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

Traffic Stops by Suffolk County Police, 2020-2021

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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. In 2020, SCPD contracted with the Institute to conduct analysis of racial and ethnic disparities in traffic stops and post-stop outcomes, and SCPD provided to the Institute data on traffic stops conducted between March 5, 2018, and March 4, 2019. The findings of our analyses were summarized in a report delivered in September, 2020.[1] SCPD subsequently extended the contract for traffic stop analysis, providing data on traffic stops conducted in calendar years 2020 and 2021, with the understanding that the same methods of analysis would be applied to the 2020-2021 data. This report summarizes the findings.

We can briefly summarize the findings of our previous analysis here, and we will note the respects in which 2020-2021 stop patterns depart from those of 2018-2019 below. Our analysis of 2018-2019 stops found that Black and Hispanic drivers were overrepresented in traffic stops relative to their proportions of the County population. Our application of an appropriate benchmark (using the "veil-of-darkness" method), however, led to a single conclusion in every test: that in making the initial stop, Suffolk County police displayed no systematic bias against either Black or Hispanic drivers. We inferred that the disparities in stops were attributable to factors other than drivers' race/ethnicity. (See Appendices A and C for our previous discussions of analytic issues and strategies in drawing inferences about bias from disparities, with respect to initial stop decisions and post-stop outcomes, respectively. Appendix A includes an explanation of the veil-of-darkness method and its utility as a benchmark.)

Our analyses of post-stop outcomes, in many instances, yielded not only evidence of disparities, but also results that were consistent with hypothesized bias, as statistical controls for potentially confounding factors did not entirely account for the observed disparities. We found unexplained disparities involving both Black and Hispanic drivers concerning:

- The likelihood of a search of their person;
- The number of violations for which they are ticketed;
- The likelihood of being arrested; and
- The duration of the stop;

We found unexplained disparities involving either Black or Hispanic drivers concerning:

- The likelihood of a vehicle search (Black 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);

[1] Robert E. Worden, Kenan M. Worden, and Hannah Cochran, *Traffic Stops by Suffolk County Police* (Albany, NY: John F. Finn Institute for Public Safety, Inc., 2020).

- Placement in the back of the police unit (Black drivers); and
- The likelihood that a vehicle search yields no contraband (Black drivers).

We cautioned that with the data that were available to us, we were unable to take account of several factors that might explain the detected disparities, in whole or in part.

Traffic Stop Data Collection and Data Quality

The 2020-2021 stop data files include records of 177,747 traffic stops and 193,869 vehicle occupants: one driver and as many as eight passengers in each stop.[2] Information on the date, time, and location of the stop are recorded, as are the reason for and 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 2020-2021 stop data are complete in all but one respect that are essential for this analysis, as accurate information on the location of stops remained elusive, as they were for our analysis of 2018-2019 stops. Each stop record includes latitude and longitude, but it is of the location at which the stop data are entered, and the data are often not entered at the location of the stop.[3] The location field is not completed in a standardized fashion that allows for later geo-coding, and the sector field is not consistently entered either with a precinct sector value or any value at all. Consequently, we followed the procedure that we developed for our previous analysis, deriving sector information 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).[4]

Patterns of Traffic Stops in Suffolk County

The geographic parameters of SCPD's patrol precincts follow township boundaries. Four precincts each serve a township: Babylon, Huntington, Islip, and Smithtown are served by the first through fourth precincts, respectively. Brookhaven

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[2] These figures, and our analyses, are based on the files shared with us when we requested data that included sector information. However, the files that were initially provided, which did not include the field for sector, included records for only 177,675 traffic stops. We note that one field in the data file, named 'IsValid,' identifies 144 records as not valid, and these records were removed for all analysis. Records of five stops each involved a single occupant identified as a passenger, all of whom we treated as the driver.

[3] For our previous analysis of 2018-2019 stops, we discovered that the latitude and longitude of 11,728 stops placed them at one of 19 locations. The same 19 locations accounted for 45,849 stops in 2020-2021. The locations included SCPD headquarters (24,392), other SCPD facilities (19,551), fire department facilities (65), and the Town of Huntington City Hall (20).

[4] 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 D for a list of sector blocks and constituent sectors.

Town spans precincts five through seven. The racial and ethnic composition of the 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.)

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

	Population	% Non-Hispanic White	% Black	% Hispanic	% Other
Suffolk County	1,525,920	66.6	8.8	20.2	4.4
Babylon [1]	213,603	55.3	17.3	21.5	5.9
Huntington [2]	204,127	76.6	4.0	11.7	7.7
Islip [3]	339,938	51.8	9.3	34.2	4.7
Smithtown [4]	116,296	85.8	1.2	7.5	5.5
Brookhaven [5-7]	485,773	72.0	6.1	15.6	6.3

https://www.census.gov/quickfacts/fact/table/suffolkcountynewyork/POP010220, April 1, 2020

Among stops by precinct units (patrol or crime section), the distribution across precincts is not dramatically skewed, though some precincts are the sites of larger proportions than others; see Table 2. Units in the fourth precinct collectively make the fewest stops and those in the sixth and second precincts the most (and twice the number of the fourth precinct).

Table 2. Stop Frequencies by Precinct

Precinct	1	2	3	4	5	6	7	Total
Counts (%s)	13,364 (13.18)	16,565 (16.34)	14,650 (14.45)	8,198 (8.08)	14,235 (14.04)	18,722 (18.46)	15,664 (15.45)	101,398 (100)

The 2020 Context

Our analysis of traffic stop patterns in 2020-2021, and any comparison of the patterns to those that we previously summarized for the one-year period of March 5, 2018, through March 4, 2019, must be based on a recognition of the events of 2020 that form an extraordinary context. In January, 2020, the federal Secretary of Health and Human Services declared that the coronavirus pandemic was a public health emergency, and as cases proliferated, it prompted many states and localities to adopt mitigation measures that upended life as it had been known. In New York State, in mid-March, then-Governor Cuomo signed the "New York State on PAUSE" executive order (Policy to Assure Uniform Safety for Everyone), reducing occupancy to zero in non-essential businesses, closing retail businesses, prohibiting on-premises consumption in bars and restaurants, and banning non-essential gatherings. Widespread job losses quickly ensued. Educational institutions transitioned to remote instruction. Office-based work transitioned to work-from-home. Across the state, a phased resumption of normal economic activity turned on regional COVID-19 metrics, and under that regime, the first such phase in Suffolk County began May 27 and the fourth and final phase began July 8.[5] Thus, there is good reason to suppose that from mid-March through at least late-May and possibly early-July, the driving population was not only much smaller but also perhaps of a different demographic composition, consisting disproportionately of workers in industries that were deemed essential. Traffic safety research confirms that, across the nation, vehicle miles traveled and daily trips declined during the early months of the pandemic.[6]

Furthermore, the immediate effects of the pandemic on police included changes in the demands for police service and changes in police practices.[7] Calls for service, overall, declined in most cities, though calls for some types of problems (such as dead bodies) increased. Domestic violence calls and calls relating to mental disorder were up

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[5] On March 16, 2020, Governor Cuomo closed schools for two weeks. Gyms, bars, movie theaters, and casinos were also closed. Restaurants were restricted to takeout and delivery only. On March 20, Governor Cuomo closed all nonessential businesses. On March 26, the governor extended school closures to April 15. On May 1, Governor Cuomo canceled in-person school attendance for the remainder of the school year. On May 15, Governor Cuomo announced certain low-risk recreational activities could resume. On May 22, the governor reopened state beaches, with capacity limited to 50 percent. On May 27, Suffolk County was cleared for phase-one economic reopening. Construction, agriculture, fishing, hunting, forestry, manufacturing, wholesale trade, and retail (with some restrictions) were allowed to resume doing business. On July 8, the Long Island region entered phase four of the economic reopening plan. Gatherings of no more than 50 people were then allowed. See https://www.easthamptonstar.com/health-villages/202135/covid-19-east-end-timeline.

[6] See Essie Wagner, Randolph Atkins, Amy Berning, Arryn Robbins, and Christine Watson, and Jonlee Anderle, *Examination of the Traffic Safety Environment during the Second Quarter of 2020: Special Report*, Report No. DOT HS 813 011 (National Highway Traffic Safety Administration, 2020). Also see Office of Behavioral Safety Research, *Update to Special Reports on Traffic Safety during the COVID-19 Public Health Emergency: Third Quarter Data*, Report No. DOT HS 813 069 (Washington, D.C.: National Highway Traffic Safety Administration, 2021); and B. C. Tefft, L. Villavicencio, A. Benson, L. S. Arnold, W. Kim, V. Añorve, and W.J. Horrey, *Self-Reported Risky Driving in Relation to Amount of Driving During the COVID-19 Pandemic*, Research Brief (Washington, D.C.: AAA Foundation for Traffic Safety, 2022). Also see https://www.cnn.com/2021/06/19/us/pandemic-increased-fatal-crashes-trnd/index.html; https://www.washingtonpost.com/transportation/2022/02/28/unsafe-driving-aaa-study-covid/; https://www.washingtonpost.com/opinions/2022/03/10/pandemic-risky-driving-maybe-here-to-stay/.

[7] See: Police Executive Research Forum, "How Agencies Are Responding," https://www.policeforum.org/covid-19-response#agency; Cynthia Lum, Carl Maupin, andMegan Stoltz, *The Impact of COVID-19 on Law Enforcement Agencies (Wave 2)* (International Association of Chiefs of Police and the Center for Evidence-Based Crime Policy, 2020); Matthew P.J. Ashby, "Changes in Police Calls for Service During the Early Months of the 2020 Coronavirus Pandemic," *Policing: A Journal of Policy and Practice* 14 (2020): 1054-1072; Jon Maskaly, Sanja Kutnjak Ivkovic, and Peter Neyroud, "Policing the COVID-19 Pandemic: Exploratory Study of the Types of Organizational Changes and Police Activities Across the Globe," *International Criminal Justice Review* 31 (2021): 266-285.

in many cities, but not everywhere. [8] Police departments adopted procedures to protect officers' health while maintaining service to the public. In many agencies:

- in-service training was suspended;
- roll call briefings were suspended or modified;
- public access to police facilities was limited;
- procedures were adopted to minimize in-person handling of calls (e.g., online or phone reporting of less-serious offenses) or to limit contact in calls for which police were dispatched;
- arrests for low-level offenses were discouraged;
- in-person community engagement activities were suspended; and
- procedures to reduce the physical density of employees were adopted.

Traffic safety research showed not only that vehicle miles traveled and daily trips declined due to the pandemic, but also that driving behavior changed. In particular, searching for an explanation of an increase in the fatality rate (per 1 million vehicle miles traveled), one study concluded that,

> First, there is evidence of an increase in ejection rates among people who were in crashes, suggesting a decrease in the seat belt use rate of vehicle occupants. This increase was heavily tilted toward males, people 18 to 34 years old, and people in rural areas. Second, according to State data and other reports, speeding was more prevalent on the roads. The reduction in traffic volume coupled with community efforts to reduce law enforcement personnel exposure by implementing changes in law enforcement activity provided drivers a greater opportunity to speed. Additionally, there is evidence of increased alcohol use and higher drug use (including marijuana and opioids), and survey research indicating that many individuals have started or increased drug and alcohol use to cope with pandemic-related stress. Newly released research from five trauma centers revealed a higher

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[8] Violence increased in many cities in 2020. Rosenfeld and his colleagues analyzed crime rates in 34 U.S. cities in 2020, finding that homicide rates increased 30 percent over 2019, with a "structural break" in June – i.e., a statistically significant increase over the rate predicted based on longer-terms trends and seasonal fluctuation. Gun assaults rose by 8 percent; aggravated assaults increased by 6 percent, with a structural break in July. Property crime, excepting motor vehicle theft, decreased. See Richard Rosenfeld, Thomas Abt, and Ernesto Lopez, *Pandemic, Social Unrest, and Crime in U.S. Cities: 2020 Year-End Update* (Washington: Council on Criminal Justice, 2021). In New York State, across all of the state's GIVE jurisdictions, shooting incidents involving injury rose 43.8 percent from April to May, and 68.5 percent from May to June, with a 74.5 percent increase in all of 2020 over 2019. In Suffolk County, shootings in 2020 were 37 percent higher than in 2019 and 22.5 percent higher than the previous five-year average. Overall, however, violent crime in 2020 dropped 9.1 percent from 2019 (23.4 percent from the five-year average), and property crime was up only slightly from 2019, a small deviation from a downward trend from 2017 through 2022. New York State Division of Criminal Justice Services, *Gun Involved Violence Elimination (GIVE) Initiative: Violent Crime Involving a Firearm and Shooting Activity Report* (Albany, NY: Author, 2021).

prevalence of alcohol, cannabinoids, and opioids in crash victims during the public health emergency compared to before.[9]

The pandemic is not the only notable feature of 2020. On May 25th, George Floyd was murdered by a Minneapolis police officer. Protests erupted in many cities as cell-phone video of the incident widely circulated. Calls for police reform – even to "defund" the police – were nearly ubiquitous, and the climate of public opinion about the police – particularly but not only that of Black persons – turned still more negative than it was in the aftermath of the death of Michael Brown in Ferguson in 2014.[10]

Suffolk County was not immune to the unrest.[11] The protests in Suffolk County were largely peaceful, however; in a survey by the Major Cities Chiefs Association, Suffolk County police reported that only 3.7 percent of the protests involved some level of civil disobedience, and none involved violence.[12] In addition, anti-police sentiment may have been more muted in Suffolk County than in many other locales.[13] In June of 2020, then-Governor Cuomo issued Executive Order (EO) 203, mandating that every local government with a police agency consult with stakeholders to conduct a "comprehensive review" of police "deployments, strategies, policies, procedures, and practices."[14] Further, localities were to develop a plan for improvements that would "foster trust, fairness, and legitimacy, and … address any racial bias and disproportionate policing of communities of color." The EO effectively extended the duration of more intensive public scrutiny to which local police were subject.

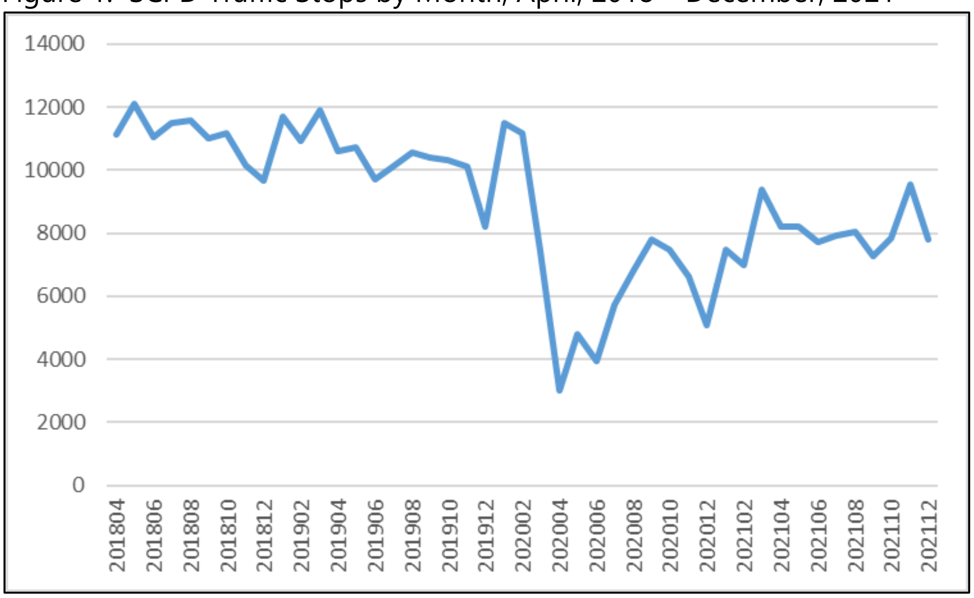
Part of the fallout from the climate of public opinion and public scrutiny appears to have been an increase in retirements and, to a lesser extent, resignations of officers. A survey conducted by the Police Executive Research Forum in January, 2022, found that

[9] Wagner, et al., *Examination of the Traffic Safety Environment during the Second Quarter of 2020*.
[10] Jeffrey M. Jones, "Black, White Adults' Confidence Diverges Most on Police" (August 12, 2020), https://news.gallup.com/poll/317114/black-white-adults-confidence-diverges-police.aspx. Also see Tyler T. Reny and Benjamin J. Newman, "The Opinion-Mobilizing Effect of Social Protest against Police Violence: Evidence from the 2020 George Floyd Protests," *American Political Science Review* (2021).
[11] See, e.g., https://abc7ny.com/long-island-protests-george-floyd-protest-jericho-turnpike-commack/6225622/; https://www.longislandpress.com/2020/06/05/thousands-of-george-floyd-protesters-again-take-over-long-island-roads/; https://www.longislandpress.com/2020/06/08/11-arrested-4-injured-during-weekend-of-george-floyd-protests-on-long-island/; https://www.newsday.com/long-island/protest-george-floyd-shirley-w85979.
[12] Major Cities Chiefs Association Intelligence Commanders Group, *Report on the 2020 Protests and Civil Unrest,* https://majorcitieschiefs.com/wp-content/uploads/2021/01/MCCA-Report-on-the-2020-Protest-and-Civil-Unrest.pdf.
[13] See, e.g., https://www.police1.com/george-floyd-protest/articles/hundreds-gather-to-support-police-during-back-the-blue-rally-in-ny-3SHKeHzuvsxY6giJ/; https://www.cityandstateny.com/policy/2020/06/long-island-land-of-beaches-billy-joel-and-protests-against-police-brutality/175885/.
[14] State of New York, *New York State Police Reform and Reinvention Collaborative*, Executive Order No. 203 (Albany, NY: Executive Chamber, 2020).

among police departments with more than 500 sworn officers, staffing was down 3.7 percent on January 1, 2022 compared with January 1, 2020. From 2019 to 2021, among the same set of agencies, resignations were up 43 percent and retirements were up 23.4 percent.[15] In Suffolk County, though publicly-available data do not allow us to pinpoint the factors contributing to changes in sworn staffing levels, counts of full-time sworn personnel declined. According to the personnel headcounts reported to DCJS on October 31 of each year, full-time sworn in SCPD dropped from 2,536 in 2017, 2,519 in 2018, and 2,518 in 2019, to 2,410 in 2020 and 2,331 in 2021. With an agency-wide loss of 108 officers between 2019 and 2020, and an additional loss of 79 officers between 2020 and 2021, we would expect to see lower levels of proactive policing, especially among the officers for whom traffic enforcement is not a specialized duty.

Unsurprisingly, then, SCPD traffic stops were abnormally low from March through June of 2020, during New York State's PAUSE. See Figure 1.[16] Stop levels began to rebound in July, and by September, the level of stops appeared to reach a new, lower normal, which with fewer sworn personnel persisted through 2021.

Figure 1. SCPD Traffic Stops by Month, April, 2018 – December, 2021



Further analysis reveals some differences in the nature of the stops over time. We differentiate among stops conducted: (a) pre-pandemic, between January 1, 2020,

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[15] See https://www.policeforum.org/index.php?option=com_content&view=article&id=1097:workforcemarch2022&catid=20:site-content. Also see Scott M. Mourtgos, Ian T. Adams, and Justin Nix, Elevated Police Turnover Following the Summer of George Floyd Protests: A Synthetic Control Study," *Criminology & Public Policy* 21 (2022): 9–33.

[16] Note that stop counts for March – December 2019 are based on the csv files posted to the SCPD website.

and March 19, 2020; (b) during New York's PAUSE, from March 20, 2020, through July 8, 2020; and (c) July 9, 2020, through December of 2021. During the PAUSE, stops by precinct units decreased disproportionately, from 189.7 stops per day, on average, to 18.5 stops per day, a 90.2 percent drop. Stops by highway patrol units decreased by 31.1 percent, from 140 to 96.5 stops per day, and they thus accounted for a much larger fraction of stops during this period; see Table 3. Stop levels rebounded thereafter, but not to their pre-pandemic (January-mid-March) levels, and not evenly across unit types. Stops per day by highway patrol units averaged 100, or 70 percent of the pre-pandemic average, while the daily rate of stops by precinct patrol units rose to 60 percent of the prior level (at 114.4).[17]

Table 3. Stops by Unit Type by Time Period

Unit Type	Jan 1, 2020-Mar 19, 2020	Mar 20, 2020-Jul 8, 2020	Jul 9, 2020-Dec 31, 2021	Totals
Highway Patrol	10,900 (37.36)	10,712 (77.21)	54,472 (40.44)	76,084 (42.80)
Precinct Crime	3,398 (11.65)	1,056 (7.61)	17,790 (13.21)	22,244 (12.51)
Precinct Patrol	14,797 (50.72)	2,058 (14.83)	61,911 (45.96)	78,766 (44.31)
Other	79 (0.27)	48 (0.35)	526 (0.39)	653 (0.37)
Total	29,174 (100)	13,874 (100)	134,699 (100)	177,747

Note: Cell entries are counts and, in parentheses, column percentages.

The reasons for stops also changed over time, to some extent reflecting the variation in the units responsible. See Table 4, below. The proportion of stops for speeding more than doubled during the pause, with the proportionately greater activity of highway patrol units, and then dropped to the pre-pandemic proportion. Stops for equipment violations dropped and did not entirely rebound. (That stops for equipment violations remained low, proportionally, was not due to extended deadlines for vehicle inspections and registrations, inasmuch as the proportions among 2021 stops resembled those in the latter half of 2020.)

Variation over time in the racial and ethnic composition of drivers stopped was much less pronounced. See Table 5, below. During the PAUSE, slightly smaller proportions of drivers stopped were Black or Hispanic. White drivers are more likely to be stopped for speeding and to be stopped by highway patrol units, and their representation among stopped drivers increased during the PAUSE. Thereafter, the proportion of Whites decreased to a level below the pre-pandemic level, while the proportions of Blacks and Hispanics increased to levels above those that preceded the pandemic.

[17] As Figure 1 suggests, this pre-pandemic baseline is somewhat inflated, as it spans only the period of January to mid-March of 2020; the same period in 2019 formed a high-water mark for traffic stops, with a decline through the remainder of the year.

Table 4. Reasons for Stops by Time Period

Reason to Stop	Jan 1, 2020-Mar 19, 2020	Mar 20, 2020-Jul 8, 2020	Jul 9, 2020-Dec 31, 2021	Totals
BOLO	15 (0.05)	7 (0.05)	96 (0.07)	118
Cell Call/Text	1,358 (4.65)	719 (5.18)	8,634 (6.41)	10,711
Equipment Violation	5,738 (19.67)	881 (6.35)	19,322 (14.34)	25,941
Other Moving Violation	5,969 (20.46)	2,891 (20.84)	28,024 (20.8)	36,884
Red Light	552 (1.89)	205 (1.48)	2,918 (2.17)	3,675
RSC	219 (0.75)	133 (0.96)	1,335 (0.99)	1,687
Seat Belt	457 (1.57)	175 (1.26)	3,388 (2.52)	4,020
Speeding	6,794 (23.29)	6,832 (49.24)	31,746 (23.57)	45,372
Stop Sign	2,801 (9.6)	640 (4.61)	17,828 (13.24)	21,269
VTL	5,271 (18.07)	1,391 (10.03)	21,408 (15.89)	28,070
Total	29,174 (100)	13,874 (100)	134,699 (100)	177,747

Note: Cell entries are counts and, in parentheses, column percentages.

Table 5. Driver Race/Ethnicity by Time Period

Driver Race/Ethnicity	Jan 1, 2020-Mar 19, 2020	Mar 20, 2020-Jul 8, 2020	Jul 9, 2020-Dec 31, 2021	Totals
Hispanic	6,656 (22.81)	2,886 (20.8)	33,616 (24.96)	43,158
Black	5,407 (18.53)	2,463 (17.75)	26,687 (19.81)	34,557
White	15,304 (52.46)	7,632 (55.01)	64,385 (47.8)	87,321
Asian	672 (2.3)	298 (2.15)	3,032 (2.25)	4,002
Other	1,135 (3.89)	595 (4.29)	6,979 (5.18)	8,709
Total	29,174 (100)	13,874 (100)	134,699 (100)	177,747

Note: Cell entries are counts and, in parentheses, column percentages.

Across the entire two-year period, stops during the PAUSE constitute 7.8 percent of all stops. Despite the differences noted above, it is informative to parsimoniously describe other patterns in the aggregate, though we will be cognizant of the differences in assessing bias in stops and post-stop outcomes and note the caveats accordingly.

Reasons for Stops

Stops by highway patrol units are preponderantly for speeding or other moving violations, while stops by precinct units tend to be for stop sign, equipment, and other vehicle and traffic (V&T) law violations in addition to other (non-speeding) violations. See Table 6. As we found in our previous analysis of traffic stops, a very small fraction are for reasonable suspicion.

Table 6. Reasons for Stops by Unit Type

	Unit Type			
Reason	Highway Patrol %s	Precinct Crime %s	Precinct Patrol %s	Other %s
Speeding	46.25	14.18	8.72	24.5
Red Light	0.63	2.84	3.24	2.14
Stop Sign	2.30	22.49	18.36	7.96
Other Moving Violation	27.32	14.84	16.08	19.75
Equipment Violation	3.62	11.75	26.01	13.17
Seat Belt	2.41	3.59	1.76	0.61
Cell Call/Text	8.33	8.03	3.26	2.6
Other V&T Law	8.89	19.78	21.23	28.33
BOLO	0.02	0.08	0.11	0.15
Reasonable Suspicion	0.24	2.41	1.22	0.77
Total N	76,084	22,244	78,766	653

Reasons for stops exhibit only fairly minor differences across precincts: uniformly less than 5 percent for each of four categories (red light and seat belt violations, BOLOs, and reasonable suspicion), 6 to 12 percent for speeding, 13 to 30 percent for stop sign and equipment violations, 12 to 20 percent for other moving violations, and 17 to 28 percent for other V&T law violations. See Table 7.

Table 7. Reasons for Stops by Precinct

	Precinct						
Reason	1 %s	2 %s	3 %s	4 %s	5 %s	6 %s	7 %s
Speeding	11.49	11.61	5.77	10.14	11.58	8.00	11.59
Red Light	3.56	3.49	2.44	4.00	4.50	2.73	1.86
Stop Sign	16.28	13.46	21.37	19.88	24.34	20.84	18.95
Other Moving Violation	19.51	19.27	12.35	18.07	12.74	14.42	15.49
Equipment Violation	23.61	25.26	30.07	17.70	17.25	18.26	26.03
Seat Belt	2.83	1.32	2.94	0.93	1.88	2.15	2.65
Cell Call/Text	1.77	5.61	2.96	3.49	9.60	3.90	2.46
Other V&T Law	16.96	19.06	20.44	24.98	17.34	28.08	19.69
BOLO	0.22	0.07	0.16	0.05	0.08	0.03	0.13
Reasonable Suspicion	3.78	0.85	1.50	0.77	0.68	1.58	1.14
Total N	13,364	16,565	14,650	8,198	14,235	18,722	15,664

Drivers Stopped

Table 8 summarizes information on the characteristics of drivers stopped by the different types of SCPD units. About half of the drivers stopped by SCPD – 45 to 55 percent by each type of unit – are White. Hispanic drivers constitute about one-fifth to one-quarter of those stopped, and Black drivers represent about 20 percent of stopped drivers; each minority 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. 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 to three-quarters of those stopped are men.

Table 8. Driver Characteristics by Unit Type

	Unit Type			
	Highway Patrol	Precinct Crime	Precinct Patrol	Other
Race/Ethnicity				
White	54.88	45.54	44.58	49.46
Black	15.73	21.93	22.36	14.85
Hispanic	20.99	27.45	26.55	26.03
Asian	2.46	1.59	2.22	3.22
Other	5.94	3.49	4.28	6.43
Approximate Age				
Under 16	0.03	0.05	0.07	0.15
16 to 25	18.47	25.80	26.16	30.47
26 to 35	30.89	31.84	30.4	28.94
36 to 45	22.75	20.66	19.34	20.06
46 to 55	16.86	13.24	14.05	12.25
56 to 65	8.29	6.79	7.56	5.67
Over 65	2.71	1.62	2.43	2.45
Gender				
Female	27.81	32.88	30.26	26.03
Male	72.19	67.12	69.74	73.97
Total N	76,084	22,244	78,766	653

The racial/ethnic composition of the drivers who are stopped varies some across precincts. Though drivers obviously are not confined to travel within the precincts in which they reside, this variation coincides to some degree with the differences in the residential populations of the 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 9.

Table 9. Driver Race/Ethnicity by Precinct

	Precinct						
Driver Race/Ethnicity	1 %s	2 %s	3 %s	4 %s	5 %s	6 %s	7 %s
White	27.30	41.87	21.70	56.71	57.06	55.89	53.73
Black	41.57	19.59	23.97	12.27	16.01	17.19	23.87
Hispanic	24.84	30.49	49.56	22.64	22.49	20.19	17.06
Asian	1.86	3.08	1.12	3.10	1.50	2.71	1.39
Other	4.42	4.97	3.65	5.28	2.94	4.01	3.95
Total N	13,364	16,565	14,650	8,198	14,235	18,722	15,664

We caution readers to bear in mind that neither the population of a precinct nor the stops conducted within the precinct are evenly distributed across the precinct. For example, in the first precinct, 41.57 percent of the drivers stopped were Black, which exceeds by a substantial margin the representation of Black persons (17.3 percent) in the population. However, one-quarter of the stops were in the sector block that (approximately) corresponds to Wyandanch, which comprises only 6 percent of the precinct's population. Three-fifths of the Wyandanch population is Black, comprising 21 percent of the precinct's Black population. In the Wyandanch sector block, 64 percent of the drivers stopped were Black, such that stops of Black drivers were approximately proportionate to the Black population. Black drivers stopped in the Wyandanch sector block represent one-third of all Black drivers stopped in first precinct. Such intra-precinct variation in the composition of the residential population and the drivers stopped by police is one of numerous reasons to be guarded in treating population characteristics as a basis for assessing racial and ethnic patterns in traffic stops.

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 10.

Table 10. Reasons for Stops by Driver Race/Ethnicity

	Driver Race/Ethnicity				
Reason	Black %s	Hispanic %s	White %s	Asian %s	Other %s
Speeding	23.09	20.41	28.73	29.86	26.49
Red Light	1.72	2.45	2.02	2.87	1.66
Stop Sign	9.03	12.16	12.94	16.74	10.70
Other Moving Violation	20.89	20.40	20.57	22.79	22.85
Equipment Violation	19.51	18.10	11.41	9.42	12.03
Seat Belt	2.46	2.49	2.22	0.82	1.46
Cell Call/Text	3.56	5.54	7.37	5.32	5.02
Other V&T Law	18.10	17.44	13.93	11.54	19.03
BOLO	0.12	0.07	0.04	0.02	0.09
Reasonable Suspicion	1.53	0.93	0.77	0.60	0.67
Total N	34,557	43,158	87,321	4,002	8,709

The racial/ethnic composition of stopped drivers varies hardly at all across days of the week (see Table 11), and though the variation across the hours of the day is not pronounced (see Table 12, below), it is somewhat disproportionately Black between 8 p.m. and 4 a.m., and disproportionately White between 4 a.m. and 8 p.m.

Table 11. Driver Race/Ethnicity by Day of the Week

	Day of Week						
Driver Race/Ethnicity	%s Sunday	%s Monday	%s Tuesday	%s Wednesday	%s Thursday	%s Friday	%s Saturday
White	45.64	50.63	50.35	49.80	50.08	48.73	45.94
Black	20.37	18.05	19.03	19.33	19.16	20.35	20.56
Hispanic	26.62	24.02	23.81	23.62	23.95	23.49	26.19
Asian	2.40	2.23	2.13	2.20	2.10	2.44	2.42
Other	4.97	5.08	4.68	5.05	4.71	4.98	4.89
Total	15,929	24,859	30,583	31,797	29,806	26,261	18,512

Table 12. Driver Race/Ethnicity by Time of Day

	Time of Day					
Driver Race/Ethnicity	%s 00:00-03:59	%s 04:00-07:59	%s 08:00-11:59	%s 12:00-15:59	%s 16:00-19:59	%s 20:00-23:59
White	41.47	50.18	52.82	50.43	49.72	43.92
Black	24.05	15.82	17.74	19.48	18.25	22.92
Hispanic	26.39	26.52	22.63	23.44	25.20	24.89
Asian	2.27	2.16	2.21	2.03	2.23	2.66
Other	5.82	5.31	4.60	4.62	4.61	5.61
Total	14,159	9,251	46,518	36,334	43,394	28,091

Analysis of Traffic Stops in Suffolk County

As we explained in our previous report (and in Appendix A of this report), analyses of police officers' decisions to execute traffic stops are bedeviled by an inability to apply a wholly satisfactory benchmark against which the racial/ethnic composition of stopped drivers can be compared. Ideally, the proportion of stopped drivers who are, e.g., Black, could be compared with the corresponding proportion of drivers who could be legitimately stopped, but such a benchmark remains a hypothetical abstraction. Practically, analyses designed to detect racial/ethnic bias must rely on benchmarks that suffer from various shortcomings of greater or lesser severity. The "veil-of-darkness" benchmark, which has been widely applied, is arguably the best and most economical benchmark. Another acceptable benchmark, based on the race of drivers involved in vehicle crashes, is not feasible to form in New York State, where the standard report of a motor vehicle accident (MV-104 of the Department of Motor Vehicles) does not capture drivers' race.

The veil-of-darkness benchmark exploits variation in daylight – and with it, the visibility of drivers – within a confined range of hours of the day, within which the composition of the driving population presumably does not vary so much as to be confounded with officers' discretionary traffic stop decisions. Between the earliest and latest times of sunset across the days of the year, in what is called the inter-twilight period, a traffic stop might be made in daylight or darkness. In darkness, officers' ability to detect the race of drivers they observe is impaired, such that stops made during hours of darkness form a benchmark that is, relative to daylight stops, race-neutral.

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.[18] Thus, these times of day were identified for each of seven different zones, separated by longitude.[19] The earliest time, on December 9, 2020, in the easternmost part of the SCPD police district, was 4:55 p.m., and the latest time, on June 26, 2021, in the westernmost part of the police district, was 9:04 p.m. We also note that the spring switches to daylight savings time occurred on March 8, 2020, and March 14, 2021, and the fall switches from daylight savings were on November 1, 2020, and November 7, 2021.

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 2, below).

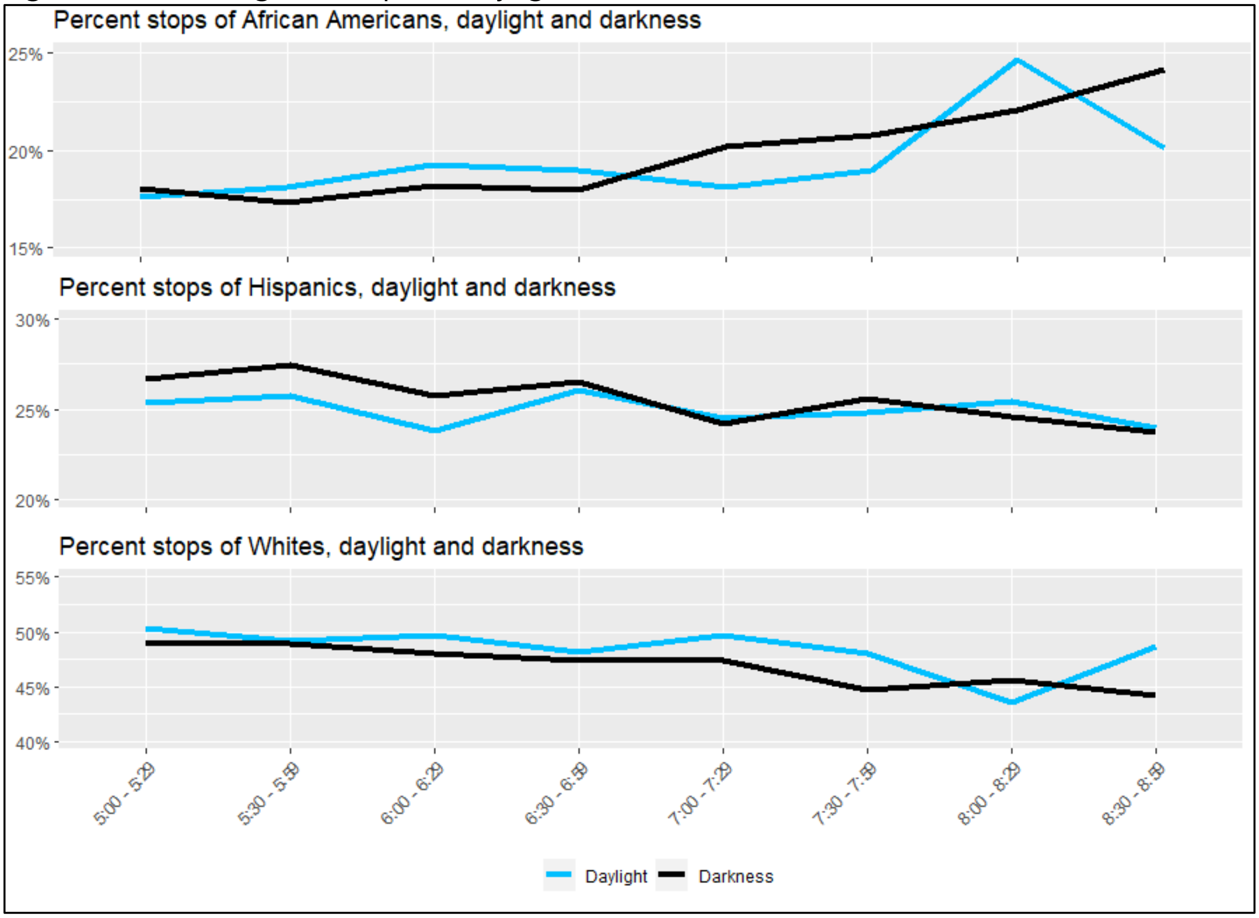
Veil-of-Darkness Findings

As we did previously, we conducted statistical analysis of drivers stopped using multinomial logistic regression with a trichotomous outcome denoting driver race/ethnicity: Black, Hispanic, or – the reference category – non-Hispanic White. Results are shown in Table 19, below. We estimated the parameters of eight models to test the sensitivity of the results to different model specifications. In addition to models for all stops, we estimated models for highway stops (models 9 through 12) and non-highway stops (models 5 through 8) separately. Some models include Asian and "other" in the reference category (the odd-numbered models in the table), and for others (the even-numbered models), the reference category is restricted to non-Hispanic Whites. Some models (3, 4, 7, and 8) are restricted to stops within 30 days of the switches to and from daylight savings time to more stringently control for seasonal variation.

[18] 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. R version 4.1.2 (2021-11-01).

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

Figure 2. Percentage of Stops in Daylight/Darkness



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. For each RRR, we estimate the probability that the RRR value differs from 1.0 by chance; by convention, probabilities that exceed 0.05 (or one in twenty) 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.

Table 19. Veil-of-Darkness Results, 2020-2021 and 2018-2019

Model	Description	RRR_{Black} (95% conf.)	$RRR_{Hispanic}$ (95% conf.)
1: 2020-2021	All Stops	0.95 (0.86, 1.05)	0.94 (0.86, 1.03)
1: 2018-2019	All Stops	0.973	0.986
2: 2020-2021	All Stops; B, H, W only	0.96 (0.87, 1.06)	0.95 (0.87, 1.05)
2: 2018-2019	All Stops; B, H, W only	0.99	1
3: 2020-2021	All Stops; +/- 30 days DST	0.96 (0.86, 1.07)	0.96 (0.86, 1.06)
3: 2018-2019	All Stops; +/- 30 days DST	0.951	1.064
4: 2020-2021	All Stops; +/- 30 days DST; B, H, W only	0.96 (0.86, 1.08)	0.96 (0.87, 1.07)
4: 2018-2019	All Stops; +/- 30 days DST; B, H, W only	0.957	1.063
5: 2020-2021	Non-highway stops	0.99 (0.88, 1.12)	0.91 (0.81, 1.01)
5: 2018-2019	Non-highway stops	1.04	0.99
6: 2020-2021	Non-highway stops; B, H, W only	1.00 (0.88, 1.12)	0.91 (0.81, 1.02)
6: 2018-2019	Non-highway stops; B, H, W only	1.01	0.97
7: 2020-2021	Non-highway stops; +/- 30 days DST	1.04 (0.91, 1.18)	0.94 (0.83, 1.07)
7: 2018-2019	Non-highway stops; +/- 30 days DST	1.1	0.95
8: 2020-2021	Non-highway stops; +/- 30 days DST; B, H, W only	1.04 (0.90, 1.19)	0.94 (0.83, 1.07)
8: 2018-2019	Non-highway stops; +/- 30 days DST; B, H, W only	1.07	0.93
9: 2020-2021	Highway stops	0.80* (0.67, 0.95)	1.04 (0.89, 1.21)
9: 2018-2019	Highway stops	0.91	1.27
10: 2020-2021	Highway stops; B, H, W only	0.81* (0.68, 0.97)	1.07 (0.91, 1.25)
10: 2018-2019	Highway stops; B, H, W only	0.95	1.3
11: 2020-2021	Highway stops; +/- 30 days DST	0.76** (0.63, 0.92)	1.03 (0.86, 1.23)
11: 2018-2019	Highway stops; +/- 30 days DST	0.82	0.99
12: 2020-2021	Highway stops; +/- 30 days DST; B, H, W only	0.78* (0.64, 0.95)	1.05 (0.88, 1.26)
12: 2018-2019	Highway stops; +/- 30 days DST; B, H, W only	0.85	1.04

With one notable exception, to which we turn momentarily, the estimated parameters parallel those based on 2018-2019 stops, and none of them support an inference of bias against either Black or Hispanic drivers. We also estimated models for each precinct separately; the results for Model 1 are shown in Table 20; results for the other models did not differ substantively from those for Model 1. In none of the precincts do we see evidence of bias.

Table 20. Veil-of-Darkness Results, 2020-2021, by Precinct

Model	**Description**	**RRR_{Black} (95% conf.)**	**$RRR_{Hispanic}$ (95% conf.)**
1: 2020-2021	All Stops	0.95 (0.86, 1.05)	0.94 (0.86, 1.03)
1: 2020-2021	Precinct 1	0.90 (0.69, 1.18)	0.79 (0.58, 1.07)
1: 2020-2021	Precinct 2	1.06 (0.82, 1.37)	1.04 (0.83, 1.29)
1: 2020-2021	Precinct 3	0.81 (0.61, 1.08)	0.98 (0.76, 1.25)
1: 2020-2021	Precinct 4	0.79 (0.57, 1.08)	0.95 (0.72, 1.25)
1: 2020-2021	Precinct 5	0.89 (0.73, 1.10)	0.88 (0.74, 1.06)
1: 2020-2021	Precinct 6	0.97 (0.74, 1.27)	0.92 (0.72, 1.18)
1: 2020-2021	Precinct 7	1.13 (0.87, 1.47)	0.91 (0.69, 1.22)

Only the models for highway stops yield an estimated effect of daylight on the likelihood that Black drivers would be stopped, and the effect is negative – that is, Black drivers on highways are *less* likely to be stopped during daylight. No comparable effect is detectable for Hispanics, nor do we find such an effect among non-highway stops. The effect of daylight on the likelihood that stopped drivers are Black was more pronounced during the pandemic PAUSE (between March 20 and July 8, 2020), when fewer drivers were on the road. Among a single year of stops in 2018-2019, the estimated parameters similarly indicated a lower probability that Black drivers on highways would be stopped in daylight, but the imprecision of the estimates rendered them statistically insignificant. In the two-year 2020-2021 time frame, the larger number of highway stops in the inter-twilight period support more precise estimates, which achieve statistical significance.

The findings regarding stops of Black drivers on highways are consistent with the proposition that Black motorists adjust their driving during daylight hours in order to reduce their risk of (presumptively discriminatory) stops. Kalinowski, et al., found evidence that African Americans (but not non-Hispanic Whites) drive at lower speeds during daylight than darkness during the inter-twilight period, and that African Americans (but not non-Hispanic Whites) are less likely to be involved in fatal motor vehicle crashes during daylight.[20] They analyzed data on stops for speeding in Massachusetts and Tennessee, "the only statewide data available with information on the speed of traffic stops resulting in a warning, rather than only for tickets/fines,"[21] and national data on fatal crashes. These differences were not equally pervasive: they were more pronounced and had greater implications for the veil-of-darkness results in some locations than others.

Such a phenomenon is not ubiquitous, however. One study that provided for direct observation of driver race and calibration of speed found that Black drivers were overrepresented among the drivers exceeding the speed limit by at least 15 miles per hour. Moreover, they found that,

> Black drivers make up relatively higher percentages of drivers—particularly speeders—during the late-night and early-morning hours, and are overrepresented. White drivers make up relatively high percentages of drivers during morning, afternoon, and evening hours. The distribution of Black and White speeders over time approximates closely the pattern of police stop rates.[22]

In general, however, the more that Black drivers adapt their driving to daylight, the greater the chance that veil-of-darkness results will underestimate racial bias in stops.

Data on fatal crashes in Suffolk County would not suffice for the purpose of estimating differences in driving behavior in daylight and darkness by drivers of different races/ethnicities: there were 107 fatal crashes in 2020 and 137 in 2021, too few for this analytical purpose.[23] SCPD's stop data do not capture speeds for any of the stops, regardless of disposition. Thus, we are unable to estimate the extent to which the veil-of-darkness results might underestimate bias. However, we disaggregated highway stops to apply the veil-of-darkness analysis to two subsets: stops for speeding, and stops for other reasons. We expected to find that the daylight reduction in stops of Black drivers would be either confined to or more pronounced in stops for speeding.

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[20] Jesse Kalinowski, Matthew B. Ross, Stephen L. Ross, "Endogenous Driving Behavior in Tests of Racial Profiling in Police Traffic Stops," Department of Economics Working Paper 2017-03R, University of Connecticut, 2020.

[21] Ibid., p. 4.

[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, p. 210.

[23] See https://www.itsmr.org/sas-guest-portal/.

This expectation was contradicted by the results (see Table 21); instead, the reduction appears to hold mainly (if not exclusively) among stops for reasons other than speeding.

Table 21. Veil-of-Darkness Results, 2020-2021 Highway Stops, by Speeding/Other

Model	**Description**	**RRR_{Black} (95% conf.)**	**$RRR_{Hispanic}$ (95% conf.)**
9a: 2020-2021	Highway stops -speeding	0.89 (0.67, 1.18)	1.08 (0.84, 1.40)
9a: 2020-2021	Highway stops -other	0.72** (0.57, 0.90)	1.01 (0.83, 1.23)
10a: 2020-2021	Highway stops; B, H, W only -speeding	0.90 (0.68, 1.19)	1.10 (0.84, 1.43)
10a: 2020-2021	Highway stops; B, H, W only -other	0.74* (0.58, 0.93)	1.05 (0.85, 1.28)
11a: 2020-2021	Highway stops; +/- 30 days DST -speeding	0.90 (0.67, 1.21)	1.04 (0.78, 1.38)
11a: 2020-2021	Highway stops; +/- 30 days DST -other	0.64*** (0.49, 0.83)	1.01 (0.80, 1.28)
12a: 2020-2021	Highway stops; +/- 30 days DST; B, H, W only -speeding	0.91 (0.68, 1.24)	1.07 (0.80, 1.43)
12a: 2020-2021	Highway stops; +/- 30 days DST; B, H, W only -other	0.65** (0.50, 0.85)	1.03 (0.81, 1.32)

These findings certainly do not invalidate the veil-of-darkness method, but they underscore the caution that must be used in interpreting its results. It remains desirable – but in New York State, infeasible – to corroborate such results with the application of another plausible benchmark, the racial/ethnic composition of drivers involved in vehicle crashes.

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 present our analyses of post-stop outcomes in Suffolk County. A discussion of how previous research has addressed the analytical challenges of isolating potential bias from data on disparities in these outcomes, which we included in our previous report, is reproduced in Appendix C.

Searches

Searches of either persons or vehicles are conducted in a small fraction – less than 3 percent – of all SCPD traffic stops. In most instances of any search, both types – of the vehicle and of one or more occupants – 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/or a person (see Table 22b). Either type of search is performed by precinct patrol units in 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 much more likely to involve a search, followed by stops in the third precinct (see Table 22a).

Table 22a and 22b. Search Frequencies by Precinct and Unit Type

22a. Precinct	Vehicle Searches	Person Searches		22b. Unit Type	Vehicle Searches	Person Searches
1	15.44	19.23		Highway Patrol	0.05	0.29
2	3.66	4.88		Precinct Crime	5.79	8.20
3	4.81	6.62		Precinct Patrol	3.66	4.98
4	1.10	1.42		Other	1.07	1.85
5	1.28	2.31				
6	0.69	0.95				
7	2.52	3.34				
Search Ns	4,171	6,247			4,220	6,497
Total %	4.11	5.67			2.37	3.35
Total Ns	101,398	110,164			177,747	193,869

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 23, below. 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 23. Search Frequencies by Driver Race/Ethnicity

	Driver Race/Ethnicity					
Race/Ethnicity	White	Black	Hispanic	Asian	Other	All
Stops (N)	87,321	34,557	43,158	4,002	8,709	177,747
Vehicle searched	1.44	5.50	2.15	0.75	1.17	2.37
Driver searched	1.67	6.06	2.63	0.90	1.24	2.72
Stops with passengers (N)	4,714	3,295	3,640	310	498	12,457
Passenger searched	6.20	20.00	7.71	2.14	4.35	10.36

Focusing first on vehicle searches, by far the most commonly recorded reason for the search was probable cause for illicit drugs, identified in about two-thirds of the vehicle searches conducted by precinct patrol and precinct crime units, and nearly 60 percent of those by other units. The same reason was cited in 30 percent of the small number of vehicle searches by highway patrol units. See Table 24.

Table 24. Reasons for Vehicle Search by Unit Type

	Unit Type			
Vehicle Search Reason	Highway Patrol %s	Precinct Crime %s	Precinct Patrol %s	Other %s
Consent	0	8.07	11.57	28.57
Founded Suspicion & Permission	0	1.55	2.74	0
Plain View	7.5	10.40	10.88	14.29
Probable Cause - Drugs	30	69.36	63.20	57.14
Probable Cause - Other	62.5	10.63	11.61	0
Total	40	1,289	2,886	7

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 73 percent (see Table 25). Consent searches were most common in the fifth and seventh precincts.

Table 25. Reasons for Vehicle Search by Precinct

	Precinct						
Vehicle Search Reason	1 %s	2 %s	3 %s	4 %s	5 %s	6 %s	7 %s
Consent	7.51	12.38	10.50	11.11	23.63	10.08	16.92
Founded Suspicion & Permission	3.1	0.83	2.13	3.33	2.20	2.33	1.26
Plain View	11.86	6.93	10.64	15.56	10.44	12.40	9.34
Probable Cause - Drugs	64.12	72.61	67.09	61.11	55.49	60.47	62.37
Probable Cause - Other	13.41	7.26	9.65	8.89	8.24	14.73	10.10
Total	2,065	606	705	90	182	129	396

Consent searches, which are normally considered the most discretionary of searches, were more commonly conducted of vehicles driven by White drivers (see Table 26). The data do not allow us to determine whether officers were more likely to request consent from White drivers, White drivers were more likely to grant consent, or both.

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

	Driver Race/Ethnicity				
Vehicle Search Reason	Black %s	Hispanic %s	White %s	Asian %s	Other %s
Consent	7.09	10.65	15.27	10.00	10.78
Founded Suspicion & Permission	2.73	1.83	1.91	6.67	3.92
Plain View	8.09	12.04	13.37	10.00	14.71
Probable Cause - Drugs	68.52	63.33	60.14	63.33	64.71
Probable Cause - Other	13.56	12.15	9.31	10.00	5.88
Total	1,903	930	1,257	30	102

Vehicle searches by precinct crime units were the most successful in terms of recovering contraband, as nearly 65 percent led to the recovery of drugs, weapons, or other items (see Table 27, below). Precinct patrol units were successful in this sense in slightly more than half of their vehicle searches, while the small number of searches by highway patrol and other units were the least successful. The most commonly recovered type of contraband was drugs.

Table 27. Vehicle Search Outcome by Unit Type

	Unit Type			
Vehicle Search Outcome	Highway Patrol %s	Precinct Crime %s	Precinct Patrol %s	Other %s
Nothing	70	34.52	48.61	57.14
Drugs	25	59.35	44.56	28.57
Weapon	0	1.86	2.15	0
Other	5	4.27	4.68	14.29
Total	40	1,289	2,886	7

Searches of White drivers' vehicles were more successful than those of Black or Hispanic drivers (see Table 28), or in other words, searches of Black and Hispanic drivers' vehicles were more likely to yield no contraband. On its face, this disparity could be taken to imply that searches of Black and Hispanic drivers rest on a lower evidentiary threshold than those of White drivers, but an inference about bias can be drawn more confidently from the analysis summarized in the next section of the report.

Table 28. Vehicle Search Outcome by Driver Race/Ethnicity

	Driver Race/Ethnicity				
Vehicle Search Outcome	Black %s	Hispanic %s	White %s	Asian %s	Other %s
Nothing	47.40	46.02	40.57	23.33	32.35
Drugs	46.30	48.92	51.95	60.00	54.9
Weapon	2.42	1.18	1.83	6.67	3.92
Other	3.89	3.87	5.65	10.00	8.82
Total	1,903	930	1,257	30	102

Considering searches of individual drivers, precinct patrol and precinct crime units exhibited comparable distributions of reasons, with about 30 to 40 percent based on probable cause, slightly less than one-quarter incident to arrest, and less than 10 percent for each of plain view and consent searches (see Table 29, below). Highway patrol and other units were most likely to conduct searches incident to arrest, which are normally are regarded as non-discretionary, and correspondingly less likely to conduct searches based on probable cause. Precinct and other units conducted frisks of one-quarter to one-third of the drivers, up substantially from the proportions of drivers frisked in 2018-2019 (9 to 18 percent).

Table 29. Reasons for Driver Search by Unit Type

	Unit Type			
Driver Search Reason	Highway Patrol	Precinct Crime	Precinct Patrol	Other
Protective Frisk	1.66	24.31	28.60	36.36
Consent	0	4.61	6.29	18.18
Founded Suspicion & Permission	0	0.57	1.14	0
Probable Cause	17.84	38.34	33.69	9.09
Plain View	0.41	8.58	7.14	0
Incident to Arrest	80.08	23.60	23.14	36.36
Total	241	1,411	3,164	11

Reasons for searches of drivers varied across precincts (see Table 30). Frisks were most common in the first, second, and third precinct, in all of which frisks represented a larger proportion of "searches" than in 2018-2019 (though presumably frisks might have preceded other types of searches, which became the reason of record). Searches incident to arrest represented half of the searches in the fifth precinct, about 40 percent in the sixth precinct, and about one-third in the fourth and seventh precincts. Probable cause searches represented 31 to nearly 50 percent of the searches of drivers in all but the fourth and fifth precincts.

Table 30. Reasons for Driver Search by Precinct

	Precinct						
Driver Search Reason	1 %s	2 %s	3 %s	4 %s	5 %s	6 %s	7 %s
Protective Frisk	33.2	27.52	26.2	14.13	15.12	12.84	14.58
Consent	3.64	8.41	4.56	9.78	12.37	5.41	9.34
Founded Suspicion & Permission	1.2	0.15	0.63	3.26	1.37	2.03	0.46
Plain View	8.24	4.89	5.95	17.39	6.19	7.43	9.57
Probable Cause	33.43	42.51	44.18	22.83	15.12	31.08	32.8
Incident to Arrest	20.3	16.51	18.48	32.61	49.83	41.22	33.26
Total	2,172	654	790	92	291	148	439

The reasons for searches of drivers (see Table 31, below) do not vary markedly across drivers' race/ethnicity, excepting the incidence of frisks of Black and Hispanic drivers (and setting aside the small numbers of searches of Asian or "other" race drivers). Somewhat greater proportions of White drivers were searched (a) with their consent or (b) incident to arrest, and correspondingly fewer subject to a probable cause search.

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

	Driver Race/Ethnicity				
Driver Search Reason	Black %s	Hispanic %s	White %s	Asian %s	Other %s
Protective Frisk	31.49	25.46	19.38	13.89	19.44
Consent	3.87	5.02	8.32	0	6.48
Founded Suspicion & Permission	0.96	0.62	1.03	2.78	0.93
Plain View	5.21	7.22	9.07	11.11	19.44
Probable Cause	37.51	33.3	30.03	41.67	33.33
Incident to Arrest	20.97	28.37	32.16	30.56	20.37
Total	2,093	1,135	1,455	36	108

As with vehicle searches, precinct crime units' searches of drivers were the most successful in recovering contraband (see Table 32). Precinct patrol units were somewhat less successful than precinct crime units. Highway patrol units seldom recovered contraband from drivers, though most of their searches were incident to arrest.

Table 32. Driver Search Outcome by Unit Type

	Unit Type			
Driver Search Outcome	Highway Patrol %s	Precinct Crime %s	Precinct Patrol %s	Other %s
Nothing	94.31	60.02	69.81	69.23
Contraband	4.07	33.43	23.65	30.77
Contraband & Other	0.41	0.2	0.23	0
Weapon	0	1.88	1.76	0
Weapon & Contraband	0	0.61	0.52	0
Weapon & Other	0	0.05	0.05	0
Weapon, Contraband, & Other	0	0.1	0.02	0
Other	1.22	3.7	3.96	0
Total	241	1,411	3,164	11

The outcomes of searches of drivers varies across precincts, with the greatest success among searches in the fourth precinct. See Table 33, below.

Table 33. Driver Search Outcome by Precinct

	Precinct						
Driver Search Outcome	1 %s	2 %s	3 %s	4 %s	5 %s	6 %s	7 %s
Nothing	64.8	68	73.42	50.81	75.94	70.59	59.82
Contraband	28.76	26.51	20.36	37.9	18.84	21.93	31.68
Contraband & Other	0	0.34	0.38	0.81	0	0	1.06
Weapon	2.54	1.03	1.34	0	0.58	1.07	1.06
Weapon & Contraband	0.64	0.69	0.19	0.81	0.87	1.07	0
Weapon & Other	0.06	0	0.1	0	0	0	0
Weapon, Contraband, & Other	0.03	0	0.1	0	0	0	0.18
Other	3.16	3.43	4.11	9.68	3.77	5.35	6.19
Total	3,105	875	1,046	124	345	187	565

The success of searches of drivers does not vary much across drivers of different race/ethnicity (see Table 34), excepting the somewhat greater success of searches of Asian drivers and those of other race/ethnicity.

Table 34. Driver Search Outcome by Driver Race/Ethnicity

	Driver Race/Ethnicity				
Driver Search Outcome	Black %s	Hispanic %s	White %s	Asian %s	Other %s
Nothing	69.52	70.99	66.12	55.56	54.63
Contraband	24.32	22.57	27.77	33.33	39.81
Contraband & Other	0.19	0.26	0.27	0.00	0.00
Weapon	2.01	1.23	1.37	2.78	1.85
Weapon & Contraband	0.24	0.53	0.55	2.78	0.93
Weapon & Other	0.10	0.00	0.07	0.00	0.00
Weapon, Contraband, & Other	0.10	0.09	0.00	0.00	0.00
Other	3.54	4.32	3.85	5.56	2.78
Total	2,093	1,134	1,455	36	108

Considering searches of individual passengers, precinct patrol and precinct crime units exhibited comparable distributions of reasons, as they did with searches of drivers (see Table 35, below). Frisks, searches based on probable cause, searches incident to arrest comprised all but a small fraction of passenger searches. Highway patrol and other units rarely searched passengers.

Table 35. Reasons for Passenger Search by Unit Type

Passenger Search Reason	Highway Patrol	Precinct Crime	Precinct Patrol	Other
Protective Frisk	100	33.39	36.23	0
Consent	0	2.5	3.35	0
Founded Suspicion & Permission	0	0.89	1.36	0
Plain View	0	6.79	7.43	0
Probable Cause	0	42.5	36.87	50
Incident to Arrest	0	13.93	14.76	50
Total	5	560	1,104	2

The reasons for searches of passengers vary somewhat across precincts (see Table 36), though the numbers of passengers searched in several of the precincts are small enough (under 100) that caution should be exercised in characterizing patterns. Where searches are more frequent – in the first, second, and third precincts – they tend to be protective frisks or based on probable cause. In the remaining precincts, a larger fraction of searches are incident to arrest.

Table 36. Reasons for Passenger Search by Precinct

	Precinct						
Passenger Search Reason	1 %s	2 %s	3 %s	4 %s	5 %s	6 %s	7 %s
Protective Frisk	36.83	43.89	29.69	15.62	16.67	53.85	24.6
Consent	2.57	1.36	3.12	3.12	12.96	5.13	4.76
Founded Suspicion & Permission	1.39	0	1.56	3.12	0	0	1.59
Plain View	8.78	2.26	4.69	12.5	5.56	7.69	8.73
Probable Cause	36.3	43.89	49.22	31.25	46.3	10.26	35.71
Incident to Arrest	14.13	8.6	11.72	34.38	18.52	23.08	24.6
Total	934	221	256	32	54	39	126

Reasons for searches of passengers differ somewhat across passengers of different race/ethnicity, as White passengers were more likely to be searched incident to arrest and less likely to be frisked. See Table 37, below.

Searches of passengers by precinct crime units tend to be slightly more successful than those by precinct patrol units (see Table 38, below), though more than half of those by either type of unit have negative results.

Searches of Black and Hispanic passengers are less successful than those of White passengers are; see Table 39, below.

Table 37: Reasons for Passenger Search by Passenger Race/Ethnicity

	Passenger Race/Ethnicity				
Passenger Search Reason	Black %s	Hispanic %s	White %s	Asian %s	Other %s
Protective Frisk	37.68	40.50	25.00	22.22	33.33
Consent	1.86	1.65	7.02	0	10.00
Founded Suspicion & Permission	1.53	0.55	0.84	0	3.33
Plain View	6.68	6.06	8.99	11.11	13.33
Probable Cause	39.10	41.05	36.52	44.44	20.00
Incident to Arrest	13.14	10.19	21.63	22.22	20.00
Total	913	363	356	9	30

Table 38. Passenger Search Outcome by Unit Type

Passenger Search Outcome	Highway Patrol %s	Precinct Crime %s	Precinct Patrol %s	Other %s
Nothing	100	61.96	67.93	0
Contraband	0	31.96	25.09	100
Contraband & Other	0	0.36	0.18	0
Weapon	0	2.32	1.81	0
Weapon & Contraband	0	0.36	1	0
Other	0	3.04	3.99	0
Total	5	560	1,104	2

Table 39: Passenger Search Outcome by Passenger Race/Ethnicity

	Passenger Race/Ethnicity				
Passenger Search Outcome	Black %s	Hispanic %s	White %s	Asian %s	Other %s
Nothing	68.67	67.77	57.3	77.78	60
Contraband	24.1	26.72	37.08	0	30
Contraband & Other	0.11	0.55	0.28	0	0
Weapon	2.85	0.83	0.56	0	6.67
Weapon & Contraband	0.99	0.28	0.84	0	0
Other	3.29	3.86	3.93	22.22	3.33
Total	913	363	356	9	30

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 14 percent of passengers were ordered out of the car (see Table 40b). 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 most prevalent among stops in the first precinct, followed by stops in the third precinct (see Table 40a).

Table 40a and 40b. Commands to Exit Vehicle by Precinct and Unit Type

40a. Precinct	Driver	Passenger		40b. Unit Type	Driver	Passenger
1	17.95	39.81		Highway Patrol	1.04	0.36
2	4.90	19.52		Precinct Crime	7.65	41.41
3	6.70	28.48		Precinct Patrol	5.05	20.48
4	1.93	8.83		Other	1.83	4.00
5	3.20	15.87				
6	1.40	6.02				
7	3.98	19.45				
Total %	5.62	24.69			3.64	13.61
Total N	101,398	8,766			177,747	16,122

Once removed from the vehicle, Black drivers and passengers are more likely than those of other races/ethnicities to be placed in the back of the police unit (see Table 41).

Table 41. Commands to Exit Vehicle – Placement by Race/Ethnicity

	Driver Race/Ethnicity				
Exit Vehicle (Placement)	Black %s	Hispanic %s	White %s	Asian %s	Other %s
Back of Unit	47.17	42.82	40.19	37.04	44.16
Side of Road	52.83	57.18	59.81	62.96	55.84
Total	2,523	1,616	2,130	54	154
	Passenger Race/Ethnicity				
Back of Unit	40.51	36.6	36.53	7.14	36.11
Side of Road	59.49	63.4	63.47	92.86	63.89
Total	1,143	470	531	14	36

Restraints

Among those removed from their vehicles, about one-third are restrained (see Table 42). Restraints are most commonly applied to drivers stopped in the fifth precinct, and to passengers in the fourth precinct. A small proportion of passengers are restrained by highway patrol units.

Table 42a and 42b. Restraints by Precinct and Unit Type

42a. Precinct	Driver	Passenger		42b. Unit Type	Driver	Passenger
1	38.47	35.35		Highway Patrol	32.61	11.54
2	31.90	27.78		Precinct Crime	35.49	26.89
3	33.30	22.46		Precinct Patrol	36.88	32.26
4	35.44	44.90		Other	33.33	100
5	45.39	30.19				
6	37.26	25.86				
7	34.29	20.65				
Total %	36.60	30.50			35.99	30.26
Total N	5,694	2,164			6,477	2,194

The application of restraints does not vary markedly by driver or passenger race/ethnicity; see Table 43.

Table 43. Restrained by Race/Ethnicity

	Race/Ethnicity				
Restrained	Black	Hispanic	White	Asian	Other
Driver %	36.07	35.21	36.62	35.19	34.42
Passenger %	31.92	23.83	31.83	42.86	33.33

Use of Physical Force

Physical force was rarely used in SCPD traffic stops. Precinct patrol and precinct crime units were about equally likely to use force in traffic stops (see Table 44b, below), but the proportions of drivers or passengers subjected to physical force were very small. Among stops in the precincts, stops by the first and third precincts were more likely to involve force (see Table 44a), but again, the prevalence was very low.

Black drivers and passengers were more likely to be subjected to physical force than drivers of other races/ethnicities (see Table 45, below).

Table 44a and 44b. Use of Force by Precinct and Unit Type

44a. Precinct	Driver	Passenger		44b. Unit Type	Driver	Passenger
1	0.07	0.22		Highway Patrol	0.00	0.03
2	0.04	0.36		Precinct Crime	0.04	0.22
3	0.05	0.26		Precinct Patrol	0.03	0.17
4	0.00	0.00		Other	0.00	0.00
5	0.01	0.00				
6	0.02	0.21				
7	0.01	0.00				
Total %	0.03	0.18			0.02	0.11
Total N	101,398	8,766			177,747	16,122

Table 45. Use of Force by Race/Ethnicity

	Race/Ethnicity				
Subject to Force	Black %s	Hispanic %s	White %s	Asian %s	Other %s
Driver %	0.05	0.01	0.01	0.00	0.01
Passenger %	0.26	0.04	0.07	0.00	0.00

Stop Duration

Overall, 91.3 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 46). Compared with stops of White drivers, stops of Black drivers are 27 percent more likely to last more than 30 minutes, and stops of Hispanic drivers are 143 percent more likely to last more than 30 minutes.

Table 46. Durations of Stop by Driver Race/Ethnicity

	Driver Race/Ethnicity				
Duration of Stop	Black %s	Hispanic %s	White %s	Asian %s	Other %s
Up to 15 minutes	89.22	88.53	93.16	94.23	93.26
16-30 minutes	8.36	7.83	4.93	4.45	4.81
More than 30 minutes	2.42	3.64	1.91	1.32	1.93
Total	34,557	43,158	87,321	4,002	8,709

The modal disposition in stops by any type of SCPD unit is a ticket (see Table 47, below). Nearly half of the stops by precinct patrol units culminate in a ticket, as do about two-thirds of the stops by precinct crime units and highway patrol units. Most of the remaining stops – one-quarter of those by precinct crime units, nearly one-third or more of those by highway patrol units, and half 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.

Table 47. Dispositions by Unit Type

	Unit Type			
Disposition	Highway Patrol	Precinct Crime	Precinct Patrol	Other
Arrest	0.59	5.09	2.47	2.6
Field Appearance Ticket	0	0.71	0.19	0.31
Ticket Issued	64.92	69.45	46.25	36.75
Verbal Warning Issued	31.69	24.23	50.35	58.65
Other	2.8	0.51	0.75	1.68
Total	76,084	22,244	78,766	653

Among stops in the precincts, warnings are most likely in the fourth 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. See Table 48.

Table 48. Dispositions by Precinct

	Precinct						
Disposition	1 %s	2 %s	3 %s	4 %s	5 %s	6 %s	7 %s
Arrest	8.98	2.49	3.23	1.04	2.04	1.13	2.83
Field Appearance Ticket	1.11	0.27	0.38	0.17	0.06	0.05	0.18
Ticket Issued	45.52	54.66	53.22	44.49	68.16	49.93	40.81
Verbal Warning Issued	43.26	42.18	42.48	53.5	29.29	48.22	55.31
Other	1.14	0.4	0.7	0.81	0.46	0.67	0.87
Total	13,364	16,565	14,650	8,198	14,235	18,722	15,664

Dispositions vary with the reason for the stops, as one might expect. See Table 49, below, in which the percentages are calculated across rows. 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.

Table 49. Dispositions by Reasons for Stops

	Disposition					
Reason	Arrest	Ticket	App Tick	Warning	Other	Total N
Speeding %s	0.97	65.14	0.05	31.77	2.08	45,372
Red light %s	1.55	57.18	0.03	40.30	0.24	3,675
Stop sign %s	1.29	53.31	0.13	45.08	0.19	21,269
Other moving violation %s	2.56	56.09	0.11	39.75	1.49	36,884
Equipment violation %s	2.51	47.16	0.25	37.20	0.48	25,941
Seatbelt %s	2.66	70.35	0.17	49.60	0.92	4,020
Cell phone %s	0.36	68.15	0.01	30.96	0.51	10,711
Other V&T law %s	2.16	53.33	0.31	41.23	2.97	28,070
BOLO %s	21.19	22.88	0.85	27.97	27.12	118
Reasonable suspicion %s	23.89	26.62	3.32	33.61	12.57	1,687

Dispositions also vary with the race/ethnicity of the drivers and passengers (see Tables 50 and 51). Black drivers and passengers are more likely than those 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 50. Dispositions by Driver Race/Ethnicity

	Driver Race/Ethnicity				
Disposition	Black %s	Hispanic %s	White %s	Asian %s	Other %s
Arrest	3.54	2.07	1.50	0.80	1.00
Field Appearance Ticket	0.27	0.25	0.11	0.05	0.11
Ticket Issued	52.50	61.76	57.03	57.87	52.91
Verbal Warning Issued	42.44	34.74	39.53	39.31	43.52
Other	1.26	1.18	1.83	1.97	2.46
Total	34,557	43,158	87,321	4,002	8,709

Table 51. Dispositions by Passenger Race/Ethnicity

	Passenger Race/Ethnicity				
Disposition	Black %s	Hispanic %s	White %s	Asian %s	Other %s
Arrest	6.88	2.61	3.80	0.95	2.61
Field Appearance Ticket	0.48	0.34	0.23	0	0.14
Ticket Issued	2.50	3.29	2.89	1.67	1.16
Verbal Warning Issued	33.01	21.00	16.85	8.10	17.54
Other	57.13	72.75	76.23	89.29	78.55
Total	4,565	4,709	5,738	420	690

Analysis of Post-Stop Outcomes in Suffolk County

Our analysis of post-stop outcomes relies on propensity score matching to statistically control for factors whose effects on the outcomes could be confounded with those of drivers' or passengers' race/ethnicity. As Neil and Winship observe, "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."[24] For this analysis, we "match" Black and Hispanic drivers, respectively, as closely as possible to a group of White drivers based on propensity scores that are statistically weighted combinations of the potentially confounding factors (or covariates), including:

- 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

Individuals with similar propensity scores have similar values of the observed covariates, and groups comprised of individuals paired by similar propensity scores will have similar distributions of the observed covariates. This construction allows for stronger causal inferences by reducing the influence of covariates and better isolating the effect of drivers' race/ethnicity. The point of propensity score matching is to compare two groups that differ by no observable variable aside from the variable of interest – for this analysis, race/ethnicity.

For our analysis, one-to-one matching was executed using nearest neighbor matching without replacement.[25] 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 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

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[24] Roland Neil and Christopher Winship, "Methodological Challenges and Opportunities in Testing for Racial Discrimination," *Annual Review of Criminology* 2 (2019): 73–98, p. 91.

[25] 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/.

groups that were sufficiently similar.[26] Post-stop analyses on the matched data sets were completed with logistic regression and Poisson regression, as appropriate to the properties of the outcome variable.

Table 52, below, 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.[27] 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 whether the p-value achieves statistical significance at each of several levels – i.e., 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.

We focus first on stops of Black drivers, compared with similarly-situated (i.e., matched) White drivers. Black drivers were:

- More than twice as likely to be subjected to a vehicle search;
- 35 percent more likely to have a search of their vehicles yield no contraband;
- More than twice as likely to be subjected to a search of their person;
- 16 percent less likely to be ticketed, but ticketed for a larger number of violations;
- 57 percent more likely to be arrested;
- 16 percent more likely to receive a warning;
- 19 percent more likely to be placed in the back of the police unit (given that they are removed from their own vehicles); and
- 16 percent *less* likely to be detained for more than 15 minutes (taking account of whether they were subject to a search).

With two exceptions, these findings parallel those based on 2018-2019 stops. The exceptions are with respect to the likelihood of being restrained (which was 84 percent more likely for Black drivers in 2018-2019) and the likelihood of being detained for more than 15 minutes (which was 15 percent *more* likely for Black drivers in 2018-2019).

[26] 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.

[27] We note that our analysis of 2018-2019 stops included use of force as an outcome, albeit an outcome that occurred with very low frequency. Among 2020-2021 stops, force was so seldom used that analysis based on propensity score matching was not statistically feasible. We also note that Models 3 and 10 include as additional covariates whether vehicle and/or person searches were conducted.

Table 52. Post-Stop Outcome Differences, Blacks and Hispanics Matched to Whites

Outcome	**Black / White**	**Hispanic / White**
1. Vehicle search (logistic) n_B = 69,114; n_H = 86,316	OR = 2.30*** (2.11, 2.51)	OR = 0.87** (0.79, 0.96)
2. Person search (logistic) n_B = 69,114; n_H = 86,316	OR = 2.31*** (2.13, 2.51)	OR = 0.96 (0.88, 1.05)
3. Exit vehicle (logistic) n_B = 69,114; n_H = 86,316	OR = 1.10 (0.97, 1.26)	OR = 1.09 (0.96, 1.23)
4. Restrained (logistic) n_B = 69,114; n_H = 86,316	OR = 1.10 (0.95, 1.27)	OR = 0.97 (0.83, 1.14)
5. Total tickets (Poisson) n_B = 69,114; n_H = 86,316	IRR = 1.20*** (1.18, 1.22)	IRR = 1.22*** (1.21, 1.24)
6. Warning (logistic) n_B = 69,114; n_H = 86,316	OR = 1.16*** (1.12, 1.20)	OR = 0.86*** (0.83, 0.88)
7. Placed in back of unit (logistic) n_B = 4,656; n_H = 3,418	OR = 1.19** (1.06, 1.35)	OR = 1.09 (0.95, 1.26)
8. Arrest (logistic) n_B = 69,114; n_H = 86,316	OR = 1.57*** (1.43, 1.73)	OR = 0.95 (0.86, 1.05)
9. UTT (logistic) n_B = 69,114; n_H = 86,316	OR = 0.84*** (0.82, 0.87)	OR = 1.19*** (1.15, 1.22)
10. Duration > 15 minutes (logistic) n_B = 69,114; n_H = 86,316	OR = 0.84*** (0.76, 0.93)	OR = 1.58*** (1.45, 1.64)
11. Vehicle search = nothing (logistic) n_B = 2,268; n_H = 1,512	OR = 1.35*** (1.12, 1.64)	OR = 1.29* (1.02, 1.64)
12. Person search = nothing (logistic) n_B = 3,264; n_H = 2,282	OR = 1.17 (0.99, 1.38)	OR = 1.40** (1.15, 1.72)

* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$

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:

- 13 percent *less* likely to be subjected to a vehicle search;
- 29 percent more likely to be subjected to a vehicle search that yields no contraband;
- 40 percent more likely to be subjected to a person search that yields no contraband;
- 19 percent more likely to be ticketed;
- Ticketed for a larger number of violations;
- 14 percent less likely to receive a warning; and
- 58 percent more likely to be detained for more than 15 minutes.

With a few exceptions, these findings parallel those based on 2018-2019 stops. The exceptions are with respect to: the likelihood of being subjected to a search of their person (which was 16 percent more likely for Hispanic drivers in 2018-2019); the greater likelihood of a search – either of the vehicle or person – yielding no contraband (differences that were not statistically significant in 2018-2019); and the likelihood of being arrested (which was 16 percent more likely for Hispanic drivers in 2018-2019).

Thus, as we did in our previous analysis, 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. Other explanations, noted in our previous report, are conceivable, though we could not examine them with the data available to us.

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 two-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 – but not eliminated – 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. We caution, however, that we also found some evidence that Black drivers might drive differently – more carefully and lawfully – during daylight hours; if so, then the veil-of-darkness findings would to some degree underestimate the degree of bias.

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. The available data do not enable us to conduct analyses that take account of several other factors that might account for these differences. We advise readers to exercise caution in drawing inferences about bias in any of these forms of enforcement action.

APPENDIX A[28]

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.[29] 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.[30] 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 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

[28] Excerpted from Robert E. Worden, Kenan M. Worden, and Hannah Cochran, *Traffic Stops by Suffolk County Police* (Albany, NY: John F. Finn Institute for Public Safety, Inc., 2020), pp. 8-15.

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

[30] 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).

that members of one group commit this offense at a higher rate than the comparison group.[31]

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.[32] The hypothetical conditions under which only legal factors affect police behavior form a benchmark, which can be statistically approximated. This 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

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

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

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.[33] 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."[34]

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

[33] 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.

[34] 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.

driving population.[35] 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.[36] 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.[37]

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.[38] 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 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

[35] 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.
[36] John Lamberth, *A Report to the ACLU* (New York: American Civil Liberties Union, 1996).
[37] 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.
[38] 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.

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.[39]

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.[40] It has also been used

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[39] 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.

[40] 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, "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).

to analyze stop patterns across the state of Connecticut.[41] 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.[42] 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.[43] Ross and his colleagues found in some Connecticut cities that minority drivers were more likely to be stopped in daylight.[44] Pierson, et al. found evidence suggesting bias in the 56 agencies whose stops they analyzed.[45] The analysis of stops by Durham (NC) police revealed that Blacks were 12 percent more likely to be stopped during daylight.[46]

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.[47] Analyzing the same Oakland data, Grogger and Ridgeway likewise found no evidence of racial bias.[48] None of Ridgeway's analyses yielded evidence of racial profiling in Cincinnati.[49] Analyses of stops by Syracuse police yielded results consistent with the conclusion that Syracuse police have not exhibited racial bias in making vehicle stops.[50] In three of the four North Carolina cities scrutinized by Taniguchi and his colleagues, no evidence of bias was reported.[51] Findings in San Diego were mixed: some analyses detected evidence of

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[41] 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).

[42] 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.

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

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

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

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

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

[48] Grogger and Ridgeway, "Testing for Racial Profiling in Traffic Stops from Behind a Veil of Darkness."

[49] Ridgeway, *Cincinnati Police Department Traffic Stops*.

[50] Worden, et al., "Testing for Racial Profiling with the Veil-of-Darkness Method."

[51] 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*.

bias in 2014 but not in 2015, and other analyses yielded no evidence of bias.[52] 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).[53] 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.[54] Another critique is based on the hypothesis that minority drivers adapt their driving behavior during daylight to reduce their susceptibility to being stopped.[55] Notwithstanding these critiques, we believe that the veil-of-darkness test of bias in vehicle stops is the best (and most economical) benchmark available.[56] 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.[57]

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[52] Chanin, *et al.*, *Traffic Enforcement in San Diego, California*.

[53] *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.

[54] 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.

[55] 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).

[56] 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.

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

APPENDIX B
Stops in the Inter-Twilight Period

Table B-1a. Stop Frequencies by Precinct: Inter-twilight Period

Precinct	Count (%)
1	2,644 (12.64)
2	3,579 (17.12)
3	3,194 (15.27)
4	1,529 (7.31)
5	3,238 (15.49)
6	3,494 (16.71)
7	3,232 (15.46)
Total	20,910 (100)

Table B-1b. Stop Frequencies by Unit Type: Inter-twilight Period

Unit Type	Count (%)
Highway Patrol	13,619 (39.38)
Precinct Crime	5,475 (15.83)
Precinct Patrol	15,328 (44.32)
Other	165 (0.48)
Total	34,587 (100)

Table B-2. Reasons for Stops by Unit Type: Inter-twilight Period

Reason To Stop	Highway Patrol	Precinct Crime	Precinct Patrol	Other
BOLO	0 (0)	7 (0.13)	20 (0.13)	0 (0)
Cell Call/Text	1,143 (8.39)	299 (5.46)	439 (2.86)	5 (3.03)
Equipment Violation	523 (3.84)	723 (13.21)	3,944 (25.73)	33 (20)
Other Moving Violation	4,470 (32.82)	785 (14.34)	2,662 (17.37)	19 (11.52)
Red Light	129 (0.95)	161 (2.94)	512 (3.34)	3 (1.82)
RSC	29 (0.21)	140 (2.56)	198 (1.29)	2 (1.21)
Seat Belt	247 (1.81)	144 (2.63)	239 (1.56)	2 (1.21)
Speeding	5,615 (41.23)	690 (12.6)	1,118 (7.29)	30 (18.18)
Stop Sign	379 (2.78)	1,430 (26.12)	2,998 (19.56)	18 (10.91)
VTL	1,084 (7.96)	1,096 (20.02)	3,198 (20.86)	53 (32.12)
Total	13,619 (100)	5,475 (100)	15,328 (100)	165 (100)

Table B-3. Driver Race/Ethnicity by Unit Type: Inter-twilight Period

Driver Race/Ethnicity	Highway Patrol	Precinct Crime	Precinct Patrol	Other
Hispanic	2,942 (21.6)	1,643 (30.01)	4,101 (26.75)	41 (24.85)
Black	2,076 (15.24)	1,142 (20.86)	3,424 (22.34)	31 (18.79)
White	7,388 (54.25)	2,407 (43.96)	6,775 (44.2)	79 (47.88)
Asian	357 (2.62)	101 (1.84)	400 (2.61)	6 (3.64)
Other	856 (6.29)	182 (3.32)	628 (4.1)	8 (4.85)
Total	13,619 (100)	5,475 (100)	15,328 (100)	165 (100)

Table B-4. Driver Race/Ethnicity by Precinct: Inter-twilight Period

Driver Race/Ethnicity	1	2	3	4	5	6	7
Hispanic	649 (24.55)	1,072 (29.95)	1,638 (51.28)	362 (23.68)	757 (23.38)	733 (20.98)	565 (17.48)
Black	1,099 (41.57)	710 (19.84)	742 (23.23)	209 (13.67)	491 (15.16)	593 (16.97)	745 (23.05)
White	732 (27.69)	1,482 (41.41)	692 (21.67)	825 (53.96)	1,829 (56.49)	1,911 (54.69)	1,759 (54.42)
Asian	65 (2.46)	122 (3.41)	34 (1.06)	69 (4.51)	58 (1.79)	112 (3.21)	41 (1.27)
Other	99 (3.74)	193 (5.39)	88 (2.76)	64 (4.19)	103 (3.18)	145 (4.15)	122 (3.77)
Total	2,644 (100)	3,579 (100)	3,194 (100)	1,529 (100)	3,238 (100)	3,494 (100)	3,232 (100)

Table B-5. Reasons for Stops by Driver Race/Ethnicity: Inter-twilight Period

Reason To Stop	Black	Hispanic	White	Asian	Other
BOLO	10 (0.15)	7 (0.08)	8 (0.05)	0 (0)	2 (0.12)
Cell Call/Text	204 (3.06)	446 (5.11)	1,119 (6.72)	41 (4.75)	76 (4.54)
Equipment Violation	1,339 (20.07)	1,626 (18.63)	1,979 (11.89)	90 (10.42)	189 (11.29)
Other Moving Violation	1,515 (22.7)	1,898 (21.75)	3,889 (23.36)	219 (25.35)	415 (24.79)
Red Light	131 (1.96)	230 (2.64)	376 (2.26)	34 (3.94)	34 (2.03)
RSC	113 (1.69)	86 (0.99)	156 (0.94)	6 (0.69)	8 (0.48)
Seat Belt	151 (2.26)	173 (1.98)	279 (1.68)	7 (0.81)	22 (1.31)
Speeding	1,292 (19.36)	1,458 (16.71)	4,080 (24.51)	204 (23.61)	419 (25.03)
Stop Sign	685 (10.27)	1,179 (13.51)	2,554 (15.34)	185 (21.41)	222 (13.26)
VTL	1,233 (18.48)	1,624 (18.61)	2,209 (13.27)	78 (9.03)	287 (17.14)
Total	6,673 (100)	8,727 (100)	16,649 (100)	864 (100)	1,674 (100)

Table B-6. Driver Race/Ethnicity by Day of the Week: Inter-twilight Period

Driver Race/Ethnicity	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Hispanic	736 (25.87)	1,205 (24.49)	1,586 (25.92)	1,584 (24.83)	1,457 (25)	1,271 (24.51)	888 (26.83)
Black	599 (21.05)	897 (18.23)	1,121 (18.32)	1,207 (18.92)	1,101 (18.89)	1,051 (20.27)	697 (21.06)
White	1,306 (45.91)	2,443 (49.65)	2,994 (48.94)	3,107 (48.71)	2,866 (49.17)	2,473 (47.69)	1,460 (44.11)
Asian	71 (2.5)	131 (2.66)	136 (2.22)	139 (2.18)	142 (2.44)	150 (2.89)	95 (2.87)
Other	133 (4.67)	244 (4.96)	281 (4.59)	342 (5.36)	263 (4.51)	241 (4.65)	170 (5.14)
Total	2,845 (100)	4,920 (100)	6,118 (100)	6,379 (100)	5,829 (100)	5,186 (100)	3,310 (100)

APPENDIX C[58]

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.

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[58] Excerpted from Robert E. Worden, Kenan M. Worden, and Hannah Cochran, *Traffic Stops by Suffolk County Police* (Albany, NY: John F. Finn Institute for Public Safety, Inc., 2020), pp. 33-45.

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.[59] 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.[60]

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.[61] Others have performed a hybrid analysis of high-discretion searches by combining consent and

[59] 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.

[60] 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 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).

[61] 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.

probable cause searches into one measure.[62] 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.[63] 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.[64] 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." [65]

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."[66] Rojek, Rosenfeld, and Decker combined consent and other high-discretion 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."[67] 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)."[68] Other

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[62] 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).
[63] Schafer et al., "Decision Making."
[64] Baumgartner et al., "Racial Disparities."
[65] Rosenfeld et al, "Age Matters," p. 37.
[66] 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.
[67] Jeff Rojek, Richard Rosenfeld, and Scott Decker, "Policing Race: The Racial Stratifications of Searches in Police Traffic Stops," *Criminology* 50 (2012): 1008.
[68] Tillyer and Klahm, "Discretionary Searches," p. 383.

research has operationalized searches or consent search requests as those performed on passengers *or* drivers.[69] Joseph Schafer and colleagues excluded consent searches of passengers from their analysis when the driver or vehicle was not searched.[70]

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.[71] 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.[72] 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 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.[73]

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.[74] The authors computed four dichotomous variables representing

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[69] Chanin et al., "Traffic Enforcement"; Pickerill et al., "Search and Seizure."

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

[71] Alpert et al., *Pedestrian and Motor Vehicle Data Analysis Report;* Engel et al., *Cleveland Division of Police Traffic Stop Data Study*.

[72] 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").

[73] Schafer et al, "Decision Making in Traffic Stop Encounters," p. 198.

[74] Rojek et al., "Policing Race."

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.[75] 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.[76] 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 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."[77]

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.[78] 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.[79] The former analysis consisted of a simple rate ratio of stop outcomes of one race to another.

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[75] Rosenfeld et al., "Age Matters."
[76] Fallik and Novak, "The Decision to Search."
[77] Ibid, p. 153.
[78] Tillyer, "Opening the Black Box."
[79] Baumgartner et al., "Racial Disparities."

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 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." [80]

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."[81] 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.

[80] Alpert et al., *Pedestrian and Motor Vehicle Data Analysis Report*, p. 13.
[81] 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.

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).[82] 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.[83] 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.[84] 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.

Barnum and Perfetti likewise analyzed disparities at the macro (organizational) and micro (officer) levels.[85] 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.

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[82] 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.
[83] 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).
[84] Roh and Robinson, "A Geographic Approach."
[85] Barnum and Perfetti, "Race-Sensitive Choices."

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."[86] 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.[87] 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 warning was issued, though they did not differentiate between search discretion in this analysis.[88] 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.[89] 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

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[86] 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."

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

[88] Schafer et al., "Decision Making in Traffic Stop Encounters."

[89] Engel et al., *Cleveland Division of Police Traffic Stop Data Study*.

> 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.[90]

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.[91] 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.[92]

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.[93]

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.[94] 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,

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[90] Ibid, p. 137.
[91] Roh and Robinson, "A Geographic Approach."
[92] Chanin et al, "Traffic Enforcement."
[93] 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 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.
[94] 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.

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.[95]

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.[96] Several researchers found that minority drivers, and particularly Black drivers, are more likely to be subjected to a high-discretion search than White drivers.[97] In comparing the search rates of matched Black and White drivers, Chanin and colleagues found that Black drivers were consent 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."[98] 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.[99] 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'

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95 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.

96 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".

97 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."

98 Fallik and Novak, "The Decision to Search," p. 159.

99 Tillyer and Klahm, "Discretionary Searches."

demeanor had no bearing on their likelihood of being searched.[100] 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.[101] 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.[102]

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.[103] Roh and Robinson found racial disparities in consent searches less severe than those found in searches performed on the basis of probable cause.[104]

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.[105] 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, leading some officers to conclude that such persons 'must be up to no good'."[106] 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.[107]

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.[108] Alpert and colleagues found that when low-discretion arrests were excluded from analysis, racial

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[100] Tillyer et al, "The Discretion to Search."
[101] Tillyer, "Opening the Black Box of Officer Decision-Making."
[102] Alpert et al., *Pedestrian and Motor Vehicle Data.*
[103] Alpert et al., *Pedestrian and Motor Vehicle Data;* Chanin et al., "Traffic Enforcement"; Schafer et al., "Decision Making."
[104] Roh and Robinson, "A Geographic Approach."
[105] Engel et al, *Cleveland Division of Police Traffic Stop Data Study;* Rojek et al, "Policing Race"; Rosenfeld et al, "Age Matters".
[106] Rojek et al. "Policing Race": 1017.
[107] Schafer et al,"Decision Making"; Rosenfeld et al, "Age Matters"; Pickerill et al., "Search and Seizure".
[108] 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.*

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.[109] Chanin and colleagues' propensity matching analysis showed no statistically significant differences in arrest patterns of White and Black drivers.[110]

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.[111] 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.[112] 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.[113] Schafer and colleagues found that minority drivers and older drivers were more likely to be issued warnings, and that warnings were more likely to follow a stop for equipment violations.[114]

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.[115] Engel and colleagues found higher hit rates for discretionary searches made of Black drivers than for White drivers, despite the finding that Black

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[109] Roh and Robinson, "A Geographic Approach."
[110] Chanin et al., "Traffic Enforcement."
[111] 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."
[112] Ibid.
[113] Tillyer and Engel, "The Impact of Driver's Race".
[114] Schafer et al., "Decision Making".
[115] 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).

drivers are searched more often than White drivers.[116] 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,"[117] 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.[118] 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. [119] 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.[120]

Other Outcomes

Alpert and colleagues further examined the post-stop outcomes of "requests to exit the vehicle" and "no action taken."[121] 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.

[116] Engel et al., *Cleveland Division of Police Traffic Stop Data Study*.
[117] Chanin et al, "Traffic Enforcement," p. 570.
[118] Pickerill et al., "Search and Seizure."
[119] Rob and Robinson, "A Geographic Approach."
[120] Engel et al., *Cleveland Division of Police Traffic Stop Data Study*.
[121] Alpert et al., *Pedestrian and Motor Vehicle Data*.

APPENDIX D
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 E
Propensity Score Matching Tables

Table E-1: Black/White

	Black Drivers		White Drivers			
	n = 34,557		n = 87,321		n = 34,557	
Variable	**%**	**n**	**Pre-Match %**	**Pre-Match n**	**Post-Match %**	**Post-Match n**
Reason to Stop						
Reasonable Suspicion	1.53	529	0.77	673	1.44	498
Other Moving Viol.	20.88	7217	20.57	17959	21.22	7333
Equipment Viol.	19.51	6742	11.41	9961	19.05	6582
Speeding	23.09	7979	28.73	25083	23.87	8248
Cell Phone	3.56	1230	7.37	6439	3.42	1182
BOLO	0.12	41	0.04	39	0.1	34
Red Light	1.72	595	2.02	1762	1.47	508
Stop Sign	9.03	3119	12.94	11300	8.49	2933
Seatbelt	2.46	850	2.22	1937	2.34	810
Other VTL	18.1	6255	13.93	12168	18.6	6429
Precinct						
1	17.66	6104	5.71	4990	7.03	2431
2	13.31	4599	12.76	11138	12.54	4335
3	13.65	4718	7.56	6602	7.8	2694
4	8.02	2770	12.6	11001	10.79	3727
5	22.1	7638	30.8	26897	27.59	9533
6	12.71	4393	17.55	15323	18.69	6459
7	12.47	4309	12.87	11242	15.42	5328
9	0.08	26	0.15	128	0.14	50
Sex						
Female	30.58	10566	32.42	28312	30.25	10454
Male	69.42	23991	67.58	59009	69.75	24103
Age						
<16	0.06	1	0.03	1	25.38	8771
16 to 25	25.35	0	19.57	0	0.05	18
26 to 35	36.96	3	27.35	2	37.65	13010
36 to 45	19.76	1	20.32	2	19.67	6798

46 to 55	11.75	1	18.03	1	11.61	4011
56 to 65	5.17	1	10.72	0	4.8	1659
>65	0.94	0	3.97	1	0.84	290
Time of Day						
00:00 – 03:59	9.86	3406	6.72	5872	9.95	3439
04:00 – 07:59	4.24	1464	5.32	4642	4.1	1418
08:00 – 11:59	23.88	8252	28.14	24572	24.17	8353
12:00 – 15:59	20.48	7077	20.98	18323	20.13	6955
16:00 – 19:59	22.92	7919	24.71	21575	22.59	7808
20:00 – 23:59	18.63	6439	14.13	12337	19.05	6584
Day of Week						
Sunday	9.39	3244	8.33	7270	15.36	5309
Monday	12.98	4486	14.41	12585	13.07	4515
Tuesday	16.84	5820	17.64	15400	10.98	3796
Wednesday	17.78	6145	18.14	15836	9.24	3192
Thursday	16.53	5711	17.1	14928	16.49	5697
Friday	15.47	5345	14.66	12797	16.94	5853
Saturday	11.01	3806	9.74	8505	17.93	6195
Month						
January	10.19	3523	10.92	9537	10.31	3562
February	10.38	3586	10.34	9026	9.11	3149
March	9.44	3261	9.67	8440	9.18	3172
April	5.92	2047	6.57	5737	7.52	2600
May	6.88	2376	7.63	6665	10.46	3616
June	6.16	2130	6.74	5885	9.61	3321
July	7.63	2637	7.77	6782	6.18	2137
August	8.52	2943	8.13	7096	6.95	2402
September	8.76	3028	8.18	7144	6.09	2103
October	9.31	3218	8.25	7201	7.61	2631
November	9.37	3237	8.75	7644	8.42	2910
December	7.44	2571	7.06	6164	8.55	2954
Number of Occupants						
1	90.47	31262	94.6	82607	92.01	31795
2	7.36	2542	4.42	3862	6.01	2078
3	1.57	543	0.72	625	1.39	480
4	0.5	172	0.21	184	0.47	161

5	0.09	32	0.04	34	0.1	34
6	0.01	5	0.01	5	0.01	5
7	0	0	0	3	0.01	3
9	0	0	0	1	0	1
Equipment Viol.						
0	87.54	30250	92.61	80868	88	30410
1	8.77	3029	5.58	4876	8.71	3011
2	2.4	829	1.21	1053	2.11	730
3	0.55	191	0.32	281	0.6	208
4	0.42	145	0.12	107	0.25	88
5	0.33	113	0.16	136	0.32	110
Violent Crime Rate (previous 30 days)						
Mean	3.48		2.56		3.32	
Median	3		2		2	

Table E-2: Hispanic/White

	Hispanic Drivers		White Drivers			
	n = 43,158		n = 87,321		n = 43,158	
Variable	**%**	**n**	**Pre-Match %**	**Pre-Match n**	**Post-Match %**	**Post-Match n**
Reason for Stop						
Reasonable Suspicion	0.93	403	0.77	673	0.86	371
Other Moving Viol.	20.4	8806	20.57	17959	20.77	8966
Equipment Viol.	18.1	7813	11.41	9961	16.82	7261
Speeding	20.41	8808	28.73	25083	20.85	8998
Cell Phone	5.54	2392	7.37	6439	5.74	2476
BOLO	0.07	29	0.04	39	0.06	28
Red Light	2.45	1058	2.02	1762	2.51	1085
Stop Sign	12.16	5248	12.94	11300	12.16	5250
Seatbelt	2.49	1073	2.22	1937	2.38	1026
Other VTL	17.44	7528	13.93	12168	17.83	7697
Precinct						
1	9.24	3987	5.71	4990	6.81	2939
2	16.02	6913	12.76	11138	12.92	5574
3	21.3	9191	7.56	6602	7.56	3263
4	9.51	4106	12.6	11001	11.28	4867
5	23.56	10169	30.8	26897	28.27	12199
6	12.5	5393	17.55	15323	18.59	8021
7	7.76	3348	12.87	11242	14.45	6235
9	0.12	51	0.15	128	0.14	60
Sex						
Female	24.08	10393	32.42	28312	23.99	10353
Male	75.92	32765	67.58	59009	76.01	32805
Age						
<16	0.07	31	0.03	25	27.11	11701
16 to 25	28.01	12090	19.57	17092	0.05	23
26 to 35	33.09	14283	27.35	23884	34.26	14785
36 to 45	22.55	9730	20.32	17746	22.8	9842
46 to 55	11.65	5028	18.03	15747	11.45	4941
56 to 65	3.9	1684	10.72	9361	3.69	1593
>65	0.72	312	3.97	3466	0.63	273
Time of Day						
00:00 – 03:59	8.66	3736	6.72	5872	8.6	3713
04:00 – 07:59	5.69	2454	5.32	4642	5.61	2420
08:00 – 11:59	24.39	10526	28.14	24572	25.17	10862
12:00 – 15:59	19.73	8516	20.98	18323	19.67	8491

16:00 – 19:59	25.33	10934	24.71	21575	25.1	10832
20:00 – 23:59	16.2	6992	14.13	12337	15.85	6840
Day of Week						
Sunday	9.83	4241	8.33	7270	14.34	6187
Monday	13.84	5972	14.41	12585	13.95	6022
Tuesday	16.87	7280	17.64	15400	11.22	4844
Wednesday	17.4	7510	18.14	15836	9.64	4160
Thursday	16.54	7138	17.1	14928	16.5	7120
Friday	14.29	6169	14.66	12797	16.97	7325
Saturday	11.23	4848	9.74	8505	17.38	7500
Month						
January	10.57	4562	10.92	9537	10.58	4564
February	9.96	4297	10.34	9026	8.89	3835
March	8.97	3871	9.67	8440	9.45	4077
April	6	2590	6.57	5737	7.23	3120
May	6.99	3017	7.63	6665	9.98	4309
June	6.51	2810	6.74	5885	8.95	3864
July	7.69	3319	7.77	6782	6.06	2615
August	8.76	3779	8.13	7096	7.02	3029
September	8.93	3852	8.18	7144	6.48	2797
October	8.86	3822	8.25	7201	7.76	3351
November	9.56	4124	8.75	7644	8.77	3785
December	7.22	3115	7.06	6164	8.83	3812
Number of Occupants						
1	91.57	39518	94.6	82607	92.68	39997
2	6.36	2743	4.42	3862	5.67	2448
3	1.43	616	0.72	625	1.17	505
4	0.51	220	0.21	184	0.38	166
5	0.12	50	0.04	34	0.08	34
6	0.02	9	0.01	5	0.01	4
7	0	2	0	3	0.01	3
9	0	0	0	1	0	1
Equipment Viol.						
0	86.49	37326	92.61	80868	88.45	38173
1	9.31	4018	5.58	4876	8.33	3594
2	2.55	1101	1.21	1053	2.11	912
3	0.71	307	0.32	281	0.57	247
4	0.46	200	0.12	107	0.24	102
5	0.48	206	0.16	136	0.3	130
Violent Crime Rate (previous 30 days)						
Mean	3.35		2.56		3.16	

Median	3		2		2	

Table E-3: Black/White Vehicle Search

	Black Drivers		White Drivers	
	n = 1,902	n = 1,134	n = 1,256	n = 1,134
Variable	**Pre-Match %**	**Post-Match %**	**Pre-Match %**	**Post-Match %**
Reason to Stop				
Reasonable Suspicion	9.1	11.02	12.58	11.38
Other Moving Viol.	18.98	21.08	23.09	22.93
Equipment Viol.	27.97	23.63	21.26	22.75
Speeding	9.52	10.49	10.91	10.85
Cell Phone	1.16	1.85	1.99	1.68
BOLO	0.26	0.44	0.4	0.44
Red Light	0.79	1.23	1.11	1.06
Stop Sign	8.89	7.5	7.32	7.58
Seatbelt	5.47	3.17	3.34	3.7
Other VTL	17.88	19.58	17.99	17.64
Precinct				
1	58.2	56.35	41.48	42.77
2	13.2	14.64	16.32	16.4
3	14.88	15.43	8.52	8.11
4	0.68	0.97	5.33	4.76
5	3	3.35	6.53	6.61
6	2.26	2.73	4.94	4.59
7	7.2	6	15.37	15.61
9	0.58	0.53	1.51	1.15
Sex				
Female	12.2	18.43	22.93	18.78
Male	87.8	81.57	77.07	81.22
Age				
<16	0.11	32.45	0.16	32.63
16 to 25	40.54	0.18	30.81	0.18
26 to 35	39.17	36.51	33.2	35.19
36 to 45	11.2	17.37	19.9	17.55
46 to 55	6.73	10.41	12.34	11.11
56 to 65	2	2.73	3.11	3
>65	0.26	0.35	0.48	0.35

Time of Day				
00:00 – 03:59	6.83	8.02	8.84	8.64
04:00 – 07:59	1.21	1.5	1.11	1.23
08:00 – 11:59	18.45	17.64	17.83	17.99
12:00 – 15:59	25.76	22.75	21.58	21.69
16:00 – 19:59	23.55	24.16	25.16	25.31
20:00 – 23:59	24.19	25.93	25.48	25.13
Day of Week				
Sunday	9.83	17.99	7.56	17.11
Monday	10.41	8.55	8.2	8.55
Tuesday	16.67	13.93	19.19	13.76
Wednesday	17.98	8.38	17.99	8.11
Thursday	14.98	15.87	15.92	15.52
Friday	17.51	18.34	17.6	19.14
Saturday	12.62	16.93	13.54	17.81
Month				
January	15.14	15.52	14.89	14.9
February	15.3	9.79	15.05	9.61
March	11.25	9.26	11.78	8.47
April	1.89	6.7	2.47	6.44
May	5.52	14.99	6.69	15.34
June	3.47	11.73	3.5	11.2
July	5.73	1.94	5.81	2.2
August	8.04	6.17	7.4	6.7
September	8.73	3.26	8.76	3.62
October	9.31	5.82	9.08	5.91
November	8.78	6.88	8.28	7.41
December	6.83	7.94	6.29	8.2
Number of Occupants				
1	64.35	68.61	69.98	69.05
2	25.45	23.81	22.93	23.1
3	7.89	6.7	5.18	5.73
4	1.89	0.71	1.75	1.94
5	0.37	0.18	0.16	0.18
Equipment Violation				
0	77.81	80.07	80.57	79.81

1	14.67	13.93	13.61	14.11
2	4.78	4.14	3.9	4.14
3	0.95	0.71	1.11	1.15
4	1	0.62	0.16	0.18
5	0.79	0.53	0.64	0.62
Violent Crime Rate (previous 30 days)				
Mean	5.18	4.62	4.49	4.58
Median	5	4	4	4

Table E-4: Black/White Person Search

	Black Drivers		White Drivers	
	n = 1,811	n = 1,632	n = 3,006	n = 1,632
Variable	**Pre-Match %**	**Post-Match %**	**Pre-Match %**	**Post-Match %**
Reason to Stop				
Reasonable Suspicion	8.89	10.85	10.1	10.85
Other Moving Viol.	19.64	23.04	23.92	22.37
Equipment Viol.	26.28	22	19.04	20.89
Speeding	10.46	11.34	13.26	12.01
Cell Phone	1.1	1.1	1.58	1.53
BOLO	0.43	0.61	0.62	0.61
Red Light	0.81	0.98	1.58	0.92
Stop Sign	9.13	8.76	9.62	9.01
Seatbelt	5.64	4.04	3.44	3.55
Other VTL	17.63	17.28	16.84	18.26
Precinct				
1	55.9	54.35	36.56	38.85
2	12.66	13.66	14.36	13.91
3	15.29	15.2	7.01	7.6
4	0.91	0.98	4.47	4.47
5	3.82	4.17	9	8.7
6	2.05	2.45	4.88	4.41
7	7.79	7.54	14.02	15.26
9	1.58	1.65	9.69	6.8
Sex				
Female	9.36	17.28	17.11	18.26
Male	90.64	82.72	82.89	81.74
Age				
<16	0.1	30.64	0.21	30.09
16 to 25	37.84	0.25	27.22	0.25
26 to 35	40.23	36.76	34.23	36.89
36 to 45	12.09	18.2	21.03	18.5
46 to 55	7.21	10.91	12.71	10.66
56 to 65	2.2	2.88	4.12	3.19
>65	0.33	0.37	0.48	0.43
Time of Day				

00:00 – 03:59	8.79	10.91	14.3	11.27
04:00 – 07:59	1.1	1.78	1.72	1.47
08:00 – 11:59	18.25	17.28	17.39	17.4
12:00 – 15:59	24.65	20.16	18.63	20.4
16:00 – 19:59	23.55	22.86	21.99	22.98
20:00 – 23:59	23.65	27.02	25.98	26.47
Day of Week				
Sunday	9.99	17.28	10.1	16.42
Monday	10.32	7.41	7.56	7.97
Tuesday	16.24	13.36	16.63	14.4
Wednesday	18.01	10.05	17.11	9.93
Thursday	15.38	16.79	17.59	16.61
Friday	17.1	15.75	15.53	16.3
Saturday	12.95	19.36	15.46	18.38
Month				
January	14.48	13.66	13.88	13.73
February	14.43	8.88	13.88	9.31
March	10.51	9.13	11.82	9.01
April	2.2	7.17	3.02	6.8
May	5.59	14.52	6.39	14.64
June	3.63	11.27	4.05	11.03
July	6.12	2.51	7.22	2.51
August	8.98	6.25	7.63	5.94
September	8.84	4.04	8.38	4.11
October	9.51	6.07	8.73	6.56
November	8.36	8.39	8.66	7.97
December	7.36	8.09	6.32	8.39
Number of Occupants				
1	68.8	57.9	76.01	59.56
2	22.36	30.7	18.21	28.25
3	6.93	8.88	4.4	8.76
4	1.62	2.21	1.24	3.12
5	0.24	0.31	0.14	0.31
6	0.05	0	0	0
Equipment Violations				
0	79.31	81.37	82.54	82.29

1	14.14	12.93	12.44	12.25
2	4.01	3.68	3.16	3.55
3	0.86	0.74	1.1	1.23
4	0.91	0.67	0.27	0.25
5	0.76	0.61	0.48	0.43
Violent Crime Rate (previous 30 days)				
Mean	5.16	4.48	4.26	4.47
Median	5	4	4	4

Table E-5: Hispanic/White Vehicle Search

	Hispanic Drivers		White Drivers	
	n = 930	n = 756	n = 1,256	n = 756
Variable	**Pre-Match %**	**Post-Match %**	**Pre-Match %**	**Post-Match %**
Reason to Stop				
Reasonable Suspicion	12.47	12.96	12.58	12.3
Other Moving Viol.	20	21.16	23.09	20.11
Equipment Violation	30.11	28.31	21.26	25.79
Speeding	9.25	9.52	10.91	10.32
Cell Phone	0.86	1.06	1.99	1.19
BOLO	0.43	0.53	0.4	0.53
Red Light	0.75	0.93	1.11	1.46
Stop Sign	7.2	6.48	7.32	6.75
Seatbelt	3.44	3.84	3.34	3.97
Other VTL	15.48	15.21	17.99	17.59
Precinct				
1	40.65	40.74	41.48	42.86
2	14.19	14.55	16.32	17.06
3	29.89	29.1	8.52	7.8
4	0.86	0.79	5.33	3.31
5	4.19	4.5	6.53	8.07
6	2.26	2.12	4.94	5.03
7	6.02	6.22	15.37	14.29
9	1.94	1.98	1.51	1.59
Sex				
Female	10.43	12.57	22.93	11.38
Male	89.57	87.43	77.07	88.62
Age				
<16	0	0	0.16	0
16 to 25	52.37	47.09	30.81	43.78
26 to 35	34.41	37.04	33.2	40.21
36 to 45	10.11	12.04	19.9	12.04
46 to 55	2.37	2.91	12.34	2.91
56 to 65	0.75	0.93	3.11	1.06
>65	0	0	0.48	0

Time of Day				
00:00 – 03:59	11.08	10.58	8.84	10.58
04:00 – 07:59	2.8	2.12	1.11	1.59
08:00 – 11:59	15.27	15.61	17.83	16.53
12:00 – 15:59	20.65	20.37	21.58	19.97
16:00 – 19:59	23.87	24.07	25.16	25.4
20:00 – 23:59	26.34	27.25	25.48	25.93
Day of Week				
Sunday	10.22	15.61	7.56	16.4
Monday	10.86	10.58	8.2	9.26
Tuesday	16.24	14.81	19.19	14.02
Wednesday	15.59	9.66	17.99	10.19
Thursday	16.24	17.06	15.92	16.53
Friday	15.81	17.59	17.6	18.52
Saturday	15.05	14.68	13.54	15.08
Month				
January	16.24	15.21	14.89	17.33
February	16.99	8.86	15.05	7.8
March	13.66	8.2	11.78	8.07
April	1.94	6.35	2.47	6.61
May	4.52	17.99	6.69	16.8
June	3.55	12.17	3.5	11.77
July	3.23	2.25	5.81	2.25
August	6.67	4.63	7.4	5.42
September	10.86	3.57	8.76	3.7
October	8.17	3.7	9.08	4.1
November	7.74	6.61	8.28	7.01
December	6.45	10.45	6.29	9.13
Number of Occupants				
1	67.1	69.05	69.98	69.18
2	23.01	22.22	22.93	22.75
3	7.63	6.75	5.18	5.95
4	1.94	1.72	1.75	1.85
5	0.32	0.26	0.16	0.26
Equipment Violations				
0	76.13	77.38	80.57	78.44

1	15.81	15.48	13.61	14.68
2	4.73	3.7	3.9	4.5
3	1.51	1.32	1.11	1.19
4	0.97	1.19	0.16	0.26
5	0.86	0.93	0.64	0.93
Violent Crime Rate (previous 30 days)				
Mean	4.77	4.68	4.49	4.59
Median	4	4	4	4

Table E-6: Hispanic/White Person Search

	Hispanic Drivers		White Drivers	
	n = 1,497	n = 1,141	n = 1,811	n = 1,141
Variable	**Pre-Match %**	**Post-Match %**	**Pre-Match %**	**Post-Match %**
Reason to Stop				
Reasonable Suspicion	11.2	12.18	10.1	11.66
Other Moving Viol.	23.1	22.96	23.92	22.44
Equipment Violation	26.37	23.66	19.04	23.4
Speeding	9.79	10.34	13.26	10.6
Cell Phone	1.06	1.31	1.58	1.75
BOLO	0.62	0.53	0.62	0.7
Red Light	0.97	1.14	1.58	1.58
Stop Sign	7.94	8.15	9.62	8.5
Seatbelt	3.62	3.33	3.44	3.16
Other VTL	15.34	16.39	16.84	16.21
Precinct				
1	35.89	35.58	36.56	39.26
2	14.37	15.51	14.36	14.64
3	29.45	28.57	7.01	7.19
4	0.53	0.53	4.47	3.51
5	6.44	6.13	9	8.85
6	2.65	2.98	4.88	4.82
7	5.56	5.87	14.02	14.99
9	5.11	4.82	9.69	6.75
Sex				
Female	6.35	10.6	17.11	10.87
Male	93.65	89.4	82.89	89.13
Age				
<16	0.09	42.68	0.21	40.14
16 to 25	46.03	0.26	27.22	0.35
26 to 35	38.18	39.26	34.23	41.54
36 to 45	11.55	13.23	21.03	14.29
46 to 55	3.26	3.59	12.71	2.89
56 to 65	0.79	0.88	4.12	0.7
>65	0.09	0.09	0.48	0.09

Time of Day				
00:00 – 03:59	16.49	15.69	14.3	15.16
04:00 – 07:59	3.53	2.72	1.72	2.19
08:00 – 11:59	14.02	14.64	17.39	14.72
12:00 – 15:59	18.17	19.37	18.63	19.98
16:00 – 19:59	20.55	21.74	21.99	22.17
20:00 – 23:59	27.25	25.85	25.98	25.77
Day of Week				
Sunday	13.49	16.56	10.1	15.95
Monday	10.49	8.15	7.56	8.24
Tuesday	15.17	15.25	16.63	15.07
Wednesday	14.29	11.74	17.11	11.22
Thursday	15.61	16.74	17.59	18.4
Friday	15.87	16.56	15.53	15.78
Saturday	15.08	14.99	15.46	15.34
Month				
January	15.17	14.64	13.88	14.64
February	15.17	8.76	13.88	8.85
March	11.82	8.85	11.82	9.47
April	1.85	7.36	3.02	6.49
May	5.73	14.9	6.39	15.16
June	3.44	12.53	4.05	11.57
July	4.67	2.37	7.22	2.37
August	7.32	6.13	7.63	6.31
September	10.41	4.29	8.38	4.47
October	8.2	4.73	8.73	5.78
November	8.82	7.01	8.66	6.66
December	7.41	8.41	6.32	8.24
Number of Occupants				
1	73.02	59.95	76.01	60.21
2	18.69	26.47	18.21	26.56
3	6.17	9.64	4.4	9.82
4	1.76	3.16	1.24	3.07
5	0.26	0.7	0.14	0.35
7	0.09	0.09	0	0
Equipment Violations				

0	77.6	80.46	82.54	81.16
1	15.43	13.67	12.44	13.06
2	4.32	3.59	3.16	3.86
3	1.15	1.05	1.1	1.23
4	0.97	0.61	0.27	0.26
5	0.53	0.61	0.48	0.44
Violent Crime Rate (previous 30 days)				
Mean	4.82	4.62	4.26	4.5
Median	4	4	4	4

Table E-7: Black/White Exit Vehicle

	Black Drivers		White Drivers	
	n = 3,666	n = 2,328	n = 2,661	n = 2,328
Variable	**Pre-Match %**	**Post-Match %**	**Pre-Match %**	**Post-Match %**
Reason to Stop				
Reasonable Suspicion	8.32	10.31	9.3	10.4
Other Moving Viol.	19.14	21.61	24.55	22.9
Equipment Violation	26.6	22.94	16.76	19.2
Speeding	11.49	13.06	16.24	13.87
Cell Phone	1.03	1.33	1.6	1.25
BOLO	0.52	0.52	0.42	0.52
Red Light	0.87	0.86	1.46	1.12
Stop Sign	8.28	7.39	8.17	8.2
Seatbelt	5.39	3.35	2.58	3.05
Other VTL	18.35	18.64	18.92	19.5
Precinct				
1	50.77	49.01	28.5	32.17
2	12.21	13.53	12.44	11.9
3	15.3	15.21	6.15	7.13
4	1.27	1.55	4.69	4.68
5	4.84	5.11	10.14	9.58
6	2.26	2.23	6.34	5.8
7	8.09	8.08	14.88	16.71
9	5.27	5.28	16.85	12.03
Sex				
Female	13	21.74	21.13	22.51
Male	87	78.26	78.87	77.49
Age				
<16	0.12	30.84	0.19	30.15
16 to 25	37.22	0.3	26.62	0.39
26 to 35	38.72	37.93	33.38	36.68
36 to 45	13.32	17.57	19.81	17.96
46 to 55	8.01	9.84	13.85	11.25
56 to 65	2.3	3.18	5.45	3.22
>65	0.32	0.34	0.7	0.34

Time of Day				
00:00 – 03:59	10.74	12.63	16.38	13.14
04:00 – 07:59	1.7	1.93	2.11	2.06
08:00 – 11:59	17.88	17.18	16.62	16.67
12:00 – 15:59	23.42	21.56	18.64	20.19
16:00 – 19:59	22.87	22.16	21.08	22.34
20:00 – 23:59	23.38	24.53	25.16	25.6
Day of Week				
Sunday	10.34	15.85	10	16.32
Monday	10.34	7.86	8.22	8.25
Tuesday	16.61	14.48	17.14	14.18
Wednesday	17.99	9.28	17.18	9.88
Thursday	15.18	16.15	16.85	16.58
Friday	17	17.31	14.51	16.19
Saturday	12.52	19.07	16.1	18.6
Month				
January	14.03	13.75	13	13.92
February	13.95	9.54	12.49	9.71
March	10.23	8.33	11.22	8.2
April	2.77	6.53	4.04	6.31
May	5.79	13.62	6.95	13.45
June	4.16	10.48	4.88	9.97
July	6.42	2.88	7.37	3.14
August	8.52	6.79	8.03	6.57
September	8.72	4.47	9.44	4.51
October	9.67	6.4	8.92	7.22
November	8.72	8.16	7.65	8.55
December	7.02	9.06	6.01	8.46
Number of Occupants				
1	68.49	55.46	76.15	57.95
2	22.47	31.06	17.89	28.52
3	6.98	10.7	4.51	9.84
4	1.66	2.1	1.17	3.14
5	0.36	0.64	0.23	0.47
6	0.04	0.04	0	0.04
7	0	0	0.05	0.04

Equipment Violations				
0	78.99	81.49	83.24	82.43
1	14.63	12.97	11.55	12.29
2	4.08	3.44	3.33	3.31
3	0.71	0.69	1.03	1.16
4	0.91	0.6	0.42	0.43
5	0.67	0.82	0.42	0.39
Violent Crime Rate (previous 30 days)				
Mean	4.98	4.61	4.07	4.44
Median	5	4	3	4

Table E-8: Hispanic/White Exit Vehicle

	Hispanic Drivers		White Drivers	
	n = 2,086	n = 1,709	n = 2,661	n = 1,709
Variable	**Pre-Match %**	**Post-Match %**	**Pre-Match %**	**Post-Match %**
Reason to Stop				
Reasonable Suspicion	9.34	10.71	9.3	10.94
Other Moving Viol.	23.64	24.22	24.55	23.87
Equipment Violation	22.83	20.89	16.76	20.71
Speeding	12.13	12.17	16.24	12.87
Cell Phone	1.24	1.35	1.6	1.35
BOLO	0.5	0.59	0.42	0.53
Red Light	1.18	1.35	1.46	1.11
Stop Sign	7.12	7.26	8.17	7.61
Seatbelt	3.34	3.63	2.58	2.87
Other VTL	18.69	17.85	18.92	18.14
Precinct				
1	27.23	28.2	28.5	32.01
2	13.49	14.34	12.44	12.11
3	26.24	25.22	6.15	6.55
4	1.24	1.11	4.69	4.62
5	6.37	6.38	10.14	11
6	3.71	3.57	6.34	6.03
7	5.63	6.38	14.88	14.69
9	16.09	14.8	16.85	12.99
Sex				
Female	9.16	15.04	21.13	15.04
Male	90.84	84.96	78.87	84.96
Age				
<16	0.12	39.67	0.19	37.39
16 to 25	43.07	0.35	26.62	0.35
26 to 35	35.83	37.21	33.38	38.97
36 to 45	14.42	16.03	19.81	17.55
46 to 55	5.01	5.09	13.85	4.39
56 to 65	1.36	1.46	5.45	1.23
>65	0.19	0.18	0.7	0.12

Time of Day				
00:00 – 03:59	18.19	17.73	16.38	16.91
04:00 – 07:59	4.15	3.16	2.11	2.52
08:00 – 11:59	13.86	13.87	16.62	13.46
12:00 – 15:59	18.63	19.13	18.64	19.54
16:00 – 19:59	21.16	21.53	21.08	22.18
20:00 – 23:59	24.01	24.58	25.16	25.39
Day of Week				
Sunday	13.55	15.74	10	15.04
Monday	11.08	9.13	8.22	8.72
Tuesday	15.59	15.68	17.14	15.74
Wednesday	14.67	12.17	17.18	11.76
Thursday	14.98	16.09	16.85	15.97
Friday	14.67	16.44	14.51	16.15
Saturday	15.47	14.75	16.1	16.62
Month				
January	13.24	13.4	13	13.87
February	13.3	9.36	12.49	9.3
March	11.01	8.6	11.22	7.96
April	3.34	6.55	4.04	6.67
May	5.94	13.58	6.95	13.69
June	4.7	11.35	4.88	10.53
July	5.14	3.34	7.37	3.34
August	7.74	6.14	8.03	6.61
September	11.88	4.92	9.44	5.27
October	8.6	5.56	8.92	5.97
November	8.35	6.9	7.65	7.31
December	6.75	10.3	6.01	9.48
Number of Occupants				
1	73.21	59.57	76.15	60.44
2	19.43	25.98	17.89	25.92
3	5.26	10.06	4.51	9.71
4	1.86	3.1	1.17	3.22
5	0.19	1.23	0.23	0.59
6	0	0	0	0.06
7	0.06	0.06	0.05	0.06

Equipment Violations				
0	77.41	79.99	83.24	80.63
1	14.48	13.34	11.55	13.34
2	5.07	4.21	3.33	3.92
3	1.36	1.35	1.03	1.17
4	1.05	0.7	0.42	0.53
5	0.62	0.41	0.42	0.41
Violent Crime Rate (previous 30 days)				
Mean	4.31	4.29	4.07	4.2
Median	4	4	3	4