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RACIAL DISPARITIES IN TRAFFIC STOP OUTCOMES

FRANK R. BAUMGARTNER, LEAH CHRISTIANI, DEREK A. EPP, KEVIN ROACH, KELSEY SHOUB[†]

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INTRODUCTION

In American politics, the issue of racial disparity is never far from the surface, in particular as it relates to encounters with the police. We are currently in a period when – thanks to the Black Lives Matter movement – the behavior of police officers toward minorities is receiving intense scrutiny.¹ As usual, Americans are deeply divided on the issue: where one side perceives injustice and violence toward black bodies, the other focuses on the difficulties of law enforcement and the need to respect those in blue.² In this paper, we document the ubiquity of substantial racial disparities in the odds of adverse outcomes stemming from routine traffic stops. We do so with the largest database yet compiled of this most common form of citizen-police interaction. We show that it occurs in every state where we can find data, that it affects Black as well as Hispanic drivers, that the effects are very large, and that the simple bivariate comparisons are consistent with more sophisticated and demanding multivariate statistical tests. Racial disparities in traffic stops are large, ubiquitous across the nation, and troubling.

Our current focus on race and justice is all too familiar, but the most recent surge in attention to these issues offers perhaps a special promise of progress because our abilities to document citizen interactions with police have never been better. First, almost everyone today has a video camera on their cell phone, allowing them to film their interactions with police officers.³ It is much harder to dismiss a victim's claims of police misconduct when footage of the incident is posted on Facebook for the world to see.⁴ Second, increasing numbers of police departments are mandating the use of dash cameras and body cameras for police cars and police officers.⁵ Third, we now have access to extensive databases of police traffic stops that record the demographic information of stopped motorists

1 Ryan J. Gallagher et al., *Divergent discourse between protests and counter-protests: #BlackLivesMatter and #AllLivesMatter* (Oct. 20, 2016) (unpublished manuscript), <http://arxiv.org/pdf/1606.06820.pdf> (last visited April 3, 2017); Jennifer Chernega, *Black Lives Matter: Racialised Policing in the United States*, 14 COMP. AMERICAN STUDIES 234 (2016); Sara M. Hockin & Rod K. Brunson, *The Revolution Might Not Be Televised (But It Will Be Lived Streamed): Future Directions for Research on Police-Minority Relations*, RACE AND JUSTICE 1-17 (2016); Deen Freelon, et al., *Beyond the Hashtags: #Ferguson, #Blacklivesmatter, and the Online Struggle for Offline Justice*, CENTER FOR MEDIA & SOCIAL IMPACT, AMERICAN U. (2016)

2 See generally Frank Newport, *Pub. Opinion Context: Americans, Race & Police*, THE GALLUP BLOG (July 8, 2016), <http://www.gallup.com/opinion/polling-matters/193586/public-opinion-context-americans-race-police.aspx> (summarizing data on Americans' attitudes toward police and police brutality).

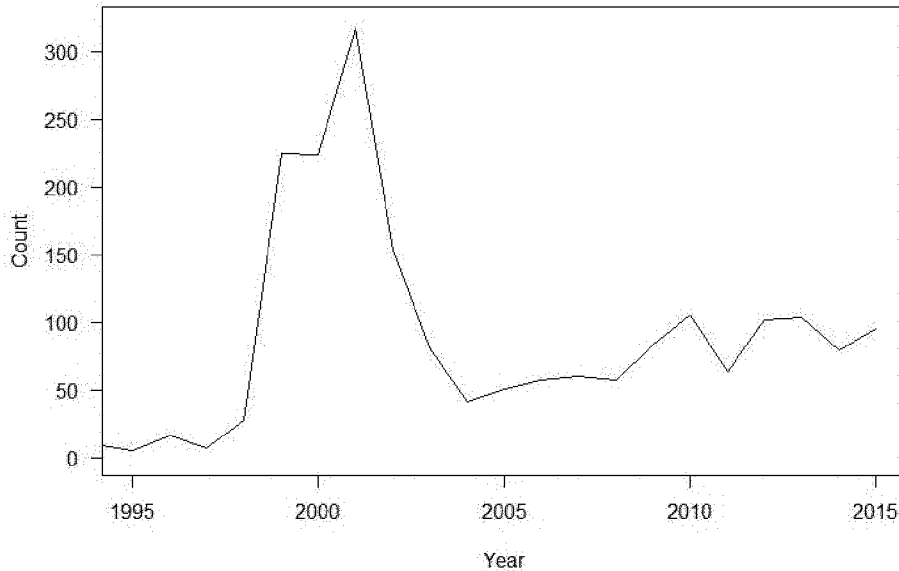
3 See generally Monica Anderson, *Technology Device Ownership: 2015*, PEW RESEARCH CENTER FACT TANK (Oct. 29, 2015), <http://www.pewinternet.org/2015/10/29/technology-device-ownership-2015/>.

4 See Mark Speltz, *How Photographs Define the Civil Rights and Black Lives Matter Movements*, TIME MAGAZINE (Sep. 22, 2016), <http://time.com/4429096/black-lives-matter-civil-rights-photography/>.

5 In 2000, just 11 percent of state police and highway patrol vehicles had in-car video; by 2003 the percentage was over 72. See International Association of Chiefs of Police, *The Impact of Video Recording on Modern Policing. Prepared for the US Department of Justice*, OFFICE OF COMMUNITY-ORIENTED POLICING SERVICES, <https://www.bja.gov/bwc/pdfs/IACPIn-CarCameraReport.pdf> (last visited April 3, 2017); Michael D. White, *Police Officer Body-Worn Cameras: Assessing the Evidence*, OFFICE OF COMMUNITY-ORIENTED POLICING SERVICES (2014). White notes that all forms of video recordings are increasing, from Closed Circuit TVs to smart phones, dash cams, body cams and beyond.

alongside information about what transpired during the stop.⁶ Efforts to collect this type of data were put in place during the last wave of attention toward “driving while black” disparities in the late 1990s and early 2000s. Figure 1 shows the surge of attention as well as its later decline.⁷

Figure 1. Newspaper Articles on Driving While Black Published in the Baltimore Sun, Los Angeles Times, Washington Post, New York Times, and USA Today



“Driving while black” (DWB) was the term used to refer to the problem of racial bias in traffic stops, with some others also referring to the issue of “walking while black” referring to the issue of disparate stops of black pedestrians. These ironic phrases sought to bring attention to the fact that being black is not a crime and that driving or walking while black should not generate increased police scrutiny. During the time when attention to the concept of “driving while black” or “driving while brown” surged, a number of states passed laws for the first time mandating the collection of data on routine traffic stops.⁸ They sought to document any racial disparities that were alleged to be occurring so that the phenomenon could be either dismissed if the data revealed there was no such thing, or better understood so that solutions could be implemented if the data showed that allegations were indeed accurate.⁹ The figure shows that attention has declined, but a new wave of attention to police violence, based on shootings of unarmed black men, has kept

⁶ See *supra* Figure 1.

⁷ Data collected by the authors. Counts of newspaper articles published in the Baltimore Sun, Los Angeles Times, Washington Post, New York Times, and USA Today came from searching LexisNexis. The search parameters used were: SUBJECT(“racial profiling” AND ((police) OR (“traffic stop”))).

⁸ See *infra* Table 1 and Table 2.

⁹ See *id.*

police-minority relations in the headlines. One major difference between the 1990s and today was mentioned above: video confirmation. Another is data, which is our focus here.

We have collected publicly available information from hundreds of police agencies across 16 states. These include enormous computer files listing every traffic stop individually, sometimes for an entire state¹⁰ and in some cases for large agencies such as the State Highway Patrol (or equivalent).^{11,12} In other cases, we can use published reports to calculate search rates by race¹³; these are available for hundreds of police agencies of all types. In all, we present data here on search rates by race for 132 agencies in Connecticut, Illinois, Maryland, North Carolina, Florida, Ohio, Texas, Vermont, Arizona, Colorado, Missouri, Nebraska, Oregon, Tennessee, Washington, and West Virginia covering 649 agency-years. We exclude agencies with fewer than 10,000 traffic stops in any given year from these totals. This results in an analysis of over 55 million traffic stops. While all of this data is publicly available, to our knowledge this is the first paper to compile it in a comparable manner. Our particular focus here is on police searches following a traffic stop. After being pulled over, what is the likelihood that a motorist is searched by the police and how does that likelihood change depending on the race of the driver?

Our expectation based on previous studies is that black drivers will experience higher rates of search than whites and that this disparity will be evident in the data collected from all sixteen states. In other words, we suspect that racial disparity in traffic stops is a national issue, not one limited to Southern or politically conservative states.¹⁴ Further, we believe these disparities are driven in large part by “investigatory traffic stops”.¹⁵ This is a term developed by Epp et al. (2014) in their investigation into racial disparities in traffic stops in Missouri.¹⁶

10 These states are Connecticut, Illinois, Maryland, and North Carolina.

11 These states are Florida, Ohio, Texas, and Vermont.

12 Wisconsin also collects micro-level data and makes that data available, but we do not use it here. In the Wisconsin data, 45 percent of the observations are missing on the race and gender variables alone. It is not clear that this is random, and there appear to be numerous errors in the reporting with what seem to be data on gender appearing in the race column, and birth dates placed in the race and gender columns. Because of these concerns and obvious errors, we exclude Wisconsin here.

13 These states are Arizona, Colorado, Missouri, Nebraska, Oregon, Tennessee, Washington, and West Virginia.

14 See Frank R. Baumgartner et al., *Targeting Young Men of Color for Search and Arrest During Traffic Stops: Evidence from North Carolina, 2002-2013*, POLITICS, GROUPS, & IDENTITIES, at 17 (2016), <http://dx.doi.org/10.1080/21565503.2016.1160413>; see also Matthew Petrocelli et al., *Conflict Theory and Racial Profiling: An Empirical Analysis of Police Traffic Stop Data*, 31 J. CRIM. JUSTICE 1, 1-11 (2003); see also Rob Tillyer et al., *The Discretion to Search: A Multilevel Examination of Driver Demographics and Officer Characteristics*, 28 J. CONTEMP. CRIM. JUSTICE 184, 199 (2012); see also Rob Tillyer & Robin S. Engel, *The Impact of Drivers' Race, Gender, and Age During Traffic Stops: Assessing Interaction Terms and the Social Conditioning Model*, 59 CRIME & DELINQUENCY 369, 385 (2013); see also Donald Tomaskovic-Devey et al., *Looking for the Driving While Black Phenomena: Conceptualizing Racial Bias Processes and Their Associated Distributions*, 7 POLICE Q. 3, 4-5 (2004).

15 CHARLES R. EPP ET AL., *PULLED OVER 12* (John M. Conley & Lynn Mather eds., 2014); see also Seth W. Fallik & Kenneth J. Novak, *The Decision to Search: Race or Ethnicity Important?*, 28 J. CONTEMP. CRIM. JUSTICE 146, 160 (2012).

16 See EPP ET AL., *supra* note 12.

They argue that there are two types of traffic stops: **safety and investigatory**.¹⁷

Safety stops are about making the roads a safe place to drive, which, of course, is an essential component of police work.¹⁸ When officers stop motorists for excessive speeding, running a red light or stop sign, or drunk driving, they are making a safety stop. However, police officers will often pursue other goals in making traffic stops. Specifically, officers are trained to use traffic stops as a general enforcement strategy aimed at reducing violent crime or drug trafficking.¹⁹ When officers are serving these broader goals, they are making an investigatory stop, and these stops have little (if anything) to do with traffic safety and everything to do with who looks suspicious.²⁰ Racial disparities are more likely to ensue from investigatory stops compared to safety ones. Investigatory stops may also be highly related to poverty, such as stops for equipment failures or expired registration. These may be statistically related to race (as in the example of poverty-related stops), or they may be subject to high levels of officer discretion. While there may be good reasons to enforce these laws, they may have different impacts and serve different purposes than keeping unsafe drivers off the roads, or encouraging those who may be tempted to drive too fast not to do so. We therefore expect safety stops to have less racial difference, and investigatory stops to show higher racial disparities.

Note that we are not going to analyze the stops themselves, but rather the outcome of the stops: whether the driver is searched. Analyzing who is stopped is an interesting question but typically requires some comparison point, such as who is driving. As we do not have estimates of the racial breakdown of the driving populations in each community we study, we eschew any analysis of the distribution of stops in this paper. Rather, we focus only on the outcome of the stop. Given the stop, what is the conditional probability of search? How does this differ by race?

Investigatory traffic stops were introduced as a policing tactic as part of a national effort to crack down on crime during the 1980s and 1990s.²¹ Their usage **spread rapidly across the country as part of a new wave of “broken glass policing”** that emphasized maintaining a strong police presence in certain neighborhoods.²² But investigatory stops were always a blunt instrument for stopping crime because drug dealers and violent criminals do not have any strong systematic driving tendencies that distinguish them from innocent motorists. Thus, the policing strategy quickly devolved into a numbers game, or, as one California highway patrol officer put it, “It’s sheer numbers . . . [o]ur guys make a lot of stops. You’ve

17 *Id.* at 13-14.

18 *Id.* See also Fallik & Novak, *supra* note 15, at 151.

19 See Fallik & Novak, *supra* note 15, at 153; See also MICHAEL LIPSKY, STREET-LEVEL BUREAUCRACY: DILEMMAS OF THE INDIVIDUAL IN PUBLIC SERVICES 122-3 (Russell Sage Foundation, 30th ann. ed., 2010); see also EPP ET AL., *supra* note 15, at 7-8.

20 See EPP ET AL., *supra* note 15, at 12; see also Fallik & Novak, *supra* note 15, at 160.

21 See George L. Kelling & James Q. Wilson, *Broken Windows: The Police and Neighborhood Safety*, THE ATLANTIC, Mar. 1982, <https://www.theatlantic.com/magazine/archive/1982/03/broken-windows/304465/>; D.W. Miller, *Poking Holes in the Theory of “Broken Windows,”* THE CHRONICLE OF HIGHER EDUC., Feb. 9, 2001, <http://www.chronicle.com/article/Poking-Holes-in-the-Theory-of/13568>.

22 See Kelling & Wilson, *supra* note 21; Miller, *supra* note 21.

got to kiss a lot of frogs before you find a prince.”²³

With marching orders to make a lot of stops in order to find drug dealers, but without any clear indicators of who the drug dealers are, Epp et al. (2014)²⁴ argue that police officers utilize stereotypical criminal profiles to decide who gets stopped. In America, people of color and young black men in particular are associated (either implicitly or explicitly) with criminality²⁵ and thus more likely to arouse police suspicions. Crucially, even if for most officers these biases are slight, with only a small marginal likelihood of affecting their behavior, the cumulative effect could still be very great. That is, even if most officers are only slightly more likely to search a black driver, on average black drivers would experience many more searches than whites.

This is exactly what we find in our analysis of traffic stops data. With few exceptions, police agencies across the thirteen states search black drivers at higher rates than they do whites, often dramatically higher. For example, the Evanston, Illinois Police Department is seven times more likely to search a black driver. It is clear then that blacks are policed much more heavily than whites, not just in a handful of unusual police departments or in certain regions of the country, but almost everywhere we look.

We proceed by describing the various datasets used in our analysis. Then, we show the distribution of search rates by race, for white, black, and Hispanic drivers. Next, we introduce the “search-rate ratio,” which is simply the rate for blacks (or Hispanics) divided by the rate for whites. Finally, for those states and large agencies where we have micro-level data, we present a more complete multivariate statistical model to predict the likelihood of search, and show that the results from the search-rate ratio analyses are highly robust.

I. PUBLICLY AVAILABLE DATA

As we showed in Figure 1, the late-1990s saw a surge of attention to issues of disparate policing. Tables 1 and 2 show that there was a significant legislative response. Many states mandated the collection of demographic data for all traffic stops, and most issued periodic statistical summaries of the findings.²⁶ Three states in the current study enacted such policies in 1999, two in 2000, two more in 2001, and four states enacted such policies or commissioned such studies between 2003 and 2004.²⁷ These efforts gained national recognition and inclusion with former President Barack Obama’s White House Initiative on 21st Century Policing, which launched in 2014. Of course, attention to police violence has surged in the period since the 2012 shooting of 17-year-old Trayvon Martin and the mobilization

23 Gary Webb, *Driving While Black: Tracking Unspoken Law-Enforcement Racism*, ESQUIRE (Jan. 29, 2007), <http://www.esquire.com/news-politics/a1223/driving-while-black-0499/>.

24 EPP ET AL., *supra* note 15, at 33-34, 45-47.

25 Jennifer Eberhardt et al., *Believing is Seeing: The Effects of Racial Labels & Implicit Beliefs on Face Perception*, 29 PERSONALITY & SOC. PSYCHOLOGY BULLETIN 360, 366 (2003); Jennifer Eberhardt et al., *Seeing Black: Race, Crime, & Visual Processing*, 87 J. OF PERSONALITY & SOC. PSYCHOLOGY 876, 881 (2004); Jennifer Eberhardt et al., *Looking Deathworthy: Perceived Stereotypicality of Black Defendants Predicts Capital-Sentencing Outcomes*, 17 CORNELL L. FACULTY PUBL’NS 383, 385 (2006); Aneeta Rattan et al., *Race & the Fragility of the Legal Distinction between Juveniles & Adults*, 7 PUB. LIBRARY OF SCIENCE, at 4 (2012).

26 See *infra* Table 1.

27 See *infra* Table 1.

around such themes as “Black Lives Matter”.²⁸ Pressures today focus on body cameras, availability of video footage, and investigating incidents of violence. But agencies continue to be concerned with disparities associated with routine traffic stops, and more agencies continue to be added to the list of those which collect such statistics. California, for example, passed the Racial and Identity Profiling Act of 2015, mandating data collection as well as an advisory board to analyze the stop data and make suggestions to address any disparities found.²⁹

Several things are clear from Tables 1 and 2. **First, the most common enactment of policies to study traffic stops is through legislation by the state.** This occurred in Connecticut, Illinois, Maryland, North Carolina, Texas, Missouri, Nebraska, and Tennessee. Almost all other states in this study saw voluntary documentation and reporting by one or more agencies. These states are Florida, Ohio, Vermont, and Oregon. Arizona initially voluntarily collected data to diagnose racially biased policing; however, the state only began to analyze the data due to a class action lawsuit.

Second, as is clear from the Tables 1 and 2, **different state laws mandate the collection of different elements of data, and for different time periods.** Additionally, many jurisdictions have voluntarily produced reports.³⁰ Occasionally, we have identified commissioned reports using administrative data not generally made public as well.³¹ As there is no central repository for these data, we have scoured official web sites, contacted agencies directly, and sought to compile the fullest set of data on traffic stop statistics.

In this paper, we make use of every report we have been able to find which meets three criteria. First, the agency in question must report a minimum of 10,000 traffic stops in a given year. We do this only to exclude small agencies, which might skew the results of our study, which focuses on search rates. If a search rate is three percent, 10,000 stops would result in only 300 searches, and breaking that down by race can generate even smaller numbers. So **we impose first a threshold on the number of traffic stops.** Second, the agency must indicate the total number of searches of the driver or vehicle. And finally, these numbers must be broken down by race. With those elements, we can calculate the rate of search for drivers of different racial and ethnic groups. We should note that most agencies provide further breakdowns (such as by gender, type of stop, or type of search, and different possible outcomes of the stop such as ticket, warning, or arrest), and for those states listed in Table 1 we often have very extensive records of the exact

28 See, e.g., BLACK LIVES MATTER, <http://www.blacklivesmatter.com> (last visited April 3, 2017); MAPPING POLICE VIOLENCE, <http://mappingpoliceviolence.org> (last visited April 3, 2017); Daniel Funke & Tina Susman, *From Ferguson to Baton Rouge: Deaths of black men and women at the hands of police*, LOS ANGELES TIMES (July 12, 2016), <http://www.latimes.com/nation/la-na-police-deaths-20160707-snap-htmstory.html>.

29 Governor Brown Signs Groundbreaking Data Collection Bill to Combat Racial Profiling, ACLU OF NORTHERN, CALIFORNIA (Oct. 3, 2015), <https://www.adunc.org/news/governor-brown-signs-groundbreaking-data-collection-bill-combat-racial-profiling>.

30 See *infra* Table 2.

31 For example, we received the micro-level individual stops database from the Illinois Department of Justice through email correspondence; this is the database which underlies their published reports providing agency-by-agency summaries. The full database allows a more complete analysis however, as shown below in Table 14.

Table 1. States with Micro-Level Traffic Stops Data

State	Data Collected	Publicly Available	Why were/are the data collected?	Who reports?
Connecticut	2000 to Today	2013 to 2014	In 1999, The Alvin W. Penn Racial Profiling Prohibition Act (Public Act 99-198) was enacted, which prohibits profiling based on race, gender, age, or ethnicity. As a part of this law, data on who is stopped began to be collected and stored for analysis. In 2012, several changes were made to this law including a provision that shifted responsibility for its implementation.	All Agencies
Florida	1999 to Today	2010 to 2015	In 1999, the Florida Highway Patrol conduct its first (public) analysis of traffic stop data. Beginning January 1, 2000, the Florida Highway Patrol voluntarily began to collect data on every discretionary traffic stop.	SHP
Illinois	2004 to Today	2004 to 2015	In 2003, public law 93-0209 was signed into law. This law established an initial statewide study of traffic stops to identify racial bias. The study was extended with Public Act 98-0686 to run until July 1, 2019.	All Agencies
Maryland	2002 to Today	2003 to 2009 & 2011 to 2016	In 2001, the Maryland General Assembly passed TR 25-113 requiring data collection on every law eligible traffic stop in Maryland to provide information about the pervasiveness of racial profiling. Data collection began in 2002. The system went fully electronic in 2013.	All Agencies
North Carolina	2000 to Today	2000 to 2015	In 1999, Senate Bill 76 was passed, which required traffic stop statistics be collected for State law enforcement officers effective as of January 1, 2000. This was expanded in include all county Sheriffs' Office and almost all police departments. It was further amended and remodified in 2009 and 2014.	All Agencies
Ohio	2011 to 2015	2011 to 2015	Data obtained through a Freedom of Information Request (FOIA)	SHP
Texas	2000 to Today	2009 to 2015	Senate Bill 1074, which passed in the 77th Regular Session of the Texas Legislature, requires Texas law enforcement agencies to collect certain traffic stop data and to report the data annually.	DPS
Vermont ³³	2010 to Today	2011 to 2014	In 2014, the White House launched the Task Force on 21st Century Policing to identify the best means to provide an effective collaboration within communities that reduces crime and increases trust. As a part of this task force, the DPS released their data on traffic stops in the state for a set of years.	VSP

characteristics of every traffic stop.³²

³³ See Peter Hirschfeld, *Many Vt. Police Agencies Aren't Following Traffic-Stop Data Collection Law*, N.H. PUB. RADIO (Apr. 25, 2016), <http://nhpr.org/post/many-vermont-police-agencies-arent-following-traffic-stop-data-collection-law#stream/0>.

Table 2. States and Agencies with Published Reports but no Micro-data.				
State	Data Collected	Publicly Available	Why were/are the data collected?	Who reports?
Arizona	2003 to 2008	2003 to 2008	In 2003, the Department of Public Safety began to voluntarily collect and store information about traffic stops. In 2006, the Department of Public Safety began analyzing the collected data and making public the final reports as a result of a class action lawsuit.	DPS
Colorado	6/1/2001-5/31/2002 and 6/1/2002-5/31/2003	6/1/2001-5/31/2002 and 6/1/2002-5/31/2003	In November 2001, a Biased Policing Task Force was formed to investigate racial bias in policing. Part of this effort consisted of data collection about traffic stops that began on June 1, 2001. They committed to collecting this data for two years.	Denver PD
Missouri	2000 to Today	2000 to 2015	On August 28, 2000, state law Section 590.605 was passed. This law requires all officers to report information about drivers that they stop to determine the pervasiveness of racial profiling. Reports are to be made to the state by June 1 of each year.	All Agencies
Nebraska	2002 to Today	2002 to 2013	In 2001, LB593 was passed. The law specifically prohibits racial profiling and requires law enforcement agencies to collect data on traffic stops made within their jurisdiction. In 2004, LB1162 amended the definition of a motor vehicle stop to exclude the stop of a motor truck, tractor-trailers or semitrailer at the state weighing stations. Additionally, the amendment created the Racial Profiling Advisory Committee (RPAC).	All Agencies
Oregon	2004 to 2010	2004 to 2010	Reports posted on City of Portland Police Bureau web site.	Portland PD
Tennessee	2006	2006	In 2005, the legislature requested (Public Chapter 193 of 2005) a report on whether racial profiling plays a role in State Troopers' decisions to stop drivers.	SHP
Washington	11/1/2005-9/30/2006	11/1/2005-9/30/2006	This National Highway Traffic Safety Administration (NHTSA) provided a grant to study racial profiling in Washington state.	All Agencies
West Virginia	4/2007-9/2008	4/2007-9/2008	The West Virginia Legislature passed the Racial Profiling Data Collection that required law enforcement officers to collect traffic stop data beginning January 1, 2007. The published report provides statistics for an 18-month period.	All Agencies

³³ See Peter Hirschfeld, *Many Vt. Police Agencies Aren't Following Traffic-Stop Data Collection Law*, N.H. PUB. RADIO (Apr. 25, 2016), <http://nhpr.org/post/many-vermont-police-agencies-arent-following-traffic-stop-data-collection-law#stream/0>.

I. DESCRIPTIVE STATISTICS

Our datasets reflect a diversity of types of police agencies. These are: (1) state agencies, such as the Department of Public Safety (DPS) or the State Highway Patrol (SHP); (2) municipal and county police departments, such as the Chicago Police Department or the Durham Police Department; (3) county Sheriff's departments, such as the Orange County Sheriff's Department; (4) other types of departments, such as those that patrol universities and hospitals; and (5) aggregated information from multiple departments within a state. As is clear from Tables 1 and 2 above, many states only require the DPS or SHP to report information on traffic stops and drivers. These states are: Florida, Ohio, Texas, Vermont, Arizona, and Tennessee. Most other states with reporting requirements require all law enforcement agencies in the state to report either raw traffic stops information or summary statistics to the state. These states are: Connecticut, Illinois, Maryland, North Carolina, Missouri, and Nebraska. The one exception to this is Oregon, where the Portland Police Department is the only department to make public studies on racial bias in the state. The last column in Tables 1 and 2 indicates what types of agencies report in each state included in this study. Table 3 shows how many reports we have compiled from each type of agency with descriptive statistics on the total numbers of agencies, observations (annual reports for each agency), stops, searches, as well as the average search rate.

Table 3: Descriptive Statistics					
Type of Agency	Agencies	Reports	Stops	Searches	Search Rate
State Highway Patrols (or equivalent)	11	54	33,160,416	703,679	2.12
Police Departments	97	507	14,706,378	930,424	6.33
Sheriff Departments	19	66	945,240	36,492	3.86
State Totals (Multiple Agencies Combined)	2	13	6,531,874	224,273	3.43
Miscellaneous and Specialized Agencies	3	9	364,195	4,126	1.13
Total	132	649	55,708,103	1,898,994	3.37
Note: The vast majority of reports reflect calendar years. Where micro-data are available, we calculate annual statistics for each agency and report here all agencies with at least 10,000 traffic stops in any given year.					

The search rate is calculated by dividing the total number of searches by the total number of stops, and multiplying that number by 100 to obtain a percentage. Overall, the average search rate across all types of agencies is about 3.37%. That is to say that when a driver is pulled over, they have about a 3% chance of being searched by the police. The average search rate is highest among police departments (6.33%) and lowest among miscellaneous and specialized agencies (1.13%) and state highway patrols (2.12%).

II. DISPARITIES IN SEARCH RATES BY RACE

With data collected reflecting over 50 million traffic stops, our task then is simple. What is the search rate for drivers of different races, and how do these search rates compare? To make this comparison we calculate a Search Rate Ratio. This is simply the black (or Hispanic) search rate divided by the white search rate. If whites and blacks were searched at the same rate, then the black-white search rate ratio would equal 1. If the black search rate is double that of the white search rate, then the black-white search rate ratio would equal 2. Values below 1 indicate that whites are searched at higher rates than blacks while values above 1 indicate that blacks are searched at higher rates than whites. We then do the same for Hispanic drivers, comparing them to whites. We can calculate search rate ratios for every agency in the database.³⁴

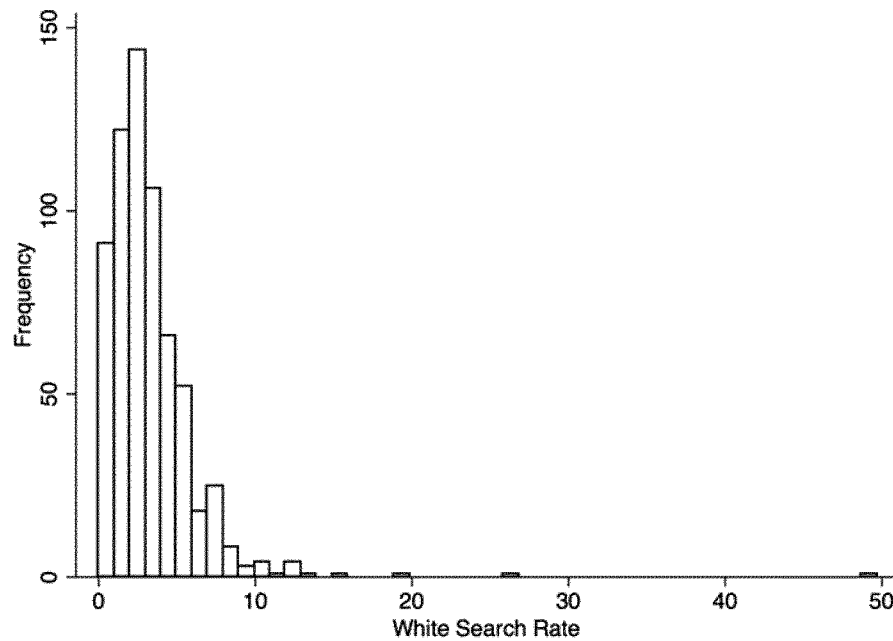
For those agencies where we have micro-level data, we can do a more complex logistic regression incorporating a wide variety of possible confounding factors to see if the patterns of racial disparity that we observe using the search rate ratios are explained by these other factors. For example, perhaps police officers are more likely to search drivers at night, and perhaps blacks are more likely to drive at night than whites. In that case, we would find that blacks are more likely to be searched (a search rate ratio above 1) but the effect would hinge on driving tendencies and not on race per say. In fact, we find that the disparities also appear in the multivariate statistical treatment, so they are not easily explained with nonracial co-varying factors.

A. Search Rates Among White Drivers

We begin by looking at rates of search for white drivers. Figure 2 shows how many agencies show search rates of varying levels, ranging from zero to almost 50 percent. Tables 4 and 5 show which agencies report the ten lowest highest values for any given year. The range of outcomes that we see, from very low to extremely high, is typical. When we look at policing, we first want to understand that it is controlled locally in a decentralized system, and that outcomes vary dramatically from place to place. Of course, later in this paper we will show that this variation, while extreme, is not random. In any case, search rates of white drivers can be taken as a baseline from which we can compare rates for minority drivers. We should note that this includes drivers of both genders, since the published reports typically do not allow us to separate out the males and females. Where we have full micro-databases, we observe that search rates are significantly higher with male drivers, no matter the race.

³⁴ We impose one more threshold on our data to ensure robust findings. We do not calculate a rate for any group which has fewer than 100 traffic stops in that year. Some agencies, for example, have very few Hispanic traffic stops even though all agencies in the database have at least 10,000 stops overall.

Figure 2: White Search Rates



Note: N = 649, Min = 0.00, Mean = 3.32, Max = 49.69. Includes only agencies with at least 10,000 total stops, 100 white stops, 100 black stops, and 100 Hispanic stops.

Figure 2, based on 649 annual observations, shows that the average rate for police agencies is about 3.3, but that the range is very significant. Table 4 then lists the ten cases with the lowest search rates, and Table 5 shows the ten with the highest rates. Note the spike in Carol Stream, IL for the year 2006 when the police department reported searching half of all white drivers. In that same year, the agency searched even higher proportions of black and Hispanic drivers, as later tables will show.

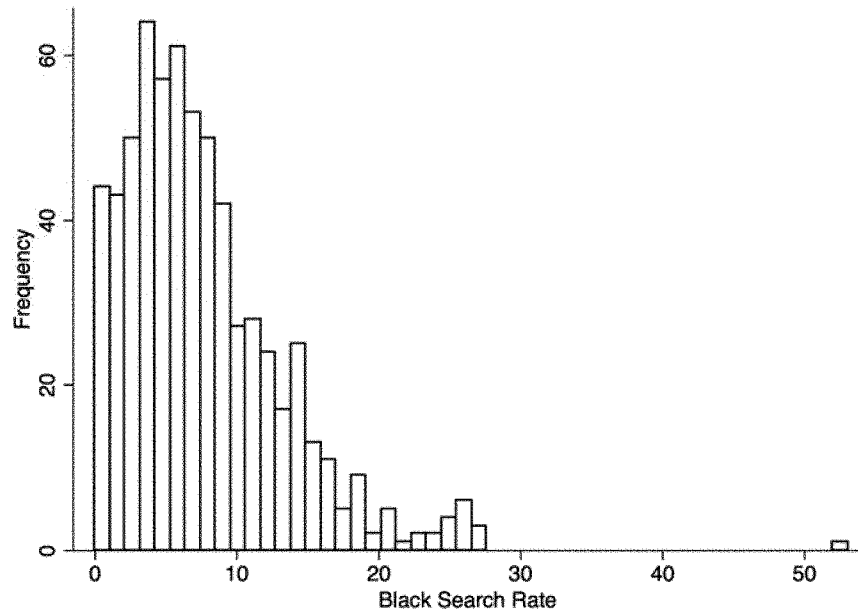
Table 4: White Search Rates, 10 Lowest Values					
State	Agency	Year	Total Stops	Total Searches	Search Rates
IL	Lombard PD	2013	7,801	0	0
NC	Greenville PD	2015	4,748	0	0
OR	Portland PD	2015	29,351	0	0
NC	Greenville PD	2013	5,561	0	0
IL	Palos Heights PD	2014	8,905	0	0
NC	Greenville PD	2014	4,476	0	0
IL	Univ. of Chicago PD	2013	2,268	0	0
IL	Skokie PD	2012	7,169	3	0.04
IL	Palos Heights PD	2013	9,017	5	0.06
IL	Lake County Sheriff	2011	10,633	6	0.06
Note: The total stops, total searches, and search rate all pertain to totals for white drivers.					

Table 5: White Search Rate, 10 Highest Values					
State	Agency	Year	Total Stops	Total Searches	Search Rate
OR	Portland PD	2008	30,640	3,380	11.03
IL	Fairview Heights PD	2012	6,137	732	11.93
OR	Portland PD	2004	56,607	7,052	12.46
OR	Portland PD	2005	54,218	6,803	12.55
OR	Portland PD	2007	41,940	5,368	12.80
OR	Portland PD	2006	45,008	6,203	13.78
NC	Gaston County PD	2002	9,304	1,420	15.26
MO	Maryland Heights PD	2015	9,856	1,896	19.24
IL	Normal PD	2006	8,572	2,288	26.69
IL	Carol Stream PD	2006	14,463	7,186	49.69
Note: The total stops, total searches, and search rate all pertain to totals for white drivers.					

B. Search Rates Among Black Drivers

Figure 3 reports the distribution for black search rates. They center on a mean of about 7.62%. This rate is more than double the white search rate and the overall average search rate for all drivers (compare to Figure 2 or the statistics in Table 3). The black search rate ranges from a minimum of 0% to a maximum of 53.07%. The wide distribution, indicating dramatic differences from agency to agency, is similar to that of the white search rate, but of course substantially shifted to the right, with more agencies showing higher search rates. Tables 6 and 7 report the low and high outliers. Again, Carol Stream Police Department has the highest search rate of black drivers, searching more than half of the black drivers that they pulled over in 2006. Note, however, that in Table 5 the threshold to be in the “top 10” for white search rates was about 11 percent, for black drivers that threshold is over 25 percent. Figure 3 shows that large numbers of agencies search black drivers at rates where only the most extreme agencies search whites.

Figure 3: Black Search Rates



Note: N = 649, Min = 0.00, Mean = 7.68, Max = 53.07. Includes only agencies with at least 10,000 total stops, 100 black stops, 100 white stops, and 100 Hispanic stops.

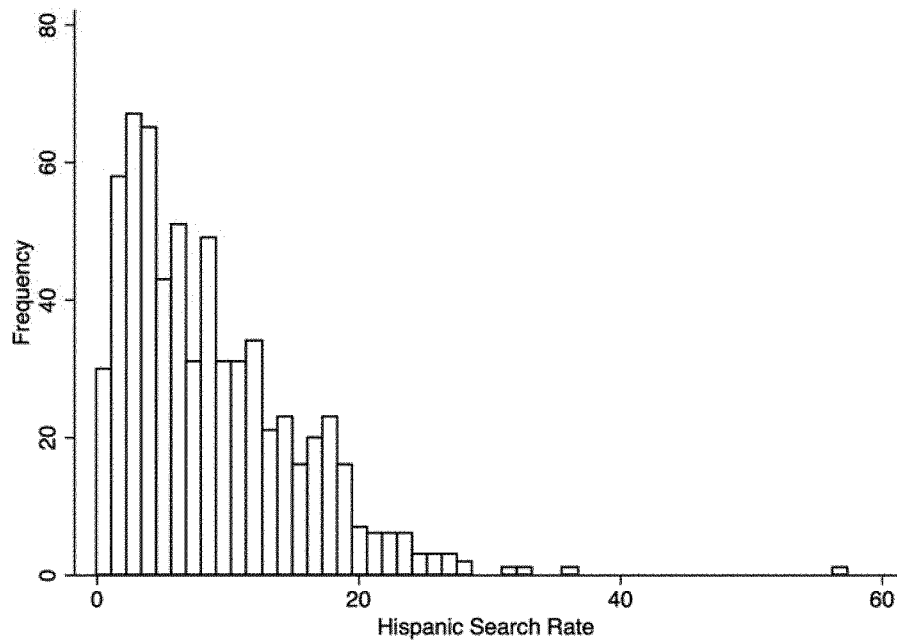
Table 6: Black Search Rates, 10 Lowest Values					
State	Agency	Year	Total Stops	Total Searches	Search Rate
IL	Univ. of Chicago PD	2013	8,676	0	0
NC	Greenville PD	2015	6,033	0	0
IL	Palos Heights PD	2014	1,276	0	0
IL	Lombard PD	2013	1,385	0	0
OR	Portland PD	2015	5,548	0	0
NC	Greenville PD	2014	5,608	0	0
NC	Greenville PD	2013	5,755	0	0
IL	Lake County Sheriff	2011	1,574	1	0.06
IL	Palos Heights PD	2013	1,182	1	0.08
NC	SHP - Motor Carrier Enforcement	2004	6,287	11	0.17
Note: The total stops, total searches, and search rate all pertain to totals for black drivers.					

Table 7: Black Search Rates, 10 Highest Values					
State	Agency	Year	Total Stops	Total Searches	Search Rate
OR	Portland PD	2004	10,533	2,691	25.55
CO	Denver PD	2001/2002	25,538	6,556	25.67
IL	Chicago PD	2006	85,975	22,118	25.73
IL	Chicago PD	2005	87,834	23,060	26.25
CO	Denver PD	2002/2003	21,283	5,631	26.46
OR	Portland PD	2006	9,427	2,499	26.51
IL	Peoria PD	2006	6,212	1,701	27.38
OR	Portland PD	2005	10,702	2,933	27.41
IL	Normal PD	2006	2,136	588	27.53
IL	Carol Stream PD	2006	1,547	821	53.07
Note: The total stops, total searches, and search rate all pertain to totals for black drivers.					

C. Search Rates Among Hispanic Drivers

Figure 4 reports the distribution of Hispanic search rates across all agencies. The mean of Hispanic search rates is 8.69%, the highest average search rate compared with that of whites and blacks. It is more than double the mean white search rate and the overall average search rate of all drivers. Again the distribution shows very high variance, with rates spanning from about 0% to over 57%. Tables 8 and 9 report the low and high outliers. Again, the Carol Stream Police Department has the highest search rate, at 57.42% in 2006. This is the highest search rate from this police department, though their search rates across all three racial groups were high in that same year. The low outliers belong to agencies with a very low number of stops of Hispanic drivers.

Figure 4: Hispanic Search Rates



Note: N = 649, Min = 0.00, Mean = 8.77, Max = 57.42. Includes only agencies with at least 10,000 stops, 100 white stops, 100 black stops, and 100 Hispanic stops.

Table 8: Hispanic Search Rate, 10 Lowest Values					
State	Agency	Year	Total Stops	Total Searches	Search Rate
IL	Lombard PD	2013	1,170	0	0
OR	Portland PD	2015	3,213	0	0
NC	Greenville PD	2013	336	0	0
NC	Greenville PD	2015	366	0	0
IL	Univ. of Chicago PD	2013	507	0	0
NC	Greenville PD	2014	337	0	0
IL	Skokie PD	2012	1,292	1	0.08
IL	Palos Heights PD	2014	882	1	0.11
IL	Lake County Sheriff	2011	2,847	5	0.18
IL	Palos Heights PD	2013	757	2	0.26
Note: the total stops, total searches, and search rate all pertain to totals for Hispanic drivers					

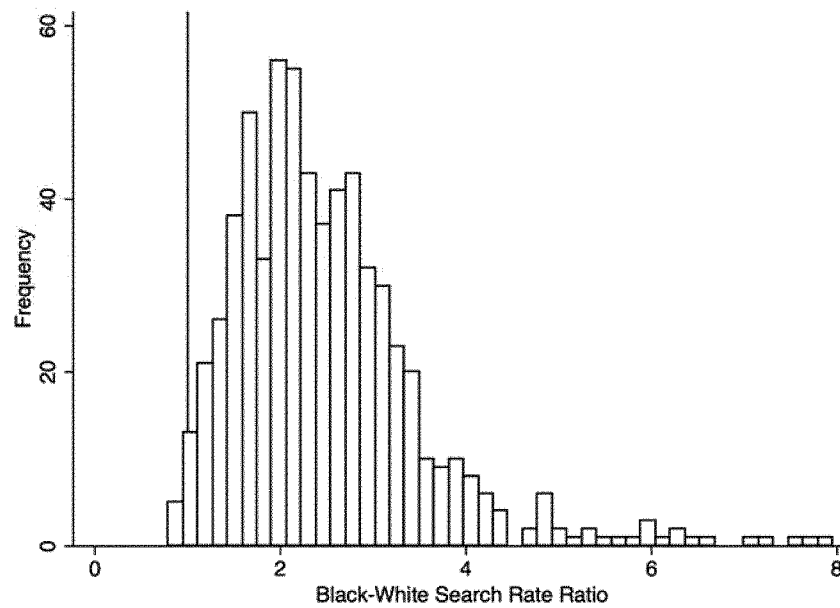
Table 9: Hispanic Search Rates, 10 Highest Values					
State	Agency	Year	Total Stops	Total Searches	Search Rate
OR	Portland PD	2005	6,801	1,750	25.73
IL	Palatine PD	2006	604	161	26.66
OR	Portland PD	2006	6,253	1,681	26.88
OR	Portland PD	2007	6,133	1,657	27.02
IL	Aurora PD	2006	11,134	3,117	28.00
IL	Aurora PD	2005	10,475	2,959	28.25
IL	Fairview Heights PD	2012	195	62	31.79
IL	Normal PD	2006	321	104	32.40
IL	Bloomington PD	2006	395	142	35.95
IL	Carol Stream PD	2006	1,975	1,134	57.42
Note: The total stops, total searches, and search rate all pertain to totals for Hispanic drivers.					

D. Black-White Search Rate Ratios

Figure 5 plots the distribution of the black-white search rate ratios. A vertical line marks 1, which would indicate an equal search rate. The average search rate ratio is 2.51, indicating that black drivers are 2.51 times more likely to be searched than white drivers. The rate ranges from a minimum of 0 to a maximum of 7.96. Just seven agencies have ratios that are below or equal to 1, whereas 635 have ratios that exceed 1. This suggests that a vast majority of agencies search blacks at higher rates than whites. The outliers are reported in Tables 10 and 11.

Tables 10 and 11 show the number of stops for drivers of the two races, the percent of each race of rivers searched, and the ratio of those two search rates. That ratio is presented in Figure 5 for all agencies with available data. Table 10 shows the ten cases furthest to the left in Figure 5, and Table 11 shows the 10 cases furthest to the right: the “high outliers.” These are the U.S. police agencies with the highest racial disparities in search rates.

Figure 5: Black-White Search Rate Ratios



Note: N = 642, Min = 0.86, Mean = 2.51, Max = 7.96. Below or equal to 1.0: 7; Above 1.0: 635. Includes only agencies with at least 10,000 total stops, 100 white stops, 100 black stops, and 100 Hispanic stops.

State	Agency	Year	White Stops	Black Stops	White Search Rate	Black Search Rate	B-W Search Rate Ratio
NC	Guilford County Sheriff	2013	4,868	4,179	5.55	4.79	0.86
IL	Mundelein PD	2006	8,796	377	4.16	3.71	0.89
IL	Bloomington PD	2014	7,402	1,266	0.88	0.79	0.90
NC	Gaston County PD	2002	9,304	1,654	15.26	13.97	0.92
IL	Melrose Park PD	2006	2,915	2,960	0.86	0.81	0.95
MD	BACOPD	2014	29,158	37,653	3.01	2.90	0.96
MD	Frederick	2014	9,049	1,530	5.02	4.90	0.98
NC	SHP - Motor Carrier Enforcement	2003	24,046	6,868	0.23	0.23	1.02
IL	Normal PD	2006	8,572	2,136	26.69	27.53	1.03
NC	Concord PD	2011	9,935	4,554	2.12	2.22	1.04

Table 11: Black-White Search Rate Ratios, 10 Highest Values							
State	Agency	Year	White Stops	Black Stops	White Search Rate	Black Search Rate	B-W Search Rate Ratio
IL	Evanston PD	2011	7,306	3,469	1.18	7.15	6.07
IL	Chicago PD	2008	59,237	91,223	1.97	12.32	6.26
IL	Chicago PD	2009	60,253	84,177	1.42	8.95	6.28
IL	New Lenox PD	2013	11,529	1,008	0.22	1.39	6.41
IL	Evanston PD	2012	7,454	3,887	1.19	7.90	6.61
IL	Evanston PD	2014	5,545	3,250	1.71	12.12	7.08
IL	Chicago PD	2010	51,133	68,371	1.41	10.19	7.21
IL	Evanston PD	2013	6,123	2,989	1.49	11.34	7.63
IL	Evanston PD	2010	7,055	3,453	1.22	9.47	7.77
IL	Evanston PD	2009	5,730	3,113	1.62	12.91	7.96

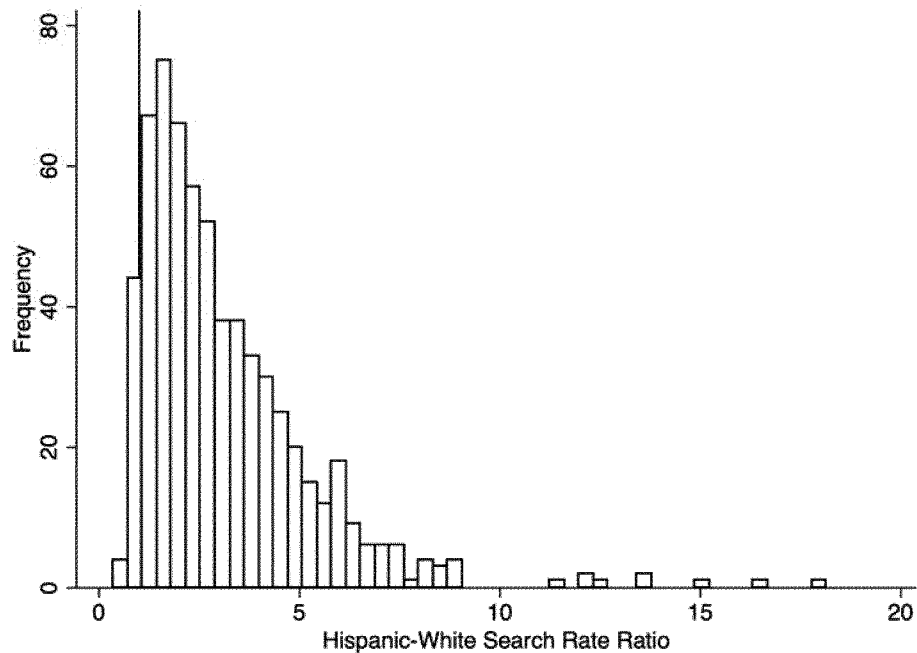
Whereas Carol Stream, IL searched extremely high proportions of drivers in 2006, it did so at high rates for all three racial / ethnic groups (e.g., search rates of 50, 53, and 57 percent for whites, blacks, and Hispanics respectively). Such uniformly high search rates generate search rate ratios of just 1.06 and 1.14, below average. So search rate ratios tell us something quite different from search rates, which are interesting and important in their own right. They tell us the degree to which minority drivers are targeted for search, over and above the degree to which white drivers are subject to search.

Evanston Police Department has the highest black-white search rate ratio. On average, in some years, they search blacks about seven times the rate that they search white drivers. They have the highest disparity for three years: 2009, 2010, and 2013. For the entire 2009-2014 range, Evanston PD places in the top ten outliers, with black-white search rate ratios ranging from about six to seven. The Chicago Police Department from 2008-2010 displays a similar disparity, with black-white search rate ratios that range from a little over six to a little over seven. The top ten outliers are all agencies from Illinois.

E. Hispanic-White Search Rate Ratios

Figure 6 reports the distribution of the Hispanic-white search rate ratio across every agency-year. It displays a similar trend to that of the black-white search rate ratio. The average search rate ratio is about 3.14, as compared to 2.51 in Figure 5 for the black-white comparison. Thus Hispanics, on average, are 3.14 times as likely to be searched as whites. This rate ratio ranges from 0 to 18.14, and the outliers are reported in Tables 12 and 13. This maximum, a search rate ratio of 18.14, is more than double the maximum black-white search rate ratio.

Figure 6: Hispanic-White Search Rate Ratios



Note: N = 642, Min = 0.48, Mean = 3.16, Max = 18.14. Below or equal to 1.0: 35; above 1.0: 607. Includes only agencies with at least 10,000 total stops, 100 white stops, 100 black stops, and 100 Hispanic stops

Agencies that are less likely to search Hispanics are predominately from Maryland and North Carolina. For example, officers from the Mooresville, NC Police Department are more than twice as likely to search white drivers as they are Hispanics; Figure 6 shows that 35 agencies have search rate ratios below 1.0, indicating that Hispanic drivers are less likely to be searched than whites. On the other hand, Table 13 shows that, once again, Illinois police agencies appear to have highly targeted practices of searching minorities. The Cook County Sheriff in Illinois has the four highest disparity scores, for the years 2008-2011, with Hispanics 18 times as likely as whites to be searched, in 2009. The Palatine, IL Police Department follows Cook County with high search rate ratios. From 2008 to 2011, the Palatine Police Department had a search rate ratio that ranges from about 12 to 13 percent. Evanston, IL and the Dupage County, IL Sheriff round out the top 10 high disparity agencies.

Table 12: Hispanic-White Search Rate Ratios, 10 Lowest Values							
State	Agency	Year	White Stops	Hispanic Stops	White Search Rate	Hispanic Search Rate	H-W Search Rate Ratio
NC	Mooreville PD	2013	8,098	823	2.54	1.22	0.48
MD	Frederick	2014	9,049	467	5.02	3.21	0.64
NC	Guilford County Sheriff	2013	4,868	824	5.55	3.64	0.66
NC	Guilford County Sheriff	2014	4,957	820	5.57	3.90	0.70
MD	Harford	2016	7,699	329	4.05	3.04	0.75
MD	Frederick	2015	10,804	639	3.67	2.82	0.77
MD	State Police	2016	93,652	10,322	1.86	1.45	0.78
NC	Wilmington PD	2015	10,252	540	3.27	2.59	0.79
NC	Winston-Salem PD	2011	17,488	4,838	1.77	1.41	0.80
IL	Bolingbrook PD	2014	7,259	3,408	1.23	1.00	0.81

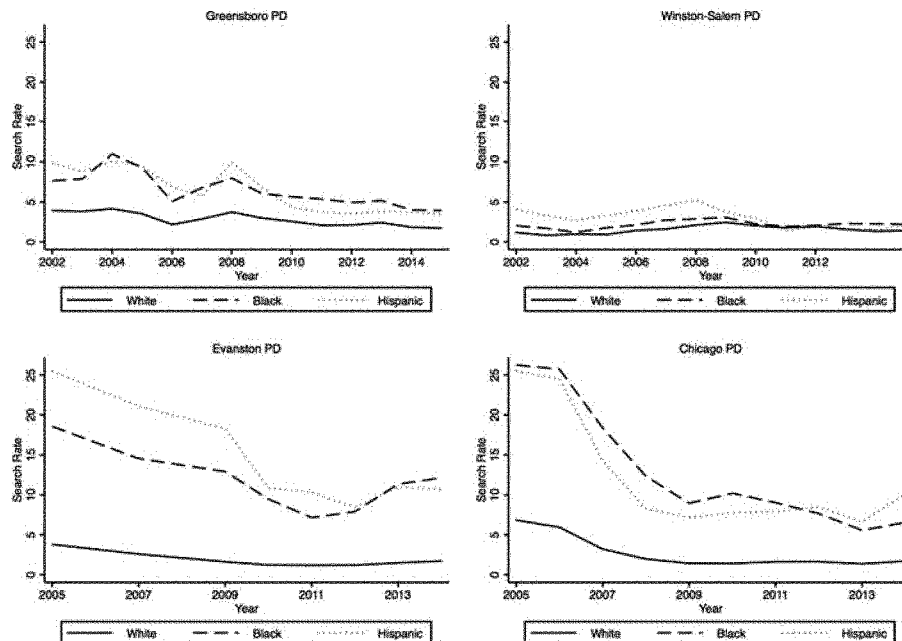
Table 13: Hispanic-White Search Rate Ratios, High Outliers							
State	Agency	Year	White Stops	Hispanic Stops	White Search Rate	Hispanic Search Rate	H-W Search Rate Ratio
IL	Dupage Co. Sheriff	2012	8,473	1,346	0.33	2.97	8.99
IL	Evanston PD	2009	5,730	990	1.62	18.28	11.26
IL	Palatine PD	2009	8,737	647	0.88	10.82	12.28
IL	Palatine PD	2010	10,584	827	1.04	12.82	12.33
IL	Palatine PD	2011	9,734	891	1.06	13.24	12.52
IL	Palatine PD	2008	9,487	689	1.12	15.09	13.51
IL	Cook County Sheriff	2011	11,020	3,823	0.27	3.71	13.64
IL	Cook County Sheriff	2010	15,704	4,222	0.19	2.89	15.13
IL	Cook County Sheriff	2008	10,764	2,894	0.29	4.73	16.44
IL	Cook County Sheriff	2009	13,530	3,537	0.23	4.16	18.14

Analyzing the search rates and search rate ratios, it appears that the vast majority of agencies in our dataset search blacks and Hispanics at higher rates than whites. Hispanics exhibit even higher disparities, as they are on average about three times as likely to be searched as whites. Blacks were about two and a half times as likely as whites to be searched on average. It also appears that the search rate ratio for Hispanics spans a greater range, and even reaches about 18 for some agency-years.

The Chicago Police Department and the Evanston Police Department both

stood out as outliers, with high black-white search rate ratios, indicating greater disparities between white and black search rates. In order to obtain a better picture of the traffic stop disparities for those two agencies, Figure 7 plots their search rates for whites, blacks, and Hispanics over time. These are plotted in comparison with the Winston-Salem NC Police Department, which exhibits fairly low search rates, and the Greensboro NC Police Departments, which exhibits fairly average search rates.

Figure 7: White, Black, and Hispanic Search Rates over Time for Four Police Departments



The Chicago and Evanston Police Department both show high search rates for blacks and Hispanics, especially during the time period of 2005 through about 2010. After 2010, the rates settle at about the average for all departments, around eight percent. Of course, this average is still significantly higher than the average search rates for white drivers, which is about three percent. However, both Chicago and Evanston show an uptick in black and Hispanic search rates around 2013. Over time, both departments have fairly average to low search rates for whites, which are typically around three percent overall.

So, as expected, racial disparities in traffic stops are widespread. They exist in Southern, conservative states, but also in Northern states. In fact, Illinois stands out as having by far the largest disparities. We would further note that these disparities tend to be extremely large. Some level of disparity is to be expected and perhaps inevitable (it would be remarkable if every agency had a search rate ratio of exactly 1). But what we document goes well beyond marginal fluctuations around racially equitable searching. Rather, we find a profound divergence in

police behavior that appears to hinge on race, with people of color being subjected to a much higher degree of scrutiny than their white counterparts.

III. A MULTIVARIATE ANALYSIS

As a measure of disparity, the search rate ratio has a number of advantages. Chiefly, it is simple to calculate and interpret. Most important, it requires only three pieces of information: the number of stops, the number of searches, and racial demographic indicators. As traffic stop data is often scarce, these are important qualities. However, there are concerns that the search rate ratio may be oversimplified and mistakenly identify race as the crucial factor driving disparities when in fact race is of secondary importance and that certain driving behaviors, which may co-vary with race, do a better job of explaining search disparities. For example, perhaps people of color are more likely to drive run-down cars, or more likely to drive at night, or more likely to break traffic laws. These behaviors may make a search more likely for both white and black drivers, but if people of color were more likely to engage in them, then they would experience higher search rates on average, but that disparity would not be explained by race alone, but rather by different behaviors.

Fortunately, the micro-level data available for eight states allows us to investigate this possibility further because we can control for various factors (including race) in the context of a multivariate logistic regression. If, even after controlling for factors like gender, age, out-of-state license plates, and so forth, we still find that race is a statistically significant predictor of a search, then it would go a long way toward confirming that race itself is important. That is, that the search rate ratios we report in the previous section are a valid measure of racial disparities and not merely picking up some other type of disparity that might co-vary with race. In Table 14 we estimate a logistic regression for every state where we have micro-level data. This includes eight states. In each state, we present the fullest model that the available data allow. In general, the models take this form:

$$\begin{aligned} \text{Probability of Search} = & \text{White Male} + \text{Black Male} + \text{Black Female} + \\ & \text{Hispanic Male} + \text{Hispanic Female} + \text{Driver Age} + \text{Stop Purpose} + \\ & \text{Out of State} + \text{Black Disparity Officer} + \text{Hispanic Disparity Officer} \\ & + \text{Vehicle Age} + \text{Hour of Day} + \text{Day of Week} + \text{Error.} \end{aligned}$$

We start with dummy variables for each of six gender-race variables, with white females as the excluded category. This means that coefficients for the variables included in the table can be interpreted as showing the increased odds of search for a driver of that race and gender, as compared to the rate for a white female driver with the same other characteristics. We add driver age, measured in years. Stop purpose is measured in many different ways for the different states, so for consistency we distinguish between Investigatory stops (coded 1) and all others (coded 0). Investigatory stops are everything except speeding, stop sign / light violations, and driving while intoxicated, and therefore include a wide variety of equipment, registration and other factors. If minority drivers are more often pulled over because of expired tags, this variable should capture that effect, leaving the race and gender variables above to show the remaining effect once this has been accounted for. Some states allow us to give an indicator variable for out

of state plates, also sometimes seen as an indicator of a drug courier profile. We define Black Disparity Officer and Hispanic Disparity Officer as an individual police officer whose pattern of traffic stops and searches includes: (A) have more than 50 white and 50 minority stops, (B) search drivers at a rate higher than the agency mean, and (C) search minorities at twice the rate they search white drivers. This allows us to control for the “bad apple” hypothesis, again leaving the race and gender variables to show the remaining effect, once this has been accounted for. The standard model includes a variable for vehicle age, measured in years. If minorities drive older cars on average, then this is again accounted for here. Finally we control for the day of the week and the hour of the day. Practically speaking, day of week makes little difference, but search rates vary dramatically depending on the hour of the day, as one might expect. Controlling for these factors allows us to interpret the race and gender variables with confidence that they are not proxies for something else not included in the model.

Our model for Florida is slightly different because of what data are available. We do not have a gender variable for Florida, so we combine men and women and leave white drivers as the reference category with indicator variables for black and Hispanic drivers. Florida allows us to look at officer demographics, so we use white officers as the reference category and control for whether the driver was stopped by a black or a Hispanic officer. The state also makes available a variable indicating years of experience of the officer, and we control for that in the Florida model. Table 14 presents the results.

Reading across the rows of the table, we can see consistent patterns across the states. Compared to white female drivers (not shown in the table, as they constitute the baseline), white male drivers are 40 percent more likely to be searched in Connecticut, 136 percent more likely in Maryland, 55 percent more likely in Texas, and so on. Note that to interpret an odds-ratio, one can say that 1.00 reflects equality and 1.10 would reflect a ten percent increased likelihood, or 1.10 times the likelihood. An odds-ratio of 0.88 would reflect a 0.88 likelihood or a 12 percent decreased likelihood. Black male drivers have odds-ratios of 3.2, 3.6, 2.9, 2.1, 2.0, and 5.8, across the different states. Black female drivers face much lower likelihoods. Hispanic males have very high likelihoods.

Age systematically reduces the likelihood of stop in each state where we can test for it. Investigatory stops increase the likelihood of search in every state but one, as expected. Out-of-state plates reduce search likelihood in Connecticut but increase it in Maryland and Texas. High disparity officers dramatically increase the likelihood of search in every case but one. Controlling for this variable is an important way to ensure that the patterns we see for race and gender higher in the table are not due only to these high-disparity officers, which constitute a minority of all officers.

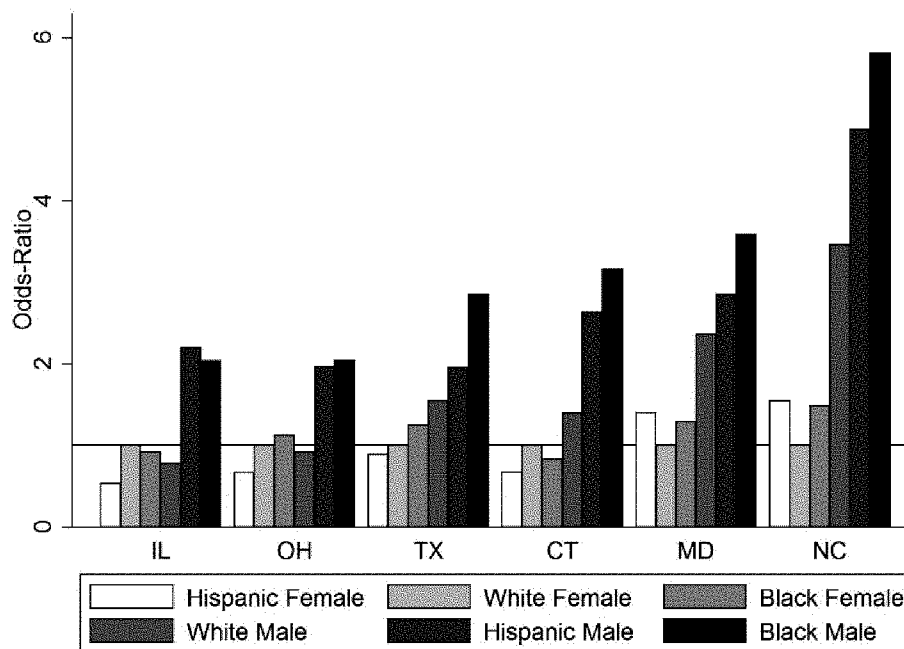
Our model for Florida is by necessity slightly different, as we cannot control for driver gender, but can control for certain other elements relating to the demographics of the state trooper. Black drivers are much more likely (2.69 times as likely) to be searched, as are Hispanic drivers (1.90 times as likely). Trooper characteristics that increase search likelihood include: male, white, Hispanic and high seniority.

Table 14. Logistic Regressions Predicting Search

[illegible]

Table 14. Logistic Regressions Predicting Search							
Pseudo R2	0.10	0.08	0.06	0.13	0.12	0.09	0.10
Notes: Entries are logistic odds-ratios, with standard errors in parentheses. * $p < .05$. These models exclude those drivers who are not Black, White, or Hispanic, as well as those pulled over for other stop purposes beyond safety or investigatory. We exclude the Vermont State Patrol from this table because of a relatively low N (51,664) and few minority drivers.							

Figure 8. Relative Likelihood of Search by Race and Gender



Note: See Table 14 for exact odds-ratios. Likelihoods are expressed in relation to the white female search rate, defined as 1.00.

Figure 8 illustrates the findings from Table 14 by showing the relative likelihood of search for different race and gender categories, compared to white females.

This makes very clear that gender and race go a long way in determining search rates, and that these factors are consistent, though varying in degree, across the states reviewed. Women have relatively low, and relatively equal, rates of search compared to men. White men have rates of search similar to or even lower than women in Connecticut, Illinois, and Ohio. Hispanic men have higher rates in every state, and the highest rate of all categories in Illinois. Black men consistently have the highest rate of search in every state except Illinois, where their rate of search is nearly equal to that of Hispanic men, and three times higher than that of white men. The states are ordered in the Figure by the black male odds-ratio, putting North Carolina and Maryland far to the right. Note that Illinois shows lower disparities than might be expected given the analysis above because here

our reference category is white females. White males in Illinois have lower search rates even than females, but black and Hispanic males have much higher rates. The figure illustrates both the gender difference, apparently much higher in Maryland and North Carolina, and the racial difference among men, present in each state.

In all, the evidence suggests that racial disparities in traffic stops are extremely robust. Moreover, the levels of disparity indicated by the logistic regressions are very similar to those suggested by the search rate ratios. The use of more rigorous statistical techniques does nothing to change the nature of our findings, and simply serves to reinforce the stark racial differences we reported in the previous section.

IV. CONCLUSION

American law enforcement is in a state of crisis as city after city have seen protests about allegations of racially biased policing and headlines have brought examples of police shootings into the living rooms of all Americans.³⁵ Our paper is a first step in addressing the question of whether the large databases that states have mandated to be collected can be of use in assessing the degree to which citizens of different demographic groups are subjected to different experiences in their interactions with the police. Indeed, they are. We focus on perhaps the most routine, and certainly the most common, police-citizen interaction: the routine traffic stop. Such encounters typically result in a citation or a warning. However, about three percent of them lead the officer to search the driver's vehicle. That rate, three percent, differs systematically depending on the circumstances. State highway patrol departments search less; police departments search more. Some individual departments search all drivers much more than others, following a much more aggressive policing posture than other departments. Search rates vary over time for any individual department. But the most politically and legally relevant point of variation in search rates is the demographic characteristic of the driver. With over 649 annual observations in more than a dozen states, we show huge variability by the race of the driver, with Hispanic and black drivers searched, *on average*, at more than double the rate of whites. In our multivariate analysis, we control for possible rival hypotheses such as the purpose of the stop, and we show consistent and dramatic racial disparities. Such findings suggest that public concern for racially disparate policing deserves more attention and that the suspicions that led various states to adopt data collection efforts were indeed very well founded. We hope that this research project, as it grows, will not only document these dramatic disparities, but move to explaining them so that reforms can be put in place to reduce them.

³⁵ See, e.g., *Ferguson unrest: From Shooting to Nationwide Protests*, BBC (Aug. 10, 2014), <http://www.bbc.com/news/world-us-canada-30193354>.

V. APPENDIX: DESCRIPTIVE STATISTICS.

For each of the states included in Table 14, we provide here descriptive statistics on the variables and an explanation of the number of cases included. Starting with the raw data we received from each respective state or agency, our analysis excludes the following types of observations: a) those from years where the full 12 months of data were not reported (if any); b) stop purposes other than safety or investigatory (for example, arrest warrants); c) race other than white, black, or Hispanic (for example, Asian, Native American, or “other”); or d) missing or obviously erroneous data on any other variable (for example, miscoded data showing age as 255 years, time or date variables of incorrect format, etc.). For each state, we provide first a table that shows the initial N, the number of cases dropped for each reason, and the final N available for analysis. (Note that because the same traffic stop could be excluded for more than one reason, the total number of cases dropped is typically lower than the sum of the cases dropped for each individual reason.) The second table for each state below gives summary statistics for each variable included in Table 14.

Connecticut

Table CT1: Excluded Observations in the Connecticut Dataset

Variable		Count
Initial N		595,967
Excluded Stop Type(s)	95,766	
Other Race	46,952	
Missing Some or All Information	576	
Total Number of Cases Dropped		134,391
N for Analysis		461,576

Table CT2: Summary Statistics of Observations Included in Connecticut Dataset

Variable	N	Mean	Std. Dev.	Min	Max
Driver Characteristics					
White Male	595,967	0.43	0.50	0	1
White Female	595,967	0.24	0.43	0	1
Black Male	595,967	0.08	0.28	0	1
Black Female	595,967	0.04	0.20	0	1
Hispanic Male	595,967	0.08	0.27	0	1
Hispanic Female	594,535	0.24	0.43	0	1
Age	595,967	38.36	14.65	16	100
Out of State	595,950	0.13	0.33	0	1

Variable	N	Mean	Std. Dev.	Min	Max
Stop Type					
Investigatory Stop	500,201	0.28	0.45	0	1
Safety Stop	500,201	0.72	0.45	0	1
Officer Characteristics					
Black Disparity Officer	595,967	0.06	0.24	0	1
Hispanic Disparity Officer	595,967	0.05	0.22	0	1

Maryland

Table MD1: Excluded Observations in Maryland Dataset

Variable	Count
Initial N	2,854,963
Excluded Stop Type(s)	503,435
Other Race	186,245
Missing Some or All Information	15,434
Total Number of Cases Dropped	674,927
N for Analysis	2,180,036

Table MD2: Summary Statistics of Observations Included in Maryland Dataset

Variable	N	Mean	Std. Dev.	Min	Max
Driver Characteristics					
White Male	2,851,373	0.31	0.46	0	1
White Female	2,851,373	0.19	0.39	0	1
Black Male	2,851,373	0.22	0.42	0	1
Black Female	2,851,373	0.14	0.34	0	1
Hispanic Male	2,851,373	0.06	0.24	0	1
Hispanic Female	2,851,373	0.19	0.39	0	1
Age	2,851,373	38.61	14.57	16	100
Out of State	2,840,117	0.15	0.36	0	1
Stop Type					
Investigatory Stop	2,351,528	0.46	0.50	0	1
Safety Stop	2,351,528	0.54	0.50	0	1
Officer Characteristics					
Black Disparity Officer	2,854,963	0.06	0.24	0	1
Hispanic Disparity Officer	2,854,963	0.02	0.15	0	1

Texas

Table TX1: Excluded Observations in Texas Dataset

Variable	Count
Initial N	10,910,267
Other Race	887,830
Missing Some or All Information	677,640
Total Number of Cases Dropped	1,565,470
N for Analysis	9,344,797

Table TX2: Summary Statistics of Observations Included in Texas Dataset

Variable	N	Mean	Std. Dev.	Min	Max
Driver Characteristics					
White Male	10,910,267	0.44	0.50	0	1
White Female	10,910,267	0.23	0.42	0	1
Black Male	10,910,267	0.07	0.25	0	1
Black Female	10,910,267	0.03	0.18	0	1
Hispanic Male	10,910,267	0.11	0.31	0	1
Hispanic Female	10,910,267	0.23	0.42	0	1
Vehicle Age	10,236,349	8.27	5.60	0	59
Out of State	10,808,145	0.11	0.31	0	1
Officer Characteristics					
Black Disparity Officer	10,910,267	0.11	0.31	0	1
Hispanic Disparity Officer	10,910,267	0.09	0.28	0	1

Ohio

Table OH1: Excluded Observations in Ohio Dataset

Variable	Count
Initial N	5,201,818
Other Race	545,893
Missing Some or All Information	554
Total Number of Cases Dropped	546,447
N for Analysis	4,655,371

Table OH2: Summary Statistics of Observations Included in Ohio Dataset

Variable	N	Mean	Std. Dev.	Min	Max
Driver Characteristics					
White Male	5,201,818	0.51	0.50	0	1
White Female	5,201,818	0.25	0.43	0	1

Variable	N	Mean	Std. Dev.	Min	Max
Black Male	5,201,818	0.08	0.27	0	1
Black Female	5,201,818	0.04	0.19	0	1
Hispanic Male	5,201,818	0.02	0.12	0	1
Hispanic Female	5,201,818	0.25	0.43	0	1
Officer Characteristics					
Black Disparity Officer	5,201,818	0.15	0.36	0	1
Hispanic Disparity Officer	5,201,818	0.09	0.28	0	1

Florida

Table FL1: Excluded Observations in Florida Dataset

Variable	Count
Initial N	1,048,575
Excluded Stop Type(s)	155,535
Other Race	37,345
Missing Some or All Information	80,113
Total Number of Cases Dropped	269,728
N for Analysis	778,847

Table FL2: Summary Statistics of Observations Included in Florida Dataset

Variable	N	Mean	Std. Dev.	Min	Max
Driver Characteristics					
Black	1,048,575	0.21	0.41	0	1
Hispanic	1,048,575	0.21	0.41	0	1
Stop Type					
Investigatory Stop	893,040	0.21	0.41	0	1
Safety Stop	893,040	0.79	0.41	0	1
Officer Characteristics					
Black Disparity Officer	1,048,575	0.08	0.26	0	1
Hispanic Disparity Officer	1,048,575	0.04	0.19	0	1
Male Officer	941,518	0.93	0.26	0	1
White Officer	1,048,575	0.56	0.50	0	1
Black Officer	1,048,575	0.13	0.34	0	1
Hispanic Officer	1,048,575	0.07	0.27	0	1
Officer Experience	1,042,299	5.63	7.77	0	60

Illinois

Table IL1: Excluded Observations in Illinois Dataset

Variable	Count
Initial N	22,405,714
Excluded Stop Type(s)	95,089
Other Race	749,564
Missing Some or All Information	4,450,040
Total Number of Cases Dropped	5,292,625
N for Analysis	17,113,089

Table IL2: Summary Statistics of the Observations Included in Illinois Dataset

Variable	N	Mean	Std. Dev.	Min	Max
Driver Characteristics					
White Male	22,405,714	0.42	0.49	0	1
White Female	22,405,714	0.24	0.43	0	1
Black Male	22,405,714	0.11	0.32	0	1
Black Female	22,405,714	0.07	0.25	0	1
Hispanic Male	22,405,714	0.09	0.29	0	1
Hispanic Female	22,002,394	0.24	0.43	0	1
Age	22,405,714	35.65	14.18	16	100
Vehicle Age	22,338,015	9.17	5.65	0	59
Stop Type					
Investigatory Stop	22,310,078	0.29	0.45	0	1
Safety Stop	22,310,728	0.71	0.45	0	1

North Carolina

Table NC1: Excluded Observations in North Carolina Dataset

Variable	Count
Initial N	22,405,714
Passengers	328,699
Excluded Stop Type(s)	248,999
Other Race	659,751
Missing Some or All Information	406,308
Total Number of Cases Dropped	4,094,044
N for Analysis	18,311,670

Table NC2: Summary Statistics of Observations Included in North Carolina Dataset

Variable	N	Mean	Std. Dev.	Min	Max
Driver Characteristics					
White Male	18,907,277	0.41	0.49	0	1
White Female	18,907,277	0.22	0.42	0	1
Black Male	18,907,277	0.19	0.39	0	1
Black Female	18,907,277	0.12	0.32	0	1
Hispanic Male	18,907,277	0.05	0.21	0	1
Hispanic Female	18,907,260	0.22	0.42	0	1
Age	18,907,277	35.11	13.60	16	100
Stop Type					
Investigatory Stop	18,907,277	0.44	0.50	0	1
Safety Stop	18,907,277	0.56	0.50	0	1
Officer Characteristics					
Black Disparity Officer	18,907,277	0.06	0.24	0	1
Hispanic Disparity Officer	18,907,277	0.05	0.22	0	1

