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The John F. Finn Institute
for Public Safety, Inc.

Traffic Stops by Suffolk County Police

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The John F. Finn Institute for Public Safety, Inc., is an independent, not-for-profit and non-partisan corporation, whose work is dedicated to the development of criminal justice strategies, programs, and practices that are effective, lawful, and procedurally fair, through the application of social science findings and methods. The Institute conducts social research on matters of public safety and security – crime, public disorder, and the management of criminal justice agencies and partnerships – in collaboration with municipal, county, state, and federal criminal justice agencies, and for their direct benefit. The findings of the Institute's research are also disseminated through other media to criminal justice professionals, academicians, elected public officials, and other interested parties, so that those findings may contribute to a broader body of knowledge about criminal justice and to the practical application of those findings in other settings.

The Finn Institute was established in 2007, building on a set of collaborative projects and relationships with criminal justice agencies dating to 1998. The first of those projects, for which we partnered with the Albany Police Department (APD), was initiated by John Finn, who was at that time the sergeant who commanded the APD's Juvenile Unit. Later promoted to lieutenant and assigned to the department's Administrative Services Bureau, he spearheaded efforts to implement problem-oriented policing, and to develop an institutional capability for analysis that would support problem-solving. The APD's capacity for applying social science methods and results thereupon expanded exponentially, based on Lt. Finn's appreciation for the value of research, his keen aptitude for analysis, and his vision of policing, which entailed the formulation of proactive, data-driven, and – as needed – unconventional strategies to address problems of public safety. Lt. Finn was fatally shot in the line of duty in 2003. The Institute that bears his name honors his life and career by fostering the more effective use of research and analysis within criminal justice agencies, just as Lt. Finn did in the APD.

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Introduction

In 2014, the Suffolk County Police Department (SCPD) entered into an agreement with the U.S. Department of Justice, which required that SCPD collect and analyze data on traffic stops. SCPD contracted with the Institute to conduct analysis of racial and ethnic disparities in traffic stops and post-stop outcomes. In this report, we summarize the findings of our analyses.

We first describe and assess the data on traffic stops on which the analyses are based. Then we summarize selected features of the traffic stops, including the SCPD units that made the stops, the reasons for stops, the temporal distributions of the stops (i.e., across days of the week and times of the day), and the characteristics of the drivers whose vehicles are stopped. We thereupon turn to the question of bias and the analytical challenges in drawing inferences about bias from stop data, as well as how those challenges have been addressed in previous studies of racial profiling. The findings concerning bias in the initial stop decisions by SCPD officers are then presented. We next consider various post-stop outcomes, first summarizing selected features of post-stop outcomes, then reviewing previous studies of post-stop outcomes and the analytical approaches that they have employed in an effort to detect bias, and finally, summarizing our findings concerning post-stop outcomes in SCPD stops.

Traffic Stop Data Collection and Data Quality

SCPD's effort to put into place a traffic stop data collection system, including the information technology infrastructure and the process for supervisory review to ensure that the data are complete, has been an implementation odyssey. In 2015, a "computer glitch" prevented users from identifying incomplete entries into the then-existing system, resulting in 7,748 incomplete records and a judgment that the data were of insufficient reliability for assessing stop patterns for bias.[1] This problem was largely resolved in 2016, but the scope of data collection was judged to be "inadequate to allow for the needed assessments of SCPD's enforcement practices."[2] SCPD determined that it would develop its own system, rather than rely on a system developed by an outside vendor, which was expected to be operational in early 2017.[3] The launch was delayed until August of 2017, when SCPD quickly discovered problems that prompted it to discontinue use that same day. A revamped infrastructure for data entry was tested in

[1] U.S. Department of Justice, *Compliance Status Assessment Report*, December 14, 2015, pp. 12-14.
[2] U.S. Department of Justice, *Third Report Assessing Settlement Agreement Compliance by Suffolk County Police Department*, April 18, 2016, pp. 7-8.
[3] U.S. Department of Justice, *Fourth Report Assessing Settlement Agreement Compliance by Suffolk County Police Department*, January 19, 2017, pp. 6-7.

January of 2018.[4] Finally, in late-2019, USDOJ raised a concern that the traffic stop data posted to the SCPD's website lacked data on the locations of traffic stops.[5]

SCPD provided to the Institute data on traffic stops conducted between March 5, 2018, and March 4, 2019.[6] The data file includes records on the driver and passengers (as applicable) in each stop.[7] Information on the date, time, and location of the stop are recorded, as well as the reason for the stop and the duration of the stop (recorded in terms of duration categories). Information on individual drivers and passengers include their sex, race/ethnicity, and (approximate) age.

The stop data are with a few exceptions complete. None of the records was missing data on the race/ethnicity, sex, or age of occupants, nor were any missing the information on disposition (e.g., ticket, warning). We found 86 records (of 146,320, or less than one-tenth of one percent) that were missing data on the duration of the stop, the count of tickets, and the use of force; all 86 involved stops conducted in March, 2018, the first month of data collection, including 60 by Highway Patrol units, 13 by precinct patrol, and 13 by precinct crime units. For three stops, no result for a vehicle search was entered; all three stops took place on March 6-7, the second and third days of data collection. For 48 stops, the data included records on two drivers. However, the make, model, and year of the vehicle were missing for all but a tiny fraction of the stops.

The location of stops proved to be an elusive datum. By SCPD policy, stop data are to be entered into a mobile data computer (MDC) or, if an MDC is unavailable, on a Traffic Stop Data Collection Worksheet for later entry.[8] It appears that collection through an MDC at the time of the stop locates the stop in terms of latitude and longitude, but later collection captures the latitude and longitude of the location at which the data are entered.[9] The location field is not completed in a standardized fashion that allows for later geo-coding.

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[4] U.S. Department of Justice, *Sixth Report Assessing Settlement Agreement Compliance by Suffolk County Police Department*, March 13, 2018, pp. 6-7.

[5] U.S. Department of Justice, *Eighth Report Assessing Settlement Agreement Compliance by Suffolk County Police Department*, December 18, 2019, pp. 6-7.

[6] The contract for this work, which specified a term ending December 31, 2019, was signed by the Institute's representative on April 23, 2019. The data file on traffic stops was delivered by SCPD on April 30, 2019. Work on the analysis commenced at that time, but work was suspended on September 9, 2019, when we learned that the contract had not been executed by Suffolk County. The contract for work during calendar 2019 was executed on February 14, 2020, and the amendment to extend the contract through calendar 2020 was executed on June 8, 2020.

[7] We note that one field in the data file, named 'IsValid,' identifies 178 records as not valid, and these records were removed for all analysis.

[8] Department General Order (DGO) 18-14, Traffic Stop Data Collection.

[9] The latitude and longitude information on 11,728 stops placed them at one of 19 locations, which included SCPD headquarters (4,442), other SCPD facilities (5,792), a fire department facility (524), and the Town of Huntington City Hall (61).

The field for SCPD sector appeared to be a largely but not completely reliable indicator of location, even at a level of geographic precision adequate for our analytic purposes. The sector field was empty for 22,609 stops. Some values for sectors (e.g., COPE2, CSU7) do not appear on an SCPD sector map. Most stops by highway patrol units included the unit number as the sector value, but for the analysis of post-stop outcomes, we needed to put stops in the context of the precinct sectors, for which data on crime were available. Consequently, we derived sector information as needed from the entered sector value, latitude and longitude, and the boundaries of highway patrol sectors, to form 39 blocks of contiguous sectors (4 to 7 per precinct), in order to minimize error in locating the stops.[10]

Patterns of Traffic Stops in Suffolk County

As we show below, more than 90 percent of the traffic stops by SCPD officers are effected by officers assigned to precinct patrol sections, precinct crime sections, or the Highway Patrol Bureau. We briefly describe these organizational units.

SCPD's patrols are organized into seven precincts. Four precincts each serve a township: Babylon, Huntington, Islip, and Smithtown are served by the first through fourth precincts, respectively. Brookhaven Town spans precincts five through seven. In addition to patrol units that engage in generalized patrol, each precinct has a precinct crime section, which "… is responsible for investigating most misdemeanor and violation offenses along with Domestic Incident complaints that occur within the confines of the precinct."[11] We note that the racial and ethnic composition of Suffolk County's towns varies, with the largest concentration of people of color in Islip and Babylon. See Table 1, below. (Precincts are shown in brackets. "Other" races include Asian, other Pacific Islander, American Indian, and multi-racial.)

The Highway Patrol Bureau encompasses several sections:[12]

- The Highway Enforcement Section patrols the Long Island Expressway (I-495) and the limited access portions of Sunrise Highway (Route 27) contained within the Police District.
- The Motorcycle Section is responsible for selective enforcement of Vehicle and Traffic Laws.

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[10] Contiguous sector blocks were formed by analyzing the cross-tabulations between the given sector and the mapped sector using GPS coordinates. High frequency pairings in the two sector variables, as well as municipal and geographic boundaries, were taken into consideration in order to produce blocks with minimal practical differences between sectors within blocks. All blocks lie within a single SCPD precinct. See Appendix A for a list of sector blocks and constituent sectors.

[11] The quoted passage appears on each precinct's web page, e.g., https://suffolkpd.org/Precincts/FirstPrecinct.aspx.

[12] This information is drawn from https://suffolkpd.org/SpecializedUnits/HighwayPatrolBureau.aspx.

- The Motor Carrier Safety Section enforces federal, state and local laws concerning commercial motor vehicles.
- The Selective Alcohol Fatality Enforcement Team (SAFE-T) enforces laws prohibiting driving while intoxicated.
- The Suffolk Intensified Traffic Enforcement (SITE) section conducts targeted enforcement in the high-speed corridors with high concentrations of fatalities, crashes, and aggressive drivers, and in other locations as designated by the Office of the Chief of Patrol or requested by precincts.

Table 1. Suffolk County Town and Precinct Populations: Racial/Ethnic Composition

	Population	% Non-Hispanic White	% Black	% Hispanic	% Other
Suffolk County	1,481,093	67.2	8.7	19.8	4.3
Babylon [1]	210,363	56.2	16.9	21.7	5.2
Huntington [2]	201,456	76.0	4.0	12.8	7.2
Islip [3]	330,914	55.0	10.5	31.3	3.2
Smithtown [4]	116,384	87.1	1.3	5.9	5.7
Brookhaven [5-7]	482,536	72.5	5.9	15.6	6.0

https://www.census.gov/quickfacts/fact/table/suffolkcountynewyork/PST045218

Two-thirds of the traffic stops are made by officers assigned to either precinct patrol or the precinct crime section, one-quarter by highway patrol units, and the remainder by other specialized units (see Table 2b). The seven different precincts' units are for the most part equally active in making traffic stops (see Table 2a), as stops are only somewhat lower in the fourth precinct and slightly higher in the sixth.

Tables 2a and 2b. Stop Frequencies by Precinct and Unit Type

2a. Precinct	Stops
1	12,522 (9.42%)
2	15,202 (11.44%)
3	15,315 (11.52%)
4	6,623 (4.98%)
5	10,957 (8.24%)
6	17,471 (13.15%)
7	12,142 (9.14%)
Total	90,232 (67.89%)

2b. Unit type	Stops
Precinct patrol section	75,267 (56.63%)
Precinct crime section	13,772 (10.36%)
Highway patrol	33,721 (25.37%)
Other	10,146 (7.63%)
Total	132,906

Reasons for Stops

The recorded reasons for stops vary across types of units (see Table 3). Slightly more than two-thirds of the stops by highway patrol units are for speeding or other moving violations. About one-fifth of the stops by precinct patrol units are for speeding or other moving violations; more than one-quarter are for equipment violations, and more than one-fifth for any of a variety of non-moving vehicle and traffic law violations. Very small fractions of stops by any of the types of units are for reasonable suspicion.[13]

Table 3. Reasons for Stops by Unit Type

	Unit Type			
Reason	Patrol %s	Crime %s	Highway %s	Other %s
Speeding	7.00	14.28	39.71	63.92
Red Light	2.69	1.94	0.41	0.49
Stop Sign	18.78	14.36	1.71	1.81
Other Moving Violation	13.95	14.18	30.18	15.19
Equipment Violation	27.15	17.77	4.88	5.79
Seatbelt	2.25	3.96	2.90	0.45
Cell Phone	4.29	8.95	8.65	3.29
Other V&T Law	22.48	22.58	11.28	8.69
BOLO	0.12	0.13	0.04	0.06
Reasonable Suspicion	1.27	1.84	0.24	0.31
Total	75,267	13,772	33,721	10,146

We see only some minor differences across precincts in the reasons for stops (see Table 4, below). One-fifth to one-third are for equipment violations, one-fifth to one-quarter for other vehicle and traffic law violations, and 5 to 10 percent for speeding.

Drivers Stopped

Table 5 summarizes information on the characteristics of drivers stopped by the different types of SCPD units. More than half of the drivers stopped by SCPD – 50 to 60 percent by each type of unit – are White. Hispanic drivers constitute slightly less than 20 to 25 percent of those stopped, and Black drivers represent slightly less than 20 percent of stopped drivers; each group is a smaller proportion of drivers stopped by highway patrol and a larger proportion of those stopped by precinct patrol. Overall, Black and Hispanic drivers are overrepresented relative to their shares of the Suffolk County population, while White drivers are underrepresented.

[13] SCPD also provided data on activations of license plate readers (LPRs), which appear to account at least partially for some of the stops. We have not yet had an opportunity to complete an analysis of LPR data.

Table 4. Reasons for Stops by Precinct.

	Precinct						
Reason	1 %s	2 %s	3 %s	4 %s	5 %s	6 %s	7 %s
Speeding	8.59	8.19	5.29	6.73	7.38	8.94	11.61
Red Light	2.89	3.37	2.10	2.78	2.89	2.40	1.73
Stop Sign	17.72	18.56	15.17	22.26	14.78	22.13	16.14
Other Moving Violation	15.19	16.26	10.70	17.42	13.08	14.6	12.40
Equipment Violation	26.14	27.45	32.48	21.82	23.98	19.16	28.10
Seatbelt	2.84	1.25	4.68	1.62	3.51	1.67	1.89
Cell Phone	2.77	5.56	4.72	4.92	9.16	4.97	3.13
Other V&T Law	21.35	18.47	22.62	21.58	23.92	25.12	23.60
BOLO	0.17	0.07	0.16	0.09	0.12	0.09	0.18
Reasonable Suspicion	2.35	0.82	2.09	0.79	1.18	0.92	1.20
Total	12,522	15,202	15,315	6,623	10,957	17,471	12,142

Table 5. Driver Characteristics by Unit Type

	Unit Type				
Race/ethnicity	Patrol %s	Crime %s	Highway %s	Other %s	All %s
White	49.94	50.70	61.63	55.27	53.39
Black	19.63	18.98	13.17	17.93	17.80
Hispanic	24.65	24.46	17.98	20.37	22.61
Asian	2.00	1.62	2.68	2.81	2.19
Other	3.78	4.23	4.54	3.62	4.01
Total	75,267	13,772	33,721	10,146	132,906
Age					
Under 16	0.09	0.11	0.04	0.13	0.08
16 to 25	26.71	25.49	18.44	25.42	24.38
26 to 35	29.09	30.70	28.63	31.12	29.30
36 to 45	19.57	20.32	22.07	19.89	20.31
46 to 55	14.99	14.66	18.39	14.65	15.79
56 to 65	7.40	7.16	9.16	6.93	7.79
Over 65	2.15	1.57	3.27	1.87	2.35
Total	75,267	13,772	33,721	10,146	132,906
Sex					
Male	67.12	65.74	69.00	73.30	67.80
Female	32.88	34.26	31.00	26.70	32.20
Total	75,267	13,772	33,721	10,146	132,906

Three-quarters of the drivers stopped are 16 to 45 years of age, though those stopped by highway patrol units tend to be older than those stopped by precinct units. Two-thirds of those stopped are men.

As expected, given the differences in the residential populations of the precincts, we see some variation in the racial/ethnic composition of the stopped population across precincts. A much larger proportion of drivers stopped in the third precinct are Hispanic, and a larger proportion of drivers stopped in the first precinct are Black. See Table 6.

Table 6. Driver Race/Ethnicity by Precinct

	Precinct							
Race/ethnicity	1 %s	2 %s	3 %s	4 %s	5 %s	6 %s	7 %s	All %s
White	36.57	51.02	23.89	61.09	60.6	63.67	59.62	49.92
Black	35.94	15.77	21.82	11.20	15.97	13.44	21.30	19.58
Hispanic	21.94	25.09	50.41	20.01	19.65	15.29	15.48	24.72
Asian	1.46	3.12	1.04	2.99	1.28	2.50	1.24	1.93
Other	4.10	5.01	2.84	4.71	2.50	5.11	2.36	3.85
Total	12,522	15,202	15,315	6,623	10,957	17,471	12,142	90,232

Black and Hispanic drivers are more likely than White drivers are to be stopped for equipment violations, while White drivers are more likely to be stopped for speeding. See Table 7.

Table 7. Reasons for Stops by Driver Race/Ethnicity

	Driver Race/Ethnicity				
Reason	White %s	Black %s	Hispanic %s	Asian %s	Other %s
Speeding	23.18	17.31	15.58	27.24	20.48
Red Light	1.92	1.45	2.05	2.20	1.76
Stop Sign	13.89	9.95	11.68	17.15	12.39
Other Moving Violation	18.16	17.82	17.56	21.72	21.92
Equipment Violation	15.26	24.03	24.22	13.93	17.27
Seatbelt	2.31	2.66	2.99	0.89	1.39
Cell Phone	6.98	3.48	5.13	4.43	5.09
Other V&T Law	17.46	21.44	19.63	12.14	18.77
BOLO	0.09	0.18	0.07	0.07	0.06
Reasonable Suspicion	0.76	1.69	1.09	0.24	0.88
Total	70,961	23,651	30,051	2,915	5,328

The racial/ethnic composition of stopped drivers varies hardly at all across days of the week (see Table 8), and very little by time of day (see Table 9, below).

Table 8. Driver Race/Ethnicity by Day of Week

	Day of Week						
Race/ethnicity	Mon	Tues	Wed	Thurs	Fri	Sat	Sun
White	53.53	54.18	51.26	54.14	53.96	54.48	50.92
Black	17.94	17.69	18.67	17.32	17.65	17.24	18.54
Hispanic	22.17	21.86	24.02	22.28	22.14	22.21	24.47
Asian	2.18	2.33	2.30	2.19	2.27	2.09	2.02
Other	4.18	3.95	3.75	4.07	3.99	3.98	4.05
Total	18,823	20,837	22,035	21,658	20,067	16,040	13,446

Table 9. Driver Race/Ethnicity by Time of Day

	Time of Day					
Race/ethnicity	07:00-11:59	12:00-15:59	16:00-17:59	18:00-21:59	22:00-02:59	03:00-06:59
White	55.22	54.32	54.15	52.43	49.90	54.10
Black	16.91	17.65	16.29	18.18	20.49	15.73
Hispanic	21.90	22.11	23.97	22.78	22.50	24.64
Asian	2.18	1.95	1.90	2.46	2.48	2.04
Other	3.78	3.97	3.68	4.16	4.63	3.49
Total	38,015	23,748	19,825	19,586	26,200	5,532

Bias in Traffic Stops

Long before the phrase "racial profiling" came into widespread use in the 1990s, social scientists had extensively analyzed patterns of behavior by police and other criminal justice actors for evidence of racial bias. For example, a substantial volume of empirical evidence has accumulated on the extent to which police arrest decisions and uses of force are influenced by the race of suspected offenders.[14] With the attention directed toward the application of drug courier profiles in highway traffic enforcement in the 1990s, and the ensuing nation-wide concern with racial disparities in traffic and other stops, countless analyses have been conducted to assess the use of racial profiling by state and local police agencies. Some studies have been federally supported and scientifically rigorous.[15] Some analyses have been conducted in connection with litigation. Many inquiries have been undertaken at the behest of individual municipalities, and they exhibit a wide range of methodological sophistication.

A key feature of the better analyses of racial profiling is the recognition of the distinction between racial disparity and racial bias, and the implications of this

[14] For an authoritative summary, see National Research Council, *Fairness and Effectiveness in Policing*, especially pp. 122-126.

[15] See, for example, William R. Smith, Donald Tomaskovic-Devey, Matthew T. Zingraff, H. Marcinda Mason, Patricia Y. Warren, and Cynthia Pfaff Wright, *The North Carolina Highway Traffic Study*, Report to the National Institute of Justice (Raleigh: North Carolina State University, 2003).

distinction for analytical strategies. Disparities can arise for a host of reasons, including especially differences in the prevalence or frequency of criminal offending; race and ethnicity in 21st century America are associated with social and economic factors that yield differential patterns of many behaviors. As the National Academies of Sciences, Engineering, and Mathematics (NASEM) Committee on Proactive Policing observed:

> … if non-White people are more likely to commit criminal offenses, racial disparities in police-citizen interactions are likely to occur. Earlier reviews of the empirical literature did indeed document relatively higher offending rates among Black people in the United States (Sampson and Lauritsen, 1997; Tonry, 1995), rates that were likely influenced by a range of factors known to increase crime, including differences in income, education, social networks, discrimination, neighborhood characteristics, and many others. More recently, O'Flaherty (2015, Chapter 11) reviewed empirical trends from homicide statistics and victimization surveys, which revealed a higher offending rate among Black people for homicide and robbery. Hence, a proactive effort to combat robbery may generate a racial disparity in arrest rates to the extent that members of one group commit this offense at a higher rate than the comparison group.[16]

In such an environment, even bias-free enforcement could lead to racial or ethnic disparities. Thus it is necessary in analyzing patterns of enforcement to hold constant the factors that legitimately shape enforcement decisions, such as the seriousness of the offense and the strength of the evidence of wrong-doing (with respect to arrest decisions) or the resistance offered by a citizen (with respect to the use of force).

Detecting *bias* – and not merely disparities – in police officers' decisions to stop motorists or pedestrians is particularly difficult, posing analytical challenges that are not confronted in many studies of arrest or the use of force. Direct comparisons can be drawn between those who are arrested and those who are not when trained observers accompany patrol officers on sampled tours of duty and record information about the suspected offenders whom police encounter, only some of whom are arrested.. If the data collection protocol is a sound one that captures the legal factors that are known to be potentially relevant, then statistical controls can be applied in the analysis of the data to better isolate the effects of race from those of other factors with which race might be correlated. The logic of the analytical strategy is this: legal factors that properly influence discretionary choices represent a "prescriptive ideal" for officers' behavior, and so long as the data allow us to statistically control for these legal factors in an analysis of behavior, we can estimate the influence of non-legal (or "extra-legal") factors as deviations from that ideal.[17] The hypothetical conditions under which only legal factors affect police behavior form a benchmark, which can be statistically approximated. This

[16] National Academies of Sciences, Engineering, and Medicine, *Proactive Policing: Effects on Crime and Communities* (Washington, DC: The National Academies Press, 2017), p. 7-19.

[17] Thomas J. Bernard and Robin Shepard Engel, "Criminal Justice Theory," *Justice Quarterly* 18 (2001): 1-30.

kind of analysis is feasible because it allows, for instance, the analyst to describe the pool of suspected offenders from among whom the arrestees are drawn by police, and analyze the features of the incidents in which police and suspects interact.

The ideal benchmark in analyses of vehicle or pedestrian stops would likewise represent the prescriptive ideal, deviations from which are interpreted as improper influences on police decisions to stop. Such a benchmark would describe the population whose behavior would form legitimate grounds for a stop: violations of the law or actions that otherwise arouse reasonable, articulable suspicion. Let us call it the violator population for convenience, recognizing that it encompasses not only violators but also people whose behavior meets a constitutionally acceptable standard for police intervention.

When police are mandated to record information about the people whom they stop, analysts can describe the composition of the stopped population: their race and ethnicity, sex, and age. But analysts cannot so readily describe the population of people whom officers could legitimately stop but did not stop, and therefore cannot analyze stops in the way that arrests are analyzed to statistically remove the effects of legal factors. This is the commonly described “benchmark” or “denominator” problem in analyses of racial profiling. Neither the data that reside in police records systems nor data that could be collected economically can provide a direct measure of the violator population, so we have to rely on approximations. Some such approximations are more credible and valid on their face than others.

It would be difficult to overstate the importance of valid, credible benchmarks in analyzing data on police stops for evidence of racial bias. A host of factors other than racial bias – some organizational, such as the allocation of patrol resources across police beats, and some individual – may affect the number of stops conducted by police and their distribution across social space. Any analysis that purports to estimate the magnitude of the effect of citizens’ race or ethnicity on police enforcement actions – including the initial decision to stop – must credibly control for factors that would legitimately affect those actions and that are likely to be associated with race/ethnicity. The omission of such controls is liable to produce inflated estimates of the effect of race/ethnicity and erroneous inferences about the role of bias in police enforcement.

Many attempts have been made to form benchmarks that approximate the racial and ethnic composition of the violator population. The simplest and easiest approach to this problem is to compare those who are stopped to the residential population of the surrounding jurisdiction. This approach suffers from many shortcomings, however, which are likely to lead to erroneous inferences about bias. Motorists in any jurisdiction at any time may be non-resident commuters or shoppers, for example. Conversely, some of a jurisdiction’s residents may not drive or, if they do, not drive very often. The residential population tends to diverge a great deal from the actual population potentially exposed to stops by police.[18] Tillyer, Engel and Wooldredge observe that "While there is some consensus in the research community that residential census populations are the least reliable of the benchmarks available, there is no such consensus regarding the validity of other techniques."[19]

Other approaches attempt to take better account of the driving population or, more specifically, the violator population. Alpert, Dunham, and Smith used information on not-at-fault drivers in two-vehicle crashes to estimate the racial composition of the driving population.[20] This approach requires a corollary assumption that drivers of different races and ethnicities are equally likely to violate traffic laws or otherwise attract the legitimate suspicion of police. John Lamberth conducted "rolling surveys" that tabulated the race of drivers who exceeded the speed limit by at least 5 miles per hour on the New Jersey turnpike; nearly all drivers were, by that standard, violators.[21] The utility of rolling surveys, applying a low threshold for speeding violations, is called into question by the findings of James Lange and his colleagues, who found that Blacks were overrepresented among the drivers exceeding the speed limit by at least 15 miles per hour. In their study, the composition of the stopped population closely resembled the population of these more serious violators.[22]

Veil-of-Darkness Benchmark

The "veil-of-darkness" method, devised by Jeffrey Grogger and Greg Ridgeway, is an innovative and feasible approach to forming a benchmark for analyses of vehicle stops.[23] The basic idea is to use changes in natural lighting to establish a benchmark, on the assumption that after dark, police officers suffer a degraded ability to detect motorists' race. The pattern of stops during darkness represents the presumptively more race-neutral benchmark against which the pattern of stops during daytime can be compared. It is not necessary to suppose that police cannot ascertain drivers' race at all

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[18] Geoffrey Alpert, Michael Smith, and Roger Dunham, "Toward a Better Benchmark: Assessing the Utility of Not-at-Fault Traffic Crash Data in Racial Profiling Research," *Justice Research and Policy* 6 (2004): 43-70. Greg Ridgeway and John MacDonald, "Methods for Assessing Racially Biased Policing," in Stephen K. Rice and Michael D. White (eds), Race, Ethnicity, and Policing: New and Essential Readings (New York: NYU Press, 2010). Robin Engel, Michael Smith, and Frank Cullen, "Race, Place, and Drug Enforcement," *Criminology & Public Policy* 11 (2012): 603-635.

[19] Rob Tillyer, Robin S. Engel, and John Wooldredge, "The Intersection of Racial Profiling and the Law," *Journal of Criminal Justice* 36 (2008): 138-53, p. 143.

[20] See Geoffrey P. Alpert, Roger G. Dunham, and Michael R. Smith, "Investigating Racial Profiling by the Miami-Dade Police Department: A Multimethod Approach," *Criminology & Public Policy* 6 (2007): 22–55.

[21] John Lamberth, *A Report to the ACLU* (New York: American Civil Liberties Union, 1996).

[22] James E. Lange, Mark B. Johnson, and Robert B. Voas, "Testing the Racial Profiling Hypothesis for Seemingly Disparate Traffic Stops on the New Jersey Turnpike," *Justice Quarterly* 22 (2005): 193-223.

[23] Jeffrey Grogger and Greg Ridgeway, "Testing for Racial Profiling in Traffic Stops from Behind a Veil of Darkness," *Journal of the American Statistical Association* 101 (2006): 878-887.

without natural lighting, nor is it necessary to assume that police can in every case determine drivers' race in daylight; it is necessary only to presume that officers are less able to detect the race of the motorists whom they stop in darkness than in daylight.

The analysis turns on the estimated likelihood that a Black person would be stopped, relative to that of others, in daylight rather than darkness. A binary daylight variable is included in a regression model that also controls for factors that are likely associated with the composition of the driving population at any given time – time of day or season of the year. The analysis that the veil-of-darkness method prescribes is limited to stops that occur "near the boundary of daylight and darkness," in what has been called the "inter-twilight" period. This limitation is imposed to ensure that differences in officers' decisions to stop are not confounded with changes in the composition of the driving (and violator) population across the hours of the day. To better ensure that the results are not affected by seasonal variation in the driving population, the analysis may be confined to the periods – typically 30 days – immediately before and after the annual switches to/from daylight savings time (DST).

The coefficient associated with the binary daylight/darkness variable is of primary interest, and for ease of interpretation the coefficient is converted to a more intuitively interpretable odds ratio or relative risk ratio. A ratio of 1.0 represents even odds or risk of a Black person being stopped in daylight or darkness: no difference between daylight and darkness in the estimated likelihood that a Black person would be stopped, other things being equal, and thus no evidence of bias in stops. A ratio of 1.0 also represents the "null hypothesis" of no difference. The proposition that police are biased against Blacks in their stops would be confirmed with evidence that the odds or risk of a Black person being stopped in daylight is greater than the odds or risk of a Black person being stopped in darkness – that is, a ratio greater than 1.0. By the logic of null hypothesis significance testing, we estimate the 95 percent confidence interval around the point estimate of the risk ratio, and we reject the null hypothesis of no difference (i.e., no bias) when the lower end of the confidence interval is greater than 1.0. Then we may say that the difference is "statistically significant" – that is, a difference of such magnitude that it is likely to occur by chance less than one in twenty times.[24]

To our knowledge, the veil-of-darkness method has been applied in analyses of stops in nine cities: Oakland, California; Cincinnati, Ohio; Minneapolis, Minnesota; Syracuse, New York; San Diego, California; Milwaukee, Wisconsin; and four North Carolina cities – Durham, Raleigh, Greensboro, and Fayetteville. [25] It has also been used

[24] The same logic is applied when different analytic strategies are applied and the statistic in question is a regression coefficient: we reject the null hypothesis of no bias when the statistic is sufficiently reliable that we can say with confidence that it is different from zero. Then we can appropriately consider the magnitude of the estimated effect or difference.

[25] On Oakland, see Oakland Police Department, *Cooperative Strategies to Reduce Racial Profiling: A Technical Guide* (Santa Monica, Cal.: RAND Corporation, 2004), pp. 40-43; and Grogger and Ridgeway,

to analyze stop patterns across the state of Connecticut.[26] One recent study applied the veil-of-darkness method in analyzing approximately 95 million traffic stops recorded by 21 state patrol agencies and 35 municipal police departments between 2011 and 2018.[27] Some analyses have produced evidence that is consistent with a pattern of bias, while other analyses have not, suggesting that the method differentiates between disparity due to bias and disparity attributable only to other forces.

Ritter and Bael found substantively and statistically significant differences in the probabilities with which Blacks and Latinos were stopped by Minneapolis police in daylight rather than darkness, and the differences were uniformly consistent with the racial profiling proposition.[28] Ross and his colleagues found in some Connecticut cities that minority drivers were more likely to be stopped in daylight.[29] Pierson, et al. found evidence suggesting bias in the 56 agencies whose stops they analyzed.[30] The analysis of stops by Durham (NC) police revealed that Blacks were 12 percent more likely to be stopped during daylight.[31]

Other studies have failed to detect bias. The Oakland Police Department found that Blacks were somewhat *less* likely to be stopped during the day, contrary to the pattern that would be observed if officers engaged in racial profiling.[32] Analyzing the

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"Testing for Racial Profiling in Traffic Stops from Behind a Veil of Darkness." On Cincinnati, see Greg Ridgeway, *Cincinnati Police Department Traffic Stops: Applying RAND's Framework to Analyze Racial Disparities* (Santa Monica, CA: RAND Corporation, 2009). On Minneapolis, see Joseph A. Ritter and David Bael, "Detecting Racial Profiling in Minneapolis Traffic Stops: A New Approach," *CURA Reporter* (2009): 11-17. On Syracuse, see Robert E. Worden, Sarah J. McLean and Andrew P. Wheeler, "Testing for Racial Profiling with the Veil-of-Darkness Method," *Police Quarterly* 15 (2012): 92-111. On San Diego, see Joshua Chanin, Megan Welsh, Dana Nurge, and Stuart Henry, *Traffic Enforcement in San Diego, California: An Analysis of SDPD Vehicle Stops in 2014 and 2015* (San Diego State University, 2016). On the North Carolina cities, see four studies, all by Travis Taniguchi, Josh Hendrix, Brian Aagaard, Kevin Strom, Alison Levin-Rector, and Stephanie Zimmer: *Exploring Racial Disproportionality in Traffic Stops Conducted by the Durham Police Department*; *A Test of Racial Disproportionality in Traffic Stops Conducted by the Fayetteville Police Department*; *A Test of Racial Disproportionality in Traffic Stops Conducted by the Greensboro Police Department; A Test of Racial Disproportionality in Traffic Stops Conducted by the Raleigh Police Department (*Research Triangle Park, NC: RTI International).

[26] Matthew B. Ross, James Fazzalaro, Ken Barone, and Jesse Kalinoski, *State of Connecticut Traffic Stop Data Analysis and Findings, 2014-15* (Central Connecticut State University, 2016).

[27] Emma Pierson, Camelia Simoiu, Jan Overgoor, Sam Corbett-Davies, Daniel Jenson, Amy Shoemaker, Vignesh Ramachandran, Phoebe Barghouty, Cheryl Phillips, Ravi Shroff, and Sharad Goel, 2020. "A Large-Scale Analysis of Racial Disparities in Police Stops across the United States," *Nature Human Behavior* 4: 736-745.

[28] Ritter and Bael, "Detecting Racial Profiling in Minneapolis Traffic Stops: A New Approach."

[29] Ross, et al., *State of Connecticut Traffic Stop Data Analysis and Findings, 2014-15*.

[30] Pierson, et al., "A Large-Scale Analysis of Racial Disparities in Police Stops across the United States."

[31] Taniguchi, et al., *Exploring Racial Disproportionality in Traffic Stops Conducted by the Durham Police Department*.

[32] Oakland Police Department, *Cooperative Strategies to Reduce Racial Profiling*.

same Oakland data, Grogger and Ridgeway likewise found no evidence of racial bias.[33] None of Ridgeway's analyses yielded evidence of racial profiling in Cincinnati.[34] Analyses of stops by Syracuse police yielded results consistent with the conclusion that Syracuse police have not exhibited racial bias in making vehicle stops.[35] In three of the four North Carolina cities scrutinized by Taniguchi and his colleagues, no evidence of bias was reported.[36] Findings in San Diego were mixed: some analyses detected evidence of bias in 2014 but not in 2015, and other analyses yielded no evidence of bias.[37] A veil-of-darkness analysis of vehicle stops by the Milwaukee police was conducted by a team of consultants operating under the auspices of the erstwhile Collaborative Reform Initiative of the Office of Community Oriented Policing Services (COPS).[38] They reportedly analyzed vehicle stops in 2013-2015, focusing on the subset of stops conducted thirty days before and after the DST switches. Their results did not support the rejection of the null hypothesis of no bias: the lower bound of the confidence intervals around the point estimate of the odds ratio was below 1.0 each year and for all three years combined.

Critiques

The veil-of-darkness method is not without potential drawbacks; no benchmark is perfect. One critique concerns the extent to which artificial lighting reduces the difference between daylight and darkness in the visibility of drivers' characteristics.[39] Another critique is based on the hypothesis that minority drivers adapt their driving behavior during daylight to reduce their susceptibility to being stopped.[40]

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[33] Grogger and Ridgeway, "Testing for Racial Profiling in Traffic Stops from Behind a Veil of Darkness."
[34] Ridgeway, *Cincinnati Police Department Traffic Stops*.
[35] Worden, et al., "Testing for Racial Profiling with the Veil-of-Darkness Method."
[36] Taniguchi, et al., *A Test of Racial Disproportionality in Traffic Stops Conducted by the Fayetteville Police Department*; *A Test of Racial Disproportionality in Traffic Stops Conducted by the Greensboro Police Department; A Test of Racial Disproportionality in Traffic Stops Conducted by the Raleigh Police Department.*
[37] Chanin, *et al.*, *Traffic Enforcement in San Diego, California*.
[38] *Collaborative Reform Initiative Milwaukee Police Department Assessment Report*. A draft of the report was made available to the public by the *Milwaukee Journal-Sentinel*: Ashley Luthern, "Community Leaders Push for Action on Milwaukee Police Reform Recommendations," October 24, 2017, https://graphics.jsonline.com/jsi_news/documents/doj_draftmpdreport.pdf.
[39] William C. Horrace and Shawn M. Rohlin, 2016. "How Dark is Dark? Bright Lights, Big City, Racial Profiling," *Review of Economics and Statistics* 98: 226-232.
[40] Jesse Kalinowski, Stephen L. Ross, and Matthew B. Ross, 2017. "Endogenous Driving Behavior in Veil of Darkness Test for Racial Profiling." Working Paper, Human Capital and Economic Opportunity Global Working Group, University of Chicago. Michael R. Smith, Robert Tillyer, Caleb Lloyd, and Matt Petrocelli, 2019. "Benchmarking Disparities in Police Stops: A Comparative Application of 2nd and 3rd Generation Techniques," *Justice Quarterly* (advance online publication).

Notwithstanding these critiques, we believe that the veil-of-darkness test of bias in vehicle stops is the best (and most economical) benchmark available.[41] Neil and Winship recently completed a review of the methodological challenges in detecting racial discrimination, and among their recommendations, they counsel "exploiting exogeneity" (such as changes in daylight), which they illustrate with the veil-of-darkness method.[42]

Analysis of Traffic Stops in Suffolk County

In order to execute the veil-of-darkness analysis of SCPD traffic stops, we first established the temporal boundaries of the inter-twilight period. The earliest and latest times of civil twilight, defined as when the sun reaches 6° below the horizon, are not the same across the expanse of Suffolk County, however.[43] Thus these times of day were identified for each of seven different zones, separated by longitude.[44] The earliest time, on December 6, 2018, in the easternmost part of the SCPD police district, was 4:54 p.m., and the latest time, on June 28, 2018, in the westernmost part of the police district, was 9:04 p.m. We also note that the spring switch to daylight savings time occurred on March 11, 2018, and the fall switch from daylight savings was on November 4, 2018.

First we describe the features of traffic stops in the inter-twilight period, noting the respects in which they differ from the larger population of stops, as they were summarized above. Then we present the results of the veil-of-darkness analyses.

Patterns of Inter-Twilight Stops

Stops in the inter-twilight period were made disproportionately by precinct patrol units, which accounted for more than 80 percent of the inter-twilight stops. Precinct crime sections were responsible for a small fraction of stops at these times of day, and

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[41] Smith, et al. report that, in San Jose, citation rates varied by driver race and, among Blacks, across hours of the day, consistent with the hypothesis that Blacks adjusted their driving during the day to reduce their susceptibility to being stopped. See "Benchmarking Disparities in Police Stops," p. 13. In Suffolk County, citation rates by race and time of day do not exhibit such variation.

[42] Roland Neil and Christopher Winship, "Methodological Challenges and Opportunities in Testing for Racial Discrimination," *Annual Review of Criminology* 2 (2019): 73–98.

[43] Civil twilight times were obtained using the R package "suncalc." A test to assess the accuracy of the times provided by "suncalc" was conducted by comparing them to civil twilight times obtained from the National Oceanic and Atmospheric Administration (NOAA) for Riverhead, NY (40.916667, -72.666667) in 2018. The mean absolute difference in times was 1.3 minutes, which is largely attributable to the fact that NOAA times are rounded to the minute, while "suncalc" provides times including seconds. Benoit Thieurmel and Achraf Elmarhraoui (2019). suncalc: Compute Sun Position, Sunlight Phases, Moon Position and Lunar Phase. R package version 0.5.0. https://CRAN.R-project.org/package=suncalc.

[44] The seven zones were marked by the following longitudes: 71.97, 72.2582, 72.5462, 72.8343, 73.1224, 73.4105.

highway patrol units accounted for about one in seven stops (though they accounted for one in four across all hours of the day). See Table 10b, below. The distribution of inter-twilight stops across precincts was quite similar to that for all stops: highest in precincts 2, 3, and 6, and lowest in the fourth precinct.

Table 10a-10b. Stop Frequencies by Precinct and Unit Type: Inter-twilight Period

10a. Precinct	Stops
1	2,424 (15.37%)
2	2,606 (16.52%)
3	2,225 (14.1%)
4	960 (6.09%)
5	1,435 (9.1%)
6	2,064 (13.08%)
7	1,839 (11.66%)
Total	13,553 (85.91%)

10b. Unit type	Stops
Precinct patrol section	13,033 82.61%
Precinct crime section	320 2.03%
Highway patrol	2,223 14.09%
Other	200 1.27%
Total	15,776

The reasons for inter-twilight stops by precinct patrol units were, in the aggregate, very similar to precinct patrol stops overall. The small number of inter-twilight stops by precinct crime units were disproportionately for speeding and stop sign violations. Fewer inter-twilight stops by highway patrol units were for speeding. See Table 11.

Table 11. Reasons for Stops by Unit Type: Inter-twilight Period

	Unit Type			
Reason	Patrol	Crime	Highway	Other
Speeding	4.63%	31.56%	24.61%	11.00%
Red Light	2.29	0.31	0.81	1.50
Stop Sign	20.71	22.81	6.25	23.00
Other Moving Violation	13.95	10.00	34.68	20.50
Equipment Violation	26.83	13.75	6.12	19.00
Seatbelt	2.11	1.56	6.79	3.50
Cell Phone	4.01	3.75	11.11	5.50
Other V&T Law	23.83	13.44	9.63	14.00
BOLO	0.1	NA	NA	NA
Reasonable Suspicion	1.53	2.81	NA	2.00
Total	13,033	320	2,223	200

The racial/ethnic composition of drivers stopped in the inter-twilight period is, overall, comparable to that of the population of drivers stopped (see the rightmost column of Table 12, below, compared to Table 5, on page 6). Proportionately fewer Whites were stopped by precinct crime section units in the inter-twilight period, and proportionately more Hispanics were stopped by highway patrol units. Precinct by precinct, the racial/ethnic composition of drivers stopped in the inter-twilight period parallels the composition of all drivers stopped at any time of day (compare Table 13 to Table 6, on page 7).

Table 12. Driver Race/Ethnicity by Unit Type: Inter-twilight Period

	Unit Type				
Race/ethnicity	Patrol	Crime	Highway	Other	All
White	50.95%	42.81%	59.6%	57.5%	52.09%
Black	18.71	23.12	12.01	11.50	17.77
Hispanic	24.74	25.62	22.22	25.00	24.40
Asian	2.15	4.69	2.11	1.50	2.19
Other	3.45	3.75	4.05	4.50	3.56
Total	13,033	320	2,223	200	15,776

Table 13. Driver Race/Ethnicity by Precinct: Inter-twilight Period

	Precinct							
Race/ethnicity	1	2	3	4	5	6	7	All
White	37.95%	51.61%	26.7%	65.42%	60.49%	64.87%	65.14%	50.85%
Black	34.65	14.35	21.03	8.54	14.63	12.21	16.86	18.71
Hispanic	21.66	25.25	49.08	18.75	21.81	15.6	14.46	24.76
Asian	1.65	3.72	0.99	3.44	1.46	3.05	1.2	2.2
Other	4.08	5.07	2.2	3.85	1.6	4.26	2.34	3.48
Total	2,424	2,606	2,225	960	1,435	2,064	1,839	13,553

Speeding was a less prevalent reason for inter-twilight stops across all categories of driver race/ethnicity, with correspondingly more stops for stop sign and equipment violations. See Table 14, below.

Driver race/ethnicity by day of week in the inter-twilight period was similar to that overall, but that in the inter-twilight period, proportionately fewer White drivers were stopped on weekend days. See Table 15, below.

Table 14. Reasons for Stops by Driver Race/Ethnicity: Inter-twilight Period

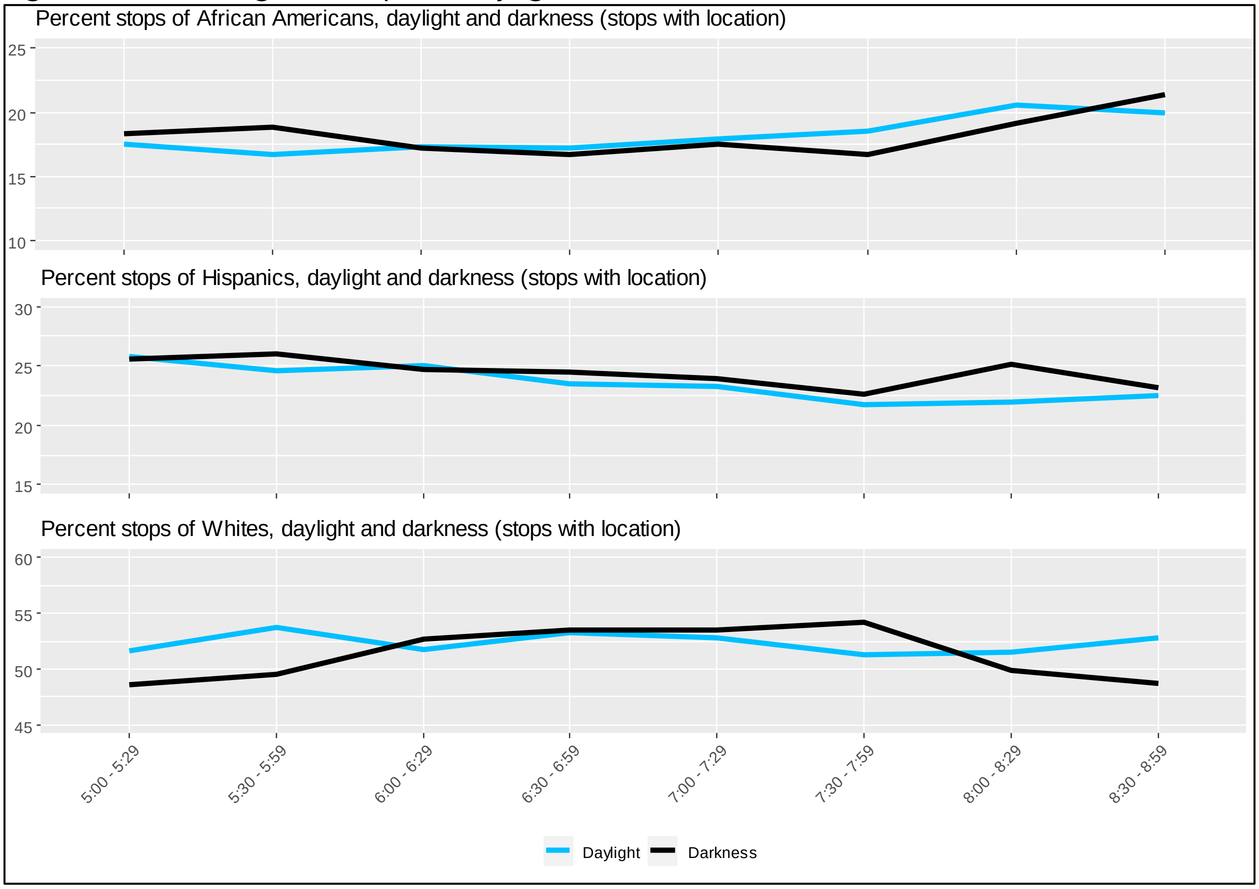
	Driver Race/Ethnicity				
Reason	White	Black	Hispanic	Asian	Other
Speeding	9.24%	5.67%	7.17%	8.99%	8.56%
Red Light	2.25	1.46	1.82	4.06	1.96
Stop Sign	21.76	13.31	15.61	27.54	17.83
Other Moving Violation	16.34	17.09	17.35	19.71	18.54
Equipment Violation	19.78	29.43	27.71	19.42	23.35
Seatbelt	2.40	2.93	3.66	1.16	2.50
Cell Phone	5.84	3.57	4.65	3.48	3.92
Other V&T Law	21.43	24.12	20.23	15.07	21.93
BOLO	0.10	0.11	0.03	NA	0.18
Reasonable Suspicion	0.86	2.32	1.77	0.58	1.25
Total	8,217	2,803	3,850	345	561

Table 15. Driver Race/Ethnicity by Day of Week: Inter-twilight Period

	Day of Week						
Race/ethnicity	Mon	Tues	Wed	Thurs	Fri	Sat	Sun
White	54.22%	54.99%	52.81%	52.35%	52.25%	48.55%	47.41%
Black	17.59	16.28	17.96	16.48	17.67	18.75	20.64
Hispanic	22.67	23.39	23.62	25.63	23.59	26.9	25.89
Asian	1.97	1.6	2.43	2.37	2.65	2.01	2.33
Other	3.55	3.74	3.18	3.16	3.84	3.78	3.73
Total	2,536	2,433	2,388	2,403	2,264	2,037	1,715

Overall, the proportions of stops that Black, Hispanic, and White drivers constituted, respectively, did not vary much across daylight and darkness in each block of time in the inter-twilight period (see Figure 1).

Figure 1: Percentage of Stops in Daylight/Darkness



Veil-of-Darkness Findings

Statistical analysis was done using multinomial logistic regression with a trichotomous outcome denoting driver race: Black, Hispanic, or – the reference category – non-Hispanic White. (Some models include Asian and "other" in the reference category, and for others, the reference category is restricted to non-Hispanic Whites.) Multinomial logistic regression uses maximum likelihood estimation to evaluate the probability of category membership based on a set of predictor variables. In this case, a binary indicator for daylight is the predictor of interest. A relative risk ratio (RRR) significantly greater than 1.0 would indicate that people of color are more likely to be stopped during daylight, while an RRR significantly greater less than 1.0 would indicate that people of color are less likely to be stopped during daylight. P values (in parentheses) represent the probability that the RRR value differs from 1.0 by chance; by convention, values that exceed 0.05 are regarded as too high to reject the null hypothesis of no difference – i.e., no bias. Covariates in the regression models include time of day, day of week, month, and precinct.

Results are shown in Table 16. None of the models support an inference of bias in stops against either Black drivers or Hispanic drivers; most of the odds ratios are very near 1.0, and all of the confidence intervals around the estimated odds ratios include 1.0, such that none of the estimated coefficients is statistically significant. Considering all stops (model 1), the estimated RRRs indicate that Black and Hispanic drivers are slightly less likely to be stopped in daylight, though the difference is well within a margin of error. When the reference category includes only non-Hispanic Whites (model 2), the RRRs indicate no difference in the likelihood that Black and Hispanic drivers are stopped in daylight. When the same two models are estimated only for stops within 30 days of the switches to and from daylight savings time (models 3 and 4), to more stringently control for seasonal variation, once again there is no evidence to support the hypothesis of biased stops.

Table 16. Veil-of-Darkness Results

Model	**Description**	**RRR_{Black} (p)**	**$RRR_{Hispanic}$ (p)**
Model 1	All Stops	0.973 (0.750)	0.990 (0.893)
Model 2	All Stops; B, H, W only	0.985 (0.857)	1.001 (0.992)
Model 3	All Stops; +/- 30 days DST	0.979 (0.836)	1.090 (0.363)
Model 4	All Stops; +/- 30 days DST; B, H, W only	0.984 (0.876)	1.087 (0.385)
Model 5	Non-highway stops	0.957 (0.625)	1.015 (0.864)
Model 6	Non-highway stops; B, H, W only	0.977 (0.797)	1.034 (0.690)
Model 7	Non-highway stops; +/- 30 days DST	0.973 (0.550)	1.087 (0.408)
Model 8	Non-highway stops; +/- 30 days DST; B, H, W only	0.953 (0.663)	1.097 (0.367)
Model 9	Highway stops	1.154 (0.618)	0.810 (0.365)
Model 10	Highway stops; B, H, W only	1.108 (0.723)	0.793 (0.327)
Model 11	Highway stops; +/- 30 days DST	1.425 (0.363)	1.144 (0.670)
Model 12	Highway stops; +/- 30 days DST; B, H, W only	1.370 (0.427)	1.073 (0.827)

Models 5 through 8 in Table 16 replicate models 1 through 4, respectively, focusing on only non-highway stops (i.e., stops by units other than highway patrol), and models 9 through 12 focus on only highway stops. In only one of these models do we see evidence supporting an inference of bias. The RRRs for Hispanic drivers in highway stops across the entire year reach or approach 1.3, but even these values are well within the 95 percent confidence interval around the estimates.

The results of the veil-of-darkness analyses all lead to the same conclusion that in making the initial stop, Suffolk County police display no systematic bias against either Blacks or Hispanics. Though Black and Hispanic drivers are overrepresented in traffic stops relative to their proportions of the County population, we surmise that the disparities are attributable to factors other than race/ethnicity.

Patterns of Post-Stop Outcomes in Suffolk County

Beyond the initial stop, disparities in a range of post-stop enforcement actions can be analyzed. The SCPD traffic stop data capture information on a number of discrete actions, including: searches of vehicles and of individual drivers and passengers; commands to vehicle occupants to exit the vehicle and where they are placed when they do so; the use of restraints and physical force; the duration of the stops; and the dispositions of the stops (e.g., tickets, arrests, or warnings).

We first describe simple patterns in the post-stop outcomes. We then discuss how previous research has addressed the analytical challenges of isolating potential bias from data on disparities in these outcomes, and thereupon present our analyses of post-stop outcomes in Suffolk County.

Searches

Searches of either persons or vehicles are conducted in a small fraction – about 3 percent – of SCPD traffic stops. In the modal case of either type of search, both types – of one or more occupants and the vehicle – are conducted, but we analyze them separately. Precinct crime section units are the most likely to conduct a search; 6 percent of their stops involve a search of a vehicle, and 7 percent involve a search of a person (see Table 17b). Either type of search is performed by precinct patrol units in under 4 percent of their stops, while highway patrol units and other types of units rarely conducted searches. Among the stops by precinct units, stops in the first precinct were the most likely to involve a search, followed by stops in the third precinct (see Table 17a).

Table 17a and 17b. Search Frequencies by Precinct and Unit Type

17a. Precinct	Vehicle searches	Person searches
1	12.39%	11.84%
2	2.07	2.2
3	5.92	5.6
4	1.18	1.57
5	3.17	3.99
6	1.21	1.49
7	1.98	2.38
Total %	4.04%	4.17%
Stops N	3,649	3,766
Total N	90,232	90,232

17b. Unit type	Vehicle searches	Person searches
Precinct patrol section	3.64%	3.71%
Precinct crime section	6.22	6.64
Highway patrol	0.14	0.55
Other	0.72	1.26
Total %	2.8%	3.01%
Stops N	3,718	4,004
Total N	132,906	132,906

Black and Hispanic drivers were more likely to be subject to either type of search than White, Asian, or drivers of other races; see Table 18. A similar pattern holds for searches of passengers in cars whose drivers were Black or Hispanic. Less than one tenth of the vehicles stopped contained occupants other than the driver. Stops with passengers were more likely to result in a passenger search than stops of unaccompanied drivers were to result in a search of the driver.

Table 18. Search Frequencies by Driver Race/Ethnicity

	Driver Race/Ethnicity					
	White	Black	Hispanic	Asian	Other	All
Stops (n)	70,961	23,651	30,051	2,915	5,328	132,906
Vehicle searched (%)	1.83%	6%	2.99%	0.79%	1.46%	2.8%
Driver searched (%)	2.04%	6.11%	3.4%	1.2%	1.35%	3.02%
Stops with passengers (n)	4,597 (6.48%)	2,245 (9,49%)	2,745 (9.13%)	286 (9.81%)	408 (7.66%)	10,281 (7.74%)
Passenger searched (%)	7.9%	15.95%	9.33%	4.2%	4.66%	9.8%

Focusing on vehicle searches, the most commonly recorded reason for the search was probable cause for illicit drugs, identified in two-thirds or more of the vehicle searches conducted by precinct patrol and precinct crime units, 40 percent of vehicle searches by highway patrol units, and 60 percent of those by other units. See Table 19.

Table 19. Reasons for Vehicle Search by Unit Type

	Unit Type			
Reason	Patrol	Crime	Highway	Other
Prob. cause – drugs	66.03%	70.83%	40.43%	60.27%
Prob. cause – other	10.65	8.75	42.55	16.44
Plain view	11.24	10.04	6.38	8.22
Consent	12.08	10.39	10.64	15.07
Total	2,741	857	47	73

The reasons for vehicle searches varied only somewhat across precincts, in all of which probable cause for drugs was the recorded reason in more than half and as much as 70 percent (see Table 20). Plain view searches were most common in the first and third precincts, while consent searches were least common in the third precinct.

Table 20. Reasons for Vehicle Search by Precinct

	Precinct						
Reason	1	2	3	4	5	6	7
Prob. cause – drugs	70.02%	69.75%	67.59%	65.38%	58.79%	66.04%	58.75%
Prob. cause – other	6.19	6.37	14.33	15.38	15.27	12.74	14.17
Plain view	12.51	6.69	12.13	6.41	9.8	5.19	9.17
Consent	11.28	17.2	5.95	12.82	16.14	16.04	17.92
Total	1,551	314	907	78	347	212	240

Consent searches, which are normally considered the most discretionary of searches, were more commonly conducted of vehicles driven by White drivers (see Table 21). The data do not allow us to determine whether officers were more likely to request consent from White drivers, if White drivers were more likely to grant consent, or both.

Table 21. Reasons for Vehicle Search by Driver Race/Ethnicity

	Driver Race/Ethnicity				
Reason	White	Black	Hispanic	Asian	Other
Prob. cause – drugs	60.55%	70.63%	68.97%	82.61%	66.67%
Prob. cause – other	9.94	9.86	13.24	13.04	10.26
Plain view	12.25	10.14	9.34	4.35	19.23
Consent	17.26	9.37	8.45	--	3.85
Total	1,298	1,420	899	23	78

Vehicle searches by precinct crime units were the most successful in terms of recovering contraband, as nearly 70 percent led to the recovery of drugs, weapons, or other items (see Table 22). Precinct patrol and other units were successful in this sense in somewhat more than half of their vehicle searches, while the small number of searches by highway patrol units were the least successful. Searches in which contraband was found most commonly featured drugs.

Table 22. Vehicle Search Outcome by Unit Type

	Unit Type			
Search Outcome	Patrol	Crime	Highway	Other
None	46.7%	30.26%	65.96%	43.84%
Drugs	49.65	64.49	27.66	50.68
Weapon	0.91	0.7	--	2.74
Other	2.74	4.56	6.38	2.74
Total	2,739	856	47	73

Searches of White drivers' vehicles were more successful than those of Black or Hispanic drivers (see Table 23), which is to say that overall, searches of Black and Hispanic drivers' vehicles were more likely to yield no contraband. We will consider what, if any, inference can be drawn from this pattern in the next section.

Table 23. Vehicle Search Outcome by Driver Race/Ethnicity

	Driver Race/Ethnicity				
Search Outcome	White	Black	Hispanic	Asian	Other
None	39.94%	46.33%	43.94%	43.48%	26.92%
Drugs	55.2	49.93	52.61	56.52	66.67
Weapon	0.85	1.2	0.33	--	2.56
Other	4.01	2.54	3.11	--	3.85
Total	1,297	1,418	899	23	78

Considering searches of individual drivers, precinct patrol and precinct crime units exhibited comparable distributions of reasons, with about 40 percent based on probable cause, slightly more than one-quarter incident to arrest, and less than 10 percent for each of plain view and consent searches (see Table 24). Highway patrol and other units were most likely to conduct searches incident to arrest, and correspondingly less likely to conduct searches based on probable cause. Searches incident to arrest normally are regarded as non-discretionary.

Table 24. Reasons for Driver Search by Unit Type

	Unit Type			
Reason	Patrol	Crime	Highway	Other
Protective frisk	17.84%	9.08%	4.3%	11.72%
Prob. cause	38.4	44.64	20.43	24.22
Plain view	7.88	9.3	1.08	1.56
Consent	8.52	7.99	2.69	6.25
Incident to Arrest	27.36	28.99	71.51	56.25
Total	2,792	914	186	128

Reasons for searches of drivers varied across precincts (see Table 25). Frisks were most common in the fourth precinct and least common in the third and fifth precincts (though presumably frisks might have preceded other types of searches, which became the reason of record). Searches incident to arrest represented nearly half of the searches in the fifth precinct and about one-third in the fourth and sixth precincts.

Probable cause searches represented 38 to nearly 50 percent of the searches of drivers in all but the fourth and fifth precincts.

Table 25. Reasons for Driver Search by Precinct

	Precinct						
Reason	1	2	3	4	5	6	7
Protective frisk	23.13%	20.06%	7.69%	31.73%	7.32%	10.73%	6.23%
Prob. cause	37.9	41.92	48.95	26.92	27.46	40.23	46.02
Plain view	10.72	5.09	9.09	2.88	5.26	2.3	7.27
Consent	7.42	12.57	5.94	6.73	10.76	9.2	13.15
Incident to Arrest	20.84	20.36	28.32	31.73	49.2	37.55	27.34
Total	1,483	334	858	104	437	261	289

The reasons for searches of drivers do not vary much across drivers' race/ethnicity, particularly if we set aside the small numbers of searches of Asian or "other" race drivers. A somewhat greater proportion of White drivers were searched with their consent, and correspondingly fewer subject to a probable cause search.

Table 26. Reasons for Driver Search by Driver Race/Ethnicity

	Driver Race/Ethnicity				
Reason	White	Black	Hispanic	Asian	Other
Protective frisk	14.72%	15.65%	14.19%	31.43%	12.5%
Prob. cause	32.34	43.56	40.02	34.29	43.06
Plain view	8.15	8.38	6.16	2.86	8.33
Consent	11.26	6.51	6.36	2.86	1.39
Incident to Arrest	33.52	25.9	33.27	28.57	34.72
Total	1,447	1,444	1,022	35	72

As with vehicle searches, precinct crime units' searches of drivers were the most successful in recovering contraband. Precinct patrol units were somewhat less successful than precinct crime units (though a somewhat larger fraction of their searches were frisks, which of course have more limited scope).

Table 27. Driver Search Outcome by Unit Type

	Unit Type			
Search Outcome	Patrol	Crime	Highway	Other
Nothing	67.08%	48.36%	89.78%	81.25%
Weapon	0.93	1.42	1.08	0.78
Contraband	28.69	42.23	6.45	15.62
Other	3.76	8.75	2.69	2.34
Total	2,792	914	186	128

The success of searches of drivers does not vary much across drivers of different race/ethnicity (see Table 28).

Table 28. Driver Search Outcome by Driver Race/Ethnicity

	Unit Type				
Search Outcome	White	Black	Hispanic	Asian	Other
Nothing	63.44%	64.2%	66.14%	77.14%	52.78%
Weapon	1.17	1.18	0.78	0	0
Contraband	31.1	30.26	29.45	22.86	31.94
Other	4.91	4.78	4.11	0	15.28
Total	1,447	1,444	1,022	35	72

Considering searches of individual passengers, as with searches of drivers, precinct patrol and precinct crime units exhibited comparable distributions of reasons, with 40 to 50 percent based on probable cause (see Table 29); precinct crime units were somewhat more likely to conduct searches incident to arrest and correspondingly less likely to conduct only a frisk. Highway patrol and other units rarely searched passengers.

Table 29. Reasons for Passenger Search by Unit Type

	Unit Type			
Reason	Patrol	Crime	Highway	Other
Protective frisk	27.1%	17.82%	45.45%	20%
Probable cause	43.06	48.51	27.27	53.33
Plain view	8.09	7.92	9.09	--
Consent	7.87	6.93	9.09	13.33
Incident to Arrest	13.88	18.81	9.09	13.33
Total	915	303	11	15

Reasons for searches of passengers vary somewhat across precincts (see Table 30, below), though the numbers of passengers searched in several of the precincts are small enough that caution should be exercised in characterizing patterns.

Table 30. Reasons for Passenger Search by Precinct

	Precinct						
Reason	1	2	3	4	5	6	7
Protective frisk	29.58%	41.49%	14.75%	50%	19.59%	19.05%	8.14%
Probable cause	41.01	29.79	63.11	28.57	34.02	46.43	45.35
Plain view	11.44	3.19	3.69	7.14	6.19	2.38	8.14
Consent	4.08	18.09	3.69	--	15.46	17.86	15.12
Incident to Arrest	13.89	7.45	14.75	14.29	24.74	14.29	23.26
Total	612	94	244	14	97	84	86

Reasons for searches of passengers differ somewhat across passengers of different race/ethnicity, as White passengers were most likely to be searched incident to arrest and to consent to a search, while probable cause searches were more likely to be conducted of Hispanic passengers. See Table 31.

Table 31. Reasons for Passenger Search by Passenger Race/Ethnicity

	Passenger Race/Ethnicity				
Reason	White	Black	Hispanic	Asian	Other
Protective frisk	21.13%	27.4%	24.75%	25%	23.08%
Probable cause	39.15	44.5	50.17	37.5	53.85
Plain view	8.45	7.5	7.8	25	7.69
Consent	11.27	5.76	7.46	NA	7.69
Incident to Arrest	20	14.83	9.83	12.5	7.69
Total	355	573	295	8	13

Searches of passengers by precinct crime units tend to be more successful than those by precinct patrol units (see Table 32), though more than half of those by precinct crime units have negative results.

Table 32. Passenger Search Outcome by Unit Type

	Unit Type			
Search Outcome	Patrol	Crime	Highway	Other
Nothing	67.32%	55.78%	81.82%	53.33%
Weapon	1.53	1.32	0	0
Contraband	29.18	37.95	18.18	46.67
Other	2.4	7.26	0	0
Total	915	303	11	15

The outcomes of searches of passengers do not vary much by passengers' race/ethnicity, as 62 to 67 percent of the searches of White, Black, and Hispanic passengers yielded no contraband (see Table 33).

Table 33. Passenger Search Outcome by Passenger Race/Ethnicity

	Unit Type				
Search Outcome	White	Black	Hispanic	Asian	Other
Nothing	62.25%	67.02%	63.39%	50%	46.15%
Weapon	1.13	2.09	0.68	0	0
Contraband	35.49	27.05	33.56	50	53.85
Other	2.25	4.71	3.05	0	0
Total	355	573	295	8	13

Commands to Exit the Vehicle

Drivers are seldom ordered to leave their vehicles; passengers are more likely to be told to exit the vehicle. Across the stops by any of the SCPD units, 4 percent of drivers and 12 percent of passengers were ordered out of the car (see Table 34b). Precinct crime units were the most likely to do so, followed by precinct patrol units. Among the stops in the precincts, commands to drivers and passengers to leave their vehicles were (like searches) most prevalent among stops in the first precinct, followed by stops in the third precinct (see Table 34a).

Tables 34a and 34b. Commands to Exit Vehicle (yes/no) by Precinct and Unit Type

34a. Precinct	Drivers	Passengers
1	13.46%	47.38%
2	2.72	10.02
3	6.88	34.45
4	2.48	4.04
5	4.89	15.16
6	2.28	9.59
7	2.96	11.32
Total %	5.11%	21.86%
Total N	90,232	7,195

34b. Unit type	Drivers	Passengers
Precinct patrol section	4.68%	20.95%
Precinct crime section	7.41	26.37
Highway patrol	1.71	0.59
Other	2.27	1.94
Total %	4.02%	12.01%
Total N	132,906	13,379

Once removed from the vehicle, Black drivers are more likely than those of other races/ethnicities to be placed in the back of the police unit (see Table 35), and Black passengers are more likely than those of other races/ethnicities to be placed in the unit (see Table 36). Hispanic drivers and passengers are more likely than White drivers and passengers, respectively, to be placed in the back of the unit.

Table 35. Commands to Exit Vehicle (placement) by Driver Race/Ethnicity

	Driver Race/Ethnicity				
Reason (driver)	White	Black	Hispanic	Asian	Other
Back of Unit	45.54%	55.67%	49.93%	41.3%	51.43%
Side of Road	54.46	44.33	51.02	58.7	48.57
Total	2,075	1,755	1,368	46	105

Table 36. Commands to Exit Vehicle (placement) by Passenger Race/Ethnicity

	Passenger Race/Ethnicity				
Reason (Passenger)	White	Black	Hispanic	Asian	Other
Back of Unit	39.22%	48.53%	46.12%	41.67%	15.79%
Side of Road	60.78	51.47	53.88	58.33	84.21
Total	464	713	399	12	19

Restraints

Neither drivers nor passengers tend to be restrained by police in Suffolk County: less than 2 percent of drivers and 3.5 percent of passengers are restrained (see Table 37b). Precinct crime units were the most likely to do so, followed by precinct patrol units. Among the stops in the precincts, the restraint of drivers and passengers was (like searches and commands to exit the vehicle) most prevalent among stops in the first precinct, followed by stops in the third precinct (see Table 37a).

Tables 37a and 37b. Restrained by Precinct and Unit Type

37a. Precinct	Drivers	Passengers
1	5.56%	16.58%
2	0.89	2.2
3	2.36	6.33
4	1.09	1.58
5	2.32	4.1
6	0.79	3
7	1.24	3.63
Total %	2%	6.39%
Total N	90,232	7,195

37b. Unit type	Drivers	Passengers
Precinct patrol section	1.81%	5.78%
Precinct crime section	3.06	9.06
Highway patrol	0.6	0.16
Other	0.74	0.58
Total %	1.55%	3.5%
Total N	132,906	13,379

Black drivers and passengers are more than twice as likely to be restrained than White drivers and passengers, respectively (see Table 38). Hispanic drivers were somewhat more likely than White drivers to be restrained, and Hispanic passengers less likely.

Table 38. Restrained by Driver Race/Ethnicity

Race	Drivers	Passengers
White	1.16%	3.01%
Black	2.93	6.72
Hispanic	1.62	2.04
Asian	0.48	1.79
Other	0.77	0.68
Total %	1.55%	3.5%
Total N	132,906	13,379

Use of Physical Force

Physical force was rarely used in SCPD traffic stops. Precinct patrol units were more likely than others to use force in traffic stops (see Table 39b), but the proportions of drivers or passengers subjected to physical force were very small even for them. Among stops in the precincts, stops by the third precinct were more likely to involve force (see Table 39a), but again, the prevalence was very low.

Tables 39a and 39b. Use of Physical Force by Precinct and Unit Type

39a. Precinct	Drivers	Passengers
1	0.07%	0.13%
2	0	0
3	0.08	1.44
4	0	0
5	0.05	0
6	0.02	0.34
7	0.01	0
Total %	0.04%	0.29%
Total N	90,232	7,195

39b. Unit type	Drivers	Passengers
Precinct patrol section	0.04%	0.35%
Precinct crime section	0.01	0
Highway patrol	0.01	0.06
Other	0.01	0.07
Total %	0.03%	0.18%
Total N	132,906	13,379

Black drivers were more likely to be subjected to physical force than drivers of other races/ethnicities (see Table 40, below). Hispanic and Black passengers were more likely to be subjected to physical force than other passengers.

Table 40. Use of Physical Force by Driver Race/Ethnicity

Race	Drivers	Passengers
White	0.02%	0.11%
Black	0.08	0.25
Hispanic	0.02	0.27
Asian	0	0
Other	0	0
Total %	0.03%	0.18%
Total N	132,906	13,379

Stop Duration

Overall, 89.2 percent of SCPD traffic stops are completed within 15 minutes. The corresponding percentages for stops of Black and Hispanic drivers are somewhat lower than that (see Table 41). Compared with stops of White drivers, stops of Black drivers are 63 percent more likely to last 16 to 30 minutes, and stops of Hispanic drivers are 49 percent more likely to last 16 to 30 minutes. Compared with stops of White drivers, stops of Hispanic drivers are 65 percent more likely to last more than 30 minutes.

Table 41. Durations of Stop by Driver Race/Ethnicity

	Driver Race/Ethnicity				
Duration of stop	White	Black	Hispanic	Asian	Other
Up to 15 minutes	91.15%	86.05%	86.5%	90.9%	91.52%
16 – 30 minutes	6.85	11.14	10.22	7.8	6.32
More than 30 minutes	1.99	2.8	3.28	1.31	2.16
Total	70,961	23,651	30,051	2,915	5,328

Dispositions

The modal stop by any type of SCPD unit is a ticket (see Table 42, below). More than half of the stops by precinct patrol units culminate in a ticket, as do two-thirds or more of the stops by precinct crime units and highway patrol units. Most of the remaining stops – one-fifth of those by precinct crime units, and nearly one-third or more of those by other types of units – are disposed with a warning. Arrests are most likely to be made by precinct crime units, and least likely to be made by highway patrol units.

Among stops in the precincts, warnings are most likely in the sixth and seventh precincts, and arrests are most likely in the first precinct (though even there, arrests are made in less than 10 percent of the stops).

Table 42. Dispositions by Unit Type

	Unit Type			
Disposition	Patrol	Crime	Highway	Other
Arrest	3.37%	6.38%	1.15%	1.28%
Ticket	58.26	70.98	67.55	58.03
Warning	37.63	21.83	29.24	35.76
Other	0.74	0.81	2.06	4.93
Total	75,267	13,772	33,721	10,146

Table 43. Dispositions by Precinct

	Precinct						
Disposition	1	2	3	4	5	6	7
Arrest	9.08%	2.03%	5.5%	1.96%	4.64%	1.67%	2.06%
Ticket	60.4	65.8	62.84	73.7	71.21	50.75	47.12
Warning	29.92	31.66	31.08	23.66	23.6	46.56	49.6
Other	0.6	0.51	0.58	0.68	0.55	1.02	1.23
Total	12,522	15,202	15,315	6,623	10,957	17,471	12,142

Dispositions vary with the reason for the stops, as one might expect. Arrests are most likely when the stop is based on either a BOLO or reasonable suspicion; in those instances, tickets are less prevalent, and other dispositions are more prevalent. Among the stops based on other reasons, tickets are issued in 60 to 70 percent, with warnings issued in most of the remainder. See Table 44.

Table 44. Disposition by Reasons for Stops

	Disposition				
Reason	Arrest	Ticket	Warning	Other	Totals
Speeding	1.39%	65.45	31.15	2.01	27114
Red light	1.73%	65.28	32.66	0.32	2480
Stop sign	1.81%	59.79	38.15	0.24	16876
Other moving violation	3.45%	61.36	33.54	1.65	24174
Equipment violation	3.29%	59.15	37.2	0.35	25115
Seatbelt	3.74%	69.87	24.92	1.47	3263
Cell phone	1.23%	67.53	30.83	0.41	7717
Other V&T law	3.31%	61.83	32.86	1.99	24714
BOLO	14.29%	39.1	31.58	15.04	133
Reasonable suspicion	37.27%	24.39	24.02	14.32	1320

Dispositions also vary with the race/ethnicity of the drivers and passengers (see Tables 45 and 46). Black drivers are more likely than drivers of other races/ethnicities to be arrested, and Black passengers are more likely than passengers of other races/ethnicities to be arrested. Hispanic drivers are more likely than either White or Black drivers to be ticketed, and least likely to be warned.

Table 45. Dispositions by Driver Race

	Driver Race/Ethnicity				
Disposition	White	Black	Hispanic	Asian	Other
Arrest	2.22%	5.15%	3.38%	0.96%	1.76%
Ticket	59.76	59.91	68.35	67.34	60.32
Warning	36.4	33.66	27.51	30.22	35.25
Other	1.62	1.27	0.75	1.48	2.67
Total	70,961	23,651	30,051	2,915	5,328

Table 46. Dispositions by Passenger Race

	Passenger Race/Ethnicity				
Disposition	White	Black	Hispanic	Asian	Other
Arrest	4.26%	9.14%	4.5%	2.04%	1.37%
Ticket	3.93	4.76	3.79	3.06	2.57
Warning	12.54	19.31	14.28	7.91	6.85
Other	79.26	66.79	77.44	86.99	89.21
Total	5,517	3,216	3,670	392	584

Bias in Post-Stop Outcomes

Following an initial traffic stop, a range of possible enforcement actions, behaviors, and prescriptions emerge. Though contextual and legal circumstances of the stop dictate, to varying degrees, the courses of actions available to an officer after a traffic stop is made, discretion – and the specter of biased decision-making – remains. A spectrum of possible actions, from frisks and searches to dispositions including arrests and tickets, represent the “post-stop outcomes” of traffic stops.

Analyses of bias in post-stop outcomes confront analytical challenges that are somewhat more tractable than those associated with analyzing bias in the initial stop decision, but the principle remains the same. In order to draw inferences about bias, the analysis must credibly account for the factors that legitimately affect enforcement decisions, e.g., to search, to cite, to effect a custodial arrest, or to use physical force. The problems are more tractable insofar as the population to which comparisons should be drawn can be – in principle – captured in police records. The more information that police records include, the better able we are to properly account for the factors that *appropriately* bear on enforcement decisions. At times, however, the records do not contain the information that is needed, leaving considerable doubt about the role of legal factors and, hence, about the role of police bias. Thus the analytical strategies adopted in previous research vary with the availability, quality, and richness of data, though where possible, researchers have prioritized analyses of discretionary outcomes to spotlight potential bias at the individual level, or patterns of bias within units, shifts, or assignments. We first review the analytical strategies and summarize the findings that emerged from their application.

Analytical Approaches and Findings

Researchers have employed varied methods to examine racial disparity in post-stop outcomes, but are limited in their analytical approach by the quantity and scope of available data, which varies widely by jurisdiction. Multivariate analysis has been used extensively in research on post-stop outcomes because of its advantages in allowing for a more comprehensive and detailed exploration of discrete and overlapping levels of data.

Searches

Searches performed in traffic stops have been a primary analytical focus of many researchers' post-stop inquiries. The range of possible searches that are executed in a traffic stop can be summarized within the conceptual bounds of nondiscretionary searches, such as those performed incident to arrest, and various types of discretionary searches. These searches are made absent a warrant, and are often the product of a stop based on reasonable suspicion or suspicion that is raised over the course of a stop, and include consent searches, plain view searches, canine searches, searches more generally related to probable cause, drug odor searches, and those performed incident to a frisk or pat-down.[45] Differentiation between searches performed on people and those of vehicles, aside from pat-downs and frisks, is not common in research on post-stop outcomes.[46]

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[45] Officer discretion becomes murky with respect to stops such as Fourth Amendment Waiver searches, or searches of individuals on probation or parole, which Chanin, Welsh, and Nurge describe as "involv[ing] an ambiguous amount of officer discretion." See Joshua Chanin, Megan Welsh, and Dara Nurge, "Traffic Enforcement through the Lens of Race: A Sequential Analysis of Post-Stop Outcomes in San Diego, California," *Criminal Justice Policy Review 29* (2018): 564.

[46] Robin Engel, James Frank, Rob Tillyer, and Charles Klahm, *Cleveland Division of Police Traffic Stop Data Study: Final Report, 2006* (University of Cincinnati); Joseph A. Schafer, David L. Carter, Andra J. Katz-Bannister, and William M. Wells, "Decision Making in Traffic Stop Encounters: A Multivariate Analysis of Police Behavior," *Police Quarterly* 9 (2006): 184-209; Geoffrey P. Alpert, Elizabeth Becker, Mark A. Gustafson, Alan P. Meister, Michael R. Smith, and Bruce Strombom, *Pedestrian and Motor Vehicle Data Analysis Report* (Analysis Group, Inc., 2006); Frank R. Baumgartner, Leah Christiani, Derek A. Epp, Kevin

While extant research has established a well-accepted operationalization for non-discretionary searches, operational definitions of higher discretion searches are more varied. Some researchers have delineated officers' discretionary bounds by differentiating consent searches, considered to be the most discretionary, from other high-discretion searches, such as those made based on probable cause.[47] Others have performed a hybrid analysis of high-discretion searches by combining consent and probable cause searches into one measure.[48] Schafer, Carter, Katz-Bannister, and Wells created an additive measure of discretionary searches, analyzing discretion with one measure that captured consent searches alone, and another measure that combined consent searches with other high-discretion searches.[49] In their analysis of stops and post-stop outcomes, Baumgartner, Christiani, Epp, Roach, and Shoub did not differentiate between high- or low-discretion searches, nor did they provide a definition or criteria for their operationalization of a search.[50] Rosenfeld, Rojek, and Decker's measure of discretionary searches excluded only those that preceded arrest or those that were performed incident to arrest, reasoning that "the data do not reliably distinguish arrests that led to a search from those that resulted from a search." [51]

Some research has analyzed high-discretion searches and consent search *requests* separately, as Geoffrey Alpert and colleagues argued: "as *outcomes*, consent searches measure suspect acquiesce to a police request, and acquiesce may itself vary by race."[52] Rojek, Rosenfeld, and Decker combined consent and other high-discretion

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Roach, and Kelsey Shoub, "Racial Disparities in Traffic Stop Outcomes," *Duke Forum for Law & Social Change* 9 (2017); Chanin et al, "Traffic Enforcement"; Seth W. Fallik and Kenneth J. Novak, "The Decision to Search: Is Race or Ethnicity Important?" *Journal of Contemporary Criminal Justice* 28 (2012) 146-165; J. Mitchell Pickerill, Clayton Mosher, and Travis Pratt, "Search and Seizure, Racial Profiling, and Traffic Stops: A Disparate Impact Framework," *Law & Policy* 31 (2009).

[47] Engel et al., *Cleveland Division of Police Traffic Stop Data Study*; Sunghoon Roh and Matthew Robinson, "A Geographic Approach to Racial Profiling: The Microanalysis and Macroanalysis of Racial Disparity in Traffic Stops," *Police Quarterly* 12 (2009): 137-169; Richard Rosenfeld, Jeff Rojek, and Scott Decker, "Age Matters: Race Differences in Police Searches of Young and Older Male Drivers," *Journal of Research in Crime and Delinquency* 49 (2012): 31-55; Rob Tillyer, Charles F. Klahm IV, and Robin S. Engel, "The Discretion to Search: A Multilevel Examination of Driver Demographics and Officer Characteristics," *Journal of Contemporary Criminal Justice* 28 (2012): 184-205.

[48] Chanin et al., "Traffic Enforcement through the Lens of Race"; Fallik and Novak, "The Decision to Search"; Pickerill et al., "Search and Seizure"; Rob Tillyer, "Opening the Black Box of Officer Decision-Making: An Examination of Race, Criminal History, and Discretionary Searches," *Justice Quarterly* 31 (2014): 961-985; Rob Tillyer and Charles F. Klahm IV, "Discretionary Searches, the Impact of Passengers, and the Implications for Police-Minority Encounters," *Criminal Justice Review* 40 (2015): 378-396).

[49] Schafer et al., "Decision Making."

[50] Baumgartner et al., "Racial Disparities."

[51] Rosenfeld et al, "Age Matters," p. 37.

[52] Alpert et al., *Pedestrian and Motor Vehicle Data Analysis Report*, p. 12. Also see Christopher Barnum and Robert L. Perfetti, "Race-Sensitive Choices by Police Officers in Traffic Stop Encounters," *Police Quarterly 13* (2010): 180-208.

searches in their analysis, asserting that this was preferable in part because the authors "[did] not know the number and characteristics of drivers who were not asked for their consent to a search or refused the officer's request."[53] Further, Alpert and colleagues separately analyzed pat-downs and frisks as a distinct form of high-discretion search based on reasonable suspicion.

Several researchers have argued that passengers in a stopped vehicle are likely to exert some level of influence over the proceeding of the stop, suggesting that analyses that do not account for this variable might generate distorted findings. Tillyer and Klahm reframed the conventional analytical approach by examining police-citizen contacts in traffic stops as the units of analysis, rather than the traffic stops themselves. This allowed for a consideration of both passengers and drivers in analyses of mandatory and discretionary searches, as "a single-occupant encounter would be counted as one case; however, a multiple-occupant vehicle involving three passengers would be counted as four cases (one case the driver and one each for the passengers)."[54] Other research has operationalized searches or consent search requests as those performed on passengers *or* drivers.[55] Joseph Schafer and colleagues excluded consent searches of passengers from their analysis when the driver or vehicle was not searched.[56]

Many researchers have employed logistic regression in analyses of searches, in which a search (or a discrete type of search) is analyzed as a binary outcome, with a set predictors such as citizen, suspect, and incident characteristics. This analytical approach was utilized in two analyses performed for the Los Angeles Police Department (LAPD) by Alpert and colleagues, and the Cleveland Division of Police (CDP) by Engel and colleagues.[57] The former research involved a series of regressions that analyzed disparate discretionary levels of behavior, first examining whether a pat-down or frisk was performed, then if a higher discretion search was conducted, and finally if the officer requested a consent search.[58] Engel and colleagues employed two separate logistic regression models to analyze variables that predict any search, with and without officer and census characteristics, and in a separate analysis, they examined three

[53] Jeff Rojek, Richard Rosenfeld, and Scott Decker, "Policing Race: The Racial Stratifications of Searches in Police Traffic Stops," *Criminology* 50 (2012): 1008.
[54] Tillyer and Klahm, "Discretionary Searches," p. 383.
[55] Chanin et al., "Traffic Enforcement"; Pickerill et al., "Search and Seizure."
[56] Schafer et al., "Decision Making."
[57] Alpert et al., *Pedestrian and Motor Vehicle Data Analysis Report;* Engel et al., *Cleveland Division of Police Traffic Stop Data Study*.
[58] Evidence concerning citizen compliance to consent search requests shows that refusal is relatively rare. Among a sample of Black and White male drivers in St. Louis, MO, compliance with consent search requests ranged from 74% to 86%, varying with regards to the driver's race and age (Rosenfeld et al., "Age Matters"). In analysis of post-stop outcomes in an unnamed Southwestern city, Tillyer found that 99% of drivers complied with consent search requests, though the author noted that this might be due to the public's high level of approval for the department, or characteristics of the stopped population. (Tillyer, "Opening the Black Box").

discrete types of searches (mandatory, discretionary, and consent) as they corresponded to officer and driver characteristics. Both studies controlled for a wide range of variables, including officer, suspect, encounter, passenger, and geographic characteristics.

Schafer and colleagues utilized logistic regression to analyze searches with respect to stop and driver characteristics in an unnamed police department, and to analyze separately consent searches and all discretionary searches. The authors also performed analysis to estimate the conditions in which officers seek consent to search "by comparing traffic stops in which no searches took place with traffic stops in which consent searches occurred," given that available data only indicated whether or not one was performed.[59]

Grounding their analysis in Black's theory of law, which holds that citizens' social status relative to the police officer in an encounter will influence that officer's behavior, Rojek and colleagues examined searches in St. Louis Metropolitan Police Department (SLMPD) traffic stops.[60] The authors computed four dichotomous variables representing possible interaction effects officers' race (Black or White) and drivers' race (Black or White), and utilized logistic regression to examine the outcomes of these racial dyads, controlling for other driver, officer, and stop characteristics. Additional analysis examined these interactional variables as they corresponded to searches of varying discretion: consent, drug odor, arrest, officer safety, and other.

Rosenfeld and colleagues also analyzed post-stop outcomes of the SLMPD by using both logistic regression and propensity score matching.[61] Logistic regression results predicting outcomes based on city residency, location of stop, time of day, officer characteristics, and driver age were used to generate propensity scores that matched Black and White drivers. The authors excluded all female drivers from analyses because of their reduced likelihood of being searched, as well as searches made by officers on special assignments. Chanin and colleagues also utilized propensity score matching of Black and White drivers to examine disparate search patterns across race and search categories. The authors were unable to discretely analyze searches made based on reasonable suspicion, given that, at the time of the analysis, agency stop forms did not include this option among search type categories. Fallik and Novak examined the predictive value of a driver's race to a discretionary or nondiscretionary search using a series of chi square, bivariate, and multivariate analyses of stop data from an unnamed, large Midwestern police department.[62] The authors controlled for driver demographics, driver residency, time of day, type of stop, type of vehicle, and reason for stop, which included a binary measure for investigatory stops. This measure accounted for the difference between routine, or "traffic," stops, and investigatory stops, which "function

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[59] Schafer et al, "Decision Making in Traffic Stop Encounters," p. 198.
[60] Rojek et al., "Policing Race."
[61] Rosenfeld et al., "Age Matters."
[62] Fallik and Novak, "The Decision to Search."

as part of a continuing investigation and are encounters where the driver, passenger(s), car, or combination of some or all entities is known by the police."[63]

In examining the outcome of a discretionary search, Tillyer employed a path analysis through a series of models that tested the effects of a citizen's race and criminal history, hypothesizing that criminal history mediated the interaction between citizen race and the performance of a discretionary search.[64] Multilevel models evaluated searches performed on citizens with and without criminal histories, holding other citizen and encounter characteristics constant.

Using publically available data from 132 law enforcement agencies in the United States, Baumgartner and colleagues employed two different analytical strategies: one that could be applied to all agencies with publicly available data in the study, and one that could be applied to agencies with a more granular level of available data.[65] The former analysis consisted of a simple rate ratio of stop outcomes of one race to another. The latter allowed for a logistic regression of post-stop outcomes and driver characteristics, and included measures for problem officers, or those whose stop and search rates were exceptionally high or disproportionate with regards to race. The authors analyzed the comparative likelihood that a series of compound variables for race and gender would be searched (Hispanic females, White males, White females, Hispanic males, Black females, and Black males).

Arrests, Citations, Warnings

Various approaches have been used to examine the effect of officer discretion, citizen characteristics, and contextual variables in examining the post-stop dispositions of warnings, citations, and arrests. Engel and colleagues presented post-stop analyses in both simple descriptive statistics reporting the prevalence of arrests, warnings, citations by patrol zone and officer characteristics, as well as in two logistic regression models analyzing the outcome of arrest, including and excluding officer and census characteristics.

In Alpert and colleagues' analysis of post-stop outcomes, warnings, citations, and arrests were examined in a series of analytical iterations, which accounted for varying levels of officer discretion. Lower-discretion outcomes, such as arrests involving charges for violent crimes or drunk-driving, warrant arrests, and citations resulting from operating with a suspended license, were removed from analyses so that the outcomes reflected only those that might emerge from highly discretionary situations. The authors

[63] Ibid, p. 153.
[64] Tillyer, "Opening the Black Box."
[65] Baumgartner et al., "Racial Disparities."

noted: "removing the lower discretion arrests from our base arrest model allowed us to evaluate the impact of race on the likelihood of truly discretionary arrests." [66]

Tillyer and Engel explored interaction terms of race, gender, and age in stop outcomes using multilevel statistical modeling techniques, basing their analysis in social conditional theory, which proposes that "officer decision making is not only influenced by unconscious profiles that are primarily based on a drivers' race/ethnicity but may also be influenced by gender and age."[67] Warnings, citations, and arrests were coded by their most serious outcome, and variables were constructed to capture the compound demographics for young, Black males (YBMs) and young, Hispanic males (YHMs) in order to investigate the disparities that might occur in the officer dispositions for these particular groups. Multilevel analysis at citizen and officer levels evaluated the predictive value of citizen, encounter, stop, officer, and interactional (YBM and YHM) variables for warnings, citations, and arrests.

Regoeczi and Kent employed logistic regression to examine the predictive value of officer, driver, and stop characteristics to receiving a ticket (1) or a warning (0).[68] The researchers conducted systematic social observations (SSO) on traffic encounters, allowing them to include in their analysis citizen demeanor, among a number of other officer, citizen, and incident characteristics.

Chanin and colleagues utilized propensity score matching to match Black and White drivers to analyze differences in outcomes of citations, arrests, and the issuance of field interviews.[69] In Roh and Robinson's analysis of disparities in stop outcomes at both macro and micro-levels, the authors examined both individual officer behaviors and patterns of officer behavior within larger spatial areas, or beats.[70] At the micro-level, the authors analyzed racial differences among drivers who were searched, cited, or arrested. At the macro-level, the authors employed spatial correlation analysis using Exploratory Spatial Analysis (ESDA) and Local Moran Lisa Cluster Mapping (LISA), which collectively facilitate analyses of disparities in enforcement within police beats, while accounting for enforcement patterns of neighboring areas.

[66] Alpert et al., *Pedestrian and Motor Vehicle Data Analysis Report*, p. 13.
[67] Rob Tillyer and Robin S. Engel, "The Impact of Drivers' Race, Gender, and Age During Traffic Stops: Assessing Interaction Terms and the Social Conditioning Model," *Crime & Delinquency* (2013): 5.
[68] Wendy C. Regoeczi and Stephanie Kent, "Race Poverty, and the Traffic Ticket Cycle: Exploring the Situational Context of the Application of Police Discretion," *Policing: An International Journal of Police Strategies and Management* 37 (2014): 190-205.
[69] Chanin et al., "Traffic Enforcement"; Propensity scores, ranging from 0-1, for individual stops were generated through a logistic regression model estimated with the following variables: the reason for the stop, location of the stop, day of week, month, time of day, driver's age, driver's gender, and driver's residency (San Diego or otherwise).
[70] Roh and Robinson, "A Geographic Approach."

Barnum and Perfetti likewise analyzed disparities at the macro (organizational) and micro (officer) levels.[71] The authors first utilized logistic regression to examine disparities in citations, arrests, and search requests across a number of variables, including driver, officer, and stop characteristics. Researchers established a baseline by conducting SSO of traffic at intersections, estimating the race and gender of drivers, and generating racial assessments for 22,000 drivers over the period of 6 months. The observer's findings closely paralleled Census data for the city as a whole, and formed a baseline that represented the driving population – not the violator population. For the microanalysis, researchers computed odds ratios for stops, citations, and search requests among officers who had similar years of service, percentage of equipment violation stops, percentage of out-of-state stops, and shift. Officer behavior, which may entail disproportionate activity, was estimated in a pathway analysis of odds ratios, beginning with stops, then citations, and finally searches. This pathway generates four possible models of behavior, which account for varying types of disproportionate activity in terms of stops, citations, and/or searches.

Contraband Discovery

Analyzing "hit rates," or the rate at which searches successfully yielded contraband, among drivers of different races provides an additional pathway for detecting potential disparities in officer behavior. This approach is also known as the "outcome test."[72] A number of researchers have employed logistic regression to analyze the predictive value of driver, officer, and stop characteristics to a successful search. Tillyer and Klahm examined hit rates of high- and low-discretion searches, controlling for citizen, stop, and officer characteristics, as well as vehicle characteristics such as vehicle condition and number of passengers.[73] Schafer and colleagues computed odds ratios for contraband discovery controlling for the reason for stop, and driver characteristics The authors also analyzed hit rates among drivers for whom only a

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[71] Barnum and Perfetti, "Race-Sensitive Choices."

[72] The outcome test has some intuitive appeal: if the recorded discovery of contraband varies substantially among racial/ethnic groups, it suggests that the searches were based on varying evidentiary standards. A lower rate of contraband discovery, by this logic, is indicative of searches that tend to rest on a weaker legal foundation. Notwithstanding its intuitive appeal, the outcome test rests on assumptions that are questionable. See Andrew Gelman, Jeffrey Fagan, and Alex Kiss, "An Analysis of the New York City Police Department's 'Stop-and-Frisk' Policy in the Context of Claims of Racial Bias," *Journal of the American Statistical Association* 102 (2007), p. 815; Robin S. Engel, "A Critique of the 'Outcome Test' in Racial Profiling Research," *Justice Quarterly* 25 (2008): 1-36; National Academies of Sciences, Engineering, and Medicine, *Proactive Policing: Effects on Crime and Communities* (Washington, DC: The National Academies Press, 2017), pp. 7-5 – 7-10; and Neil and Winship, "Methodological Challenges and Opportunities in Testing for Racial Discrimination."

[73] Rob Tillyer and Charles Klahm IV, "Searching for Contraband: Assessing the Use of Discretion by Police Officers," *Police Quarterly* 14 (2011): 166-185.

warning was issued, though they did not differentiate between search discretion in this analysis.[74] Controlling for driver and officer characteristics, Engel and colleagues examined disparities in hit rates of mandatory, discretionary, and consent searches among different patrol zones in Cleveland, also analyzing the types of contraband seized during successful searches.[75] Engel and colleagues noted the dangers of including mandatory searches in any broader analysis of hit rates:

> Outcome test comparisons of searches that are mandatory – that is, searches conducted as a result of departmental policy rather than officer discretion – should not be considered when determining racial/ethnic disparities due to officer decision making. Based on CDP policies, officers have little or no discretion over the following types of searches: inventory searches, searches incident to arrest, and searches based on a preexisting warrant. Likewise, the inclusion of consent searches in outcome test analyses is problematic because, as with mandatory searches, the decision of whether or not to search is not entirely based on the officers' decision. Although officers initially decide whom to request a consent search from, ultimately it is citizens, not officers, who decide whether or not consent searches are conducted. That is, citizens have the right to refuse search requests, and if the officer has no probable cause to conduct the search, their denial of the police request must be honored.[76]

In Roh and Robinson's micro-analysis, researchers utilized a simple discretionary search to contraband discovery ratio to determine hit rates, and macroanalyses to examine disparities across neighborhoods of varying racial composition and agency resource deployment (a measure of patrol concentration within beats) computed the ratio of successful searches to overall searches.[77] Using propensity score matching, Chanin and colleagues examined hit rates by analyzing the success of searches performed on Black and White drivers whose stops and circumstances were similarly matched.[78]

Use of Force

Police use of force has been the subject of a substantial volume of police research. Among police encounters with suspected offenders, or among recorded arrests, use of force is analyzed in regression models that control for legal factors. One clear lesson of this research is that it is essential to take account of citizen resistance.[79]

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[74] Schafer et al., "Decision Making in Traffic Stop Encounters."
[75] Engel et al., *Cleveland Division of Police Traffic Stop Data Study*.
[76] Ibid, p. 137.
[77] Roh and Robinson, "A Geographic Approach."
[78] Chanin et al, "Traffic Enforcement."
[79] See, e.g.: Joel H. Garner, Christopher D. Maxwell, and Cedrick Heraux, "Characteristics Associated with the Prevalence and Severity of Force Used by the Police," *Justice Quarterly* 19 (2002): 705-746; Geoffrey P. Alpert and Roger G. Dunham, *Understanding Police Use of Force: Officers, Suspects, and Reciprocity* (New

To our knowledge, use of force has not been analyzed as a post-stop outcome of *traffic* stops. Two studies analyzed racial/ethnic disparities in use of force by police in pedestrian stops in New York City.[80] The form on which officers recorded information about the stops did not, however, capture complete information about the key variable, resistance by the citizen who was stopped; we consider neither study to be informative about racial/ethnic disparities. As Ridgeway observes,

> All of the reported differences resulting from our analysis are potentially due to unobserved or unmeasured features of the stops rather than racial bias. For example, the 1 percent difference observed in rates of use of force between stops of white and nonwhite suspects may be due to a factor not recorded on the UF250. It is possible that nonwhite suspects were slightly likelier to attempt to flee or threaten officers.[81]

Findings of Previous Research

Searches

Disparities in search behaviors is a prevalent finding in most research on post-stop outcomes, though the nature of these findings is contingent to some degree on the analytical methods utilized in the research.[82] Several researchers found that minority drivers, and particularly Black drivers, are more likely to be subjected to a high-discretion search than White drivers.[83] In comparing the search rates of matched Black and White drivers, Chanin and colleagues found that Black drivers were consent

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York: Cambridge University Press, 2004); William Terrill, Geoffrey P. Alpert, Roger G. Dunham, and Michael R. Smith, "A Management Tool for Evaluating Police Use of Force: An Application of the Force Factor," *Police Quarterly* 6 (2003): 150-171; William Terrill, "Police Use of Force and Suspect Resistance: The Micro Process of the Police-Suspect Encounter," *Police Quarterly* 6 (2003): 51-83; William Terrill, "Police Use of Force: A Transactional Approach," *Justice Quarterly* 22 (2005): 107-138; William Terrill and Michael Reisig, "Neighborhood Context and Police Use of Force," *Journal of Research in Crime and Delinquency* 40 (2003): 291-321.

[80] Rory Kramer and Brianna Remster, "Stop, Frisk, and Assault? Racial Disparities in Police Use of Force During Investigatory Stops" *Law & Society Review* 52 (2018): 960-993; Weston J. Morrow, Michael D. White, and Henry F. Fradella, "After the Stop: Exploring the Racial/Ethnic Disparities in Police Use of Force During Terry Stops," *Police Quarterly* 20 (2017): 367-396.

[81] Greg Ridgeway, *Analysis of Racial Disparities in the New York Police Department's Stop, Question, and Frisk Practices* (Santa Monica, CA: RAND Corporation, 2007), p. 45.

[82] Engel et al., *Cleveland Division of Police Traffic Stop Data Study;* Alpert et al, *Pedestrian and Motor Vehicle Data Analysis Report*; Rosenfeld et al, "Age Matters"; Schafer et al, "Decision Making"; Chanin et al, "Traffic Enforcement"; Rojek et al, "Policing Race"; Roh and Robinson, "A Geographic Approach"; Pickerill et al, "Search and Seizure"; Baumgarter et al, "Racial Disparities".

[83] Schafer et al., "Decision Making"; Chanin et al, "Traffic Enforcement"; Roh and Robinson, "A Geographic Approach"; Pickerill et al, "Search and Seizure"; Alpert et al, *Pedestrian and Motor Vehicle Data*; Rosenfeld et al, "Age Matters."

searched at a higher rate than White drivers, and that this pattern persisted in broader analysis of all search types.

Other research has found that the effects of race are diminished when controlling for other factors. Fallik and Novak concluded that racial disparities in search patterns were more a product of other circumstances, noting "although minorities were searched (overall) more often, including discretionary searches, it was not due to driver race or ethnicity but the differing circumstances under which the citizen encountered the officer."[84] Rather, the authors found that drivers' age and sex, as well as the context of the stop itself, were more predictive of searches. The effect of passengers on search behaviors was found to increase the likelihood of discretionary searches, and Tillyer and Klahm found that this effect overcame effects of the drivers' race in traffic stops involving more than one person.[85] In 2012, Tillyer, Klahm, and Engel's analysis found that, when controlling for other factors, Black drivers were not subjected to more discretionary searchers than White drivers. Further, they determined that citizens' demeanor had no bearing on their likelihood of being searched.[86] In 2014, Tillyer determined that disparities in discretionary search patterns were explained by citizen criminal history, and when controlling for this fact, the effects of race are mediated to some extent.[87] Alpert and colleagues determined that, even after controlling for driver, officer, and stop characteristics, Black and Hispanic drivers were more likely to be subjected to a pat-down or frisk.[88]

There is evidence to suggest that Black and Hispanic drivers are likely to be asked for consent to search, and Schafer and colleagues found that though race was a strong predictor for consent searches, so too were age and sex.[89] Roh and Robinson found racial disparities in consent searches less severe than those found in searches performed on the basis of probable cause.[90]

The interaction effects of driver and officer race yielded evidence that White officers were more likely to search generally, and more likely still to search minority drivers.[91] Rojek and colleagues also found that White officers were more likely to search White drivers in predominantly Black communities, proposing: "The presence of White drivers in predominantly Black communities may attract suspicion because they violate police officers' expectations concerning conventional or normal events or persons,

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[84] Fallik and Novak, "The Decision to Search," p. 159.
[85] Tillyer and Klahm, "Discretionary Searches."
[86] Tillyer et al, "The Discretion to Search."
[87] Tillyer, "Opening the Black Box of Officer Decision-Making."
[88] Alpert et al., *Pedestrian and Motor Vehicle Data*.
[89] Alpert et al., *Pedestrian and Motor Vehicle Data;* Chanin et al., "Traffic Enforcement"; Schafer et al., "Decision Making."
[90] Roh and Robinson, "A Geographic Approach."
[91] Engel et al, *Cleveland Division of Police Traffic Stop Data Study;* Rojek et al, "Policing Race"; Rosenfeld et al, "Age Matters".

leading some officers to conclude that such persons 'must be up to no good'."[92] The effects of age were also found to influence search behaviors, mostly to the effect of emphasizing the existing search behaviors pertaining to young Black and Hispanic drivers: as driver age increases, the chances of discretionary searches decreases.[93]

Arrests, Citations, and Warnings

Previous findings regarding disparities in arrest, citation, and warning patterns are less consistent. Several authors have found that racial disparities in arrest patterns dissipate when controlling for other legal and extra-legal factors.[94] Alpert and colleagues found that when low-discretion arrests were excluded from analysis, racial disparities in arrest patterns subsided. Roh and Robinson concluded that increased rates of searches, arrests, and citations were issued to minority drivers because those drivers frequented highly patrolled areas.[95] Chanin and colleagues' propensity matching analysis showed no statistically significant differences in arrest patterns of White and Black drivers.[96]

Evidence regarding patterns in traffic citations are more diverse: some research shows that while racial disparities in arrest patterns subside when controlling for legal and extra-legal factors, disparities in citations remain for minority drivers.[97] Alpert et al found that Hispanic drivers were more likely than White drivers to be cited holding all other factors constant, while Black drivers were less likely to be cited. Chanin and colleagues likewise found that Black drivers were less likely to be cited than White drivers. The authors did find, however, that more Black drivers were searched and not subsequently arrested when compared to White drivers.[98] Tillyer and Engel found that while the interaction effects for young, Hispanic Males (YHM) were not statistically significant, they produced for young, Black Males (YBMs) a higher chance of a warning and lower chance of citation.[99] Schafer and colleagues found that minority drivers and

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[92] Rojek et al. "Policing Race": 1017.
[93] Schafer et al,"Decision Making"; Rosenfeld et al, "Age Matters"; Pickerill et al., "Search and Seizure".
[94] Engel et al, *Cleveland Division of Police Traffic Stop Data Study;* Tillyer and Engel, "The Impact of Driver's Race"; Alpert et al, *Cleveland Division of Police Traffic Stop Data Study*.
[95] Roh and Robinson, "A Geographic Approach."
[96] Chanin et al., "Traffic Enforcement."
[97] For examples: Alpert et al. found diminished disparities "arrests based on warrants, violent crimes, and DUIs"; *Pedestrian and Motor Vehicle Data Analysis Report*. Engel et al. report that "...drivers who were stopped for a moving misdemeanor, license or registration violation, preexisting information, or some other (unknown) reason were significantly more likely to be arrested compared to drivers stopped for speeding or a felony moving violation"; *Cleveland Division of Police Traffic Stop Data Study*. Tillyer and Engel found that stops initiated for moving violations were associated with a higher likelihood of arrest; "The Impact of Drivers' Race, Gender, and Age During Traffic Stops."
[98] Ibid.
[99] Tillyer and Engel, "The Impact of Driver's Race".

older drivers were more likely to be issued warnings, and that warnings were more likely to follow a stop for equipment violations.[100]

Hit Rates

Findings regarding disparities in hit rates tend to show that fewer searches of Black drivers yield successful contraband discovery, though there is some evidence to suggest otherwise.[101] Engel and colleagues found higher hit rates for discretionary searches made of Black drivers than for White drivers, despite the finding that Black drivers are searched more often than White drivers.[102] Chanin and colleagues found that among all search types, "officers had to search nearly twice as many Black drivers as they did matched White drivers to discover the same amount of contraband,"[103] however, when separately analyzing consent, inventory, or other searches, differences between matched Black and White drivers were not statistically significant. Pickerill and colleagues also found that, among high-discretion searches, differences in hit rates among different races were not statistically significant.[104] Roh and Robinson determined that while Black drivers were searched more often than White drivers, the odds of a successful search were higher in stops of Black drivers. [105] With regards to officers' characteristics that pertain to hit rates, Engel found that officers with more experience on the force are more likely to conduct a successful search.[106]

Other Outcomes

Alpert and colleagues further examined the post-stop outcomes of "requests to exit the vehicle" and "no action taken."[107] Analysis of the former showed significant disparity in the rates at which officers asked Black and Hispanic drivers to exit the vehicle, when compared to White drivers. Though "no action taken" was a rare occurrence in stops evaluated by Alpert et al., minority drivers were slightly more likely to be stopped and have no subsequent action taken.

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100 Schafer et al., "Decision Making".
101 Geoffrey Alpert, Michael Smith, and Roger G. Dunham, "Toward a Better Benchmark: Assessing the Utility of Not-At-Fault Traffic Crash Data in Racial Profiling Research," *Justice Research and Policy* 6 (2004): 43-70; Robin Engel, Jennifer Calnon Cherkauskas, Michael R. Smith, Dan Lytle, and Kristian Moore, *Traffic Stop Data Analysis Study: Year 3 Final Report*. Submitted to the Arizona Department of Public Safety (2009).
102 Engel et al., *Cleveland Division of Police Traffic Stop Data Study*.
103 Chanin et al, "Traffic Enforcement," p. 570.
104 Pickerill et al., "Search and Seizure."
105 Rob and Robinson, "A Geographic Approach."
106 Engel et al., *Cleveland Division of Police Traffic Stop Data Study*.
107 Alpert et al., *Pedestrian and Motor Vehicle Data*.

Analysis of Post-Stop Outcomes in Suffolk County

In order to test for racial bias in post-stop outcomes, we relied primarily on propensity score matching to control for potentially confounding factors. Neil and Winship advise that, "Matching methods attempt to compare individuals who differ in one dimension (e.g., race) but are otherwise similar across a set of observed covariates …. In the context of police discrimination, matching is thus a direct way to estimate whether similarly situated individuals of different races experience the same police contact outcomes."[108] A propensity score is the probability of an individual being assigned to the group of interest ("treatment" group) rather than the "control" group. In this instance, Black and Hispanic drivers are assigned to respective treatment groups, while White drivers are assigned to the corresponding control group. The propensity score is estimated using logistic regression with membership in the group of interest as a binary outcome and a set of observed confounding variables as predictors. Individuals with similar propensity scores have similar values of the observed covariates, and treatment and control groups comprised of individuals paired by similar propensity scores will have similar distributions of the observed covariates. This construction allows for causal inferences due to a significant reduction in selection bias. The end goal of propensity score matching is to compare a treatment and control group that differ by no observable variable aside from treatment status.

For our analysis, one-to-one matching was executed using nearest neighbor matching without replacement.[109] Covariates used to estimate propensity scores included:

- Initial reason to stop
- Time of day
- Day of week
- Month
- Number of occupants
- Number of equipment violations
- Driver age and sex
- Violent crime rate

The violent crime rate of the area of each stop was calculated by obtaining a count of Part I violent crimes (homicide, rape, robbery, and aggravated assault) in the relevant

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[108] Neil and Winship, "Methodological Challenges and Opportunities in Testing for Racial Discrimination," p. 91.

[109] Daniel Ho, Kosuke Imai, Gary King, and Elizabeth Stuart, "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference," *Political Analysis* 15 (2007): 199-236, http://gking. harvard.edu/files/abs/matchp-abs.shtml. Daniel Ho, Kosuke Imai, Gary King, and Elizabeth Stuart, "Matchit: Nonparametric Preprocessing for Parametric Causal Inference," *Journal of Statistical Software* (2007), http://gking.harvard.edu/matchit/.

sector block for 30 days prior to the stop using SCPD RMS data. For post-stop analyses concerning vehicle searches, person searches, and commands to exit the vehicle, a caliper of 0.1 was used to obtain treatment and control groups that were sufficiently similar.[110] Post-stop analyses on the matched data sets were completed with logistic regression, ordered logistic regression, and Poisson regression, as appropriate to the properties of the outcome variable.

Table 47 summarizes a number of the differences that emerge for the stops of Black drivers that were matched to those of White drivers, and for the stops of Hispanic drivers that were matched to those of White drivers. For each outcome, the table reports the numbers of stops (n) on which differences are calculated (one number for stops of Blacks and another for stops of Hispanics), under the outcome heading. The columns to the right of the table report the differences: odds ratios (OR); the 95 percent confidence intervals associated with the odds ratios, and the p-value as a measure of statistical significance, or the probability of obtaining an odds ratio as large or larger by chance alone. An odds ratio of 1.0 – or even odds – indicates no difference between the two sets of stops (Black and White, and Hispanic and White, respectively). An odds ratio greater than 1.0 indicates that the outcome was more likely in the stops of Black drivers or Hispanic drivers than in the matched stops of White drivers. A p-value of less than 0.05 (or 1 in 20) is the conventional standard for statistical significance; any value smaller than 0.05 represents a probability of obtaining the estimated odds ratio that is small enough to reject the hypothesis of no difference. Table 48 repeats several of the analyses of differences by taking account of additional factors, or "covariates."

Referring to both Tables 47 and 48, we focus first on stops of Black drivers, compared with similarly-situated (i.e., matched) White drivers. Black drivers are:

- More than twice as likely to be subjected to a vehicle search;
- More than twice as likely to be subjected to a search of their person;
- 84 percent more likely to be restrained;
- More than three times as likely to be subjected to physical force;
- Ticketed for a larger number of violations;
- 59 percent more likely to be arrested; and
- To be detained for a longer period of time (28 percent more likely to be detained for more than 15 minutes).

Black drivers were also more likely to be removed from their vehicles (as Table 47 indicates), but that difference is a function of the differences in the likelihood of a search (see Table 48).

We note that the use of physical force is rare in SCPD traffic stops, and the stop record includes no information on drivers' resistance in terms of which the disparity might be accounted. The difference that we estimate in the likelihoods that force is

[110] The caliper of 0.1 guarantees the propensity scores of any 2 matched individuals will differ by no more than 0.1 standard deviations of all estimated propensity scores.

used against Black and White drivers, respectively, could be an artifact of our inability to take resistance into account as either a criterion for matching or as a covariate.

Table 47. Post-Stop Outcome Differences, Blacks and Hispanics Matched to Whites

Outcome	Black / White	Hispanic / White
1. Vehicle search (logistic) $n_B = 31{,}142$; $n_H = 40{,}022$	OR = 2.17 (1.95, 2.41) (p < 0.001)***	OR = 1.08 (0.97, 1.2) (p = 0.184)
2. Person search (logistic) $n_B = 31{,}142$; $n_H = 40{,}022$	OR = 2.1 (1.89, 2.33) (p < 0.001)***	OR = 1.16 (1.04, 1.28) (p = 0.0073)**
3. Exit vehicle (logistic) $n_B = 31{,}142$; $n_H = 40{,}022$	OR = 1.79 (1.63, 1.96) (p < 0.001)***	OR = 1.09 (0.99, 1.19) (p = 0.075)
4. Restrained (logistic) $n_B = 31{,}142$; $n_H = 40{,}022$	OR = 1.84 (1.59, 2.13) (p < 0.001)***	OR = 1.07 (0.92, 1.24) (p = 0.387)
5. Force used (logistic) $n_B = 31{,}142$; $n_H = 40{,}022$	OR = 3.2 (1.25, 9.79) (p = 0.0231)*	OR = 1.2 (0.36, 4.16) (p = 0.763)
6. Total tickets (Poisson) $n_B = 31{,}142$; $n_H = 40{,}022$	IRR = 1.29 (1.26, 1.31) (p < 0.001)***	IRR = 1.27 (1.24, 1.29) (p < 0.001)***
7. Warning (logistic) $n_B = 31{,}142$; $n_H = 40{,}022$	OR = 0.99 (0.94, 1.03) (p = 0.556)	OR = 0.75 (0.72, 0.78) (p < 0.001)***
9. Arrest (logistic) $n_B = 31{,}142$; $n_H = 40{,}022$	OR = 1.59 (1.42, 1.77) (p < 0.001)***	OR = 1.16 (1.04, 1.29) (P = 0.0078)**
10. UTT (logistic) $n_B = 31{,}142$; $n_H = 40{,}022$	OR = 0.94 (0.9, 0.99) (p = 0.0098)**	OR = 1.32 (1.27, 1.38) (p < 0.001)***
11. Duration (ordered logistic) $n_B = 31{,}133$; $n_H = 40{,}014$	OR = 1.27 (1.2, 1.36) (p < 0.001)***	OR = 1.16 (1.1, 1.23) (p < 0.001)***
12. Duration > 15 minutes (logistic) $n_B = 31{,}133$; $n_H = 40{,}014$	OR = 1.28 (1.2, 1.37) (p < 0.001)***	OR = 1.16 (1.1, 1.23) (p < 0.001)***

Notes:
-Duration models dropped cases with duration = “NULL” (6 Black, 3 White);(5 Hispanic, 3 White)
-All matched data sets use drivers only to avoid matching individuals in the same stop

Table 48. Post-Stop Outcome Differences, with Covariates

Outcome	Covariates	Black / White	Hispanic / White
3a. Exit vehicle	vehicle search, person search	OR = 1 (0.84, 1.17) (p = 0.951)	OR = 0.98 (0.84, 1.14) (p = 0.746)
11a. Duration	vehicle search, person search	OR = 1.13 (1.06, 1.21) (p < 0.001)***	OR = 1.15 (1.08, 1.22) (p < 0.001)***
12a. Duration > 15 minutes	vehicle search, person search	OR = 1.15 (1.08, 1.23) (p < 0.001)***	OR = 1.15 (1.09, 1.22) (p < 0.001)***

Additional analyses focus on only applicable stops, e.g., we analyze whether drivers were placed in the back of the police unit only for stops in which they were required to leave their vehicles (see Table 49). We find that Black drivers were

- 42 percent more likely to be placed in the back of the police unit, given that they are removed from their own vehicle (a finding that holds also when vehicle and person searches are treated as covariates); and
- 29 percent more likely to have the vehicle search yield no contraband.

Though Black drivers are more likely to have their persons searched, those searches are *not* less likely to produce contraband. Though the inferences from such "outcome tests" can be misleading, as we discussed above, the findings concerning person searches that result in nothing found should give readers pause in reaching a conclusion about bias in searches of persons.

Table 49. Post-Stop Outcome Differences, with only Applicable Stops

Outcome	**Black / White**	**Hispanic / White**
8. Placed in back of unit (logistic) n_B = 2,110; n_H = 1,822	OR = 1.42 (1.2, 1.69) ($p < 0.001$)	OR = 1.09 (0.9, 1.31) ($p = 0.373$)
13. Vehicle search = nothing (logistic) n_B = 1,782; n_H = 1,400	OR = 1.29 (1.07, 1.55) ($p = 0.0078$)**	OR = 1.23 (0.99, 1.51) ($p = 0.0594$)
14. Person search = nothing (logistic) n_B = 1,966; n_H = 1,538	OR = 0.95 (0.79, 1.15) ($p = 0.631$)	OR = 1.06 (0.85, 1.31) ($p = 0.622$)

Notes:
-Model 8 uses one-one matched data set (caliper = 0.1); exit vehicle only
-Model 13 uses one-one matched data set (caliper = 0.1); vehicle searches only
-Model 14 uses one-one matched data set (caliper = 0.1); person searches only
-All matched data sets use drivers only to avoid matching individuals in the same stop

Fewer differences are detected in the comparison of stops of Hispanic and White drivers. Compared with similarly-situated (i.e., matched) White drivers, Hispanic drivers are:

- 16 percent more likely to be subjected to a search of their person;
- 16 percent more likely to be arrested;
- 32 percent more likely to be ticketed;
- Ticketed for a larger number of violations;
- 25 percent less likely to receive a warning; and
- To be detained for a longer period of time (16 percent more likely to be detained for more than 15 minutes).

Hispanic drivers are marginally more likely to be subjected to a vehicle search that yields no contraband, though the likelihood that a difference that large could be a chance result is slightly greater than the conventional 5 percent.

It is certainly conceivable that some or much of the unexplained disparity stems from stops in which arrests are made, if Black and/or Hispanic drivers are more likely to be wanted on warrants, or more likely to be driving with a suspended license. Failures to appear in court or to pay fines could eventuate in the issuance of warrants and/or the suspension of driving privileges, and insofar as Black and Hispanic individuals are more likely to have limited economic means, they could be disproportionately represented among those whom police must take into custody once they are stopped, with other differences in post-stop outcomes following from that status.[111]

To obtain some additional perspective on the forces that affect post-stop outcomes, we conducted regression analyses that promise to estimate the independent effects of hypothetically pertinent factors, controlling statistically for other factors in the analysis. The first set of regression analyses focus on searches (see Table 50). We analyze searches of persons overall and separately examine several subsets: frisks only; searches other than frisks; and searches other than those incident to arrest.

Table 50. Regression Analyses of Searches

	Vehicle	Person	Frisk only	Excluding frisks	Person – not incident to arrest
First Precinct	9.74*	6.96*	10.27*	5.56*	8.25*
Third Precinct	4.27*	2.83*	1.66*	3.03*	3.05*
Fifth Precinct	2.50*	2.38*	1.33*	2.52*	2.34*
Precinct crime	2.37*	2.78*	1.81*	2.79*	2.73*
Highway patrol	0.06*	0.31*	0.04*	0.35*	0.13*
Other unit	0.76	0.77*	0.81	0.76*	0.69*
Part I crime rate	1.11*	1.08*	0.85*	1.15*	1.05*
Reasonable suspicion	18.70*	12.97*	6.48*	11.05*	12.79*
BOLO	4.08*	3.22*	3.56*	2.89*	2.75*
Equipment	1.36*	1.12*	1.95*	1.03*	1.32*
18:00-21:59	1.24*	1.14*	1.36*	1.08	1.30*
22:00-02:59	1.12*	1.15*	1.28*	1.11*	1.22*
Driver Black		2.03*	1.90*	1.97*	2.12*
Driver Hispanic		1.23*	1.24*	1.21*	1.25*
Driver male		3.24*	5.22*	2.80*	3.35*
Constant	0.01*	<0.01*	<0.01*	<0.01*	<0.01*

Note: entries are odds ratios
* $p < 0.05$

[111] This speculation is supported by findings reported by Wendy Regoeczi and Stephanie Kent, "Race, Poverty, and the Traffic Ticket Cycle: Exploring the Situational Context of the Application of Police Discretion," *Policing: An International Journal of Police Strategies & Management* 37 (2014).

We treat precincts 2, 4, 6, and 7 as baseline precincts for comparison. In the first and third precincts, vehicle and person searches are more likely to be conducted, given a stop. Precinct crime units are more likely than precinct patrol units to conduct searches, and highway patrol and other units less likely. The likelihood of a search rises with the rate of Part I crime in the sector block. Searches are more likely given particular reasons for the stop: stops based on BOLOs, reasonable suspicion, or equipment violations. Searches are more likely in stops made after 6 p.m. and before 3 a.m. Finally, with all of the preceding factors statistically controlled, searches are more likely when the drivers are men, and when they are Black or Hispanic. Moreover, the elevated likelihood of searches of Black and Hispanic drivers remains even when stops ending in arrest are removed from the analysis.

Table 51. Regression Analyses of Searches with No Contraband Found

	Vehicle	Person	Excluding frisks
First Precinct	0.78*	0.88	0.87
Third Precinct	0.89	0.92	0.94
Fifth Precinct	1.53*	1.66*	1.68*
Precinct crime	0.48*	0.44*	0.41*
Highway patrol	0.69	2.72*	2.99*
Other unit	0.64	0.70	0.64
Part I crime	0.86*	0.96	0.96
Reasonable suspicion	0.78	0.69*	0.70*
BOLO	0.86	0.83	0.73
Equipment	1.13	1.05	1.06*
18:00-21:59	0.98	0.91	0.92
22:00-02:59	0.77*	0.92	0.89
Frisk	NA	3.10*	--
Consent	9.09*	1.03	1.02
Plain view	0.13*	0.04*	0.04*
Probable cause	NA	0.29*	0.29*
Probable cause – drugs	--	NA	
Probable cause – other	7.07*	NA	
Incident to arrest	NA	--	--
Driver Black	1.78*	1.26*	1.29*
Driver Hispanic	1.40*	1.24*	1.18
Driver male	0.85	0.96	0.96
Constant	0.89	4.49*	4.54*

Note: entries are odds ratios
* $p < 0.05$

We also conducted regression analyses of the outcomes of searches, explaining the binary outcome of no contraband found as the object of explanation (see Table 51, above). Though vehicle and person searches are more likely to be conducted in the first and third precincts (see Table 50), they are not more likely than those in the comparison precincts to yield no contraband – that is, the searches are as or more successful than those conducted in precincts that search less frequently. In the fifth precinct, however, searches are more likely, given a stop, and those searches are substantially (i.e., 50 to 80 percent) more likely to yield no contraband. Other things being equal, searches of Black and Hispanic drivers' vehicles are less likely to yield results.

With regard to searches of persons, we treat searches incident to arrest as a referent. Against that baseline, which is low in officer discretion, searches based on plain view or probable cause are much more likely to have positive results. Searches based on consent are about as likely as searches incident to arrest to yield contraband. Frisks are three times as likely as searches incident to arrest to yield no results, but this is to be expected, given the limited purpose of a frisk. Searches of Black and Hispanic drivers are, other things being equal, more likely to have negative results (though excluding frisks, the estimated difference for Hispanic drivers does not reach statistical significance).

Table 52. Regression Analyses of Restraint and Duration

	Restrained	Duration > 15 minutes
First Precinct	9.12*	1.75*
Third Precinct	2.86*	0.70*
Fifth Precinct	1.27	1.49*
Precinct crime	0.93	0.50*
Highway patrol	0.14*	1.20*
Other unit	1.11	1.18*
Part I crime	0.92	1.00
Reasonable suspicion	8.02	2.64*
BOLO	8.82*	1.30
Equipment	1.52*	1.10*
18:00-21:59	1.51*	1.00
22:00-02:59	1.09*	1.11*
Driver Black	2.16*	1.48*
Driver Hispanic	1.22	1.51*
Driver male	3.83*	1.40*

Notes:
-stops ending in arrest excluded
-entries are odds ratios
* $p < 0.05$

We analyzed whether the driver was restrained and whether the stop lasted 15 minutes or longer in regression models of the same kind, excluding stops ending in arrests. See Table 52, above. Drivers stopped in the first and third precincts are more likely to be restrained, as are those stopped between 6 p.m. and 3 a.m., or for equipment violations or based on a BOLO. Holding these factors constant, Black drivers were more likely to be restrained.

Stops in the first and fifth precincts were more likely, and stops in the third precinct less likely, to last more than 15 minutes. Stops by highway patrol and other units were more likely, and stops by precinct crime units less likely, to last more than 15 minutes. Stops based on reasonable suspicion tended to have the longer duration. Independent of these factors, stops of Black and Hispanic drivers were more likely to take more than 15 minutes.

Finally, we conducted a multinomial regression analysis of dispositions, contrasting arrests and tickets against all other disposition categories as the collective baseline (see Table 53). Formal enforcement action in the forms of arrests and Tickets were more likely in the first, third, and fifth precincts and by precinct crime units. The likelihood of each form of enforcement also rose with the rate of Part I crime in the sector block. Highway patrol units were more likely, and other units less likely, to issue tickets. Stops based on reasonable suspicion were much more likely to result in arrest

Table 53. Regression Analysis of Dispositions

	Arrest	Ticket
First Precinct	3.46*	1.30*
Third Precinct	2.28*	1.20*
Fifth Precinct	2.36*	1.32*
Precinct crime	3.82*	2.11*
Highway patrol	1.02	1.11*
Other unit	0.78	0.82*
Part I crime	1.12*	1.02*
Reasonable suspicion	5.42*	0.27*
BOLO	2.67	0.52*
Equipment	0.91*	0.90*
18:00-21:59	0.81*	0.94*
22:00-02:59	1.02	0.92*
Searched	11.30*	0.69*
Driver Black	1.36*	0.95*
Driver Hispanic	1.25*	1.28*
Driver male	2.03*	1.15*

Note: entries are odds ratios

* $p < 0.05$

and much less likely to result in a ticket. Stops for equipment violations were likely to eventuate in a warning instead of either an arrest or a ticket. As the analysis of matched stops indicated, Black and Hispanic drivers were more likely to be arrested; Black drivers were less likely and Hispanic drivers more likely to be ticketed.

Thus we find a number of disparities between sets of matched stops, matched in order to control for factors that could be associated with race/ethnicity and affect the outcomes, confounding the estimated effects of race/ethnicity and thereby complicating inferences about bias. Further analysis indicates that these remaining disparities are not a simple function of differences in drivers' offending that leads to arrest, for the disparities are found among stops that did not end in arrests. The differences in searches do not appear to stem from consent searches, though the data do not indicate when and from whom consent was *requested* but declined.[112]

Other explanations are conceivable, though we could not examine them with the data available to us. One factor, which was found in one previous study to account for racial disparities in searches, is the driver's criminal history.[113] We might expect that officers would more thoroughly question and otherwise investigate drivers with a criminal history, raising the likelihood of a search and thus the removal of the driver from the car and extending the duration of the stop. Similarly, we might expect the same sequence of events in stops involving identified or suspected members of street gangs. Our inability to take proper account of these factors is reason to be cautious in drawing inferences about the role of bias from the remaining disparities.[114]

Still other explanations include features of the vehicle and the driver that officers may take to be indicative of involvement in drug trafficking: rental vehicles; items such as luggage or a spare tire in the back seat rather than the trunk; air fresheners or carpet deodorizers to mask odors; fresh paint or body work (resulting from the formation of a hidden compartment). Drivers who are not the owners of the vehicles may also raise suspicion.[115] If these and/or other investigative practices contribute to racial and ethnic disparities in post-stop outcomes, then judgments could be made about whether the practices should be curtailed or regulated.

Finally, we would point to the context of the stops as one additional factor. We were able to take into account rates of crime (Part I crime and Part I violent crime) in blocks of police sectors, which enabled us to control for within-precinct variation in

[112] We note that it would have been useful to have information on: (1) whether consent to search was requested but declined; (2) whether any arrest was made pursuant to a warrant; and (3) the most serious charge associated with an arrest.

[113] Rob Tillyer, "Opening the Black Box of Officer Decision-Making."

[114] With information on the drivers' identities, in conjunction with other Suffolk County RMS data, some analysis of these factors could be performed.

[115] These and other explanations are discussed in Robin S. Engel and Richard Johnson, "Toward a Better Understanding of Racial and Ethnic Disparities in Search and Seizure Rates," Journal of Criminal Justice 34 (2006): 605-617.

crime. We could not take account of areas that are known or suspected for the distribution of illicit drugs. For that purpose, ideally, any analysis would rely on data that are independent of police enforcement patterns, such as citizen-initiated calls for service concerning drug activity.

Conclusions

Pursuant to the SCPD's settlement agreement with the U.S. Department of Justice, we analyzed traffic stops and post-stop outcomes over a one-year period in Suffolk County, with a view toward assessing racial and ethnic disparities for evidence of bias in enforcement. Analyses of this kind pose methodological challenges that, if not approached with due care, undermine the credibility of analytic findings. We took account of the strengths and weaknesses in the approaches adopted in previous inquiries, and on that basis, we designed and conducted analyses that we believe have minimized the methodological threats.

Analyzing the initial stop decisions by SCPD officers, using the veil-of-darkness method to establish an acceptable benchmark, we found no evidence of racial or ethnic bias. Black and Hispanic drivers were as likely to be stopped in darkness, when officers' ability to detect the features of drivers (or other vehicle occupants) is impaired, as in daylight. We infer that SCPD officers' discretionary choices to stop (or to not stop) vehicles were not systematically influenced by race or ethnicity.

Analyzing a number of post-stop outcomes by matching stops of Black and Hispanic drivers, respectively, to stops of White drivers based on a number of factors, we detected disparities on several outcomes, including:

- The likelihood of a vehicle search (Black drivers);
- The likelihood of a search of their person (Black and Hispanic drivers);
- The likelihood of being restrained (Black drivers);
- The likelihood of being subjected to physical force (Black drivers);
- The likelihood of being ticketed rather than warned (Hispanic drivers);
- The number of violations for which they are ticketed (Black and Hispanic drivers);
- The likelihood of being arrested (Black and Hispanic drivers);
- The duration of the stop (Black and Hispanic drivers);
- Placement in the back of the police unit (Black drivers); and
- The likelihood that a vehicle search yields no contraband (Black drivers).

The available data precluded analyses that take account of several factors that might account for these differences. Our analysis of the use of force, for example, could not account for citizens' resistance. We advise readers to exercise caution in drawing inferences about bias in any of these forms of enforcement action.

Additional analyses that might prove informative are feasible. Some previous research has constructed "internal" benchmarks to determine the extent to which racial or ethnic disparities stem from the enforcement practices of individual police officers. Controlling for the times and locations of stops, the racial/ethnic composition of the drivers stopped by individual officers are compared to one another to ascertain whether some officers exhibit disparities that are out of the ordinary. Findings from such analyses can form actionable information.[116]

[116] See, e.g., Ridgeway, *Analysis of Racial Disparities in the New York Police Department's Stop, Question, and Frisk Practices*. Also see Ridgeway and MacDonald, "Methods for Assessing Racially Biased Policing."

Appendix A
Sector Blocks

Blocks	Sectors	Town/ Villages/Hamlets
First Precinct Blocks	101, 104	Republic Airport
	102, 105, 106	Wyandanch
	103, 107, 108, 121	Deer Park
	109, 110, 114, 117, "1AM"	Copiague, Amityville
	111, 115, 122	N. Lindenhurst
	112, 113, 116, 120	Babylon
	118, 119	S. Lindenhurst
Second Precinct Blocks	201, 202, 203, 208, 217	Huntington
	205, 206, 216	Northport
	207, 222	Elwood
	209, 211, 213, 214	S. Huntington, Melville
	212, 219, 220	Dix Hills
	204, 210, 215, 221	Greenlawn
Third Precinct Blocks	301, 313, 317	W. Islip, W. Bay Shore
	304, 314, 315, 323, 324	Brightwaters, Bay Shore
	303, 311, 312, 322	Baywood, N. Bay Shore
	302, 310, 316, 321	N. Brentwood, N. Central Islip
	305, 308, 309, 320	Islip, Islip Terrace, Great River
	306, 307, 318	S. Central Islip
Fourth Precinct Blocks	401, 414	Kings Park
	402, 404, 406, 407, 411	E. Commack, W. Hauppauge
	403, 410, 412, 415	St. James, Nesconset, Smithtown
	405, 409, 416, 417	Islandia, Lake Ronkonkoma
	408, 413	Lake Grove
Fifth Precinct Blocks	501, 502, 503, 504, 505	Long Island, Bohemia, Oakdale, West Sayville
	506, 507	N. Patchogue
	508, 509, 510, 512, 513	Patchogue
	511, 516	S. Medford
	514, 515	Bellport, Brookhaven
Sixth Precinct Blocks	601, 602, 603, 604, 605	W. Selden, W. Farmingville
	606, 608, 609	Stonybrook, Setauket-East Setauket
	607, 610	Port Jefferson
	611, 612, 613, 614	Mt. Sinai, Port Jefferson Station
	618, 619	Farmingville, W. Yaphank
	615, 616, 617, 620	Coram, Gordon Heights
Seventh Precinct Blocks	701, 702, 703	Sound Beach, Rocky Point, East Shoreham
	704, 705	Middle Island, Ridge
	708, 709, 711, 712	Manorville, Moriches
	706, 707, 710, 713, 714, 715	Brookhaven Calabro Airport, Mastic, Mastic Beach

Appendix B
Propensity Score Matching Tables

Table B-1. Black/White

	Black Drivers		White Drivers			
	n = 15,571		n = 42,837		n = 15,571	
Variable	%	n	Pre-Match %	Pre-Match n	Post-Match %	Post-Match n
Reason to Stop						
Reasonable Suspicion	1.91	297	0.88	376	1.77	275
Other Moving Viol.	15.66	2,438	15.28	6,545	15.76	2,453
Equipment Viol.	29.34	4,568	20.29	8,691	29.14	4,537
Speeding	9.12	1,420	12.51	5,358	9.28	1,444
Cell Phone	3.01	468	6.02	2,578	2.97	462
BOLO	0.21	32	0.1	42	0.17	26
Red Light	1.85	288	2.63	1,126	1.86	289
Stop Sign	12.61	1,963	19.08	8,173	12.6	1,961
Seatbelt	3	467	2.42	1,036	3.08	479
Other VTL	23.3	3,628	20.79	8,905	23.37	3,638
Precinct						
1	25.66	3,995	9.37	4,013	10.64	1,656
2	12.38	1,927	15.69	6,721	14.4	2,242
3	17.94	2,793	7.48	3,204	9.05	1,409
4	3.38	526	7.61	3,259	6.6	1,027
5	7.35	1,144	9.06	3,881	10.81	1,683
6	11.43	1,779	21.11	9,042	20.94	3,260
7	12.65	1,969	13.82	5,920	13.57	2,112
9	9.22	1,435	15.86	6,793	13.99	2,178
Sex						
Female	34.03	5,298	36.03	15,434	33.66	5,241
Male	65.97	10,272	63.97	27,402	66.34	10,329

Age						
<16	0.1	15	0.07	29	0.12	18
16 to 25	26.87	4,183	23.71	10,156	26.6	4,141
26 to 35	35.3	5,496	25.76	11,034	35.78	5,571
36 to 45	19.43	3,025	18.29	7,834	19.36	3,014
46 to 55	11.87	1,848	18.12	7,762	11.8	1,837
56 to 65	5.27	820	10.36	4,437	5.17	805
>65	1.16	180	3.7	1,584	1.17	182
Time of Day						
00:00 – 03:59	12.66	1,971	10.45	4,476	12.94	2,014
04:00 – 07:59	3.37	524	5.08	2,176	3.28	510
08:00 – 11:59	25.57	3,981	27.36	11,720	25.7	4,001
12:00 – 15:59	17.19	2,676	17.46	7,479	16.79	2,614
16:00 – 19:59	21.58	3,360	23.23	9,951	21.37	3,327
20:00 – 23:59	19.62	3,055	16.42	7,033	19.92	3,101
Day of Week						
Monday	15.18	2,363	14.86	6,365	15.34	2,388
Tuesday	14.4	2,242	15.65	6,703	14.06	2,189
Wednesday	15.79	2,458	15.82	6,776	15.56	2,422
Thursday	15.03	2,340	15.9	6,811	15.33	2,387
Friday	14.3	2,226	14.84	6,357	14.33	2,231
Saturday	13.49	2,100	12.41	5,316	13.6	2,117
Sunday	11.82	1,840	10.52	4,506	11.77	1,832
Month						
January	8.8	1,370	8.79	3,765	8.8	1,370
February	8.56	1,332	8.56	3,666	8.57	1,334
March	7.78	1,211	8.21	3,516	8.27	1,287
April	8.25	1,284	8.1	3,469	8.52	1,326
May	8.91	1,387	8.97	3,842	8.66	1,348
June	7.96	1,239	8.47	3,628	8.14	1,267
July	8.73	1,359	8.93	3,825	8.75	1,362
August	9.32	1,451	8.94	3,829	8.59	1,337
September	8.06	1,255	8.36	3,581	7.76	1,208
October	8.36	1,301	8.17	3,499	7.92	1,233
November	8.08	1,258	7.54	3,229	8.39	1,306
December	7.17	1,116	6.96	2,981	7.63	1,188

Number of Occupants						
1	91.4	14,231	94.27	40,382	92	14,325
2	6.76	1,052	4.7	2,013	6.25	973
3	1.41	219	0.72	308	1.14	177
4	0.37	57	0.25	107	0.48	74
5	0.04	6	0.05	21	0.11	17
6	0.01	1	0.01	4	0.03	4
Equipment Viol.						
0	77.34	12,042	84.42	36,162	77.48	12,064
1	17.72	2,759	13.01	5,573	17.79	2,770
2	3.58	557	1.9	813	3.51	546
3	0.73	113	0.38	162	0.65	101
4	0.39	60	0.14	59	0.31	48
5	0.23	35	0.15	64	0.26	40
Violent Crime Rate (previous 30 days, per 10,000 people)						
Mean	1		0.71		0.92	
Median	0.78		0.55		0.75	

Table B-2: Hispanic/White

	Hispanic Drivers		White Drivers			
	n = 20,011		n = 42,837		n = 20,011	
Variable	**%**	**n**	**Pre-Match %**	**Pre-Match n**	**Post-Match %**	**Post-Match n**
Reason for Stop						
Reasonable Suspicion	1.29	258	0.88	376	1.25	250
Other Moving Viol.	15.46	3,093	15.28	6,545	15.59	3,119
Equipment Viol.	28.83	5,769	20.29	8,691	28.11	5,625
Speeding	8.94	1,788	12.51	5,358	8.94	1,788
Cell Phone	4.47	894	6.02	2,578	4.43	886
BOLO	0.08	16	0.1	42	0.06	12
Red Light	2.39	478	2.63	1,126	2.38	476
Stop Sign	14.65	2,931	19.08	8,173	14.73	2,947
Seatbelt	3.24	648	2.42	1,036	3.31	662
Other VTL	20.66	4,134	20.79	8,905	21.2	4,242
Precinct						
1	12.26	2,453	9.37	4,013	10.92	2,185
2	15.49	3,099	15.69	6,721	14.68	2,937
3	31.03	6,209	7.48	3,204	8.84	1,768
4	4.8	960	7.61	3,259	6.85	1,370
5	6.97	1,394	9.06	3,881	10.53	2,107
6	10.49	2,099	21.11	9,042	20.53	4,108
7	7.36	1,472	13.82	5,920	13.06	2,613
9	11.61	2,323	15.86	6,793	14.58	2,917
Sex						
Female	27.03	5,408	36.03	15,434	26.87	5,376
Male	72.97	14,602	63.97	27,402	73.13	14,634
Age						
<16	0.12	24	0.07	29	0.12	24
16 to 25	29.33	5,869	23.71	10,156	29.08	5,819
26 to 35	31.43	6,289	25.76	11,034	31.67	6,337
36 to 45	22.74	4,550	18.29	7,834	23.14	4,630
46 to 55	11.63	2,327	18.12	7,762	11.33	2,267
56 to 65	3.98	796	10.36	4,437	3.98	796
>65	0.75	150	3.7	1,584	0.66	132

Time of Day						
00:00 – 03:59	10.68	2,137	10.45	4,476	10.79	2,159
04:00 – 07:59	4.95	990	5.08	2,176	4.93	986
08:00 – 11:59	25.98	5,198	27.36	11,720	25.96	5,194
12:00 – 15:59	16.73	3,347	17.46	7,479	16.86	3,373
16:00 – 19:59	23.73	4,748	23.23	9,951	23.84	4,770
20:00 – 23:59	17.94	3,589	16.42	7,033	17.62	3,525
Day of Week						
Monday	14.33	2,867	14.86	6,365	14.45	2,891
Tuesday	14.59	2,919	15.65	6,703	14.54	2,909
Wednesday	15.39	3,079	15.82	6,776	15.23	3,047
Thursday	15.36	3,073	15.9	6,811	15.53	3,107
Friday	14.02	2,805	14.84	6,357	13.92	2,785
Saturday	14.14	2,829	12.41	5,316	14.34	2,869
Sunday	12.17	2,435	10.52	4,506	11.99	2,399
Month						
January	8.79	1,758	8.79	3,765	8.66	1,732
February	8.96	1,792	8.56	3,666	9.05	1,810
March	8.41	1,682	8.21	3,516	8.69	1,738
April	8.53	1,706	8.1	3,469	8.8	1,760
May	8.21	1,642	8.97	3,842	8.23	1,646
June	8.03	1,606	8.47	3,628	8.09	1,618
July	8.54	1,708	8.93	3,825	8.24	1,648
August	9.02	1,804	8.94	3,829	8.87	1,774
September	8.48	1,696	8.36	3,581	8.27	1,654
October	8.36	1,672	8.17	3,499	8.34	1,668
November	7.43	1,486	7.54	3,229	7.28	1,456
December	7.28	1,456	6.96	2,981	7.52	1,504
Number of Occupants						
1	91.72	18,354	94.27	40,382	92.22	18,454
2	6.21	1,242	4.7	2,013	6.1	1,220
3	1.54	308	0.72	308	1.11	222
4	0.4	80	0.25	107	0.46	92
5	0.1	20	0.05	21	0.09	18
6	0.02	4	0.01	4	0.02	4

Equipment Viol.						
0	75.7	15,148	84.42	36,162	76.38	15,284
1	19.2	3,842	13.01	5,573	19.1	3,822
2	3.73	746	1.9	813	3.33	666
3	0.73	146	0.38	162	0.68	136
4	0.39	78	0.14	59	0.27	54
5	0.25	50	0.15	64	0.23	46
Violent Crime Rate (previous 30 days, per 10,000 people)						
Mean	0.94		0.71		0.89	
Median	0.78		0.55		0.72	

Table B-3: Black/White Vehicle Search

	Black Drivers		White Drivers	
	n = 1,099	n = 805	n = 891	n = 805
Variable	Pre-Match %	Post-Match %	Pre-Match %	Post-Match %
Reason to Stop				
Reasonable Suspicion	11.92	11.68	11.56	12.17
Other Moving Viol.	16.83	16.02	15.38	15.4
Equipment Viol.	32.94	30.31	28.4	29.81
Speeding	5.37	5.96	5.72	5.71
Cell Phone	1.82	2.24	2.92	2.48
BOLO	0.36	0.37	0.45	0.37
Red Light	0.18	0.25	1.35	0.25
Stop Sign	9.65	10.31	9.99	10.31
Seatbelt	4.28	4.72	4.38	4.1
Other VTL	16.65	18.14	19.87	19.38
Precinct				
1	56.23	55.9	46.69	46.96
2	8.01	7.58	7.74	7.7
3	22.11	21.24	17.4	17.14
4	1	1.12	2.69	2.48
5	5.46	6.58	11.9	12.3
6	3.55	3.6	8.87	8.45
7	2.82	2.98	3.93	4.1
9	0.82	0.99	0.79	0.87
Sex				
Female	15.29	19.88	23.34	19.5
Male	84.71	80.12	76.66	80.5
Age				
<16	0.27	0.25	0.11	0.12
16 to 25	40.67	41.99	41.86	41.86
26 to 35	38.85	34.91	33.11	34.29
36 to 45	11.28	12.67	13.92	13.29
46 to 55	6.19	6.83	7.63	7.2
56 to 65	2.37	2.98	3.14	2.98
>65	0.36	0.37	0.22	0.25

Time of Day				
00:00 – 03:59	7.83	8.7	7.63	7.7
04:00 – 07:59	0.91	1.24	1.46	1.37
08:00 – 11:59	24.29	20.37	18.63	19.88
12:00 – 15:59	22.57	20.25	20.54	21.37
16:00 – 19:59	25.02	26.83	27.27	26.83
20:00 – 23:59	19.38	22.61	24.47	22.86
Day of Week				
Monday	12.92	11.93	11.67	11.93
Tuesday	13.47	14.04	13.92	14.41
Wednesday	17.29	18.51	17.51	17.02
Thursday	14.83	14.53	14.48	14.41
Friday	14.19	14.91	15.38	14.78
Saturday	13.38	14.04	15.15	14.78
Sunday	13.92	12.05	11.9	12.67
Month				
January	9.01	8.82	8.87	9.32
February	11.56	10.43	10.1	10.68
March	6.73	6.21	6.73	7.2
April	7.92	6.71	7.18	7.08
May	9.55	9.57	8.87	8.94
June	6.46	8.07	8.42	7.83
July	7.01	8.2	7.41	7.45
August	9.01	9.57	10.1	9.07
September	7.55	8.07	8.08	8.45
October	7.92	6.96	7.3	6.96
November	9.1	8.7	8.53	8.45
December	8.19	8.7	8.42	8.57
Number of Occupants				
1	70.25	69.07	67.68	68.57
2	22.29	23.11	25.81	25.34
3	5.55	5.96	4.38	4.1
4	1.73	1.74	1.8	1.74
5	0.18	0.12	0.34	0.25

Equipment Violation				
0	73.7	75.28	72.73	72.67
1	18.84	17.39	18.52	18.39
2	4.55	4.35	6.62	6.71
3	1.09	0.99	1.35	1.49
4	1.27	1.37	0.67	0.62
5	0.55	0.62	0.11	0.12
Violent Crime Rate (previous 30 days, per 10,000 people)				
Mean	1.21	1.11	1.01	1.02
Median	0.98	0.96	0.78	0.78

Table B-4: Black/White Person Search

	Black Drivers		White Drivers	
	n = 1,081	n = 812	n = 983	n = 812
Variable	Pre-Match %	Post-Match %	Pre-Match %	Post-Match %
Reason to Stop				
Reasonable Suspicion	10.92	9.98	9.46	10.59
Other Moving Viol.	16.93	18.47	19.23	17.49
Equipment Viol.	32.65	28.45	25.03	29.06
Speeding	5.55	6.65	7.83	6.03
Cell Phone	1.48	1.97	3.36	2.22
BOLO	0.37	0.25	0.31	0.25
Red Light	0.28	0.25	1.83	0.12
Stop Sign	9.34	10.22	10.68	10.59
Seatbelt	3.98	3.82	3.76	4.19
Other VTL	18.5	19.95	18.51	19.46
Precinct				
1	54.86	53.94	40.08	42.73
2	8.42	8.25	7.02	7.51
3	19.61	18.35	12.72	13.05
4	1.76	2.09	3.56	2.96
5	6.38	6.9	12.82	13.18
6	3.79	4.06	10.27	9.48
7	2.87	3.57	5.9	5.91
9	2.31	2.83	7.63	5.17
Sex				
Female	11.19	13.79	17.09	14.29
Male	88.81	86.21	82.91	85.71
Age				
<16	0.09	0	0.1	0
16 to 25	36.91	37.56	37.33	38.67
26 to 35	40.98	36.58	33.06	34.73
36 to 45	12.21	14.41	15.36	15.27
46 to 55	7.49	8.37	9.46	7.88
56 to 65	2.04	2.71	3.87	3.08
>65	0.28	0.37	0.81	0.37

Time of Day				
00:00 – 03:59	8.88	10.84	15.67	11.7
04:00 – 07:59	1.11	1.35	1.63	1.72
08:00 – 11:59	24.79	21.43	18.11	20.44
12:00 – 15:59	21.46	19.7	18.11	20.2
16:00 – 19:59	23.96	24.51	23.91	25
20:00 – 23:59	19.8	22.17	22.58	20.94
Day of Week				
Monday	12.77	12.44	11.8	12.32
Tuesday	13.23	12.44	13.02	13.42
Wednesday	17.21	18.6	17.7	17.24
Thursday	15.08	14.53	14.24	14.9
Friday	14.52	14.16	15.56	14.41
Saturday	13.78	14.41	14.75	13.92
Sunday	13.41	13.42	12.92	13.79
Month				
January	9.44	8.5	9.16	9.98
February	11.38	11.58	9.77	10.59
March	6.48	6.77	6.31	6.65
April	7.4	7.02	6.21	7.02
May	8.33	8.13	9.36	9.48
June	6.57	6.65	7.53	6.9
July	7.59	7.51	7.63	7.64
August	9.34	9.85	9.66	9.24
September	8.33	8.74	9.16	7.64
October	7.96	7.39	7.93	8
November	8.6	8.87	8.65	8.5
December	8.6	8.99	8.65	8.37
Number of Occupants				
1	74.65	74.63	73.86	72.41
2	18.32	17.98	21.06	22.29
3	5.27	5.42	3.76	3.82
4	1.67	1.85	1.02	1.11
5	0.09	0.12	0.31	0.37

Equipment Violations				
0	73.73	75.49	75.38	73.52
1	18.32	16.87	16.79	17.98
2	5	4.8	5.9	6.65
3	1.2	1.11	1.42	1.23
4	1.2	1.23	0.41	0.49
5	0.56	0.49	0.1	0.12
Violent Crime Rate (previous 30 days, per 10,000 people)				
Mean	1.23	1.05	0.95	1
Median	1.07	0.85	0.68	0.75

Table B-5: Hispanic/White Vehicle Search

	Hispanic Drivers		White Drivers	
	n = 700	n = 605	n = 891	n = 605
Variable	Pre-Match %	Post-Match %	Pre-Match %	Post-Match %
Reason to Stop				
Reasonable Suspicion	16.71	13.22	11.56	14.71
Other Moving Viol.	17.57	17.19	15.38	15.54
Equipment Violation	25.71	27.44	28.4	27.44
Speeding	6.14	6.45	5.72	6.28
Cell Phone	1.86	1.98	2.92	1.98
BOLO	0.29	0.33	0.45	0.5
Red Light	0.86	0.99	1.35	1.32
Stop Sign	6.86	7.93	9.99	7.27
Seatbelt	5	4.63	4.38	4.46
Other VTL	19	19.83	19.87	20.5
Precinct				
1	31.29	31.4	46.69	45.95
2	9	9.42	7.74	6.61
3	45.86	45.45	17.4	17.02
4	1.57	1.65	2.69	2.64
5	4.71	4.63	11.9	12.07
6	4.71	4.3	8.87	10.25
7	1.71	1.98	3.93	4.46
9	1.14	1.16	0.79	0.99
Sex				
Female	10	11.4	23.34	14.38
Male	90	88.6	76.66	85.62
Age				
<16	0.43	0	0.11	0.17
16 to 25	59.43	55.54	41.86	53.72
26 to 35	29.86	32.56	33.11	34.38
36 to 45	7.14	8.26	13.92	8.93
46 to 55	2.14	2.48	7.63	1.32
56 to 65	0.86	0.99	3.14	1.16
>65	0.14	0.17	0.22	0.33

Time of Day				
00:00 – 03:59	9.29	8.76	7.63	9.59
04:00 – 07:59	2.14	2.31	1.46	1.65
08:00 – 11:59	20.71	20.5	18.63	19.83
12:00 – 15:59	19.86	19.67	20.54	19.01
16:00 – 19:59	26.14	26.94	27.27	26.94
20:00 – 23:59	21.86	21.82	24.47	22.98
Day of Week				
Monday	13.43	12.73	11.67	12.23
Tuesday	13.29	13.72	13.92	13.39
Wednesday	14.43	14.88	17.51	14.88
Thursday	15.29	15.37	14.48	15.87
Friday	12.71	13.06	15.38	13.72
Saturday	15.14	16.03	15.15	16.53
Sunday	15.71	14.21	11.9	13.39
Month				
January	9.71	9.75	8.87	8.93
February	11.57	10.74	10.1	11.24
March	9	8.76	6.73	7.6
April	8.43	8.43	7.18	7.44
May	7.57	8.1	8.87	8.93
June	6.71	7.6	8.42	8.26
July	7.71	7.11	7.41	7.44
August	8.71	8.76	10.1	9.59
September	7	7.27	8.08	7.6
October	9.29	8.26	7.3	8.26
November	6.86	7.27	8.53	6.61
December	7.43	7.93	8.42	8.1
Number of Occupants				
1	67.43	69.92	67.68	67.11
2	23.71	22.31	25.81	25.95
3	6.14	5.45	4.38	4.79
4	2.29	1.82	1.8	1.82
5	0.43	0.5	0.34	0.33

Equipment Violations				
0	74.71	73.88	72.73	72.73
1	18.14	18.84	18.52	19.17
2	4.71	5.12	6.62	6.28
3	1	0.66	1.35	0.99
4	0.71	0.66	0.67	0.66
5	0.71	0.83	0.11	0.17
Violent Crime Rate (previous 30 days, per 10,000 people)				
Mean	1.06	1.06	1.01	1.03
Median	0.96	0.96	0.78	0.78

Table B-6: Hispanic/White Person Search

	Hispanic Drivers		White Drivers	
	n = 769	n = 667	n = 983	n = 667
Variable	Pre-Match %	Post-Match %	Pre-Match %	Post-Match %
Reason to Stop				
Reasonable Suspicion	13.78	11.54	9.46	11.54
Other Moving Viol.	20.68	20.69	19.23	20.54
Equipment Violation	24.19	25.49	25.03	26.09
Speeding	6.37	6.9	7.83	7.5
Cell Phone	2.34	2.7	3.36	1.8
BOLO	0.39	0.3	0.31	0.3
Red Light	1.3	1.35	1.83	1.05
Stop Sign	7.15	8.25	10.68	7.95
Seatbelt	4.55	4.65	3.76	4.35
Other VTL	19.25	18.14	18.51	18.89
Precinct				
1	28.61	28.49	40.08	42.13
2	9.36	9.6	7.02	6.75
3	42.78	41.68	12.72	12.74
4	1.69	1.65	3.56	3.45
5	6.5	7.05	12.82	13.64
6	5.59	5.7	10.27	9.6
7	1.95	1.8	5.9	5.1
9	3.51	4.05	7.63	6.6
Sex				
Female	7.54	8.7	17.09	8.55
Male	92.46	91.3	82.91	91.45
Age				
<16	0.39	0.3	0.1	0.15
16 to 25	53.06	49.78	37.33	47.38
26 to 35	31.86	33.28	33.06	34.03
36 to 45	10.53	11.84	15.36	13.04
46 to 55	3.12	3.6	9.46	3.75
56 to 65	0.78	0.9	3.87	1.05
>65	0.26	0.3	0.81	0.6

Time of Day				
00:00 – 03:59	14.56	14.84	15.67	15.29
04:00 – 07:59	2.99	2.55	1.63	2.1
08:00 – 11:59	17.43	17.24	18.11	18.44
12:00 – 15:59	18.86	19.19	18.11	18.44
16:00 – 19:59	24.97	24.74	23.91	24.29
20:00 – 23:59	21.2	21.44	22.58	21.44
Day of Week				
Monday	13.52	12.44	11.8	12.44
Tuesday	12.35	12.59	13.02	12.59
Wednesday	13.91	14.24	17.7	15.59
Thursday	13.39	14.24	14.24	13.94
Friday	13.39	13.04	15.56	14.99
Saturday	15.6	16.19	14.75	14.99
Sunday	17.82	17.24	12.92	15.44
Month				
January	9.49	9.15	9.16	9.75
February	12.35	11.99	9.77	11.09
March	8.58	8.4	6.31	7.35
April	8.19	7.5	6.21	7.35
May	6.37	7.2	9.36	7.5
June	7.67	7.65	7.53	7.8
July	7.67	7.95	7.63	7.95
August	8.71	9	9.66	8.85
September	7.28	7.35	9.16	8.25
October	8.97	8.1	7.93	9.15
November	6.89	7.35	8.65	6.45
December	7.8	8.4	8.65	8.55
Number of Occupants				
1	73.08	74.51	73.86	70.76
2	19.64	18.74	21.06	23.84
3	5.07	4.65	3.76	4.2
4	1.69	1.65	1.02	1.05
5	0.52	0.45	0.31	0.15

Equipment Violations				
0	74.9	75.11	75.38	74.36
1	18.6	18.59	16.79	17.99
2	3.9	4.05	5.9	5.7
3	0.91	0.6	1.42	1.35
4	0.78	0.75	0.41	0.45
5	0.91	0.9	0.1	0.15
Violent Crime Rate (previous 30 days, per 10,000 people)				
Mean	1.05	1.02	0.95	1.01
Median	0.96	0.94	0.68	0.76

Table B-7: Black/White Exit Vehicle

	Black Drivers		White Drivers	
	n = 1,314	n = 1,055	n = 1,469	n = 1,055
Variable	Pre-Match %	Post-Match %	Pre-Match %	Post-Match %
Reason to Stop				
Reasonable Suspicion	10.43	9.67	8.85	10.43
Other Moving Viol.	16.44	18.1	22.4	18.01
Equipment Violation	32.19	29.67	22.33	27.87
Speeding	6.32	7.11	10.35	6.73
Cell Phone	1.75	2.09	2.65	2.46
BOLO	0.46	0.38	0.2	0.28
Red Light	0.38	0.47	2.11	0.85
Stop Sign	9.13	9.29	8.71	9.67
Seatbelt	3.88	3.7	3.81	3.7
Other VTL	19.03	19.53	18.58	20
Precinct				
1	50.91	49	31.59	36.97
2	8.45	9.1	7.35	7.11
3	20.24	19.53	12.05	13.65
4	1.9	2.27	4.56	3.03
5	6.77	7.3	10.82	11.94
6	4.41	4.55	10.35	9.86
7	3.04	3.41	5.65	5.88
9	4.26	4.83	17.63	11.56
Sex				
Female	15.22	17.25	22.8	17.16
Male	84.78	82.75	77.2	82.84
Age				
<16	0.15	0.09	0.14	0.19
16 to 25	37.37	36.49	35.06	37.91
26 to 35	39.42	37.06	30.97	35.45
36 to 45	12.33	13.55	15.93	14.5
46 to 55	7.46	8.72	12.12	9.19
56 to 65	2.82	3.51	4.9	2.37
>65	0.46	0.57	0.88	0.38

Time of Day				
00:00 – 03:59	10.27	12.32	21.51	11.85
04:00 – 07:59	1.45	1.8	2.04	1.99
08:00 – 11:59	25.04	23.03	15.86	20.57
12:00 – 15:59	20.62	19.62	16.75	19.91
16:00 – 19:59	23.44	23.51	21.85	24.74
20:00 – 23:59	19.18	19.72	21.99	20.95
Day of Week				
Monday	13.17	12.8	11.03	12.7
Tuesday	13.17	13.93	13.07	13.65
Wednesday	16.67	16.68	17.15	17.25
Thursday	14.54	15.45	15.11	14.88
Friday	14.54	14.41	15.38	14.41
Saturday	14.31	14.5	16.07	14.79
Sunday	13.62	12.23	12.19	12.32
Month				
January	8.98	8.34	8.1	9.19
February	10.81	10.14	9.39	10.81
March	7	7.96	8.03	8.34
April	6.93	7.2	6.6	6.92
May	8.45	9.29	9.19	8.72
June	6.93	7.3	7.49	7.3
July	7.61	8.25	8.03	8.34
August	9.21	9.1	9.19	7.77
September	8.37	8.06	8.92	8.06
October	8.52	7.87	8.37	8.25
November	8.9	8.25	8.71	8.34
December	8.3	8.25	7.96	7.96
Number of Occupants				
1	73.06	74.6	75.49	72.32
2	19.48	18.96	19.26	22.18
3	5.56	4.64	3.47	3.79
4	1.75	1.8	1.43	1.33
5	0.15	0	0.27	0.28
6	0	0	0.07	0.09

Equipment Violations				
0	72.98	74.98	76.17	72.7
1	19.03	18.29	16.13	18.48
2	5.25	4.27	5.38	6.54
3	1.07	0.95	1.43	1.23
4	1.14	1.04	0.41	0.57
5	0.53	0.47	0.48	0.47
Violent Crime Rate (previous 30 days, per 10,000 people)				
Mean	1.21	1.09	0.89	1
Median	0.98	0.87	0.61	0.73

Table B-8: Hispanic/White Exit Vehicle

	Hispanic Drivers		White Drivers	
	n = 1,023	n = 911	n = 1,469	n = 911
Variable	Pre-Match %	Post-Match %	Pre-Match %	Post-Match %
Reason to Stop				
Reasonable Suspicion	10.75	10.32	8.85	9.22
Other Moving Viol.	20.23	20.2	22.4	21.41
Equipment Violation	23.17	24.04	22.33	24.26
Speeding	6.74	7.46	10.35	7.9
Cell Phone	1.96	2.09	2.65	2.09
BOLO	0.39	0.33	0.2	0.22
Red Light	1.56	1.54	2.11	1.98
Stop Sign	7.53	7.9	8.71	7.79
Seatbelt	4.5	4.06	3.81	4.06
Other VTL	23.17	22.06	18.58	21.08
Precinct				
1	23.75	23.82	31.59	34.8
2	9.78	10.1	7.35	7.46
3	39.69	38.31	12.05	12.95
4	2.05	2.09	4.56	3.4
5	5.87	6.15	10.82	11.86
6	6.26	6.59	10.35	10.1
7	1.86	1.76	5.65	5.93
9	10.75	11.2	17.63	13.5
Sex				
Female	9.87	11.09	22.8	11.53
Male	90.13	88.91	77.2	88.47
Age				
<16	0.39	0.44	0.14	0.22
16 to 25	48.19	45.77	35.06	44.79
26 to 35	32.75	33.37	30.97	35.35
36 to 45	12.41	13.39	15.93	13.06
46 to 55	4.59	5.16	12.12	4.83
56 to 65	1.17	1.32	4.9	1.21

>65	0.49	0.55	0.88	0.55
Time of Day				
00:00 – 03:59	16.52	17.23	21.51	18.66
04:00 – 07:59	4.11	3.62	2.04	2.63
08:00 – 11:59	17.6	16.68	15.86	17.01
12:00 – 15:59	18.38	18.44	16.75	17.12
16:00 – 19:59	23.56	23.82	21.85	24.04
20:00 – 23:59	19.84	20.2	21.99	20.53
Day of Week				
Monday	13.59	13.06	11.03	11.64
Tuesday	13.39	13.28	13.07	12.62
Wednesday	14.57	14.93	17.15	17.12
Thursday	14.86	15.15	15.11	14.93
Friday	12.41	13.06	15.38	13.72
Saturday	14.96	15.26	16.07	15.37
Sunday	16.23	15.26	12.19	14.6
Month				
January	8.99	9.44	8.1	8.34
February	12.61	10.76	9.39	10.54
March	10.07	9.55	8.03	9.11
April	8.41	8.12	6.6	8.34
May	7.04	7.68	9.19	7.35
June	6.94	7.57	7.49	7.03
July	8.11	7.9	8.03	8.12
August	7.62	8.34	9.19	9.44
September	7.23	7.57	8.92	7.57
October	8.8	8.89	8.37	9
November	6.45	6.59	8.71	6.92
December	7.72	7.57	7.96	8.23
Number of Occupants				
1	73.22	74.09	75.49	73.55
2	19.65	19.21	19.26	20.53
3	4.99	4.61	3.47	3.95
4	1.66	1.54	1.43	1.65
5	0.49	0.55	0.27	0.22
6	0	0	0.07	0.11

Equipment Violations				
0	74.39	74.2	76.17	73.87
1	17.79	17.34	16.13	17.12
2	4.59	4.94	5.38	6.26
3	1.56	1.65	1.43	1.76
4	0.88	0.99	0.41	0.55
5	0.78	0.88	0.48	0.44
Violent Crime Rate (previous 30 days, per 10,000 people)				
Mean	1	0.98	0.89	0.98
Median	0.93	0.87	0.61	0.71