with this category of drugs. It would improve analysis of racial disparities in traffic policing if all agencies were required to report the type of contraband found.

In the interim, we used the method of creating three hit rates, as described above. Unlike our approach, the CRG did not disaggregate hit rate data by outcome of the search. As such, their finding of a 100% hit rate for Black drivers and 90% hit rate for White drivers is opaque because it doesn't differentiate between hits with warnings and those with more serious consequences. (And of course, again, the sample size is very small and so we cannot make inferences about whether the hit rate differences are statistically significant). In contrast, in our study, we found Bennington hit rates of approximately 86% for Blacks and 73% for Whites in hits that resulted in a ticket or arrest. But in those searches in which contraband was found *and* the driver was arrested, we found that the hit rate for Blacks was *lower* than for White drivers (7.1% for Black drivers and 11.2% for White drivers). Since the White hit rate is higher than the Black hit rate, the results suggest that either Blacks were over-searched or Whites were under-searched. Neither our study nor the CRG study, however, has a sample size large enough to make statistical inferences on whether the disparity in Black-White hit rates is statistically significant. Were researchers to have access to all of Bennington's traffic stop data (from September 2014 through 2018), sample sizes would likely be more than adequate for such inferences.

4. Use of Regression Analysis to Control for Other Factors

The CRG report notes that it is useful to control for a variety of factors when assessing racial disparities in search and hit rates, using regression analysis. They argue, however, that there is not enough data from Bennington to conduct a regression analysis. Apart from the fact that more data is available than was used by CRG that might permit regression analysis of exclusively Bennington data, it is possible to get at this issue in another way. We were able to conduct an analysis (results are reported in Seguino and Brooks 2018) by combining all law enforcement agency data, using a dummy variable to account for search outcomes in individual agencies, including Bennington. In particular, we estimated the odds of being searched by race, controlling for age and gender of driver, time of day and day of week of the stop, and reason for the stop. This much larger dataset allows us to make inferences about racial disparities as well as the search behavior of individual agencies.

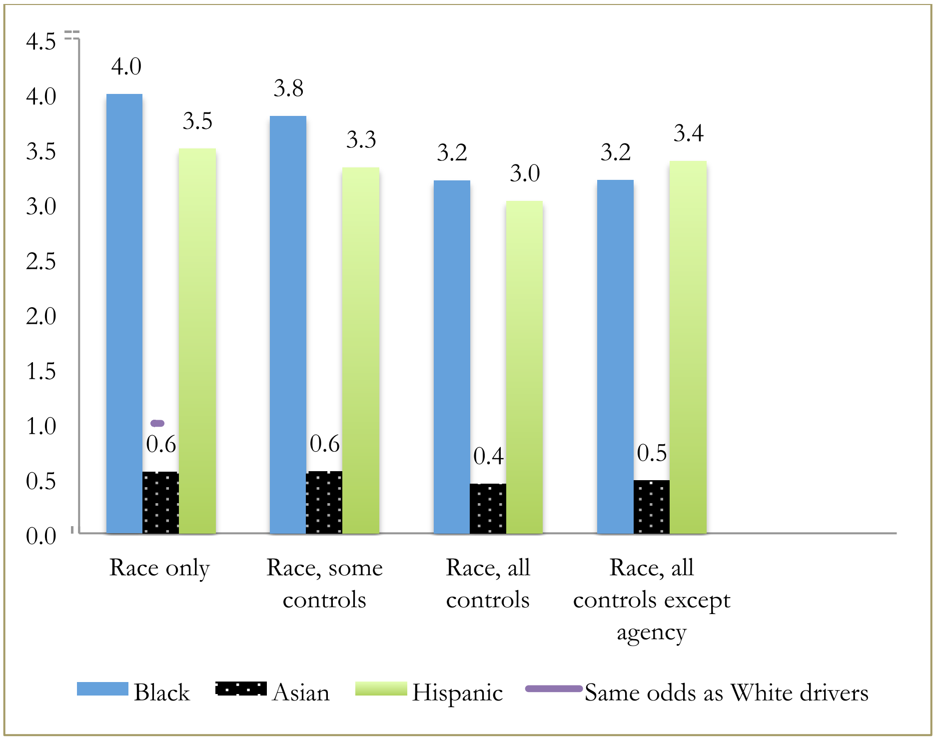
We ran several sets of regressions to account for the fact that some agencies failed to provide data on the gender and/or age of the driver as required by law. Our results were similar in the regressions that only controlled for reason for stop, day of week and time of stop to those that also included controls for the age and gender of the driver. We found that statewide, Black drivers were between 2.6 to 3.8 times more likely to be searched than White derivers. Figure 1, reported in Seguino and Brooks (2018), shows the odds of Black and Asian drivers being searched as compared to White drivers using statewide data for 2012-15.[2]

As noted, we ran several regressions to determine how various factors contribute to the odds that a driver will be searched: 1) one with race only as an explanatory variable, 2) a second with time of day, day of week, reason for stop, law enforcement agency, plus race, 3) a third that added controls for age and gender of drivers, and finally, 4) a regression with all control variables, dropping the agency as a control variable. In all cases, Black and Hispanic drivers are searched at about 3 times the rate of White drivers, while Asian drivers are about half as likely to be searched. The odds of Black drivers being searched at night was roughly 3.1 times greater than White drivers.

We also found that Bennington was 4 times more likely to search drivers of any race than Addison County Sheriff's Department, our baseline agency (Table 1 below). By way of comparison, Burlington was found to search drivers at 1.7 times the rate of Addison County, and Rutland 1.9 times the rate of Addison County. It is instructive that Bennington tends to search at a higher rate than many other Vermont agencies.

[2] Results were similar when we used only 2015 data.

Figure 1. Relative Odds of Search by Race of Minority as Compared to White Drivers, 2012-2015



Source: Seguino and Brooks (2018)

Note: The horizontal (purple) line indicates the situation of a non-White racial group having the same odds of being searched as White drivers. Columns that are above that bar indicate higher odds of a racial group being searched compared to White drivers, and below the bar indicates a lower probability of a search occurring for that racial group compared to White drivers.

III. RESPONSE TO CRG CRITIQUES OF SEGUINO AND BROOKS (2017)

A. Stop Rate Disparities and Benchmarks

To calculate stop rate disparities, analysts need a good measure of the driving population. All benchmarks are estimates of the probability that a driver from a specific racial group will be on the road in a jurisdiction at any given time. Researchers have used Census data, traffic observational surveys, not-at-fault accident data, among others, as estimates of the driving population. All of these are proxies, rather than actual measures of the driving population. As such, none of these approaches provides a perfect estimate. However, these benchmarks can provide a meaningful baseline to track trends over time.

Among the methods adopted, Census data is often used because of the low cost of accessing these data.[3] A preferable and reputable method used in our study is to use racial shares of not-at-fault accident data as a proxy for racial shares of the driving population. Although

[3] Census estimates of racial shares of the entire population and the population over the age of 16 yield very similar results.

some states do not collect race data in accident reports, Vermont does. A large amount of missing data by race raises concerns about this measure of racial shares of the driving population, and thus like other measures, is imperfect although for a different reason than the others. The CRG acknowledges that this is a good benchmark if missing data are reduced and they, like we, note the missing data problem. In the absence of better measures, however, a strategy that researchers use is to compare (imperfect) data sources to determine whether they yield similar results. Indeed, our results for Bennington yield virtually identical results of the Black driving population as the CRG report.

More specifically, while the CRG claims that our accident data for Bennington is unreliable, that approach gave us a 1.1% estimate for the Black driving population (compared to the Census data which yielded a result of 0.6% of the population). Based on that accident data estimate of the driving population, we reported in our study that Black drivers are 2.5 times more likely to be stopped than their share of the driving population. We used the accident data because it is more conservative than the Census data estimate (we would have had a Black stop rate of more than 4 times the White rate if we had used the Census data).

In the CRG's analysis, the author uses Census's Longitudinal Employer Household Dynamics (LEHD) data to estimate the commuting population, also a viable methodology (though as we note below, this approach too has weaknesses). Strikingly, the CRG's estimate of the Black driving population using LEHD data is 1.14 % (Tables 4 and 5), which rounds to 1.1%. This then is essentially *the same result we arrive at using not-at-fault accident data*. It is puzzling why the CRG report ignores that our two methodologies arrive at the same result for Blacks. Instead, they focus just on the rate of White stops compared to their estimate of the White population, drawing the conclusion that there is no stop rate disparity by race. (In fact, in Table 8 of their study, they drop the data on Black drivers).

It should also be pointed out that the CRG method itself has a notable weakness. They use the "Origin-Destination Employment Statistics" from the Census Bureau's LEHD data. This dataset is based on a sample of workers (employed or unemployed) who have paid into the insurance system, thus excluding those who are not employed in such jobs (and therefore excluding those who are self-employed, and the young and retired who may not be employed). In other words, this source of data excludes a wide swath of drivers and is thus not entirely representative of the driving population. The key point we make here is that *all benchmark* data have their limitations since they are only proxies for the driving population. That the accident data we used in our study and their LEHD data yielded the same population share for Black drivers is telling – both methods, though imperfect, yield similar results. Given that our methodology (the state's not-at-fault accident data) and CRG's (the LEHD database) yielded a similar estimate of the Black driving population, this provides strong evidence that Black drivers are indeed stopped at 2.5 times their share of the driving population in Bennington in the years covered by the data.

B. Erroneous Interpretations on Stop Rates

The CRG study erroneously reports our results on Black stop rates. While their report repeatedly says that we stated the Bennington Police Department stops Blacks at 250% *times* the rate that Whites are stopped (for example, see p. 3), instead we said that Blacks are stopped at a rate 2.5 times the rate that Whites are stopped in Bennington. Again, their comment is puzzling since our finding is almost exactly the same as what is found in their data—but they fail to point that out.

C. Erroneous Assertions on Duplicate Records

In cases of more than one outcome of a stop (for example, a driver may have been issued more than one ticket), the incident is recorded multiple times by many law enforcement agencies, one for each outcome. This could skew the results and erroneously contribute to data larger estimates of racial disparities if drivers of color were more likely to have more than one outcome per stop. We addressed that issue in our original report, and yet the CRG asserts that our results are skewed because we fail to remove duplicate records (p. 3 of CRG report). This is inaccurate. Specifically, we "de-duplicated" our data through a complex programming procedure, relying on incident numbers, and matching of age, gender, date of birth, and time of day to identify duplicates that were then removed.

D. Issues Raised Related to Data Quality

The CRG report raises an interesting issue with regard to the quality of the data on search rates and the rate at which contraband is found (p. 4). As they note, the data that law enforcement agencies have submitted include cases in which an incident report says "No search" but then "Contraband found." This is contradictory. It is an example of the errors in data entry. We meticulously combed the data to address these problems and made decisions on how to treat such inconsistencies. In this particular example, since contraband was found, it is indicative of a search having been conducted and an error in the officer's data entry.[4] We therefore counted the hit rather than discarding this information (as CRG did in its study). The overarching issue, we believe, is that greater efforts must be made to improve the quality of the data and we are hopeful that other law enforcement agencies will follow in the steps of the Vermont State Police, which has engaged in extensive training of its troopers with notable progress on data quality. Although this is a small point, we highlight this, as the CRG has critiqued the coding method we used. In such cases, they simply drop the observations where there is a contradiction. We don't believe this is a useful approach. This is an example of a gray area in the data that is best resolved by all those involved in data analysis of traffic stop data working together, rather than at cross-purposes to agree on a method to record such circumstances.

E. Other Errors in Report

The CRG report claims our study covers the period 2005 to 2015. This is inaccurate. Our study relies on data for 2011 through 2016, although the years of coverage vary by agency. While this may appear to be a minor error on the part of CRG in critiquing our study, it

[4] Two caveats are in order. VSP personnel have indicated that at least for the VSP, sometimes drivers are arrested and then contraband is found, thus "No search" is recorded. The number of instances in which we found "No search" but "Contraband found" was, however, relatively small, and among those, instances of arrest without searches were negligible.

raises concerns about the thoroughness with which they read our report and the accuracy of their understanding of that report.

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Table 1. The Odds of Being Searched by Race Relative to White Drivers, All Vermont, 2012-15

	Race only	Race and controls	Race and all controls	Race and all controls except agency
(predict)				
Black	3.994***	3.790***	3.210***	3.213***
	(0.208)	(0.203)	(0.189)	(0.186)
Asian	0.559***	0.562***	0.449***	0.478***
	(0.0939)	(0.0947)	(0.0860)	(0.0912)
Native American	2.829***	3.100***	3.427***	3.193***
	(0.909)	(1.003)	(1.123)	(1.044)
Hispanic	3.498***	3.326***	3.022***	3.387***
	(0.322)	(0.310)	(0.294)	(0.327)
Monday		0.920	0.947	0.978
		(0.0509)	(0.0557)	(0.0573)
Saturday		1.065	0.979	0.932
		(0.0563)	(0.0552)	(0.0522)
Sunday		1.050	0.950	0.938
		(0.0583)	(0.0563)	(0.0551)
Thursday		1.031	1.075	1.110*
		(0.0545)	(0.0603)	(0.0619)
Tuesday		0.963	0.981	1.007
		(0.0529)	(0.0579)	(0.0591)
Wednesday		0.947	1.010	1.038
		(0.0519)	(0.0586)	(0.0600)
Investigatory Stop		6.564***	5.978***	5.735***
		(0.390)	(0.389)	(0.359)
Suspicion of DWI		9.434***	8.637***	6.686***
		(1.219)	(1.175)	(0.890)
Unknown		3.508***	5.004***	4.491***
		(0.391)	(0.689)	(0.564)
Vehicle Equipment		1.599***	1.432***	1.479***
		(0.0569)	(0.0542)	(0.0543)
Barre City		0.796		
		(0.592)		
Barre Town		2.058**	1.488	
		(0.625)	(0.454)	
Bennington		4.241***		
		(1.042)		
Brandon		6.435***	4.082***	

	(1.659)	(1.070)
Brattleboro	0.777	0.664
	(0.238)	(0.204)
Bennington	-	-
Burlington	1.718**	1.087
	(0.403)	(0.257)
Colchester	2.423***	2.440**
	(0.611)	(0.907)
Essex	0.869	
	(0.273)	
Grand Isle	0.305**	0.252***
	(0.142)	(0.118)
Hinesburg	1.468	1.073
	(0.686)	(0.504)
Manchester	2.292***	1.593
	(0.692)	(0.486)
Middlebury	8.831***	5.405***
	(2.287)	(1.417)
Milton	1.263	0.896
	(0.374)	(0.266)
Montpelier	0.863	0.653
	(0.278)	(0.215)
Northfield	3.081***	
	(1.207)	
Randolph	4.602***	
	(1.912)	
Rutland	1.922***	1.358
	(0.466)	(0.333)
S. Burlington	1.016	
	(0.264)	
Springfield	1.306	1.106
	(0.357)	(0.304)
St. Albans	1.490	1.002
	(0.405)	(0.274)
St. Johnsbury	1.286	0.925
	(0.359)	(0.260)
UVM	1.829**	0.610
	(0.454)	(0.185)
VSP_Bradford	1.328	1.081
	(0.322)	(0.263)
VSP_Brattleboro	3.601***	2.972***
	(0.832)	(0.690)

VSP_Derby		0.172***	0.121***	
		(0.0757)	(0.0531)	
VSP_Headquarters 1		2.780***	2.811***	
		(0.646)	(0.656)	
VSP_Headquarters 2		6.570***	6.184***	
		(3.675)	(3.528)	
VSP_Middlesex		1.594**	1.217	
		(0.374)	(0.287)	
VSP_New Haven		3.076***	2.310***	
		(0.712)	(0.538)	
VSP_Rockingham		3.229***	2.639***	
		(0.747)	(0.613)	
VSP_Royalton		1.759**	1.304	
		(0.413)	(0.308)	
VSP_Rutland		1.620**	1.157	
		(0.385)	(0.277)	
VSP_Shaftsbury		2.896***	2.271***	
		(0.673)	(0.531)	
VSP_St. Albans		1.700**	1.106	
		(0.402)	(0.263)	
VSP_St. Johnsbury		0.864	0.573**	
		(0.222)	(0.148)	
VSP_Williston		3.243***	2.161***	
		(0.748)	(0.501)	
Vergennes		4.954***	3.214***	
		(1.353)	(0.888)	
Williston		4.229***	3.058***	
		(0.985)	(0.717)	
Winooski		2.838***		
		(0.708)		
Male			2.075***	2.088***
			(0.0806)	(0.0809)
Age			0.942***	0.943***
			(0.00148)	(0.00147)
Morning (4AM - Noon)			0.611***	0.649***
			(0.0308)	(0.0320)
Night (8PM - 4AM)			1.281***	1.273***
			(0.0462)	(0.0447)
Constant	0.0103***	0.00380***	0.0226***	0.0337***
	(0.000164)	(0.000859)	(0.00528)	(0.00235)

Observations	409,390	408,872	367,045	367,679

Note: One asterisk (*) indicates significance at the 10% level, two astierisks (**) indicates significance at the 5% level, and three asterisks (***) significance at the 1% level.