A Few Bad Apples?
Racial Bias in Policing*

Felipe Goncalves Steven Mello †

July 12, 2017

Abstract

We provide new evidence on the presence and distribution of racial bias in the criminal justice system using administrative data on traffic enforcement and a bunching estimation design. In many states, the punishment for speeding increases discontinuously with the speed of the driver, exhibiting large jumps in fine amounts. It is a common practice for officers to reduce the charged speed to just below this jump, avoiding an onerous punishment for the driver. Using data from the Florida Highway Patrol, we find evidence of significant bunching in ticketed speeds below a jump in punishment for all drivers but significantly more for whites than for blacks and Hispanics. We show that the bunching is reflective of officer discretion rather than driver speed choice and that the disparity is robust to all relevant controls. We further estimate the bias of each officer by comparing his lenience towards whites and non-whites, allowing us to recover the full distribution of bias. The total disparity in lenience across races can be explained by about 25% of officers.

JEL Classification: J71, K42
Keywords: Discrimination, Racial Bias, Police, Traffic Enforcement.

*We are grateful to Ilyana Kuziemko and Alex Mas for guidance and support throughout this project. We benefitted from helpful comments by Peter Bergman, Leah Boustan, Jessica Brown, Nicholas Buchholz, Janet Currie, Rebecca Diamond, Will Dobbie, Nik Engbom, Kirill Evdokimov, Hank Farber, Jeremy Fox, Nathaniel Hendren, Daniel Herbst, Bo Honoré, Andrew Langan, Neale Mahoney, Michael Makowsky, Christopher Neilson, Jakob Schlokermann, and participants of the Princeton Labor Lunch, Public Finance Working Group, Center for Health and Wellbeing Working Group, and the Hamilton-Colgate Economics Seminar. We thank Beth Allman, Jeffrey Bissainthe, Kiara Guzzo, Wilton Johnson, Timothy Kutta, Stacy Lehmann, and Brenda Paige for assistance with data from various agencies. The Industrial Relations Section, Princeton University, provided generous financial support. Any errors are our own.

†Industrial Relations Section, Princeton University, Princeton, NJ 08544. Goncalves: fmg@princeton.edu. Mello: smello@princeton.edu

1 Introduction

There are large racial disparities in criminal justice outcomes in the United States. Blacks and Hispanics are significantly more likely to be stopped, arrested, and imprisoned than whites (Walker *et al.*, 2012). A central question in research on the criminal justice system is whether the disparate outcomes of minorities are due to discrimination on the part of criminal justice agents or instead reflect underlying differences in criminality across racial groups. The view that bias is responsible has gained traction in recent years following several highly publicized police killings of minorities (West, 2015). For example, a 2013 Gallup poll revealed that half of black adults agreed that racial differences in incarceration rates are "mostly due to discrimination," while only 19% of white respondents agreed.[1]

The existence of racial bias in the criminal justice system is, however, difficult to establish empirically. Demonstrating conclusively that individuals of different races receive different treatment requires controlling for all relevant contextual factors across incidents, which is generally not possible. It is an even greater challenge to pinpoint whether bias is a widespread phenomenon or concentrated among a small group of agents, and knowing so is crucial for understand the optimal policy for mitigating its harm.

In this paper, we use a bunching methodology to estimate the distribution of racial bias across criminal justice agents. Specifically, we examine whether police officers discriminate when setting punishments for speeding. Traffic stops are the most common form of civilian-police interaction, with about 41 million speeding tickets given and over $6B in fines paid annually.[2] Although officers typically observe a driver's speed via radar before stopping them, they are free to choose what speed to *charge*. In many states, the punishment for speeding increases discontinuously with the speed of the driver, exhibiting "jumps" in harshness. A jump may involve not only a higher fine, but also a mandated court appearance or permanent mark on the driver's record. As shown in Figure 1, the distribution of speeds ticketed by the Florida Highway Patrol between 2005 and 2015 shows substantial excess mass at speeds just below the first fine increase. Meanwhile, a remarkably small portion of tickets are issued for speeds just above. We take this bunching

[1] See http://www.gallup.com/poll/175088/gallup-review-black-white-attitudes-toward-police.aspx.

[2] National Highway Traffic Safety Administration (2014). For reference, there were about 13.1 million arrests made in the U.S. in 2010, according to the FBI.

as compelling evidence that officers systematically manipulate the charged speed, commonly charging speeds just below fine increases after observing a higher speed, perhaps to avoid an onerous punishment for the driver.[3] We also find that a substantial portion of officers throughout the entire state exhibit no such bunching (Figure 2), suggesting that the aggregate bunching reflects officer discretion rather than drivers choosing to bunch below a fine.

By studying officers' choice to discount a speeding ticket, this paper makes four contributions. First, we document the presence of racial bias in officers discounting. We show that this bias is robust to accounting for all relevant contextual factors, including past driving history, and persists after accounting for racial differences in true speed. Second, and most importantly, we generate officer-level estimates of lenience and bias by comparing each officer's behavior towards whites and non-whites. We find that 25% of officers are biased against black and Hispanic drivers and reject that this number is greater than 30% of officers. Third, we correlate these estimates to officer demographics and show that officers tend to favor their own race, older officers are more racially biased, and women and college educated officers are less biased on average. We show that officers who are more lenient in general are less likely to receive complaints or use force on the job. Officers who are more biased against minorities seem to use more force, though standard errors are too large to say conclusively. Fourth, we explicitly model each officer's decision process, accounting for potential racial differences in speed, allowing us to perform various counterfactuals and evaluate which personnel policies may be useful for ameliorating the treatment gap. Directly firing biased officers and hiring more women and minorities reduces the gap, but not substantially. More effective is to re-assign the most lenient officers to heavily-minority areas.

Figure 3 presents the speed histograms, broken down by race, and clearly shows a smaller mass of minorities charged at the bunch speed. These racial disparities remain after controlling for an array of stop and driver-level characteristics, including speed limit and stop location, age, gender, vehicle type, ZIP code income level, and prior tickets, which we treat as evidence that, on average, officers behave less favorably towards minority drivers.

Our paper is not the first to provide a method to identify and document racial bias

[3] Past researchers have termed this phenomenon *speed discounting* (Anbarci and Lee, 2014).

in policing.[4] The central contribution of our paper is to further provide an estimate of the bias of *each individual officer*. Specifically, we compute an officer's lenience towards minorities relative to his own treatment of white drivers, adjusting for other features of the stop, and treat the difference as the officer's bias. While previous papers have dealt with identifying specific biased officers using comparisons with nearby officers,[5] our approach is the first to provide an absolute measure of lenience and bias, allowing us to identify each officer's bias. This exercise reveals that the majority of officers exhibit no bias, with the aggregate disparity in treatment explained by the behavior of a small minority of officers comprising about 25% of the patrol force. The difference in bias across officers cannot be fully explained by differences in overall lenience or location. We also explore how bias varies with officer-level characteristics, documenting that officers exhibit own-race preferences and that younger, female, and college-educated officers are less likely to be biased.

The rest of the paper takes advantage of our officer-level measures of lenience and bias with two applications. First, we show that, by using our measures of lenience, we can improve current predictions of which officers will use force and receive civilian complaints. While distinct concepts, racial bias and use of force by police are often linked in the popular media when discussing police misconduct, and minority communities are most likely to complain of police maltreatment (Weitzer and Tuch, 2004). We find that officers who are more lenient to all drivers are significantly less likely to receive a civilian complaint or use force while on the job. While bias against minority drivers is positively related to both complaints and use of force, standard errors are too large establish a conclusive relationship. Using a simple linear model to predict force, replacing the bottom 10% of officers most likely to use force with an average officer reduces overall complaints by 10%, relative to a 4.4% reduction when the linear predictor does not include lenience or bias.

The second application of our method is to consider various personnel policies that could be used to reduce the aggregate disparity in treatment. Knowing the distribution of bias across officers is crucial for understanding which policies can ameliorate bias. If

[4] See Persico (2009) for a review of the literature on detecting discrimination.

[5] Ridgeway and MacDonald (2010) provide an overview of the various *benchmarking* methods that have been developed to identify problem officers.

only a few officers ticket in a racially disparate manner, then firing or relocating them to predominantly white areas may be the appropriate policy. If bias is widespread, personnel policies targeting specific individuals will be much less effective, and instead the more effective policy may be a widespread training program.

To perform these counterfactuals, we estimate a simple model of officer ticketing behavior. Given a stop with an observed speed above the fine increase point, we suppose the officer charges either the true speed or the bunching speed as a function of both the true speed and his taste for the driver. The officer bears a larger cost to discounting a driver the higher his speed above the discount point. Using maximum likelihood, we estimate the speeds of drivers by race and county and the preferences of each officer for each race. Although we impose functional forms on officers' taste shocks and the underlying speed distributions to simplify the estimation, we again allow for a fully nonparametric distribution of racial bias. This model also allows us to explicitly account for differences in speeds across races, a plausible alternative to bias as the cause for differences in treatment.

The model estimates imply that when stopped by the average officer, minority drivers receive a fine reduction at the same rate as white drivers traveling four MPH faster. Surprisingly, forcing all officers to treat minority drivers as they treat white drivers removes only 33% of the gap in the probability of receiving a fine reduction and 16% of the gap in charged speed. The majority of the disparity is due to the fact that the most lenient officers patrol in counties with the fewest minorities – 47% of the white-nonwhite speed gap disappears without bias or sorting of officers across counties; the remainder is due to differences in driven speed. By construction, all of the disparity in discount treatment vanishes in the absence of racial bias and officer sorting. Without any difference in treatment, the white-minority speed gap reduces from 2.1 MPH to 1.1 MPH, suggesting that the majority of the difference in ticketed speeds is due to true differences in speeding. This finding confirms the conclusion found in other papers that minorities do drive faster [Smith *et al.* (2004), Lange *et al.* (2005)], but modifies their conclusions by demonstrating how racial bias is not ruled out by differences in speeds.

Performing the counterfactuals discussed above, we find that policies targeting bias directly are only mildly effective at reducing the treatment gap. Firing the most biased officers (both for and against minorities) reduces the gap, as does increasing the presence of minority or female officers, but the gains are limited. Imposing either minimum or maximum levels of *lenience* can substantially reduce bias with small requirements. Perhaps most effective and easily implemented, reassigning officers across counties within their troops so that minorities are exposed to more lenient officers can remove essentially the entire white-minority lenience gap.

We believe several features of our setting make it an ideal context for studying bias. When testing for discrimination in many criminal justice outcomes, a central concern is accounting for unobserved differences in criminality across individuals. In the context of speeding tickets, guilt is summarized by the driving speed, which is both one-dimensional and typically observed by the ticketing officer. Further, in many criminal justice contexts, lenience is relative, while in our setting officers make an explicit decision to reduce a driver's speed. Perhaps most importantly, we observe agents making many decisions in very similar contexts, which allows us to construct an accurate measure of bias for each officer by comparing his treatment of nonwhites and whites.

This paper falls in a broad category of recent research using "bunching" estimators to recover behavioral parameters. Predominantly used in the literature on taxation, these studies attempt to estimate the hypothetical distribution of interest in the absence of bunching by looking at the distribution outside of a region around the manipulated area and inferring out-of-sample how the distribution should look at the discontinuity.[6] They then estimate bunching to be the difference between the true and hypothetical distribution around the bunch point. Relative to the existing bunching methodology, our modeling section innovates by exploiting the heterogeneity in behavior across officers around the bunch point. Because a significant share of officers practice no lenience, we can use these officers to estimate the true distribution of ticketed speeds across racial groups.

Our study is not the first to examine the practice of speed discounting by traffic officers. Anbarci and Lee (2014) first document the phenomenon using citations from the Boston Police Department, showing that a significant proportion of tickets list 10 mph over the limit, right below a jump in charged fine. Utilizing a "rank order test" similar to Anwar and Fang (2006), Antonovics and Knight (2009), and Price and Wolfers (2010), they show that black and hispanic officers are relatively less harsh than white officers when ticketing minority drivers, suggesting that at least one race of officers is behaving in a racially discriminatory manner.

[6]See Kleven (2016) for a review of the bunching literature.

Our study departs from Anbarci and Lee (2014) in several respects. While their empirical strategy relies on comparisons across officer and driver race, our method constructs an officer-by-officer estimate of discrimination. This approach allows us to see the entire distribution of police preferences and determine how many officers account for the aggregate disparity, which to our knowledge has not been done before in a study of discrimination. Our data include a more expansive set of driver characteristics that may be correlated with driver race, including vehicle description and previous ticketing history, allowing us to rule out several alternative hypotheses for the observed disparities. We further use our estimates to determine what percentage of the overall racial speed gap can be explained by differential leniency and calculate the total annual cost of racial bias.

The rest of the paper is organized as follows. Section 2 provides some institutional background on the Florida Highway Patrol and describes the data. In Section 3, we present a basic conceptual framework. Section 4 describes our empirical strategy and we discuss the central results in Section 5. Section 6 uses our estimates to predict use of force and civilian complaints, and in Section 7 we present and estimate a model of officer behavior and perform counterfactuals. Section 8 concludes.

2 Institutional Background and Data

2.1 Institutions of the Florida Highway Patrol

State-level patrols are the primary enforcers of traffic laws on interstates and many highways. When on patrol, officers are given an assigned zone, within which they combine roving patrol and parked observation patrol. During the course of a traffic stop for speeding, officers have two primary ways to exercise discretion. They can give a written or verbal warning, which leads to no fine or points on the driver's license, or they can reduce the speed charged on the ticket. The Florida Highway Patrol officers are told explicitly in their training manuals that no enforcement actions during a traffic stop can be based upon any demographic characteristics, including race and gender.

In Florida, driving 10 MPH over the limit leads to about a $75 higher fine than at 9 MPH over.[7] While drivers receive points on their license for speeding, tickets received for

[7]The actual fine schedule depends on the county in Florida, though the jump point is the same across all counties and always includes at least a $50 jump in fine.

9 and 10 MPH over the limit carry the same number of license points. While it is common to find a jump in fine between 19 and 20 MPH over as well, the data strongly suggest that officers prefer to reduce the ticket to 9 MPH over.

2.2 Data

From the Florida Court Clerks and Comptrollers, we obtained data on traffic citations issued by the Florida Highway Patrol (FHP) for the years 2005-2015. These data include all information provided on the stopped motorist's driver's license – name, address, race, gender, height, date of birth, as well as driver's license state and number. The make, model, and year of the stopped automobile is provided, but this information is recorded inconsistently. In the final sample of citations, 69% of tickets list the vehicle make and year. The citing officer is identified by name, rank, troop number, and badge number.[8]

To supplement the citations data, we obtained officer demographic information from the Florida Department of Law Enforcement (FDLE). These data include officer race, sex, age, education level, and Florida law enforcement employment history of all law enforcement officers employed in the state of Florida. It further includes every misconduct investigation made by the state against an officer, recording the type of alleged violation and the ultimate verdict of the state.

We restrict the sample to citations where the main offense is speeding, no accident is reported, and the cited speed is between zero and 40 above the posted speed. To link the citations and officer information, we first narrowed the list of FDLE personnel to include only officers with an employment spell as a sworn officer with the FHP covering some portion of the 2005-2015 period. We then match the list of candidate officers with the citations data using the officer name. We exclude stops that cannot be matched to an officer. Lastly we restrict the sample to officers issuing at least 100 citations, with at least 20 given to minorities and 20 to whites. The final sample includes 1,123,934 citations issued by 1,334 officers. In the Appendix we include a table documenting the sample reduction from each restriction we make. In all of our analysis, we consider speed relative

[8]The full data from the FCC contain all traffic citations for 2005-2015, including tickets not given by the highway patrol. We use these tickets to measure an individual's previous driving record. We do not use non-FHP tickets in our measures of bias because officers are much harder to identify in these data. Further, many of the personnel information we collected is unique to the FHP.

to the speed limit (or posted speed) rather than absolute speed. We often refer to this quantity as *MPH Over* or simply as the speed. We do this so that each driver's speed is rescaled relative to a fine increase point, and after this rescaling, we can pool together citations issued in different speed limit zones.

While the citations record the driver race, there appear to be inconsistencies in the recording of Hispanic. For example, Miami-Dade County has less than 1% of their tickets issued to Hispanic drivers. To deal with this issue, we match the drivers' names to Census records, which record all names that appear more than 1,000 times and the share white, black, Hispanic, and other that carry that name. If an individual in our data has a name that is more than 80% Hispanic, we record them as such.

2.3 Summary Statistics

Table 1 presents summary statistics for the sample, broken out by driver race. 70% of drivers are white, 20% are black, and about 10% are Hispanic. Drivers are 35% female and about 36 years old on average, with Hispanics less likely to be female and minority drivers typically younger. In-state drivers account for 84% of tickets, and the average driver has been cited about 0.04 times in the past year. On average, minority drivers are charged with higher speeds than whites, just over one MPH higher for blacks and almost three MPH higher for Hispanics.

In Table 2, we compare the racial distributions of speeding tickets with the racial distribution of residents and drivers in Florida using the 2006-2010 American Community Survey 1% samples.[9] These data demonstrate that whites account for about 62.5% of Florida's population and 60% of its drivers (an ACS respondent is considered a driver if they indicate that they drive to work), while representing about 58% of tickets. Blacks represent around 14% of the population and driving population, but 18% of tickets. Similarly, Hispanics are 20% of the population, almost 22% of the driving population, and 24% of tickets. In columns 4 and 5, we present the racial distribution of black, white, and Hispanic drivers involved in crashes and crashes with injuries over the 2006-2010 period. These shares are computed from records provided by the Florida Division of

[9] We obtained these data from IPUMS. So that the samples are parallel, we use only citations from 2006-2010 and keep only white, black, or Hispanic individuals aged 16 or over in the ACS. We use sampling weights when computing the shares from the ACS data.

Motorist Services that contain information on all auto accidents known to police. Relative to the citations data, Hispanics are underrepresented in crashes, which may suggest that Hispanic drivers are targeted for citations relatively more often. Blacks are slightly overrepresented in crashes relative to citations, while the white shares in citations and serious crashes are nearly identical.

2.4 Evidence that Officers Use Discretion

As highlighted in the introduction, our study begins with the observation presented in Figure 1. 31% of tickets are written for exactly 9 MPH over the limit, just below a large fine increase. Less than one percent of tickets are for 8 MPH over, while just over 1% are written for exactly 10 over the limit. We posit that this bunching is due to systematic lenience, with officers choosing to reduce the charged speed, and therefore the fine faced by the driver, after observing a higher speed. In Figure 2, we present evidence for this theory. Panel A plots the officer-level distribution of lenience, defined as the share of tickets written for 9 MPH or above that are for exactly 9 MPH. A large share of officers appear to exhibit very little lenience. About 16% of officers write no tickets for exactly 9 over, while 30% write less than one percent of tickets for this bunching speed. While these numbers may seem too low even without discounting, they are consistent with how many tickets are charged for 8 and 10 MPH over, suggesting that it is rare to be ticketed for driving at speeds below 10 MPH over the limit.

Of course, this apparent dispersion in officer-level lenience could be due to differences in speeds and driver characteristics across patrol areas and shifts. To account for this possibility, we compute a residualized measure of officer-level lenience by regressing an indicator for a 9 MPH charge on year, month, day-of-week, posted speed, and county fixed effects, computing residuals, and averaging by officer. Panel B plots the officer-level distribution of these measures and demonstrates that substantial variation in lenience remains after adjusting for the time and location of stops.

We provide further evidence that lenience is an officer-level phenomenon by showing that an officer's residualized share of stops with a 9 MPH charge is highly correlated across time and space. Specifically, we residualize lenience using the same procedure as above and average at the officer $\times$ year level (Panel C) or officer $\times$ county level (Panel

D). In Panel C, we plot each officer's residualized lenience in his year with the second most stops (y-axis) against his residualized lenience in year with the most stops (x-axis). A strong correlation is evident – an officer who charges 9 MPH relatively more often in one year also does so in other years. In Panel D, we plot lenience in the county with the second most stops against lenience in the county with the most stops. The story here is the same, with officers who charge 9 MPH relatively often in one county also likely to do so in other counties. We take this as compelling evidence that bunching in the ticketed speed distribution is generated by the behavior of the officers.

2.5 Racial Disparities

Given the argument that bunching in the ticketed speed distribution results from systematic lenience on the part of officers, we examine whether the extent of bunching differs across racial groups as an initial test for the presence of bias. Figure 3 plots the speed histograms by driver race (white versus nonwhite) and demonstrates an apparent racial disparity in the likelihood of benefitting from lenience. 35% of white drivers are charged 9 MPH over, while just 25% of nonwhites are charged at the bunching speed.

To assess the magnitude, robustness, and statistical significance of racial differences in charging outcomes, we first estimate regressions of the charged speed (relative to posted) on indicators for black and Hispanic drivers. Table 3 presents these results. Black and Hispanic drivers are charged 1.2-2.86 MPH faster on average. Adding controls and fixed effects shrinks these magnitudes, particularly for Hispanics, but disparities persist and are highly statistically significant, with estimates implying that black (Hispanic) drivers are charged speeds 0.72 (0.69) MPH faster than whites. These gaps, which together we call the *white-minority speed gap*, are the disparities we hope to explain and mean that either minorities drive faster on average or officers are discriminating on average in their ticketing and discounting.

Next, we examine the statistical significance and robustness of racial differences in the probability of being charged at the bunching speed. In particular, we estimate linear probability models of the form

$$y_i = \alpha + \theta_B B_i + \theta_H H_i + \beta X_i + \epsilon_i$$

where y_i is an indicator for whether the charged speed is the bunching speed. B_i and H_i are indicators for driver race, and Z_j is a vector of stop and driver characteristics. Our goal in these regressions is for θ_R to capture the racial differences in the probability of receiving a charge at the bunching speed conditional on being observed at a higher speed. Therefore, we consider only citations for speeds at or above the bunching speed (9 MPH) in these regressions.

Table 4 presents the estimates. In Column 1, we estimate that black and Hispanic drivers are, respectively, 3.8 and 14.9 percentage points less likely than white drivers to be cited at 9 MPH above the limit. In Column 2, we add controls for driver gender, an indicator for in-State driver, and a linear and quadratic term in driver age. Columns 3 through 5 progressively saturate the model with County-Speed Zone fixed effects, month and day of week fixed effects, and hour of day fixed effects, respectively.[10] In all regressions, we find at least a 2 percentage point difference in treatment between whites and blacks and a 1.37 percentage point difference between whites and Hispanics. The greatest drop in magnitude comes from Column 2 to 3, indicating that part of the disparity is due to minorities living in counties where lenience is lower for all drivers.

Table 5 presents further controls for car type, ZIP code income, and previous ticketing history. Because these records are each available for only a subset of drivers, the odd columns present regression (4) from Table 4 on the restricted samples for which each variable is available. The broad message is that the racial disparities persist when controlling for these characteristics. In column (2), we control for a quadratic in vehicle age and vehicle make fixed effects (e.g. Ford, BMW). In column (4), we control for the log of per-capita income in the driver's zip code. To do this analysis, we matched the driver's zip code of residence indicated on the driver license to publicly available IRS data on total earnings and number of tax returns filed in each zip code. If anything, racial disparities increase when accounting for vehicle characteristics or income, suggesting that race is not picking up unobserved differences in income that are dictating the officer lenience. Perhaps most importantly, the gaps remain when accounting for previous tickets. In column (6), we add fixed effects for the number of tickets a driver has received in the past three years. We

[10] Hour is missing for about 5% of stops. Further, we are skeptical of its reliability because hour is recorded using both 12 and 24 hour methods, and although the data include an AM/PM field, it does not appear to be reliably used. After adjusting to a 24 hour method using this field, we still find a sharp drop in the number of citations at between 12 noon and 1 pm.

compute these values directly by linking drivers across tickets using the driver's license state and number. The coefficients are essentially unchanged from Column 5. While we only see ticketing history, not full criminal history, this regression suggests that differences in previous record are not generating the treatment disparity.

Across Tables 4 and 5, the greatest drop in magnitude comes from adding county-zone fixed effects, reducing the coefficient on driver black (Hispanic) from -.0276 (.-131) to -.0205 (-.0289). This reduction suggests that a large part of the disparity comes from the fact that minorities live in areas where officers are harsher to all drivers. No other controls do much to change the coefficients on black and Hispanic.

For a subset of the data after 2013, we observe the GPS location of the ticket. As a final robustness check, we link each ticket to the road segment on which it was issued and show that the disparity in treatment is robust to fixed effects at the level of year, month, day of week, hour, speed zone, county, and road segment, all interacted. Details are provided in the Appendix.

3 Conceptual Framework

The previous section served to document the disparity in treatment between whites and minorities. Our primary contribution will be to disaggregate this disparity to the officer level. First, we introduce here a simple framework of officer decision-making that can explain several features of the data and motivates our strategy for estimating officer-level bias.

Officer j stops motorist i for speeding. His observed speed x' is drawn from some discrete distribution $F(\cdot)$. We assume a simple discontinuous fine structure, where the fine for speeding depends on the charged speed x according to

$$\text{Fine}(x) = \begin{cases} \pi_L & \text{if } x \leq x_d \\ \pi_H & \text{if } x > x_d \end{cases}$$

with $\pi_H > \pi_L$. If the driver's speed is above x_d, the officer has the choice to reduce the charged speed to x_d to reduce the fine the driver will face. Otherwise the speed is set to x'. When deciding whether to reduce the ticket, we assume the officer weighs a mix of personal concerns, such as the hassle of attending traffic court, and policing objectives, such as the blameworthiness of the individual and the potential deterrence effect of ticketing the individual. We represent the benefit to reducing the ticket as $V_j(r_i, \xi_i, \epsilon_i)$, where r_i is the driver's race, ξ_i are all other characteristics observed by the officer, and ϵ_i is a random taste shock drawn from a mean-zero symmetric distribution G(·). We assume the cost of discounting is an increasing function of the observed speed, $c(x')$.

The officer discounts the drivers ticketing if the value is greater than the cost:

$$x = \begin{cases} x_d & \text{if } V(r_i, \xi, \epsilon) \geq c(x_i) \\ x' & \text{otherwise} \end{cases}$$

To add structure to the framework, we suppose officers' value of discounting is separable between observables and the taste shock:

$$V_j(r_i, \xi, \epsilon) = t_{rj} + \xi_i \cdot \beta + \epsilon_{ij}$$

where t_{rj} is officer j's mean valuation to discounting a driver of race r. For a given speed x', the probability an officer discounts the driver is given by

$$\begin{aligned} \Pr(\text{Discount} \mid \text{x, i, j}) &= \Pr(t_{rj} + \xi_i \cdot \beta + \epsilon_{ij} \geq c(x)) \\ &= G(t_{rj} + \xi_i \cdot \beta - c(x)) \end{aligned} \tag{1}$$

In this framework, it is natural to define bias in the following way: An officer is biased against group r relative to group r' if $t_{rj} < t_{r'j}$. This definition implies that a biased officer, when faced with i and i' with the same speed and observables but different races, has a higher probability of discounting i' if $t_{rj} < t_{r'j}$.

While we describe the officers' preferences as potentially reflecting bias, we are not yet taking a stand on whether any disparity in treatment is taste-based versus statistical. For example, it is possible that some officers prefer whites because they believe the likelihood of having to go to court later is lower. We discuss statistical discrimination in Section 5.3.2 and why we believe the discrimination in discounting is taste-based.

The first empirical step we take is to model the likelihood of an individual appearing at the discount point, given his observables. In our model, the probability of being charged the discount speed is the summed likelihood of appearing at or above that speed times the likelihood of being discounted:

$$\Pr(X_i = x_d | i, j) = F_i(x_d) + \sum_{k=x_d+1}^{\infty} F_i(k) \cdot G(t_{rj} + \xi_i \cdot \beta - c(k)) \tag{2}$$

4 Empirical Strategy

If the driver's true speed x′ could be observed, the framework above suggests estimating officer bias by fitting an equation in the form of equation (1):

$$y_{ij} = \gamma\xi_i + f(x_i) + \theta_j + \theta_j^B B_i + \theta_j^H H_i + \epsilon_{ij} \tag{3}$$

where y_{ij} is an indicator that motorist i is stopped by officer j is charged x_d (receives the low punishment), using a sample of stops where the true speed $x > x_d$. The vector ξ_j is a set of driver characteristics analogous to those appearing in the officer value function. θ_i is a an officer fixed effect, which captures variation in the cost function C_i across officers. $\theta_i^B B_j$ and $\theta_i^H H_j$ are officer fixed effects interacted with driver race indicators, which capture variation across officers in the t_{rj}'s. Note that if $f(\cdot)$ and the distribution of ϵ are properly specified, $\theta = t_b - t_w$ directly identifies bias in preferences.

We cannot estimate (3) directly because we cannot observe the true speed x. The alternative is to estimate equation (2) accounting for the non-linear relationship between officer preferences and the drivers' distribution of speeds F(·). While we perform exactly this procedure in Section 7, we first approximate this equation with a linear probability model, restricting to stops with $x \geq x_d$ and estimating

$$y_{ij} = \gamma\xi_i + \theta_j + \theta_j^B B_i + \theta_j^H H_i + \epsilon_{ij} \tag{4}$$

where y_{ij} is again an indicator for appearing at the discount point, and the coefficients θ_i^B and θ_i^H are our measure of officer i's bias against black and Hispanic drivers, respectively. The driver covariates include gender, whether the driver is in-state, and linear and quadratic terms for driver's age and previous number of tickets. In the estimation, we also include year, month, day-of-week, posted speed, and county fixed effects.

We run this regression with two objectives in mind. First, we hope to achieve an unbiased estimate of each officer's individual bias parameters, θ_j^B and θ_j^H. Second, we hope to identify the distribution of biases across officers, $f(\theta^B)$ and $f(\theta^H)$. As noted in the teacher value-added literature and elsewhere, the distributions of the $\hat{\theta}_i$'s will, in general, be too dispersed relative to the true distribution due to estimation error (Koedel *et al.*, 2015). The general practice is to thus estimate a random effects model where the distribution of coefficients is assumed to be normal and the mean and standard deviation are estimated through maximum likelihood. Here, we want to explicitly allow for skewness in the distribution of bias in the case where there are more officers biased against minorities than for (or vice-versa). With this consideration in mind, we instead follow a standard deconvolution procedure from Delaigle *et al.* (2008), described in detail in the Appendix, to estimate a non-parametric distribution of bias accounting for estimation error in the individual bias estimates. Such procedures are often used to estimate the distribution of persistent wage differences across individuals, as in Postel-Vinay and Robin (2002). To account for the estimation error in regressions where the θ_i's are on the left hand side, i.e. when we show which officer characteristics predict bias, we implement a weighting procedure similar to Aaronson *et al.* (2007), also described in the appendix.

Our estimators for θ_j^B and θ_j^H will be unbiased under the standard OLS assumption that $E(\epsilon_{ij}|\mathbf{X}) = 0$, which implies the assumption $E(B_i \cdot \epsilon_{ij}|\text{Officer } j) = 0$. In other words, we assume that driver race is uncorrelated with the error term conditional on the ticketing officer. Our main concerns are two potential threats to this assumption. It is possible that driver race is correlated with stopped speed. If minorities have higher average speeds, and officers are less likely to discount faster speeds, we may find negative coefficients on θ_j^B and θ_j^H that are driven solely by race-blind discounting. In Section 7, we explicitly model racial differences in speeding and account for it when estimating officer-level bias, but for here we must continue with this concern set aside.

The second potential threat is the presence of other missing variables that are observable to the police but not in the data. In particular, we do not see an individual's entire criminal history, only his previous tickets, and this missing variable may generate a finding of racial bias where there is none. As discussed in Section 2.5, our set of observable characteristics is far richer than what has been traditionally available in traffic enforcement studies, including demographics, vehicle description, home address, and driving history. The available covariates do little to change the coefficients on race that we do find, including controlling for previous tickets. We are therefore skeptical that adding any additional missing variables would remove our finding of average bias or the estimated distributions of bias.

5 Results

5.1 Officer Bias

The distributions of officer-level bias estimates are plotted in Figure 4. The lines represent kernel density plots of our measure of bias against black and Hispanic drivers, $-\theta^B$ and $-\theta^H$, so that the further right an officer is in the distribution of bias against blacks, the greater his level of bias. The unit of our bias measure is probability difference in percentage points. An officer whose bias against blacks is 0.1, for example, is ten percentage points more likely to offer a fine reduction to a white than black driver. The bias coefficient distributions both peak close to zero but are clearly skewed to the right. The distribution of Hispanic bias, in particular, has a wide right tail.

Figure 5 shows the deconvoluted estimates of bias against blacks and Hispanics. Without measurement error, the skewness of the distribution is more clear. While the mode of the distribution is centered at zero, there is a small percentage of officers with positive bias. This argument is formalized in Figure 6, which shows the CDF's of bias. We estimate that 24% of officers have some bias against black drivers, with 95% confidence interval [19.8%, 29.6%].[11] The analogous number is 25% (21.8%, 28.8%) for share biased against Hispanic drivers.

As we have mentioned before, an officer can only be biased if he has any degree of lenience, since bias is measured as a deviation in lenience across races. That leaves open the question of whether the distribution of bias we see across officers is simply a reflection of whether an officer practices *any* lenience. To answer this question, Figure 7 plots the result of our deconvolutions when calculated separately for officers above and below the median of lenience. As expected, officers below the median in lenience have almost no bias, and the distribution is strongly peaked at 0. Officers with above median lenience comprise almost the entirety of bias against both groups. However, there remain a set of officers with lenience and no bias, as the mass at 0 for this group still persists for both

[11]We use bootstrapped standard errors to calculate the share of officers with bias greater than 0.

black bias and hispanic bias.

It is worth noting here the novelty of these distributions relative to the existing literature on racial bias. Table 7 shows the results of using the benchmarking method of Anwar and Fang (2006) and Antonovics and Knight (2009) on our data. These papers compare the behavior of white officers with black officers, and take a difference in behavior as evidence that at least one group is biased in their policing. To implement a similar test, we do the same linear probability regressions as before on the likelihood of appearing at the discount point, now interacting driver race with officer race. The coefficients that identify bias in their framework are the interaction of Black Driver with Black Officer and Hispanic Driver with Hispanic Officer. These estimates reflect how much more often black officers discount black drivers than white officers and how much more often Hispanic officers discount Hispanic drivers than white officers, respectively. The values are .03 and .016, respectively, which are closely in line with our mean estimate of bias using our method. However, they miss the distribution of bias and the degree to which the aggregate disparity is due to a small percentage of officers.

5.2 Do Officer Characteristics Predict Bias?

Given an officer-level measure of racial bias, a natural question is whether officer characteristics are predictive of bias. We can tackle this question using the personnel records collected from the Florida Department of Law Enforcement and the Florida Highway Patrol.

In line with the analysis of Anwar and Fang (2006) and other existing studies, Figure 8 shows how our measure of bias varies by officer race. Perhaps consistent with intuition, white officers are much more likely to be biased against minority drivers. Among black officers, a very small percentage are biased in favor of black driver. This insight is another advancement beyond the current literature. Using the benchmarking framework, we can know that some race of officers is acting in a biased way, but not which group. Here we can see the magnitude of bias separately for each officer race.

In Table 8, we present regressions of officer-level bias on officer characteristics. All observations are weighted by the variance of the noise in our estimate of the officer's bias, as explained in the Appendix. In columns (1)-(3) the dependent variable is an officer's bias against black drivers, while in columns (4)-(6), officer bias against Hispanic drivers is on the left hand side. Columns (1) and (4) use as the outcome variable our measure of bias, columns (2) and (5) use an indicator for whether the measure is above 0, and columns (3) and (6) use an indicator for whether the the bias is above zero and statistically significant (t-value greater than 1.96).

As with the density plots, the clear takeaway from the regressions is that minority officers are more lenient towards drivers of their own race, as we might expect. Female officers appear less biased against both black and Hispanic drivers. Older officers exhibit more bias against both groups, though the standard errors are large. Officers with any higher education are less likely to be biased towards blacks but not Hispanics. Neither complaints nor seeking promotion have consistent predictive power on bias.

Table 9 presents the same results but only for officers who seek promotion to sergeant and in which we include the promotional exam score (averaged if the officer has multiple attempts). The results look similar though noisier due to the smaller sample of officers. It does not appear that an officer's test score has consistent predictive power for the level of bias and, surprisingly, the point estimates go in opposite directions for blacks versus Hispanics.[12]

5.3 Potential Concerns

In Section 7, we analyze a model that explicitly account for differences in speeds across racial groups. Here we consider two other potential concerns that must be addressed in our analysis, specifically whether there is selection into who is ticketed and the possibility that our results are detecting statistical discrimination.

5.3.1 Selection

All of our analysis is conditional on an individual being stopped and ticketed. There is certainly the potential for racial bias in the officer's choice of who to stop and who to give a warning, a possibility that may bias our estimates of discrimination in the ticketing

[12]It is unclear whether these regressions should also include the average lenience of the officers, so that comparisons are for a given probability of discounting. Though not shown, we have run these regressions with lenience included, and the results look nearly identical.

discount choice.[13] From speaking with FHP officers, it seems that reducing the charged speed is the favored method of lenience rather than simply a warning. Regardless, we think these concerns do not invalidate our results. As discussed in Fryer (2016), the overrepresentation of blacks and Hispanics among stopped drivers will likely bias downwards any measure of later discrimination, as this increases the pool of "good" minority drivers who end up ticketed.

If there is selection in the first step of deciding to ticket a driver, we should perhaps expect that officers who are more biased in terms of discounting will also have a greater share of drivers who are minority. Figure 9 presents how the share black of an officer's ticketed drivers changes with the bias of the officer, where share black is first residualized for each driver's day of week, month, speed zone, and county. While there is a significant difference across the distribution of officer bias, suggesting potential selection, the magnitude is quite small. We find that a two standard deviation change in officer's bias against blacks leads to a .075 standard deviation change in the share drivers who are black, and a -.075 standard deviation effect for Hispanics.[14]. These calculations suggest that, while there may be selection, the effect on our estimates of bias should be small.

5.3.2 Statistical Discrimination

We have thus far defined bias as the differential treatment of drivers by race who are stopped for the same speed. This definition is not innocuous, as there may be some reasons for differential treatment unrelated to observed driving speed that, while contentious in their use, are not specifically racial bias. For example, officers may be choosing treatment on the basis of how an individual's future driving responds to punishment [Gehrsitz (2015), Hansen (2015)] or the likelihood of paying a ticket [Rowe (2010), Makowsky and

[13] Several studies have examined whether officers practice racial profiling when deciding which drivers to pull over. Grogger and Ridgeway (2006) find little evidence of racial profiling in Oakland, CA by comparing the racial distributions of stopped motorists during day and night, when the race of the driver is less likely to be known to the officer ex ante. However, Horrace and Rohlin (2016) augment the test used in Grogger and Ridgeway (2006) by considering the location of streetlights in Syracuse, NY. They find that black drivers are about 15% more likely to be stopped than nonblack drivers in lighted areas/hours. Antonovics and Knight (2009) find evidence that officers are more likely to stop minority drivers in Boston.

[14] These effects are found by performing a local linear regression of residualized share black on officer bias and comparing the value for predicted share black for officers bias one standard deviation above and below the mean.

Stratmann (2009)]. If individuals systematically differ by race in these characteristics, the racial disparities we observe may reflect the fact that officers are statistically discriminating by using race as a proxy for deterrability.

However, as noted in Anwar and Fang (2006), statistical discrimination can only explain behaviors that are uniform across officers, as they are due to the relationship between race and unobserved heterogeneity rather than anything specific to the officer. The median amount of bias in our setting is small, but we find a significant and skewed right tail. Such a distribution of disparate treatment cannot be explained by statistical discrimination.

6 Relationship with Use-of-Force and Civilian Complaints

Section 5 showed how we can use our estimation strategy to generate officer-level measures of bias. Here we apply these measures to see how bias and lenience relate to misconduct, and we ask whether early measures of officer behavior can be used to help target officers prone to future misconduct.

The current debate around police-minority relations and the Black Lives Matter movement center largely on the question of whether police disproportionately use force during interactions with minorities and in particular with black Americans. While we do not directly test this hypothesis [15], we instead answer the question of whether these outcomes are related to our measures of bias and overall lenience. To do so, we collected from the Florida Highway Patrol data on all use-of-force incidents and civilian complaints for their officers in the years 2011-2016.

To make the analysis at the officer level, but account for the differences in years and locations worked, we run regressions of the following form:

$$Y_{it} = \alpha_0 + \alpha_1 \cdot \text{Lenience}_i + \alpha_2 \cdot \text{Bias}_i + X_i \cdot \beta + \sum_k \text{District}_i^k + \sum_k \text{Year}_i^k + \epsilon_i$$

where Y_{it} is an outcome of either receiving a civilian complaint or using force. District_i^k is an indicator for an officer ever working in District k in the years 2011-2016, and Year_i^k indicates whether an officer appears in our traffic data in year k. X_i are other officer-level

[15] see Fryer (2016) for a recent analysis

characteristics. For statistical power, we combined minority status so that bias is measured against both black and Hispanic drivers.

The results, reported in Table 10, indicate that lenience is statistically predictive of both civilian complaints and use of force. An increase of one standard deviation in lenience (25% change in discounting) correlates to .19 fewer civilian complaints and a 5.5% decreased likelihood of receiving any complaints. Similarly, a 1 SD increase in lenience is associated with .06 fewer incidents of force and 3% lower likelihood of any force. Black officers are less likely to engage in force, as are older officers. Female officers are less likely to receive complaints but just as likely as male officers to use force.

Bias against minorities seems to be positively related to force and complaints, though the standard errors are too large to say conclusively. Further, we know our estimates are noisy measures of true bias and lenience, leading to a bias in our coefficient estimates in potentially either direction. To attempt to account for this error, we do a split-sample instrumental variables procedure. We divide each officer's data randomly in half and estimate their bias and lenience for each sample. We then use one estimate as an instrument for the other.

The results are presented in Table 11. As expected, the coefficients on bias increase overall in magnitude, though the standard errors remain too large to definitely say whether there is a true relationship. In columns (3) and (4), the p-values on the relationship of minority bias to use of force are .108 and .120, respectively.

It should perhaps not be surprising that we struggle to find a relationship between bias and use of force. As we have mentioned, only officers who have any lenience at all can be biased, and we find a strong negative relationship between lenience and bias. While that relationship is controlled for, it means that the correlation between bias and force is estimated on weak variation.

An alternative approach to linking bias and force is seeing whether one can predict the other. Economists have grown increasingly interested in such *prediction problems*, where the interest is no longer on the causal relationship between two variables but on the ability to predict an outcome using available covariates. Chalfin *et al.* (2016a) take prediction as their objective and use machine learning to show that use-of-force by a police officer can be forecasted with information known about an officer before they start work. Here we show that with a similar exercise, we can predict force using lenience.

We restrict attention to officers for whom we observe their first full year in the department. We use their first year of traffic patrol to estimate lenience and bias, along with whether they received a civilian complaint or used force. We use these measures, along with demographics, to predict whether we observe a complaint or force within the following year. The regression results, presented in Table 12, show that lenience continues to be a strong predictor of use of force in this restricted sample. Surprisingly, lenience is a better predictor than either previous use of force or complaints.

To demonstrate the potential value of predicting force, consider the following simply policy: using column (4) in Table 12, we predict each officer's propensity to use force, and remove officers in the top 10% and replace them with average officers[16]. Doing so, we expect a 10.0% reduction in the total amount of force used. We then redo the procedure, where the prediction is done without our measures of lenience and bias. In this case, the expected reduction in force is 4.3%.

7 Model of Officer Discount Decision

In the above analysis, we proceeded under the assumption that individuals' driving speed do not vary systematically across racial groups. This section presents a model that allows us to simultaneously estimate officers' taste parameters for each racial group and speed parameters for each race-by-location. By doing so, we can also perform counterfactuals using this model to quantify the effect of various policies that change the distribution of bias across officers. The model setup is as follows.

Officer j encounters individual i driving at a speed drawn from a poisson distribution $x \sim P_{\lambda_i}(s)$, where the poisson parameter depends on the driver's county and race, $\lambda_i = \lambda_{rc}$. The officer faces the choice to either charge the driver his measured speed x or, if the speed is above the jump in fine, discount the speed to x_d. He makes this decision by weighing a cost to discounting, which we impose to have the form $c(x) = b \cdot x$, against the value of discounting, $t_{ij} = t_{rj} + \epsilon_{ij}$. So the driver has her speed reduced to x_d if

$$t_{rj} + \epsilon_{ij} > a + bx_i$$

[16]We calculate the highest 10% within the district and year an officer is working, to avoid firing based on these characteristics.

The officer's preference is allowed to vary by race r. For simplicity, we pool black and Hispanic drivers into a single nonwhite, or minority, group when estimating the model parameters. The noise term ϵ_{ij} is assumed to be a standard normal variable. Thus, for an individual driving at speed x, her probability of discount is

$$Pr(\text{Discount}|x) = \Phi(t_{rj} - b \cdot x_i)$$

Conditional on officer, county, and driver race, the likelihood for each speed is the following:

$$Pr(X = x) = \begin{cases} P_{\lambda_{rc}}(x) & \text{if } x < x_d \\ P_{\lambda_{rc}}(x_d) + \sum_{k=x_d+1}^{X} P_{\lambda_{rc}}(k) \cdot \Phi(t_{rj} - b \cdot k) & \text{if } x = x_d \\ P_{\lambda_{rc}}(x) \cdot \Phi(t_{rj} - b \cdot x) & \text{if } x > x_d \end{cases}$$

Identification

In principle our model can be identified using only aggregate information, as if the entire data came from one officer. Intuitively, the tickets provide 40 moments (for each potential speed) to estimate three parameters (discount slope, preference for discounting, and true speed). Such an estimation approach relies heavily on the functional form assumptions of a poisson speed distribution.

In practice, our estimation relies heavily on the heterogeneity across officers in discount lenience. While all officers' data enter the maximum likelihood equations, the estimation of speeds is primarily estimated using officers who exhibit no lenience, from which we get an estimate of the true distribution of speeds.

Our estimation also depends heavily on the smoothness and parameterization of the underlying speed distribution. Any excess mass at the bunch point is taken to be lenience on the part of the officer. As argued earlier, we believe this assumption is valid, and drivers are not systematically choosing to bunch below the fine increase.

7.1 Estimation

While the setup of the model is simple, non-parametrically estimating the distribution of bias is computationally complex. The model parameters to be identified are the 67×2 county-race speeds λ_{rc}, 1327×2 officer average racial preferences, t_{jr}, and the slope of the cost function b, totaling 2,789 parameters. This complexity makes estimation directly through maximum likelihood challenging.

We estimate the model by iterating across the groups of parameters until the solution converges. We solve first for a set of initial guesses by assuming that speeds and officer preferences are uniform and performing maximum likelihood on b, λ, t. We then calculate the slope, county-specific speeds, and officer-specific preferences in the following way:

1. Guess speed values $\lambda_{rc}^{(0)} = \hat{\lambda}$ and slope $b^{(0)} = \hat{b}$ from the aggregate MLE estimation.
2. Solve for officer preferences $t_{ij}^{(0)}$ by maximizing likelihood $\mathcal{L}\left(t_{jr}|x_{jr}, \{\lambda_{rc}^{(0)}\}, b^{(0)}\right)$ conditional on speed parameters and slope estimate.
3. Solve for speed parameters $\lambda_{rc}^{(1)}$ by maximizing likelihood $\mathcal{L}\left(\lambda_{rc}|x_{jr}, \{t_{jr}^{(0)}\}, b^{(0)}\right)$ conditional on officer preferences and slope estimate.
4. Solve for slope parameter $b^{(1)}$ by maximizing likelihood $\mathcal{L}(b|x_{jr}, \{t_{jr}^{(0)}\}, \{\lambda_{rc}^{(1)}\}\Big)$
5. return to step 2 and repeat until parameter guesses converge.

Because in every iteration the total likelihood increases[17], the process will converge at least to a local optimum. We check different starting values to confirm that our results achieve a global maximum.

Conditional on speed and slope, the officer parameters are separable and thus can be easily solved, and similarly for the speed parameters when conditioning on officer parameters. Further, the conditional likelihood functions are unimodal in the parameters; this means that the score functions only cross zero once, simplifying the search for an optimum. Standard errors are calculated by estimating the information matrix via the variance of the parameters' score functions.

7.2 Results

Table 13 presents the estimates of the model parameters. The columns present the mean and variance of each class of parameters, broken down by race, and the final column compares differences across racial groups in the mean parameter estimates. The slope

[17]This approach is very similar to the EM algorithm, most commonly used to deal with missing data.

parameter is positive and significant at .023. Consistent with our intuition, officers face an upwards sloping cost with respect to speed, meaning that tickets are less likely to be discounted the higher the observed speed. The parameter t represents an officer's mean valuation of a racial group. We find both significant heterogeneity and a significant disparity across whites and minorities in how officer's value discounting drivers, officers' mean valuation for whites being 0.1 higher than for minorities. While the values of t are by themselves hard to interpret, dividing them by the slope parameter b gives the interpretation of the valuation in terms of miles per hour driven. The difference of 0.1 in valuation between whites and minorities, scaled by .0228, tells us that the average officer treats a minority driver like a white driver stopped for driving 4 MPH faster.

These differences in treatment are more easily understood in terms of the probability of discount (i.e. fine reduction). *P(Discount)* represents the likelihood of receiving a reduced ticket if the driver is at the speed right above the bunching speed. Consistent with the reduced form evidence, the average officer is substantially lenient, with a large variance across officers. Officers are 3.3 percentage points less likely to discount minorities than whites, off a baseline of 35.7% likelihood of discount. Figure 10 further shows this disparity, highlighting how racial bias results in a decreased mass of officers with very high lenience and an increase in mass of officers with very low lenience.

The λ estimates tell us how races-by-counties differ in their underlying speeds prior to officers choice of lenience. We find that minorities on average drive significantly faster than whites, on the order of .5 to .7 MPH. Figure 12 presents this gap by county, showing that minority speeds stochastically dominate white speeds. These results are in line with previous studies of highway patrol ticketing, which argue that much of the gap in ticketing between whites and minorities can be explained by higher speeds by minorities [Smith *et al.* (2004), Lange *et al.* (2005)]. However, these previous studies and the news coverage that followed implicitly argued that the racial difference in speeds rules out the presence of bias by officers. Our study highlights how this thinking is incorrect by showing that disparities in driving and racial bias coexist in our setting.

Note that our estimates of driver speeds are conditional on the officer choosing to ticket the driver in question. As discussed above, there is a possibility that officers are biased in the original choice of whether to ticket a driver. If so, the threshold for minority drivers to be in the sample would be lower, suggesting that our observed gap is smaller than it would be without the presence of bias in the choice to ticket.

A central question in most studies of racial bias is the extent to which an aggregate racial disparity can be explained by the measured amount of bias. Table 14 seeks to answer this question by decomposing the measured discount probability and speed disparities across races. The first column presents the racial gap in likelihood that each individual's officer would ticket him were he at the speed right above the bunch point:

$$\text{Probability Gap} = \frac{1}{N_w}\sum_{r(i)=w} \text{Prob}(\text{Discount}_{ij}|x_i = x^{*}+1) - \frac{1}{N_h}\sum_{r(i)=m} \text{Prob}(\text{Discount}_{ij}|x_i = x^{*}+1) \quad (5)$$

While the average Florida officer only has a .03 racial difference in probability of discounting, the effective difference in the data is .09 because minority drivers are in counties with less lenient officers. Figure 13 shows how counties vary in their share minority, average bias, and white lenience. The most striking fact of these figures is that the regions with the greatest lenience towards whites are also the regions with the least minorities. This disconnect implies that even removing the bias of every officer will leave substantial disparities in treatment based on the geographic distribution of minorities and lenient officers. We formally explore the role of sorting by simulating the model in the case where individuals draw officers from a state-wide distribution in column 3, and the probability gap reduces to .03. The speed gap is reduced by 47% when bias and sorting are eliminated, reflecting the total share of the disparity that can be explained by officer lenience.

7.3 Counterfactual Analysis

The model we presented is useful for ruling out that the reduced form estimates of bias are not due to unobserved differences in speeds across races. While we find that minorities drive faster on average, we continue to find bias on the part of some officers. The model is also useful for decomposing the role of bias, lenience sorting, and speed differences in explaining the aggregate racial speed gap.

We now use the estimates to conduct a series of policy counterfactuals exploring how best to curb bias in speeding tickets. Because we provide a non-parametric estimate of the distribution of bias across officers and locations, we can explore a rich set of counterfactuals whose outcomes depend on the full distribution of bias.

It is important to note here that we steer clear of making normative statements in these counterfactuals. The only outcomes we consider are the white-minority discount gap. A full consideration of the welfare impact of the ensuing policies would likely consider additional outcomes, such as the speeding response to changes in enforcement.

7.3.1 Firing Biased Officers

The first counterfactual we consider is firing the worst officers in the sample. While it is commonly believed that officers are difficult to fire, we want to explore the degree to which aggregate disparities can be reduced by small adjustments at the extremes of bias. To make the exercise symmetric, we fire officers of similar bias both against and for minorities (i.e. reverse discrimination). We carry out the exercise as follows: we calculate the p-th percentile of most biased officers, which we denote by C, and remove all officers with bias greater than C and lower than $-C$. We re-draw each individual's ticketing officer from the distribution of remaining officers within each driver's county, weighted by their number of tickets. If there are too few remaining unbiased officers in that driver's county, we draw from the remaining officers in the troop (which encompasses 8 counties). We then calculate the aggregate disparity in probability of being discounted with the new set of assigned officers. Figure 14 explains graphically how the truncation is conducted.

The results are presented in Figure 15. The x-axis plots the percentile of bias being truncated, and the y-axis plots the racial gap in probability of discount. We see that truncating bias leads to a reduction in the probability gap. Note that this reduction is not mechanical. Officers are being removed from both directions of bias, so the decline in the racial gap is due to the greater mass of officers with pro-white bias. Removing officers who are at the 15th percentile or worse of bias reduces the gap from .093 to .08, a 14% reduction. In the limit, only officers who treat each group equally are left, and bias is cut in half to .05. Note that, because the distribution of bias is skewed and centered at a positive level of bias, the limit of no bias is at the 57th percentile. Note that the results are non-monotonic both because of simulation error and because the cutoffs on both sides of the x-axis may differentially affect the presence of pro-white or anti-white bias. Specifically, a new cutoff may remove only one additional officer, and it may be an officer who was biased against whites. As before, the gap is not reduced to zero because minorities are in areas where, regardless of race, officers are less lenient to drivers. This fact suggests that the target of interventions should not be bias per se but absolute levels of lenience.

7.3.2 Firing Lenient or Harsh Officers

Following this argument, we consider how the aggregate treatment disparity is changed with a policy targeting lenience rather than bias. We carry out two counterfactuals in this spirit, one reducing lenience and the other increasing it. Figure 16 plots what happens when the least lenient officers are removed. The x-axis is the minimum percentage of drivers at 10MPH over who must be discounted for an officer to be kept in the sample[18]. As the threshold increases, the aggregate disparity decreases substantially. In the limit, where all drivers are given a reduced ticket, the gap in treatment mechanically goes to zero because all drivers are discounted.

The opposite counterfactual is to consider removing the most lenient officers, which we present in Figure 17. The x-axis shows the threshold share of drivers discounted above which officers are removed from the sample. The reduction in disparity occurs faster than removing strict officers, due to the fact that bias can only arise in officers who exhibit lenience to at least one group. Similar to removing strict officers, the limiting case removes all of the aggregate gap.

While not the same exercise, we think of these counterfactuals as reflecting a potential policy where the highway patrol imposes a minimum or maximum standard that all officers must satisfy. Though not shown, we have performed such an analysis, and the results look nearly identical. Perhaps surprisingly, these policies targeting lenience appear to be more effective than simply removing biased officers.

7.3.3 Increasing Minority and Female Shares

We next consider increasing the share of minority or female officers. Given our earlier finding that minority and female officers exhibit lower levels of bias, we should expect that increasing their presence might lead to lower levels of aggregate bias. We do so by

[18] We look separately at the officers share of white drivers discounted and share minority. Both must satisfy the threshold.

re-simulating which officer each driver draws, taken from within his county, where the probability of drawing a minority or female officer is exogenously changed. Results are presented in Figures 18. Consistent with our intuition, the gap in probability of discount declines, though very modestly. An increase in minority officers from the empirical share of 34% to 60% reduces the gap from .093 to .088. Increasing the share of women leads to a similar effect, with a change from 9% to 25% leading to a reduction from .093 to .088 as well.

Demographic policies have been suggested in the past as a possibility for systemically changing police behavior, particularly towards poor and minority communities. Donohue III and Levitt (2001) find that an increase in minority officers leads to an increase in arrests of white offenders, no effect on non-white offenders, and vice versa for an increase in white officers. Our results, though only counterfactuals, are consistent with their findings.

7.3.4 Assigning Officers by Bias and Lenience

The final counterfactuals we consider are to reassign officers to specific areas based on their behavior and the share of minorities in each county. Officers are assigned to Troops, which patrol 6-10 counties. Within the troops, officers regularly vary in which locations they patrol. It may be potentially feasible for a senior officer to, for example, change the assignment of officers such that minorities face less biased officers. Table 15 presents the results of such a policy. The first column is the baseline simulation of the model to match the true data. The second column sorts officers within a troop such that the least biased officers are in counties with the most minorities. The third column sorts officers within a troop such that the most lenient officers are in counties with the most minorities.

Surprisingly, sorting officers to expose minorities to the least biased has a deleterious effect on the treatment gap. The least biased officers are also the least lenient on average, leading minorities to be treated poorly relative to whites, now exposed to lenient and biased officers. The gap in probability of discount increases from .097 to .102. Much more effective in reducing the gap in treatment is assigning the most *lenient* officers to minority counties. This policy reduces the treatment gap from .096 to .0047. The gap in speeds declines from -2.11 to -1.21, nearly identical to the true speed gap, -1.11.

In short, the counterfactual analyses highlight the importance of absolute lenience as a consideration separate from bias. The policy aimed at exposing minorities to lenience is much more effective, as are policies making lenience uniform, than removing overall bias through firing biased officers or hiring minority and female officers.

7.4 Caveats

Our simplified modeling framework and counterfactuals are meant to be suggestive of how the racial treatment gap might change when various personnel policies are considered. That being said, there are many caveats that must be recognized. We are not taking a strong normative stance on the social welfare function. There are potentially other outcomes that may be an important input in the policy makers's problem that we do not consider here. For example, increasing lenience uniformly may lead to increased speeding, which we show to be the case in a separate study, Goncalves and Mello (2017). Changing leniency standards may also lead officers to choose instead to give drivers verbal warnings rather than a reduced charge.

We have also assumed that officers are uniform in their treatment of drivers across counties, which we impose for modeling simplicity. However, it may be the case that officers vary in their behavior by district. In Section 7.5, we show that officers are less lenient to all drivers in areas with more minorities, suggesting that there are some differences in treatment that go unnoticed simply in comparing white versus minority drivers. However, it also means that our counterfactual where officers are resorted across counties within their troops may overstate the benefits to reassigning officers.

7.5 Explaining Spatial Differences in Treatment

In the model results, we find significant heterogeneity across counties in the level of lenience towards all groups. In particular, minorities tend to be in areas where *all* drivers are treated worse. Because of this relationship, many of the policies aimed at reducing bias are ineffectual because a large share of the disparity is spatial. In this section, we explore why this relationship exists, and whether it is truly about race or other confounding factors.

To do so, we run regressions similar to Equation (1), where the outcome variable is whether a driver is charged 9 MPH over the speed limit, and we include a set of driver characteristics. Rather than use county-level fixed effects, we include a set of county-level characteristics, including share of individuals who are minorities, share under 18 and over 65 years of age, the unemployment rate and poverty, and the share of tickets at or above a 50MPH speed limit. The results, presented in Table 16, use progressively richer fixed effects across columns.

In column (4), the standard deviation in county-level minority share is .13, meaning that a one standard deviation increase in minority presence decreases officers' average discount rate by 2.99 percentage points. This reduction is comparable to the bias faced by minority drivers.

Neighborhood-level differences in policing intensity are common, but it is exceedingly hard to infer from these differences any bias on the part of police. As argued by Persico (2009), differences in policing intensity at the neighborhood level may be due to differing elasticities of crime with respect to police, and identifying neighborhood-level elasticities are difficult. In Goncalves and Mello (2017), we study the driving response to receiving a harsher ticket and document that individuals subsequently drive slower. However, we also find no evidence of selection on gains. In other words, officers do not seem to choose who to discount on the basis of deterrability. While that may not be the only policing objective, it raises substantial doubt about the claim that neighborhood differences in lenience are due to maximizing policing objectives.

8 Conclusion

The large racial disparities in the criminal justice system have led many to claim bias as the root cause. Proving so is surprisingly hard, as it is difficult to truly control for differences in criminality and show that individuals are treated differently by race for the same offense. This study explores the question of bias in the criminal justice system and the extent to which it explains aggregate racial disparities. Specifically, we study speeding tickets and the choice of officers to discount drivers to a speed right below an onerous punishment.

By using a bunching estimator approach that allows for officer-by-race measures of lenience in tickets, we can explore the entire distribution of both lenience and bias on the part of officers. We find that about 25% of officers explain all the aggregate bias, and 46% of the gap in charged speeds can be explained by differential exposure to lenience. The rest of the gap is due to underlying differences in driving speeds across races.

We explore whether bias is predictable by regressing individual officers' bias on demographic and personnel characteristics. We find that officers tend to favor their own race, older officers are more racially biased, and women and college educated officers are less biased on average. Personnel information, such as failing an entry exam, receiving civilian complaints, and seeking a promotion, are not strongly informative about bias. Officers who are more lenient in general are less likely to receive complaints or use force on the job. Officers who are more biased against minorities seem to use more force, though standard errors are too large to say conclusively.

Using a model of driver speeding and officer decision-making, we confirm that, while minorities drive faster on average, our officer-level estimates of bias are not confounded by differences in speeding across groups. We find that setting bias to be zero across officers fails to remove the majority of the treatment gap due to the fact that minorities tend to live in regions where officers are less lenient towards all drivers. Because of this fact, we find that policies directed at reducing bias directly have a significant but modest effect on the treatment gap. Policies that instead target officers' lenience, either by firing overly harsh or lenient officers or by re-assigning lenient officers to minority neighborhoods, are much more effective at reducing the aggregate treatment disparity.

Popular debate over police misconduct tends to revolve around a discussion of whether misbehavior is systemic or the product of a few bad apples. We make progress on this question by providing a specific answer: racial bias is due to 20% of officers, and there are effective policies for mitigating their harm.

References

Aaronson, D., Barrow, L. and Sander, W. (2007). Teachers and Student Achievement in the Chicago Public High Schools. *Journal of Labor Economics*, **25** (1), 95–135.

Agan, A. Y. and Starr, S. B. (2016). Ban the box, criminal records, and statistical discrimination: A field experiment.

Alesina, A. and La Ferrara, E. (2014). A Test of Racial Bias in Capital Sentencing . *American Economic Review*, **104** (11), 3397–3433.

Anbarci, N. and Lee, J. (2014). Detecting Racial Bias in Speed Discounting: Evidence from Speeding Tickets in Boston. *International Review of Law and Economics*, **38**, 11–24.

Antonovics, K. and Knight, B. (2009). A New Look at Racial Profiling: Evidence from the Boston Police Department. *Review of Economics and Statistics*, **91** (1), 163–177.

Anwar, S. and Fang, H. (2006). An alternative test of racial prejudice in motor vehicle searches: Theory and evidence. *The American Economic Review*, **96** (1), 127–151.

Ashenfelter, O. and Greenstone, M. (2004). Using Mandated Speed Limits to Measure the Value of a Statistical Life. *Journal of Political Economy*, **112** (S1), S226–S267.

Becker, G. S. (1957). *The economics of discrimination: an economic view of racial discrimination*. University of Chicago.

Brown, M. K. (1988). *Working the street: Police discretion and the dilemmas of reform*. Russell Sage Foundation.

Chalfin, A., Danieli, O., Hillis, A., Jelveh, Z., Luca, M., Ludwig, J. and Mullainathan, S. (2016a). Productivity and selection of human capital with machine learning. *The American Economic Review*, **106** (5), 124–127.

—, —, —, —, —, — and — (2016b). Productivity and Selection of Human Capital with Machine Learning. *American Economic Review*, **106** (5), 124–127.

Coate, S. and Loury, G. (1993). Will Affirmative-Action Policies Eliminate Negative Stereotypes? *American Economic Review*, **83** (5), 1220–1240.

Coviello, D. and Persico, N. (2013). An Economic Analysis of Black-White Disparities in NYPD's Stop and Frisk Program. *NBER Working Paper*, pp. 1–28.

Day, M. V. and Ross, M. (2011). The Value of Remorse: How Drivers' Responses to Police Predict Fines for Speeding. *Law and Human Behavior*, **35** (3), 221–234.

De Paola, M., Scoppa, V. and Falcone, M. (2010). The Deterrent Effects of Penalty Point System in Driving Licenses: A Regression Discontinuity Approach. *Universita Della Calabria Economics Dept Working Paper*, pp. 1–21.

DeAngelo, G. and Hansen, B. (2014). Life and Death in the Fast Lane: Police Enforcement and Traffic Fatalities †. *American Economic Journal: Economic Policy*, **6** (2), 231–257.

— and Owens, E. G. (2014). Learning the Ropes: Task Specific Experience and the Output of Idaho State Troopers. *Working Paper*, pp. 1–50.

Dee, T., Dobbie, W., Jacob, B. and Rockoff, J. (2016). The Causes and Consequences of Test Score Manipulation: Evidence from the New York Regents Examination. *NBER Working Paper*, pp. 1–67.

Delaigle, A., Hall, P. and Meister, A. (2008). On deconvolution with repeated measurements. *The Annals of Statistics*, pp. 665–685.

Diamond, R. and Persson, P. (2016). The Long-Term Consequences of Teacher Discretion in Grading of High-Stakes Tests. *SIEPR Discussion Paper*, **16-003**, 1–70.

Donohue, J. (2014). An Empirical Evaluation of the Connecticut Death Penalty System Since 1973: Are There Unlawful Racial, Gender, and Geographic Disparities? *Journal of Empirical Legal Studies*, **11** (4), 637–696.

Donohue III, J. J. and Levitt, S. D. (2001). The impact of race on policing and arrests. *The Journal of Law and Economics*, **44** (2), 367–394.

Fryer, R. G. (2016). An Empirical Analysis of Racial Differences in Police Use of Force. *NBER Working Paper*, **22399**, 1–63.

Garrett, T. A. and Wagner, G. A. (2009). Red Ink in the Rearview Mirror: Local Fiscal Conditions and the Issuance of Traffic Tickets. *The Journal of Law and Economics*, **52** (1), 71–90.

Gehrsitz, M. (2015). Speeding, Punishment, and Recidivism Evidence from a Regression Discontinuity Design. *Unpublished Manuscript*, pp. 1–45.

Gelman, A., Fagan, J. and Kiss, A. (2007). 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** (479), 813–823.

Goldin, C. and Rouse, C. (2000). Orchestrating Impartiality: The Impact of "Blind" Auditions on Female Musicians. *American Economic Review*, **90** (4), 715–741.

Goldstein, J. (1960). Police discretion not to invoke the criminal process: Low-visibility decisions in the administration of justice. *The Yale Law Journal*, **69** (4), 543–594.

Grogger, J. and Ridgeway, G. (2006). Testing for Racial Profiling in Traffic Stops From Behind a Veil of Darkness. *Journal of the American Statistical Association*, **101** (475), 878–887.

Hansen, B. (2015). Punishment and Deterrence: Evidence from Drunk Driving †. *American Economic Review*, **105** (4), 1581–1617.

Horrace, W. C. and Rohlin, S. M. (2016). How Dark Is Dark? Bright Lights, Big City, Racial Profiling. *Review of Economics and Statistics*, **98** (2), 226–232.

Kessler, D. P. and Piehl, A. M. (1998). The role of discretion in the criminal justice system. *Journal of Law, Economics, & Organization*, pp. 256–276.

Kleven, H. J. (2016). Bunching. *Annual Review of Economics*, **8**, 435–464.

Knowles, J., Persico, N. and Todd, P. (2001). Racial Bias in Motor Vehicle Searches: Theory and Evidence. *Journal of Political Economy*, **109** (1), 203–229.

Koedel, C., Mihaly, K. and Rockoff, J. E. (2015). Value-Added Modeling: A Review. *Economics of Education Review*, **47** (C), 180–195.

Lange, J. E., Johnson, M. B. and Voas, R. B. (2005). Testing the racial profiling hypothesis for seemingly disparate traffic stops on the new jersey turnpike. *Justice Quarterly*, **22** (2), 193–223.

Lee, D. (2012). Do Traffic Tickets Reduce Motor Vehicle Accidents? Evidence from a Natural Experiment. *Unpublished Manuscript*, pp. 1–32.

Makowsky, M. D. and Stratmann, T. (2009). Political Economy at Any Speed: What Determines Traffic Citations? *American Economic Review*, **99** (1), 509–527.

— and — (2011). More Tickets, Fewer Accidents: How Cash-Strapped Towns Make for Safer Roads. *The Journal of Law and Economics*, **54** (4), 863–888.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, **142** (2), 698–714.

Morris, C. N. (1983). Parametric Empirical Bayes Inference: Theory and Applications. *Journal of the American Statistical Association*, **78** (381), 47–55.

Muir, W. K. (1979). *Police: streetcorner politicians*. University of Chicago Press.

Persico, N. (2009). Racial Profiling? Detecting Bias Using Statistical Evidence. *Annual Review of Economics*, **1** (1), 229–254.

Postel-Vinay, F. and Robin, J.-M. (2002). Equilibrium wage dispersion with worker and employer heterogeneity. *Econometrica*, **70** (6), 2295–2350.

Price, J. and Wolfers, J. (2010). Racial Discrimination Among NBA Referees. *Quarterly Journal of Economics*, **125** (4), 1859–1887.

Quintanar, S. (2011). Do Driver Decisions in Traffic Court Motivate Police Discrimination in Issuing Speeding Tickets? *LSU Department of Economics Working Paper*, pp. 1–42.

Rehavi, M. M. and Starr, S. B. (2014). Racial disparity in federal criminal sentences. *Journal of Political Economy*, **122** (6), 1320–1354.

Reiss, A. J. (1973). *The police and the public*, vol. 39. Yale University Press.

Ridgeway, G. and MacDonald, J. (2010). Methods for Assessing Racially Biased Policing. In S. Rice and M. White (eds.), *Race, Ethnicity, and Policing New and Essential Readings*, pp. 180–204.

Roach, M. (2015). Is the Highway Patrol Really Tougher on Out-of-State Drivers? An Empirical Analysis. *The B.E. Journal of Economic Analysis & Policy*, **15** (2), 769–796.

Rowe, B. (2008). Gender Bias in the Enforcement of Traffic Laws: Evidence Based on a New Test. *American Law and Economics Association Annual Meetings*, pp. 1–36.

— (2010). Discretion and Ulterior Motives in Traffic Stops: The Detection of Other Crimes and the Revenue from Tickets. *Unpublished Manuscript*, pp. 1–27.

Smith, D. A., Visher, C. A. and Davidson, L. A. (1984). Equity and discretionary justice: The influence of race on police arrest decisions. *The Journal of Criminal Law and Criminology (1973-)*, **75** (1), 234–249.

Smith, W., Tomaskovic-Devey, D., Zingraff, M., Mason, H. M., Warren, P. and Wright, C. (2004). The North Carolina Highway Traffic Study. *NCJRS Grant Report*, pp. 1–407.

Walker, S., Spohn, C. and DeLone, M. (2012). *The color of justice: Race, ethnicity, and crime in America*. Cengage Learning.

Weitzer, R. and Tuch, S. A. (2004). Race and perceptions of police misconduct. *Social problems*, **51** (3), 305–325.

West, J. (2015). Racial Bias in Police Investigations. *Working Paper*, pp. 1–29.

Wozniak, A. (2015). Discrimination and the effects of drug testing on black employment. *Review of Economics and Statistics*, **97** (3), 548–566.

Data Appendix

Citations Data

Our data cover the universe of citations written by the Florida Highway Patrol for the years 2005-2015, comprising 2,614,119 observations. We make several restrictions that reduce the number of observations:

1. speeding is the primary citation (1,677,177 observations, 64% of previous sample)
2. no crash is involved (1,676,141, 99.9%)
3. speed is between 0 and 40 over the limit (1,665,699, 99.4%)
4. posted speed limit is between 25MPH and 75MPH (1,664,570, 99.9%)
5. citations not from an airplane (1,660,355, 99.7%)
6. race/ethnicity is not missing (1,408,355, 84.8%)
7. race/ethnicity is white, black or Hispanic (1,335,887, 94.8%)
8. not missing driver's license state, gender, or age (1,333,720, 99.8%)
9. officer is identifiable (1,024,631, 76.8%)
10. officer has at least 100 tickets, and at least 20 for minorities and 20 for whites (988,096, 96.5%)

Linking Offenses to Personnel Information

Officers enter their information by hand onto each speeding ticket, leading to inconsistencies in how their names are recorded. Some names are misspelled, and sometimes officers place only their last name and first initial. The Florida Department of Law Enforcement (FDLE) maintains a record of each certified officer in the state, along with demographic information. We link these using each officer's last name and first three letters of first name (if available on ticket) using a fuzzy match algorithm in Stata (reclink). We restrict attention to officers who are unique up to last name and first three letters of first name in the FDLE data. Among tickets where only the first initial is listed, we keep matches where the last name and first initial of an officer are unique in the FDLE data. Of the 1,677,177 speeding tickets in our data, 1,651,933 have at least an officer last name and first initial listed. Of these, 1,260,900 match successfully to the FDLE data.

Hours and Shifts of Tickets

Officers manually enter time of day, and there are several inconsistencies in how these are recorded. Most officers use either a 12-hour time and clarify AM versus PM, and others use 24-hour military time. Some officers regularly use 12 hour time and do not record AM versus PM. We set these times to be missing.

The FHP has three shifts, 6am to 2pm, 2pm to 10pm, and 10pm to 6am. We record these directly from the hour of the ticket if it is properly recorded above. If there is no correct hour of day, we take a two-week moving average of the officer's modal shift for his citations and impute the shift. For the remaining tickets we leave shift as missing. Of the 1.6 million initial speeding citations, 692,416 have shift missing, and 413,560 remain missing after the imputation procedure.

Stretch-of-Road Fixed Effects

Beginning in 2013, about 40% of tickets are geocoded with the latitude and longitude of a stop (135,586 observations). The primary determinant of whether a ticket is geo-coded is whether the trooper's vehicle has a GPS tracker. Officers in more rural areas and on interstates are given priority for GPS'd vehicles, as they are not able to clearly describe the location of their ticket using street intersections. 40% of officers have fewer than 5% of their stops geocoded, and there is some variation across counties in the share of tickets geocoded.

We link the geocoded tickets to a Florida Department of Transportation's roadmap shapefile using ArcGIS.[19] The shapefile is at the level of road "segments," which are on average 6.7 miles long and roughly correspond to entire streets within cities and uninterrupted stretches of road on interstates and highways. Tickets are linked to the nearest segment, and we remove tickets that are more than 100 meters from the nearest road (dropping 1.5% of observations). Figure A-3 shows how geocoded tickets are distributed throughout the state.

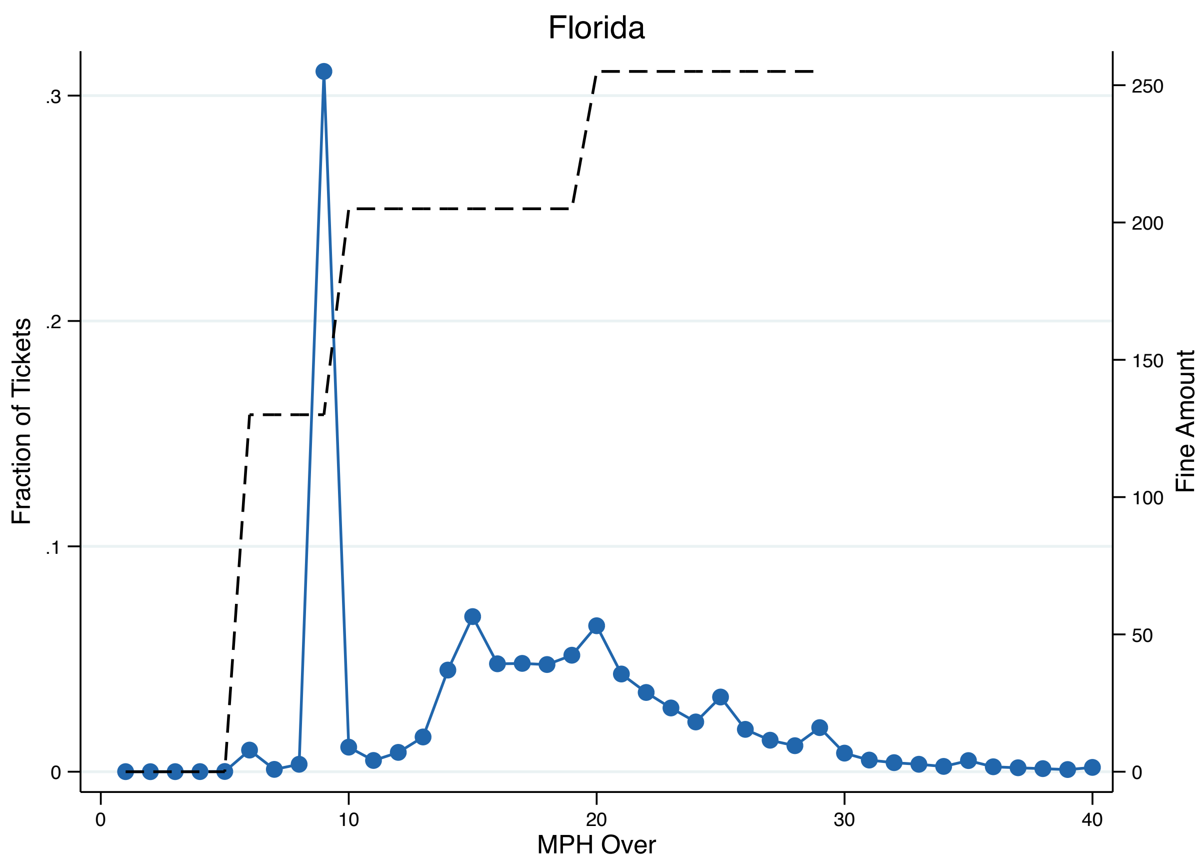
Table A-1 shows the main linear probability model results, now restricted to the sample for which we have GPS location, with a similar progression of fixed effects added across columns. The disparity between whites and minorities in the likelihood of appearing at the discount point persists when controlling for road fixed effects, even in column 5 where we control for an interaction between year, month, day of week, hour, speed zone, county, and road segment. The results look very similar to our main specification results in Table 4. The coefficients on Black and Hispanic continue to be significant, and are in fact slightly larger than in the main linear probability model results. Note that the majority of coefficients lose their significance in the most extreme fixed effects case, but race and gender are still significant.

Figure A-4 shows the deconvolution of officer fixed effects to estimate the distribution of officer bias. The further right in the figure, the more biased an officer. We simply note that the shape is qualitatively the same as in our main deconvolution results in Figure 5.

[19] http://www.fdot.gov/planning/statistics/gis/road.shtm ; We use the "Basemap Routes with Measures" shapefile.

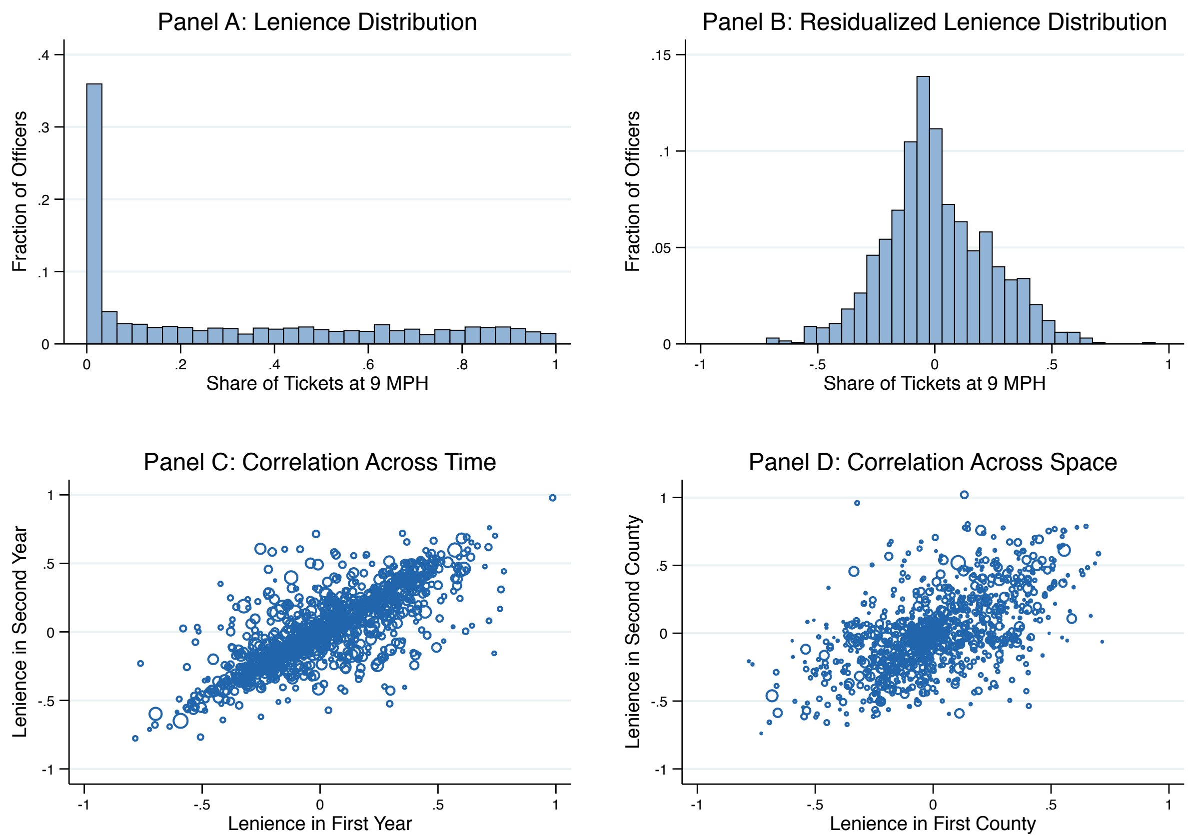
Figures and Tables

Figure 1: Distribution of Charged Speeds and Fine Schedule



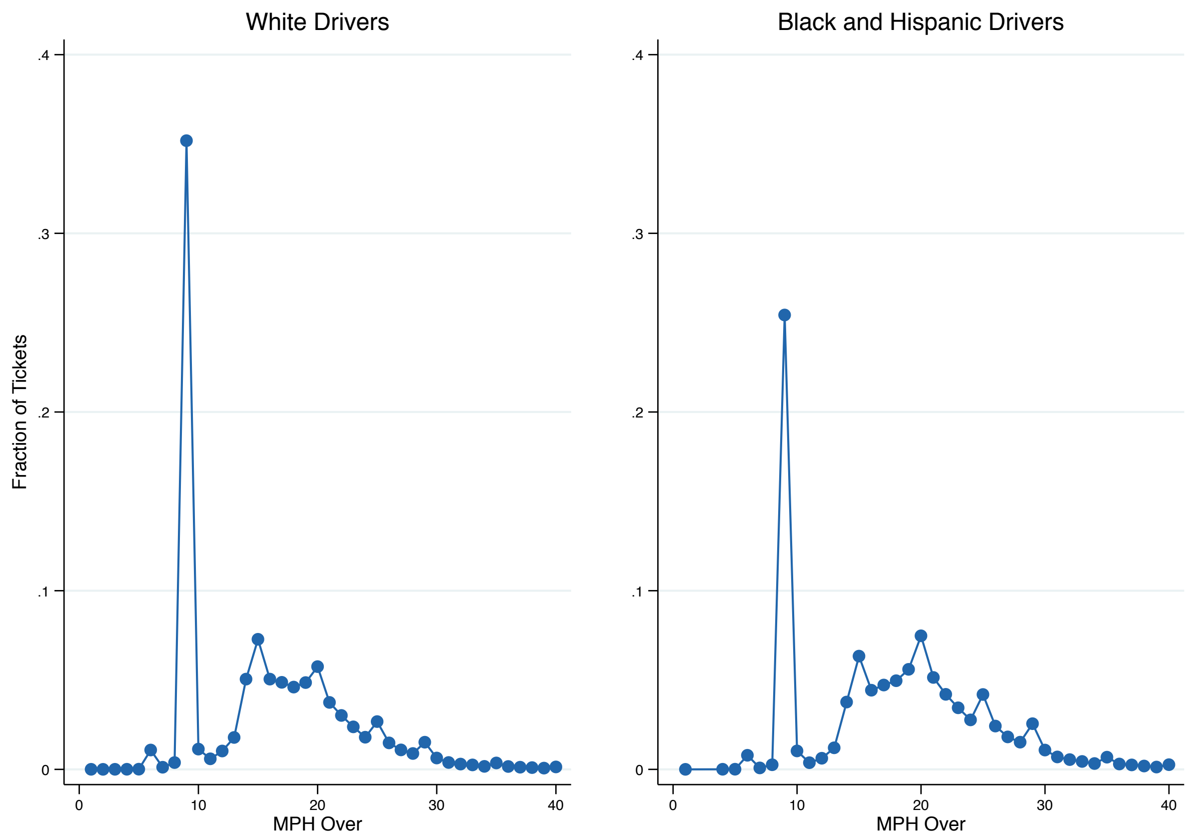
Notes: Connected line shows histogram of tickets. Dashed line plots fine schedule for Broward County. 30 MPH over is felony speeding and carries a fine to be determined following a court appearance.

Figure 2: Evidence of Officer Lenience



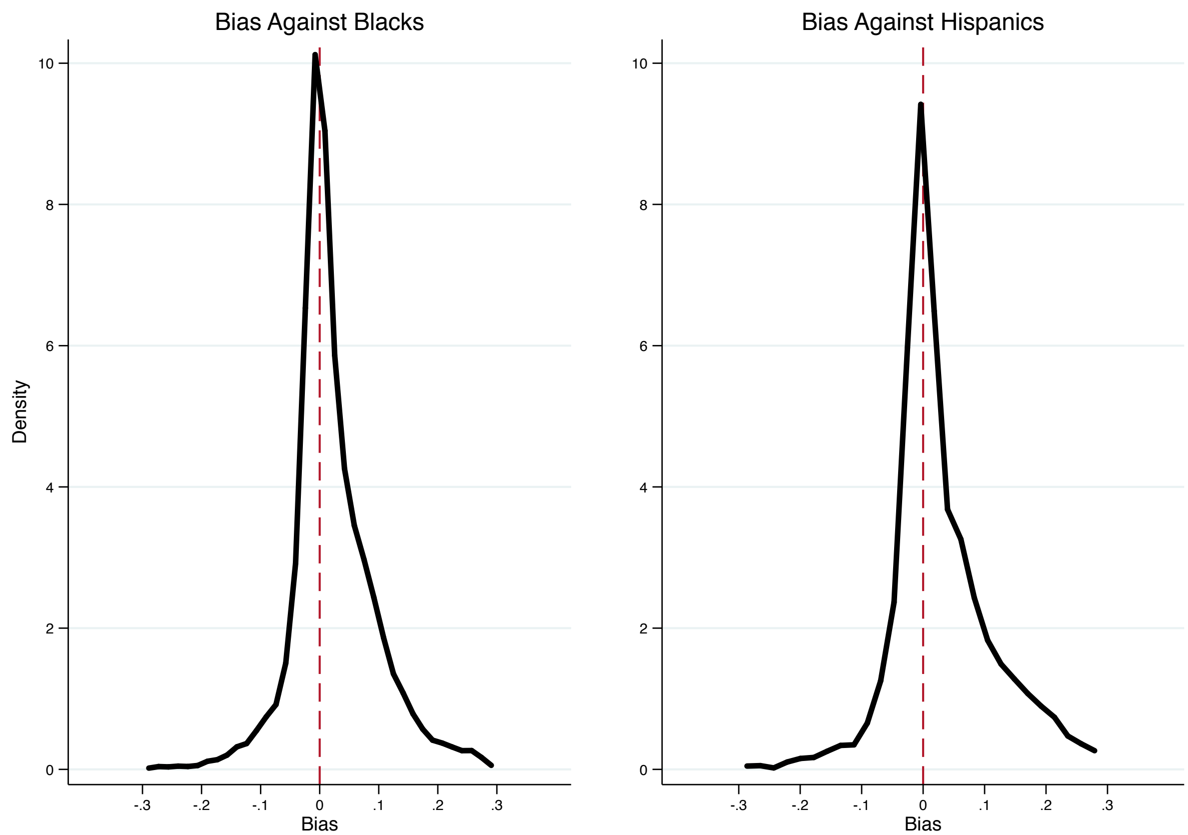
Notes: Panel A plots the across-officer distribution of lenience. Panel B plots the across-officer distribution of residualized lenience. Panel B plots officers' residualized lenience in the years with the most and second most citations. Panel D plots the residualized lenience in the county with the most and second most citations. Estimates residualized by conditioning on county fixed effects, speed zone fixed effects, year and month fixed effects, and day of week fixed effects. See text for additional details.

Figure 3: Charged Speed Distributions by Driver Race



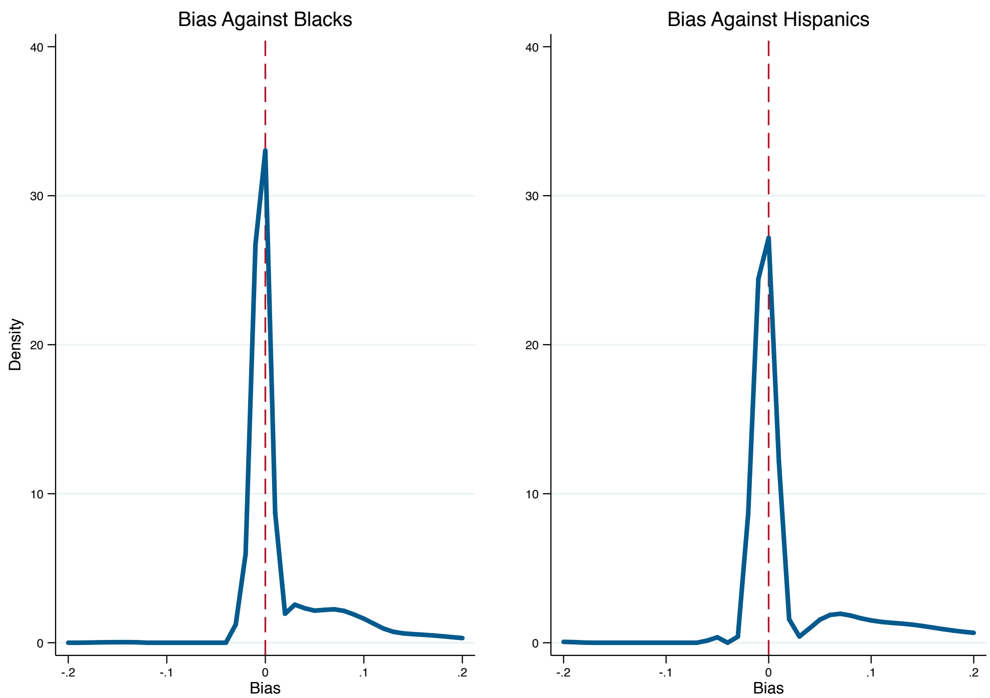
Notes: Connected line shows histogram of ticketed speeds, separately by driver race.

Figure 4: Distributions of Officer Bias Estimates



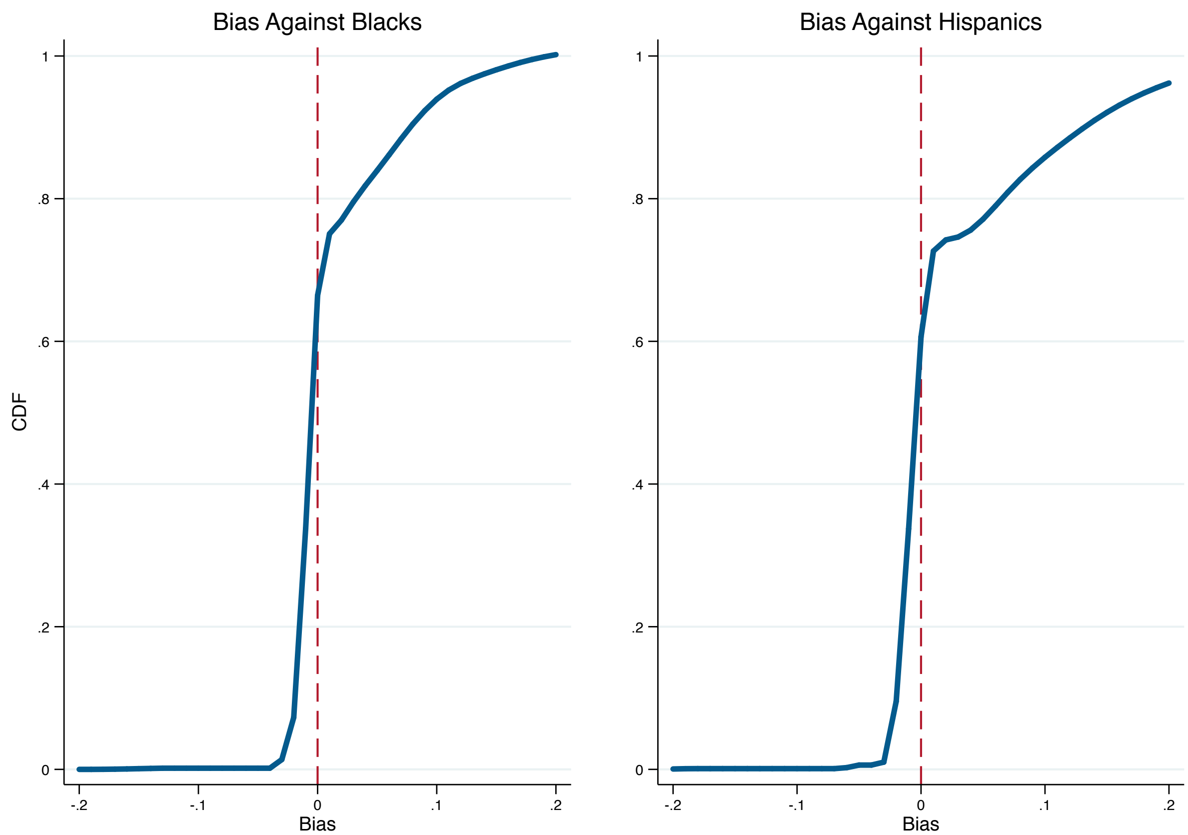
Notes: Dashed line plots kernel density estimate of the distribution of officer bias estimates. Solid line plots corresponding kernel density estimate of distribution of Bayes shrunk officer bias.

Figure 5: Estimated Distributions of Bias



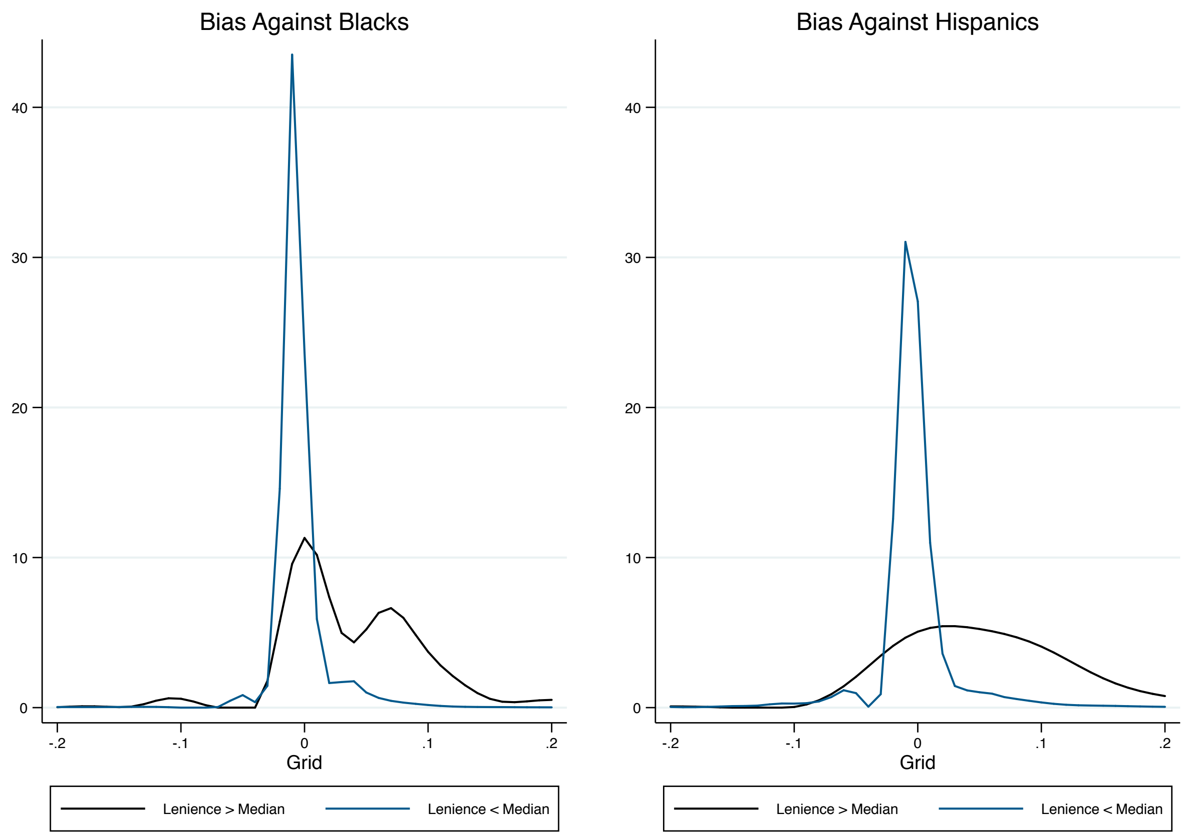
Notes: Figure plots estimated distributions of bias computed using the deconvolution technique from Delaigle and Meister (2008).

Figure 6: Estimated CDFs of Bias



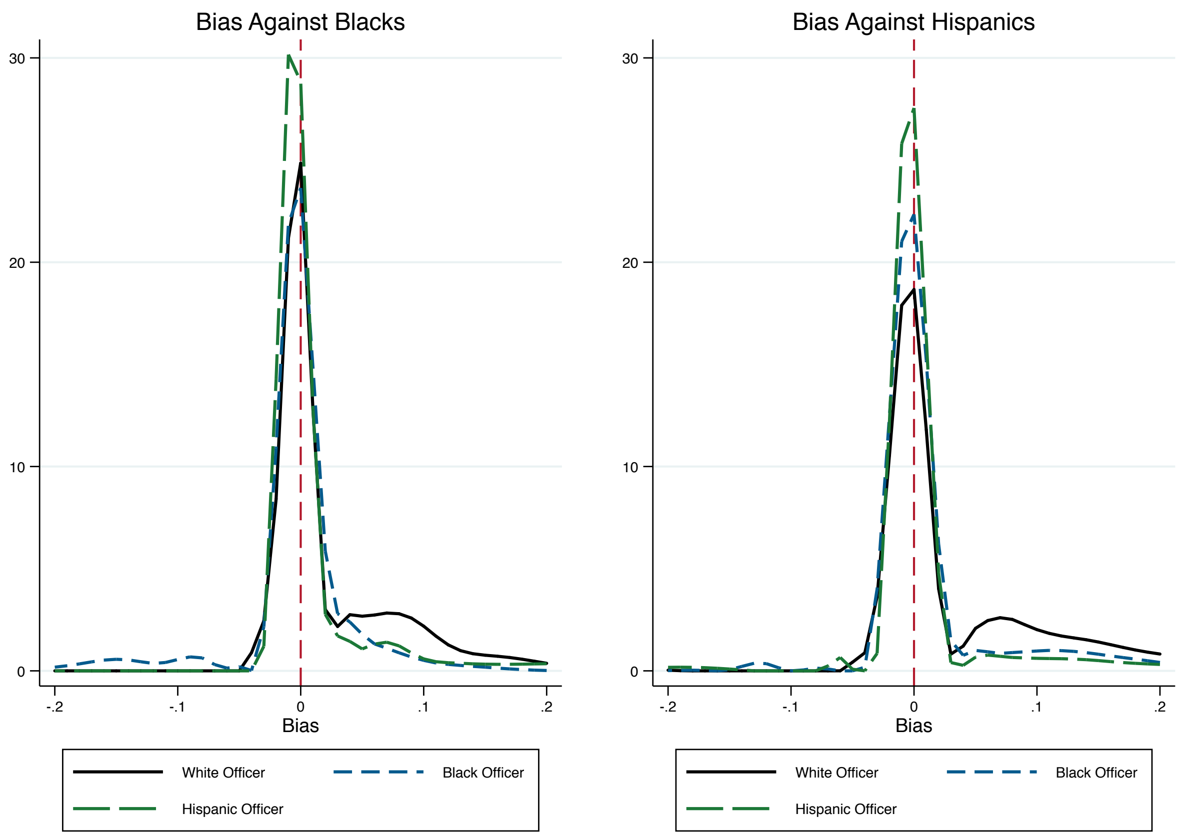
Notes: Figure plots estimated cumulative density functions of bias computed using the deconvolution technique from Delaigle and Meister (2008).

Figure 7: Estimated Distribution of Bias, by Officer Lenience



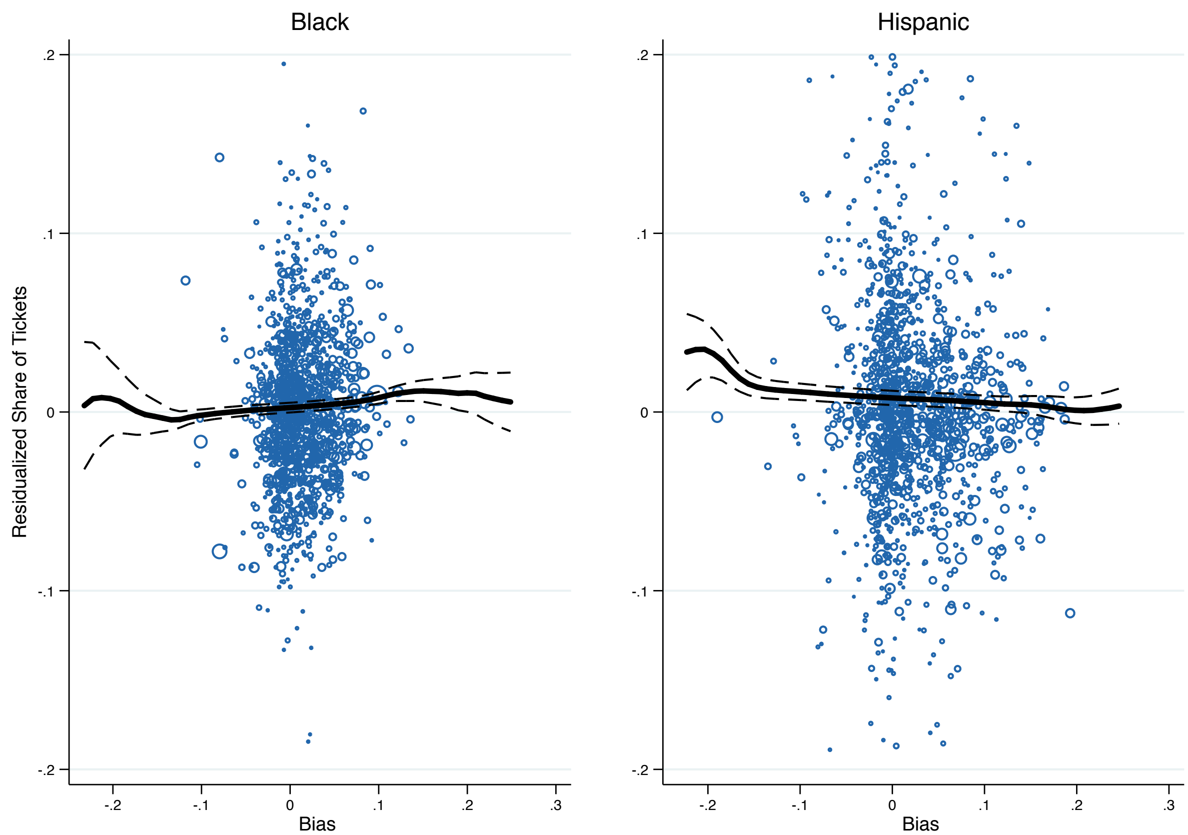
Notes: Figure plots estimated cumulative density functions of bias computed using the deconvolution technique from Delaigle and Meister (2008), where officers are split into whether their lenience is above or below the median officer's lenience.

Figure 8: Distributions of Bias by Officer Race



Notes: Figure plots estimated distributions of bias computed using the deconvolution technique from Delaigle and Meister (2008) and computed separately by officer race.

Figure 9: Driver Race Shares by Officer Bias



Notes: Figure plots an officer's residualized share of stops which are black (Hispanic) against his estimate bias against that racial group. Residualized shares are computed by regressing a black (Hispanic) indicator on year, month, day-of-week, speed zone, and county fixed effects and averaging the residuals at the officer level.

Table 1: Summary Statistics

	White	Black	Hispanic	Total
Female	0.362	0.397	0.301	0.354
	(0.481)	(0.489)	(0.459)	(0.478)
Age	37.39	34.15	34.20	36.03
	(14.89)	(12.10)	(11.93)	(13.83)
Florida License	0.818	0.853	0.893	0.842
	(0.386)	(0.355)	(0.309)	(0.365)
Zip Code Income	56.96	39.70	46.49	51.13
	(53.20)	(31.18)	(42.81)	(47.79)
Citations in Past Year	0.0391	0.0482	0.0459	0.0424
	(0.209)	(0.231)	(0.232)	(0.219)
MPH Over	15.49	16.67	18.32	16.38
	(6.518)	(7.046)	(6.972)	(6.829)
Discount	0.352	0.316	0.206	0.311
	(0.478)	(0.465)	(0.405)	(0.463)
Fine Amount	182.3	190.2	200.7	188.0
	(76.40)	(80.50)	(79.33)	(78.23)
Share	.577	.186	.237	1

Notes: Number of observations is 571,751 (White); 184,567 (Black); 234,323 (Hispanic); 990,641 (Total). Standard deviations in parentheses. Zip code income is missing for 42% of White stops, 40% of Black stops, 37% of Hispanic stops. To account for the fact that a large share of fine amounts are missing or zero in our data, we impute the fine amount with the modal non-zero fine for each county $\times$ speed over the limit cell.

Table 2: Characteristics of Cited Drivers Relative to Other Data Sources

	Citations	ACS - Any	ACS - Drivers	Crash - Any	Crash - Injury
Female	0.356	0.515	0.474	0.424	0.441
	(0.479)	(0.500)	(0.499)	(0.494)	(0.497)
Age	34.90	47.46	41.70	39.65	39.77
	(13.45)	(19.39)	(13.72)	(16.78)	(17.11)
White	0.578	0.625	0.606	0.556	0.576
	(0.494)	(0.484)	(0.489)	(0.497)	(0.494)
Black	0.181	0.138	0.136	0.189	0.193
	(0.385)	(0.345)	(0.343)	(0.391)	(0.394)
Hispanic	0.241	0.200	0.217	0.233	0.211
	(0.428)	(0.400)	(0.412)	(0.423)	(0.408)

Notes: Standard deviations in parentheses. ACS data include individuals aged 16 or older and sampling weights are used.

Table 3: White-Minority Speed Charged Gap

	(1) MPH Over	(2) MPH Over	(3) MPH Over
Black	1.097***	1.002***	0.749***
	(0.0179)	(0.0178)	(0.0164)
Hispanic	2.244***	2.047***	0.737***
	(0.0170)	(0.0171)	(0.0165)
White Mean	15.26	15.26	15.26
Controls		X	X
FE			X
Obs	1018920	1018920	1018920

Notes: Dependent variable is the ticketed speed minus the speed limit. Robust standard errors in parentheses. Dependent variable is speed charged. Age divided by 1000. Controls include gender, age, age squared, and whether driver is in-state. Fixed effects include year, month, day of week, speed zone, and county.

Table 4: Linear Probability Estimates

	(1) Discount	(2) Discount	(3) Discount	(4) Discount	(5) Discount
Black	-0.0294	-0.0259	-0.0198***	-0.0213***	-0.0177***
	(0.0189)	(0.0182)	(0.00402)	(0.00392)	(0.00509)
Hispanic	-0.122***	-0.112***	-0.0329***	-0.0318***	-0.0330***
	(0.0307)	(0.0302)	(0.00711)	(0.00678)	(0.0102)
Driver Female		0.0487***	0.0362***	0.0300***	0.0278***
		(0.00464)	(0.00471)	(0.00373)	(0.00556)
Florida License		-0.0602**	0.000234	0.00208	0.00484
		(0.0270)	(0.00424)	(0.00409)	(0.00410)
Age		2.273*	3.382***	3.084***	2.422**
		(1.306)	(0.820)	(0.727)	(1.013)
Age Squared		-10.20	-19.92***	-20.82***	-14.47
		(14.03)	(7.046)	(6.537)	(8.941)
White Mean	.36	.36	.36	.36	.36
Zone X County FE			X	X	
Year X Month FE				X	
DOW X Hour FE				X	
Saturated FE					X
Observations	1002381	1002381	1002381	1002381	1002381

Notes: County-level clustered standard errors in parentheses. Dependent variable is an indicator for charged speed equals 9 MPH above the limit. Age divided by 1000. Saturated fixed effects are at the level of speed zone by county by year by month by day of week by hour.

Table 5: Linear Probability Estimates with Additional Controls

	(1) Discount	(2) Discount	(3) Discount	(4) Discount
Black	-0.0213***	-0.0215***	-0.0236***	-0.0212***
	(0.00392)	(0.00384)	(0.00367)	(0.00362)
Hispanic	-0.0318***	-0.0309***	-0.0322***	-0.0313***
	(0.00678)	(0.00681)	(0.00686)	(0.00685)
Log Zip Code Income			-0.00681***	-0.00757***
			(0.00238)	(0.00240)
1 Prior Ticket				-0.0151***
				(0.00239)
2 Prior Tickets				-0.0274***
				(0.00388)
3 Prior Tickets				-0.0327***
				(0.00521)
4+ Prior Tickets				-0.0477***
				(0.00802)
White Mean	.36	.36	.36	.36
Vehicle Chars		X	X	X
Controls	X	X	X	X
Fixed Effects	X	X	X	X
Observations	1002381	1002381	1002381	1002381

Notes: Robust standard errors in parentheses. Dependent variable is an indicator for charged speed equals 9 MPH above the limit. Odd columns repeat the specification from Column (4) of Table 4 but restricting the sample to stops where the relevant variable is non-missing, and even columns add those controls. All regressions include controls, year and month fixed effects, day-of-week fixed effects county fixed effects, and speed zone fixed effects

Table 6: Characteristics of Distribution of Estimated Bias

	Bias Against Blacks	Bias Against Hispanics
Mean	.013	.022
Standard Deviation	.031	.058
10th Percentile	-.02	-.03
25th Percentile	-.007	-.009
50th Percentile	.01	.011
75th Percentile	.02	.051
90th Percentile	.053	.096
Officers <0	101	160
Officers >0	161	236
Officers	1337	1339

Notes: This table presents the distributional statistics of shrunken Officer-level estimated racial bias (graphed in Figure 4).

Table 7: Benchmarking Estimates

	Discount
Black Driver	-0.0297***
	(0.00123)
Hispanic Driver	-0.0369***
	(0.00117)
Black Officer	-0.00415***
	(0.00129)
Hispanic Officer	-0.0123***
	(0.00136)
Black Driver x Black Officer	0.0304***
	(0.00272)
Hispanic Driver x Hispanic Officer	0.0163***
	(0.00199)
White Mean	.36
Controls	Yes
Fixed Effects	Yes
Observations	976821

Notes: Robust standard errors in parentheses. Dependent variable is an indicator for charged speed equals 9 MPH above the limit.

Table 8: Predicting Officer Bias

	(1) Black	(2) Black	(3) Black	(4) Hispanic	(5) Hispanic	(6) Hispanic
Black	-0.0213***	-0.128***	-0.0650**	-0.0202***	-0.0973**	-0.0586**
	(0.00359)	(0.0426)	(0.0261)	(0.00520)	(0.0403)	(0.0298)
Hispanic	-0.00959***	-0.122***	-0.0720***	-0.0231***	-0.0862**	-0.0925***
	(0.00315)	(0.0393)	(0.0248)	(0.00517)	(0.0378)	(0.0256)
Other	0.0135	0.161	0.0546	0.000741	0.129	-0.109
	(0.0111)	(0.100)	(0.0990)	(0.0127)	(0.101)	(0.0713)
Female	-0.0154***	-0.139***	-0.0680**	-0.0150***	-0.130***	-0.0609*
	(0.00375)	(0.0522)	(0.0279)	(0.00543)	(0.0496)	(0.0326)
Age	0.0155*	0.298***	0.138**	0.0156	0.189**	0.0668
	(0.00854)	(0.0912)	(0.0586)	(0.0126)	(0.0879)	(0.0688)
Age Squared	-0.00263**	-0.0470***	-0.0198**	-0.00246	-0.0269**	-0.00421
	(0.00129)	(0.0136)	(0.00883)	(0.00198)	(0.0133)	(0.0107)
Experience	-0.00623	0.0155	-0.0690	-0.0118	-0.0535	-0.130***
	(0.00584)	(0.0626)	(0.0452)	(0.0102)	(0.0562)	(0.0488)
Exp Squared	0.00406*	0.0183	0.0306*	0.00864**	0.0447**	0.0448**
	(0.00243)	(0.0241)	(0.0177)	(0.00406)	(0.0211)	(0.0198)
Failed Entrance Exam	-0.00558	-0.0881	-0.0464	-0.000403	-0.103**	-0.0351
	(0.00519)	(0.0537)	(0.0314)	(0.00651)	(0.0521)	(0.0355)
Any College	-0.00443	-0.0876***	-0.0422*	0.000194	0.0112	0.0166
	(0.00297)	(0.0330)	(0.0220)	(0.00450)	(0.0317)	(0.0249)
Any Complaints	-0.00267	-0.127***	0.0337	0.00117	-0.0353	0.0142
	(0.00428)	(0.0451)	(0.0340)	(0.00545)	(0.0452)	(0.0346)
Sought Promotion	-0.00143	-0.0138	0.0162	-0.00319	0.0133	0.0102
	(0.00282)	(0.0315)	(0.0216)	(0.00459)	(0.0303)	(0.0234)
Dep Var	Bias	Bias<0	Bias<0 (Sig)	Bias	Bias<0	Bias<0 (Sig)
Mean	.023	.582	.124	.029	.59	.178
Observations	1332	1332	1332	1334	1334	1334

Notes: Robust standard errors in parentheses. In Columns (1) and (4), dependent variable is our measure of the officer's bias. In Columns (2) and (5), it is an indicator for whether our bias estimate is positive. In Columns (3) and (6), it is an indicator for whether the estimate is positive and statistically significant. Columns (1)-(3) refer to bias against blacks while Columns (4)-(6) refer to bias against Hispanics.

Table 9: Predicting Officer Bias, Sergeant's Exam Takers

	(1) Black	(2) Black	(3) Black	(4) Hispanic	(5) Hispanic	(6) Hispanic
Black	-0.0267***	-0.167**	-0.147***	-0.0158*	-0.0518	-0.0983**
	(0.00606)	(0.0698)	(0.0343)	(0.00924)	(0.0689)	(0.0489)
Hispanic	-0.0100**	-0.0420	-0.116***	-0.0230***	-0.0544	-0.149***
	(0.00492)	(0.0627)	(0.0404)	(0.00746)	(0.0602)	(0.0408)
Other	0.0279	0.302**	0.204	-0.00414	-0.00917	-0.271***
	(0.0299)	(0.153)	(0.214)	(0.0225)	(0.204)	(0.0392)
Age	-0.00697**	-0.0306	-0.0407*	0.00434	-0.0305	0.0326
	(0.00335)	(0.0390)	(0.0237)	(0.00615)	(0.0371)	(0.0297)
Experience	0.00754*	0.0836*	0.0214	-0.000691	0.0391	-0.0565
	(0.00405)	(0.0458)	(0.0308)	(0.00719)	(0.0444)	(0.0353)
Failed Entrance Exam	-0.00541	-0.00951	-0.119***	0.00466	-0.0406	-0.0237
	(0.00914)	(0.0873)	(0.0374)	(0.00879)	(0.0838)	(0.0600)
Any College	-0.00695	-0.0853*	-0.0160	-0.0138*	-0.0176	-0.0349
	(0.00471)	(0.0494)	(0.0335)	(0.00716)	(0.0477)	(0.0369)
Any Complaints	-0.00730	-0.193***	-0.000890	0.00178	-0.0705	0.0453
	(0.00748)	(0.0712)	(0.0472)	(0.00828)	(0.0715)	(0.0574)
Sgt Exam Score	-0.0000730	-0.00102	-0.00368**	0.000481	0.00359	0.00270
	(0.000222)	(0.00253)	(0.00161)	(0.000320)	(0.00245)	(0.00187)
Dep Var	Bias	Bias<0	Bias<0 (Sig)	Bias	Bias<0	Bias<0 (Sig)
Mean	.023	.582	.124	.029	.59	.178
Observations	513	513	513	514	514	514

Notes: Same as Table 8 except that only the subset of officers ever to take the Sergeant's Promotional exam are included.

Table 10: Predicting Officer Complaints/Force

	(1) # Complaints	(2) Any Complaints	(3) # Use of Force	(4) Any Use of Force
Lenience	-0.721***	-0.206***	-0.246	-0.113**
	(0.223)	(0.0588)	(0.150)	(0.0530)
Minority Bias	0.355	0.321	0.444	0.0793
	(0.642)	(0.216)	(0.462)	(0.183)
Black	0.112	0.00156	-0.190**	-0.0847**
	(0.176)	(0.0400)	(0.0905)	(0.0336)
Hispanic	-0.00683	0.0170	0.0340	0.00730
	(0.144)	(0.0372)	(0.0993)	(0.0373)
Other	0.184	0.0261	-0.234	-0.0720
	(0.380)	(0.0998)	(0.181)	(0.0939)
Female	-0.296*	-0.110**	-0.0145	0.0135
	(0.158)	(0.0496)	(0.104)	(0.0442)
Age	-0.121	0.161*	-0.735***	-0.193**
	(0.332)	(0.0898)	(0.213)	(0.0794)
Age Squared	0.0166	-0.0247*	0.0608**	0.0136
	(0.0478)	(0.0131)	(0.0266)	(0.0109)
Experience	-0.0636	-0.0821	-0.559*	-0.0108
	(0.413)	(0.130)	(0.331)	(0.117)
Exp Squared	-0.0265	0.0332	-0.00401	-0.00118
	(0.0767)	(0.0249)	(0.0460)	(0.0196)
Failed Entrance Exam	0.256	0.0429	-0.104	-0.00344
	(0.205)	(0.0483)	(0.109)	(0.0458)
Any College	-0.186*	-0.0263	0.102	0.0135
	(0.104)	(0.0294)	(0.0946)	(0.0264)
Sought Promotion	-0.199*	-0.0680**	-0.0407	0.0243
	(0.113)	(0.0294)	(0.0887)	(0.0277)
Mean	1.259	.551	.560	.294
Observations	1401	1401	1401	1401
Regression	OLS	OLS	OLS	OLS

Notes: Heteroskedasticity-robust standard errors in parentheses. Column title indicates the dependent variable. Data is at the officer-year level. Regressions have fixed effects for years and fixed effects for district of officer assignment.

Table 11: Predicting Office Complaints/Force, Split Sample IV

	(1) # Complaints	(2) Any Complaints	(3) # Use of Force	(4) Any Use of Force
Lenience	-0.722***	-0.227***	-0.333**	-0.141**
	(0.230)	(0.0631)	(0.145)	(0.0558)
Minority Bias	0.154	0.693	1.636	0.522
	(1.177)	(0.440)	(1.024)	(0.354)
Black	0.106	0.0129	-0.155*	-0.0716**
	(0.174)	(0.0415)	(0.0874)	(0.0344)
Hispanic	-0.0106	0.0232	0.0525	0.0139
	(0.142)	(0.0375)	(0.0997)	(0.0372)
Other	0.183	0.0177	-0.257	-0.0800
	(0.374)	(0.102)	(0.182)	(0.0923)
Female	-0.300*	-0.107**	-0.00655	0.0167
	(0.156)	(0.0488)	(0.103)	(0.0436)
Age	-0.117	0.160*	-0.741***	-0.196**
	(0.326)	(0.0888)	(0.211)	(0.0790)
Age Squared	0.0160	-0.0246*	0.0616**	0.0139
	(0.0469)	(0.0129)	(0.0265)	(0.0108)
Experience	-0.0621	-0.0919	-0.583*	-0.0193
	(0.407)	(0.129)	(0.331)	(0.116)
Exp Squared	-0.0264	0.0356	0.00239	0.000910
	(0.0757)	(0.0249)	(0.0458)	(0.0194)
Failed Entrance Exam	0.255	0.0423	-0.104	-0.00283
	(0.202)	(0.0476)	(0.109)	(0.0457)
Any College	-0.184*	-0.0269	0.0996	0.0124
	(0.103)	(0.0290)	(0.0932)	(0.0262)
Sought Promotion	-0.198*	-0.0657**	-0.0355	0.0261
	(0.111)	(0.0291)	(0.0867)	(0.0274)
Mean	1.259	.551	.560	.294
Observations	1401	1401	1401	1401
Regression	2SLS	2SLS	2SLS	2SLS
1st Stage F-stat	159.3	159.3	159.3	159.3

Notes: Heteroskedasticity-robust standard errors in parentheses. Column title indicates the dependent variable. Data is at the officer-year level. Regressions have fixed effects for years and fixed effects for district of officer assignment.

Table 12: Predicting Complaints/Force for Young Officers

	(1) # Complaints	(2) Any Complaints	(3) # Use of Force	(4) Any Use of Force
Complaints 1st Year	0.215**	0.164**	0.0725	0.0505
	(0.0993)	(0.0712)	(0.0634)	(0.0451)
Use-of-Force 1st Year	0.136	0.129	0.000104	0.00558
	(0.109)	(0.0885)	(0.102)	(0.0632)
Lenience	-0.117	-0.0936	-0.280*	-0.175*
	(0.150)	(0.122)	(0.145)	(0.0985)
Minority Bias	0.776	0.541	0.233	0.364
	(0.536)	(0.347)	(0.456)	(0.323)
Black	-0.103	-0.0941	0.0763	0.0683
	(0.137)	(0.0993)	(0.0952)	(0.0885)
Hispanic	-0.0987	-0.0558	0.0978	0.0830
	(0.103)	(0.0890)	(0.0770)	(0.0649)
Other	0.294	0.326	-0.276	-0.219
	(0.417)	(0.399)	(0.228)	(0.142)
Female	0.0979	0.123	0.0544	0.0546
	(0.160)	(0.140)	(0.116)	(0.107)
Age	-0.0952	-0.0360	-0.238	-0.147
	(0.324)	(0.226)	(0.212)	(0.170)
Age Squared	0.0170	0.00780	0.0263	0.0156
	(0.0458)	(0.0328)	(0.0308)	(0.0250)
Failed Entrance Exam	-0.201*	-0.175*	-0.224*	-0.137*
	(0.110)	(0.0935)	(0.124)	(0.0766)
Any College	-0.167*	-0.104	0.0818	0.00408
	(0.0960)	(0.0707)	(0.106)	(0.0508)
Mean	.247	.194	.142	.105
Observations	190	190	190	190
Regression	OLS	OLS	OLS	OLS

Notes: Heteroskedasticity-robust standard errors in parentheses. Column title indicates the dependent variable. Data is at the officer-year level. Regressions have fixed effects for years and fixed effects for district of officer assignment.

Table 13: Model Parameter Estimates

	White			Minority			
	μ	σ^2	# Param	μ	σ^2	# Param	Mean Diff
b, slope	.0228***	—	1	—	—	—	—
	(9.38 X 10^{-5})						
t, officer valuations	-2.41***	20.12***	1327	-2.52***	19.50***	1327	0.10***
	(.046)	(0.781)		(.057)	(0.757)		(.013)
λ, *speeds*	18.387***	2.905***	67	19.107***	2.186***	67	-0.720***
	(0.002)	(0.506)		(0.003)	(0.381)		(0.004)
Pr(Discount)	0.357***	0.125***	1327	0.325***	0.112***	1327	0.033***
	(6.90 X 10^{-4})	(0.005)		(7.98 X 10^{-4})	(0.004)		(0.001)

Standard errors in parentheses

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

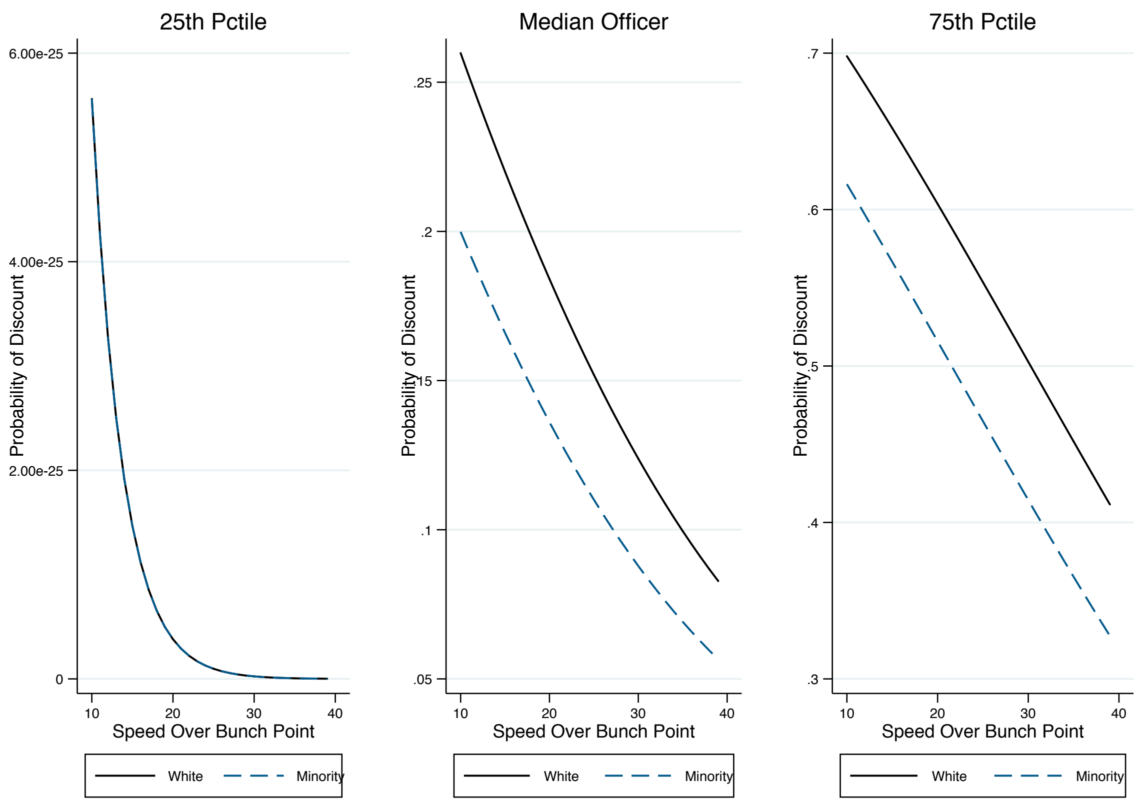
Notes: This table presents estimates of the model introduced in section 7. b is the slope parameter for how officers weight the speed of drivers in choosing to discount, t is each officer's mean valuation of a racial group in choosing to discount, and λ is the poisson speed parameter for each race by county. Pr(Discount) = $\Phi(t - 10b)$, i.e. the probability of being discounted when driving right above the bunch point. Note that the discount probabilities are not technically parameters but rather are calculated using the estimated t's and b. The variances are empirical variances of the estimates, not adjusted for sampling error.

Table 14: Racial Gap Decomposition

	Baseline	No Bias	No Sorting	Neither
Probability Gap	0.0968	0.0653	0.0341	0
Speed Gap	-2.114	-1.783	-1.475	-1.1135

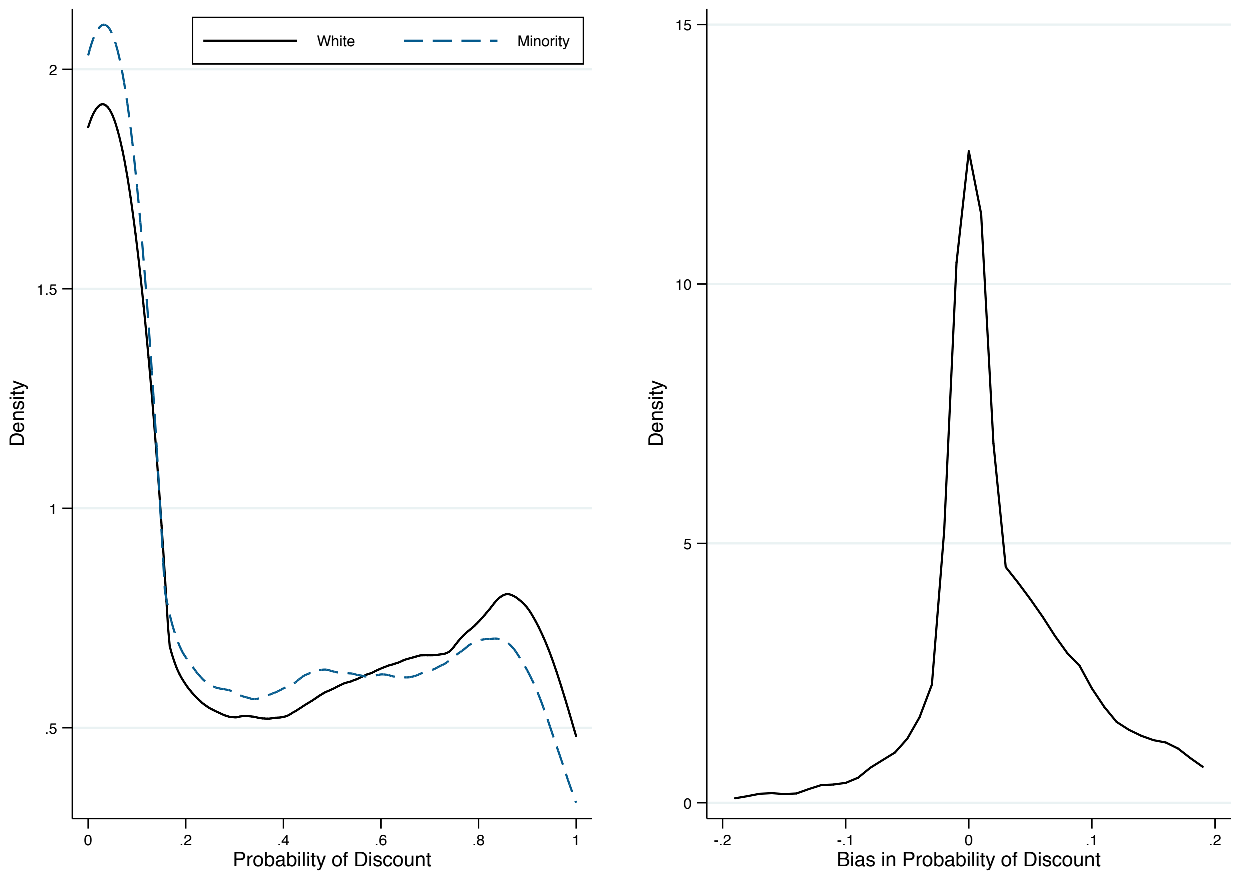
Notes: This table presents how the racial gap in discounting and speeds change without bias and sorting of officers across counties. The probability gap is the probability of being discounted if you are at the speed right above the jump in fine. Both gaps are the white drivers' outcome minus minority drivers' outcome. No bias is calculated by assigning each officer's preferences towards minorities to be the same as his preference to whites. No sorting is calculated by simulating a new draw of officers for each driver, where the draw is done at the state level.

Figure 10: Model Discount Probability Across Officer Lenience



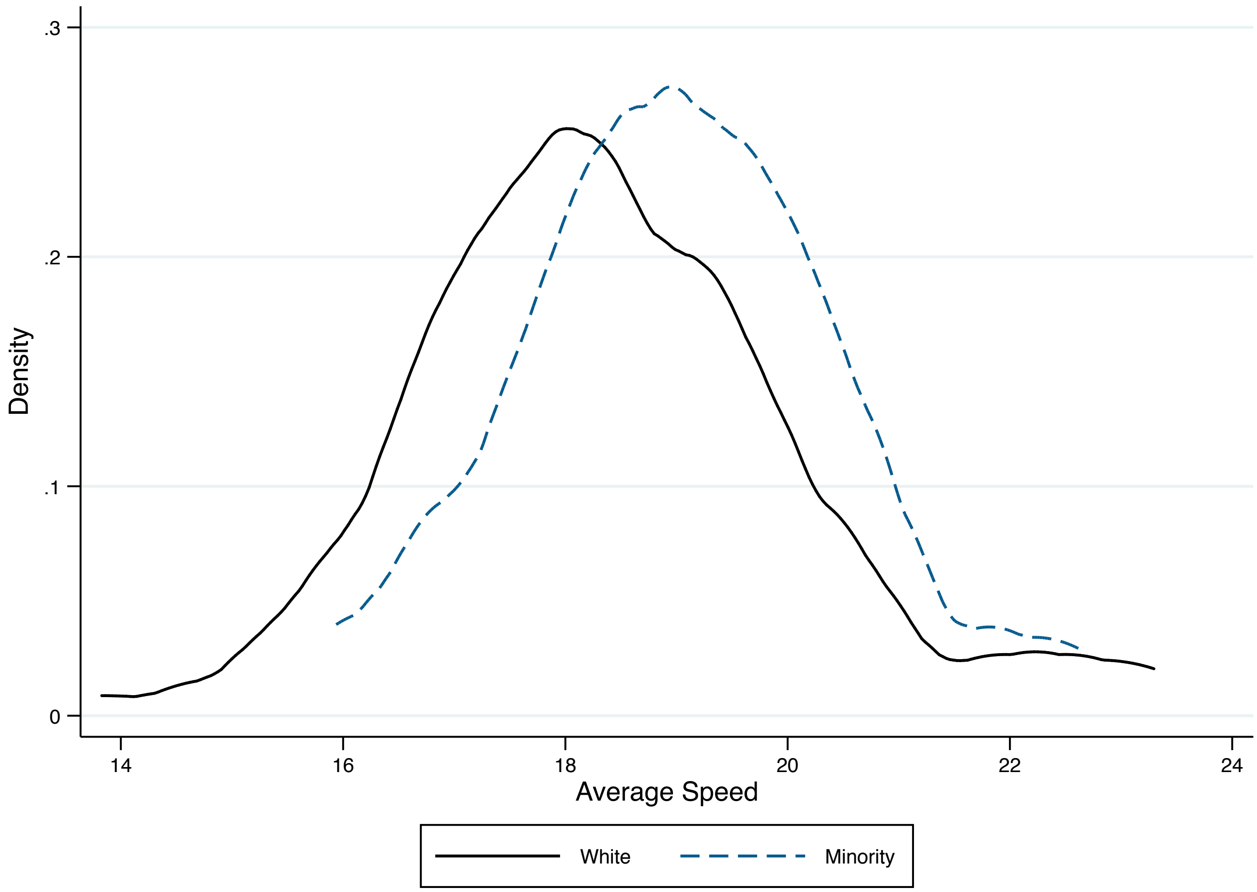
Notes: Each figure plots the probability of being discounted to 9MPH over for each speed above 9, separately by race. The left panel presents the discount probabilities for officers at the 25th percentile of *lenience*, the second panel for the median lenience, and the third panel for the 75th percentile of lenience. The most important fact to note is that bias only appears for officers that have some degree of lenience.

Figure 11: Discount Probability Across Officer Distribution



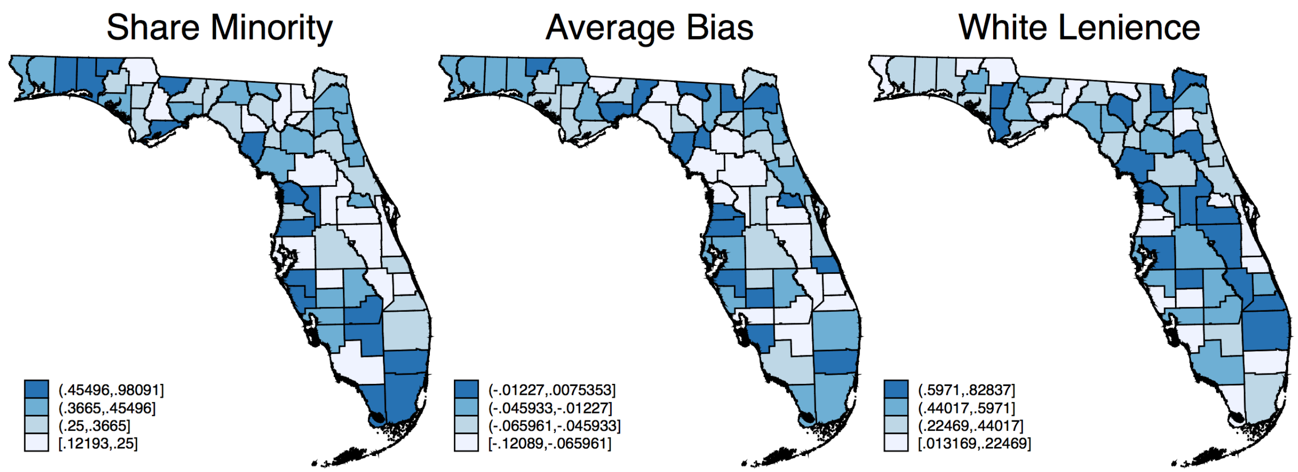
Notes: The left panel plots the kernel density estimate of the distribution of discount probabilities across officers, calculated separately for whites and minorities. The discount probability is calculated as $\Pr(\text{Discount}) = \Phi(t - 10b)$, i.e. the probability of being discounted when driving right above the bunch point. The right panel plots the kernel density estimate of each officer's difference in discount probability between whites and minorities. The further right, the more biased an officer is towards whites.

Figure 12: Speeds By Race Across Counties



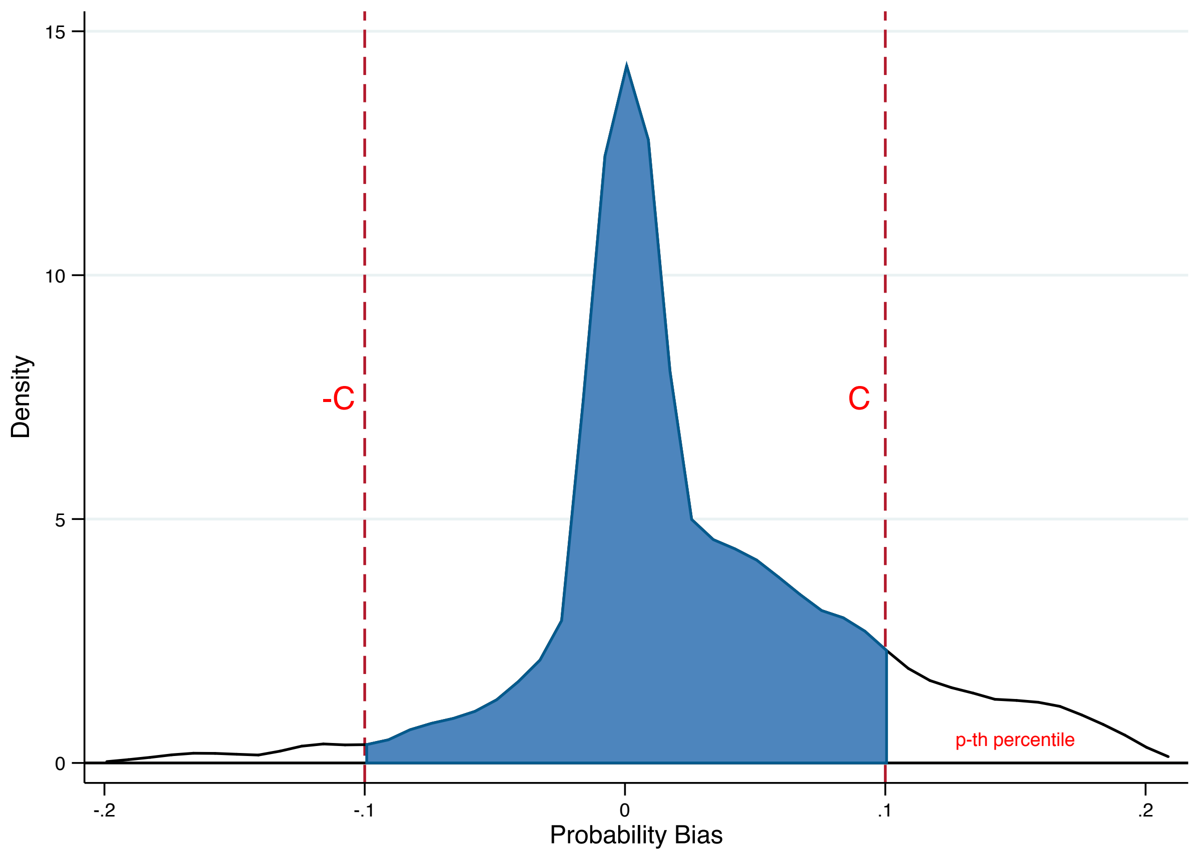
Notes: This figure plots the kernel density estimate of average speeds across counties, calculated separately by race. The average speeds correspond to the λ calculated in the model.

Figure 13: Speeds By Race Across Counties



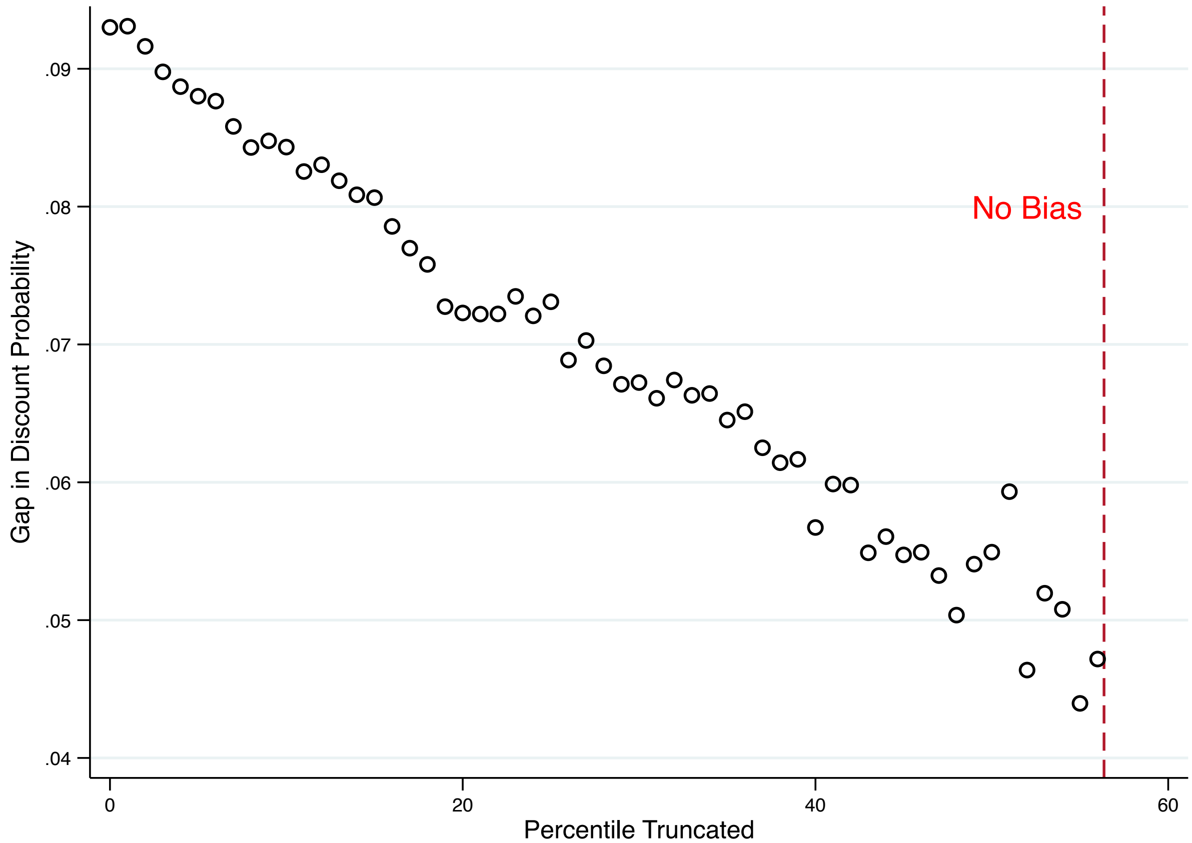
Notes: This figure plots the degree of minorities, bias, and lenience across counties of Florida. The darker the shade of blue, the more minorities, bias, and white lenience are present in the county, respectively across panels. The most important fact from these graphs is that white lenience is greatest in counties with few minorities.

Figure 14: Removing Most Biased Officers, Explanation



Notes: This plot describes how the first counterfactual is conducted. For a p-th percentile chosen, officers are removed for bias greater than C, the level of bias at the p-th percentile, and -C at the opposing end of bias. Individuals are all re-assigned officers from within their county who are not 'fired,' with the probability of encountering a certain officer proportional to the number of tickets he writes in that county.

Figure 15: Removing Most Biased Officers



Notes: Plot of the counterfactual of removing the most biased officers. The x-axis is the p-th percentile being truncated, and the y-axis is the average gap in probability of discount across whites and minorities. The extreme of no bias is at the 57th percentile rather than 50 because the median officer is slightly biased against minorities.

Figure 16: Removing Least Lenient Officers

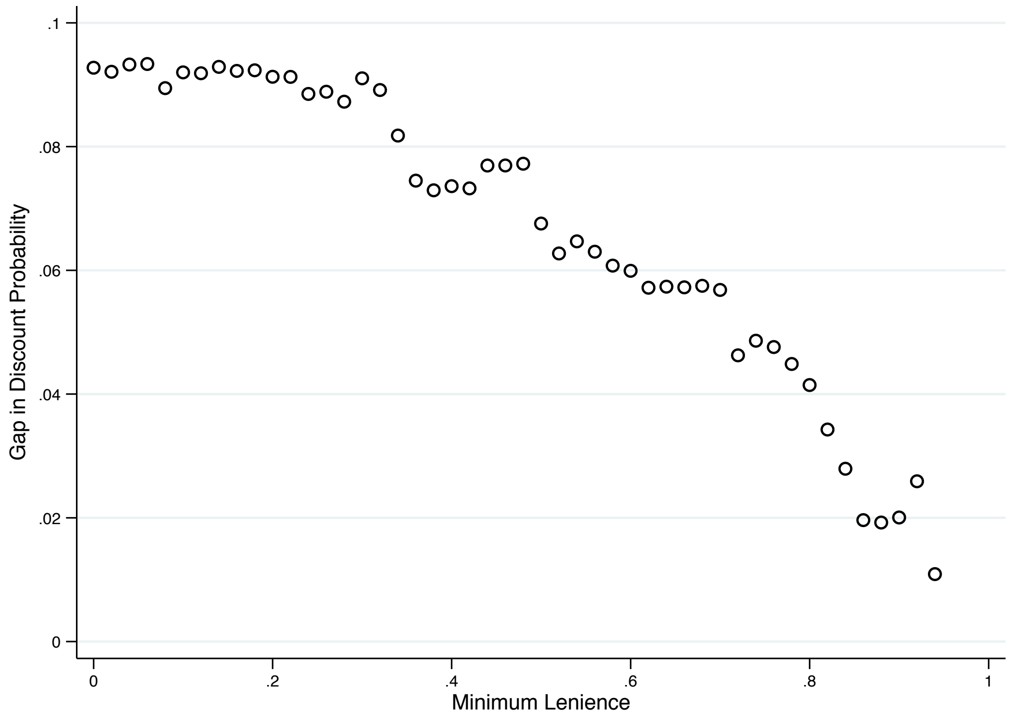
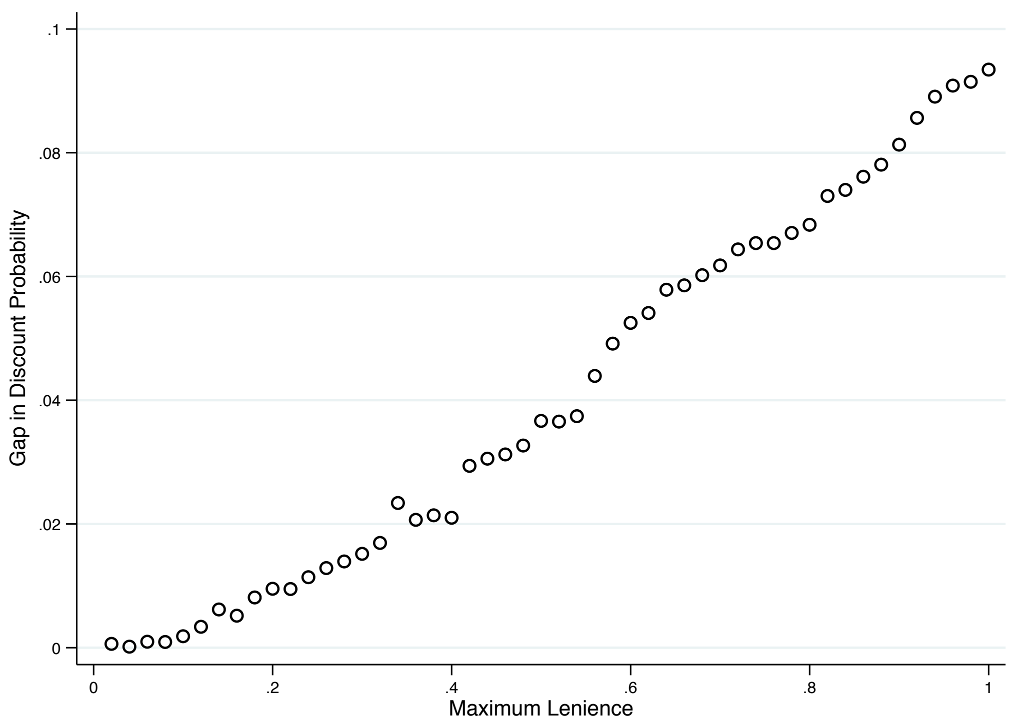
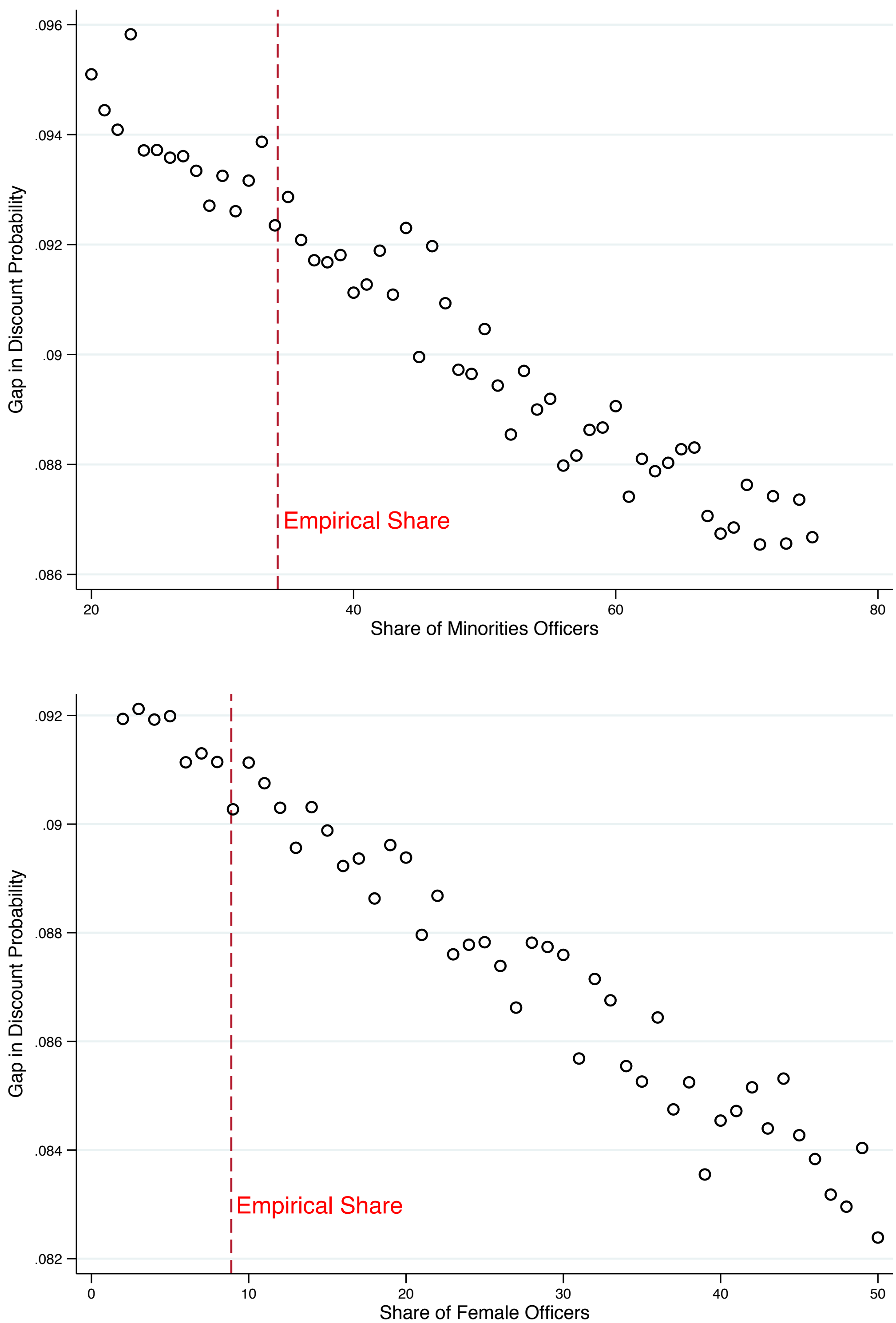


Figure 17: Removing Most Lenient Officers



Notes: Plot of the counterfactuals of removing the most harsh and most lenient officers. The x-axis of the first figure is the minimum lenience of the officers allowed in the sample, below which officers are fired, and the y-axis is the gap in the probability of discount between whites and minorities. The x-axis of the second figure is the maximum lenience of the officers allowed in the sample. Lenience is defined as the probability of discounting drivers going at 10MPH over. As in the first counterfactual, individuals receive a new draw of officers within their county.

Figure 18: Changing Share of Minority and Female Officers



Notes: Plot of the counterfactuals of increasing the share of minority and female drivers in the sample. The x-axis of the first and second figures are the share minority and share female, respectively, and the y-axis is the gap in probability of discount between whites and minorities.

Table 15: Assigning Officers Based on Bias and Lenience

	Baseline	Assigning on Bias	Assigning on Lenience
Probability Gap	0.097	0.102	.0047
Speed Gap	-2.114	-2.116	-1.210

Notes: This table presents how the racial gap in discounting and speeds change when officers are assigned to minimize minorities' exposure to bias and officer harshness. The first column is the baseline simulation of the model to match the true data. The second column sorts officers within a troop (which comprise 6-10 counties) such that the least biased officers are in counties with the most minorities. The third column sorts officers within a troop such that the most lenient officers are in counties with the most minorities.

Table 16: Discounting and County Minority Share

	(1) Discount	(2) Discount	(3) Discount	(4) Discount
County Minority Share	-0.803***	-0.732***	-0.539**	-0.220***
	(0.138)	(0.135)	(0.226)	(0.0601)
Driver Black		-0.00687	-0.0213***	-0.0247***
		(0.00909)	(0.00414)	(0.00371)
Driver Hispanic		-0.0571***	-0.0451***	-0.0325***
		(0.0154)	(0.00918)	(0.00488)
County Under 18	1.063	1.028	-0.487	0.225
	(1.543)	(1.492)	(1.088)	(0.415)
County Over 65	-1.559**	-1.517**	-0.379	-0.0727
	(0.614)	(0.601)	(0.499)	(0.180)
County Unemployment Rate	-0.937	-0.884	1.489	-0.811
	(1.698)	(1.632)	(2.045)	(0.659)
County Poverty Rate	0.872	0.698	0.811	0.621**
	(0.785)	(0.761)	(0.665)	(0.244)
Share Speed Limit 50+	-0.0322	-0.0226	0.0681	-0.106**
	(0.190)	(0.188)	(0.169)	(0.0428)
White Mean	.35	.35	.35	.35
Zone FE	X	X	X	X
Time FE	X	X	X	X
Covariates		X	X	X
Troop FE			X	X
Officer FE				X
R^2	0.118	0.124	0.200	0.498
Observations	1125673	1125673	1125673	1125673

Notes: Robust standard errors in parentheses. Dependent variable is an indicator for charged speed equals 9 MPH above the limit. Minority Share is the fraction of individuals in a county who are not (non-Hispanic) white. Covariates include gender, age, age squared, and in-state.

Technical Appendix

Calculating Weights for Bias Prediction Regressions

In Section 6.2, we estimate regressions predicting officer bias, where each officer's left-hand side variable is measured with noise:

$$\begin{aligned}\hat{\theta} &= X_i\beta + \epsilon_i \\ \theta &= X_i\beta + \epsilon_i + u_i\end{aligned}$$

where $V_u = V(u_i)$ is the variance of the parameter estimate, and $V_e = V(\epsilon_i)$ is the true variation in bias. We therefore use a weighted least squares regression approach to deal with heteroskedasticity.

While we know V_u from our estimation procedure for θ, we have to calculate V_e. We do so using the following iterative procedure, from Morris (1983) :

$$\begin{aligned}
&(1) \quad \text{guess starting } \mu,\ \mu^{(0)} \equiv \frac{1}{N}\sum_i \hat{\theta}_i \\
&(2) \quad \text{guess starting V}(\theta_i),\ V^{(0)} \equiv \frac{1}{N}\sum_i^N \left[(\hat{\theta}_i - \mu^{(0)})^2 - V(\epsilon_i)\right] \\
&(3) \quad \text{update guess of } \mu,\ \mu^{(1)} = \frac{\sum_i^N \hat{W}_i \cdot \hat{\theta}}{\sum_i^N \hat{W}_i}, \quad \text{where } \hat{W}_i = \frac{1}{V^{(0)} + V(\epsilon_i)} \\
&(4) \quad \text{update guess of V}(\theta_i),\ V^{(1)} = \frac{\sum_i^N \hat{W}_i\left[\frac{N}{N-1}(\hat{\theta} - \mu^{(1)})^2 - V(\epsilon_i)\right]}{\sum_i^N \hat{W}_i} \\
&(5) \quad \text{iterate until } \mu^{(k)} \approx \mu^{(k+1)}, V^{(k)} \approx V^{(k+1)}
\end{aligned}$$

The use of weights $\hat{W}_i$ reflects the fact that some officers' bias parameters are more precisely estimated than others and should thus be given more weight in estimating the distribution of θ_i. In practice, the final optimal estimates of μ and $V(\theta_i)$ are very close to the initial unweighted estimates, and some papers use these initial guesses as their values for the distribution of θ_i (Aaronson *et al.*, 2007). We then weight each observation by $W = \frac{1}{V_e + V_{ui}}$.

DeConvolution Procedure

While the Morris (1983) procedure gives us an estimate of the true variance in bias, we are also interested in getting the full distribution of bias, after accounting for the estimation error in the parameters. We do so by using the deconvolution method from Delaigle and Meister (2008), which provides the density estimator

$$\hat{f}_n(\theta) = \frac{1}{2\pi} \int \exp(-it\theta) K^{\text{ft}}(t/\omega_n) \Phi_n(t) dt,$$

where

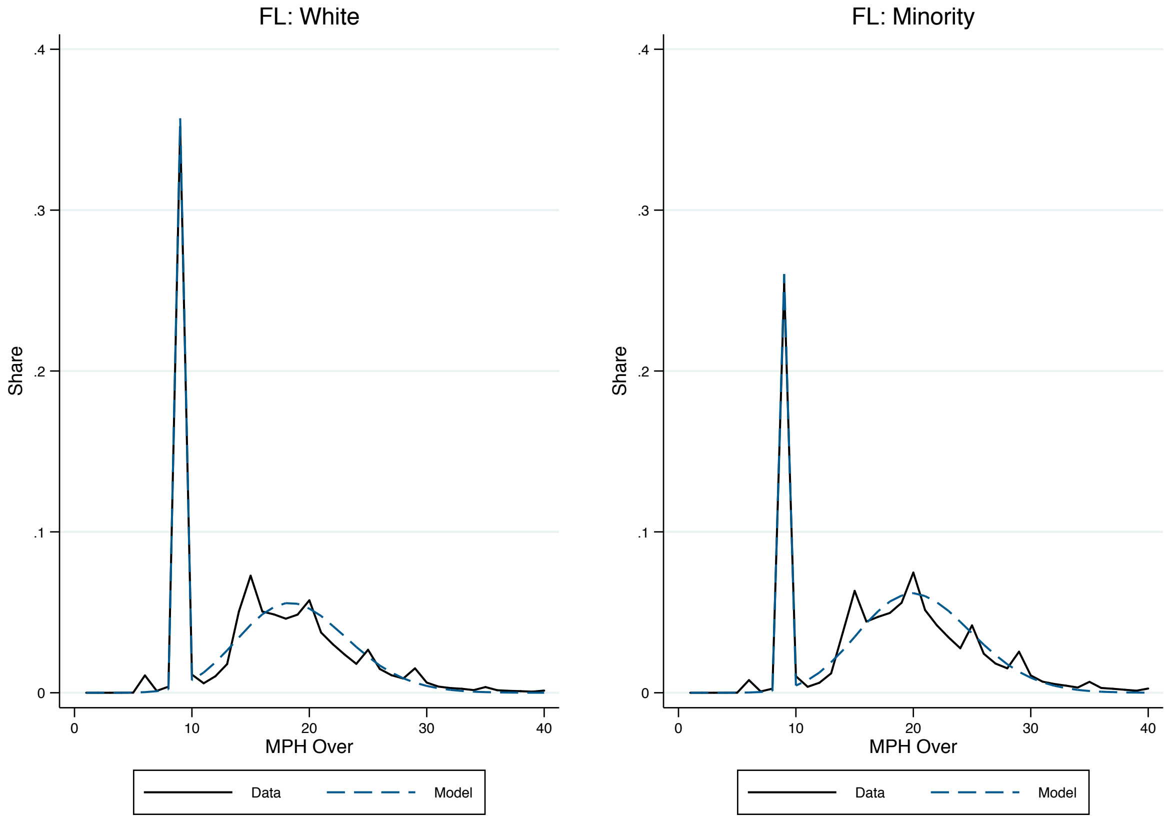
$$\Phi_n(t) = \sum_{j=1}^{n} f_{\epsilon_j}^{ft}(-t) \exp(itY_j) / \Big(\sum_{k=1}^{n} |f_{\epsilon_k}^{ft}(t)|^2 \Big),$$

K is a square-integrable kernel function, ω_n is a smoothing parameter, and f_{ϵ_k} are the distributions of the error terms. We use the stndard normal distribution for the kernel, and distribution of the error terms are normal with standard deviation equal to the standard error of the parameter estimate.

The deconvolution takes advantage of the fact that when a random variable is a sum of two other random variables, its characteristic function is the product of the variables' characteristic functions. In our case, where we $\hat{\theta} = \theta + \epsilon$, we solve for the distribution of θ by taking the quotient of the characteristic functions of $\hat{\theta}$ and ϵ and applying the characteristic function inversion.

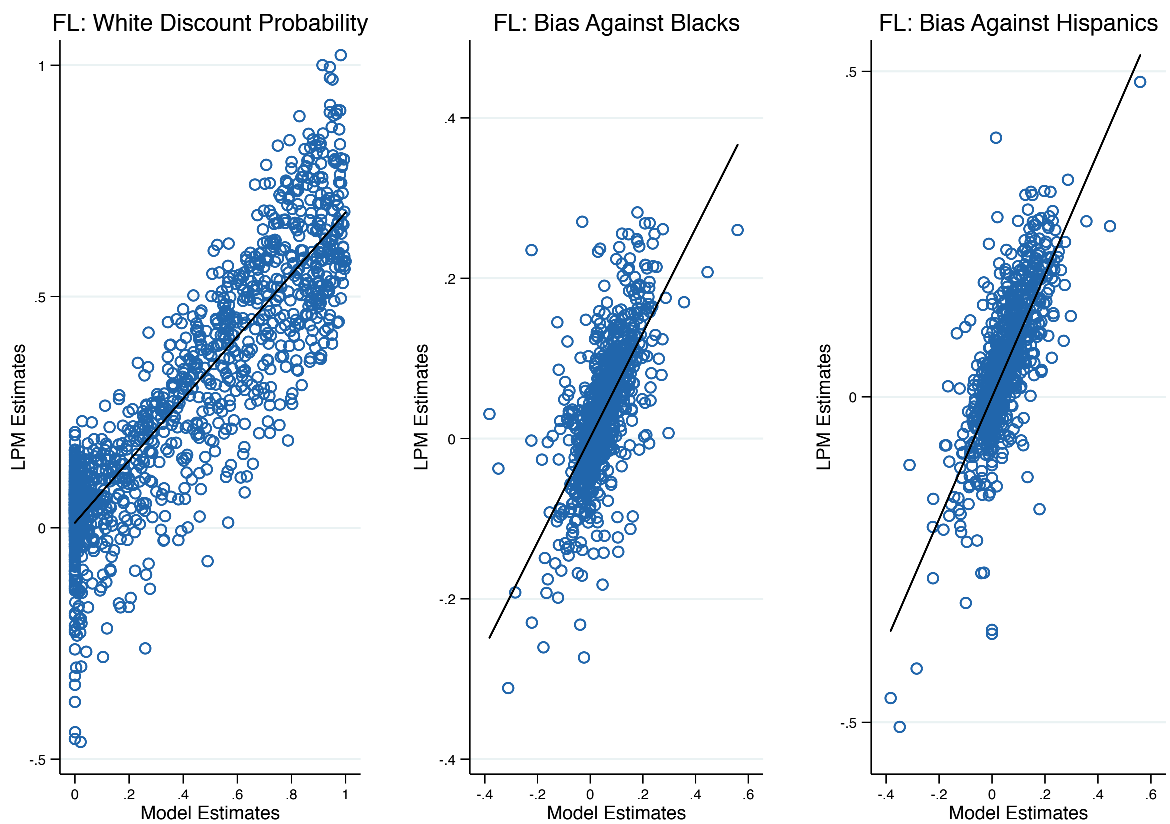
Appendix Figures and Tables

Figure A-1: Model Goodness of Fit



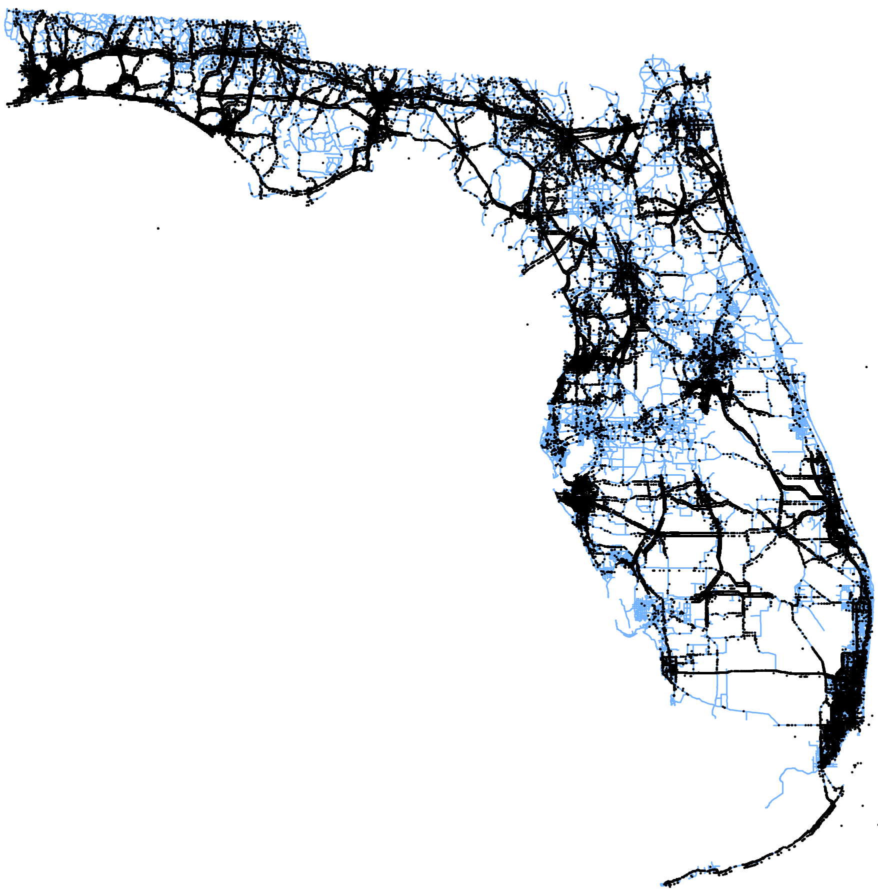
Notes: Figure plots observed versus model-estimated speed distributions for white and nonwhite drivers.

Figure A-2: Model Goodness of Fit



Notes: Figure plots the officer-level relationship between lenience towards whites and bias against nonwhites estimated via the simple linear probability model approach (y-axis) and the structural model approach (x-axis).

Figure A-3: Map of GPS Data



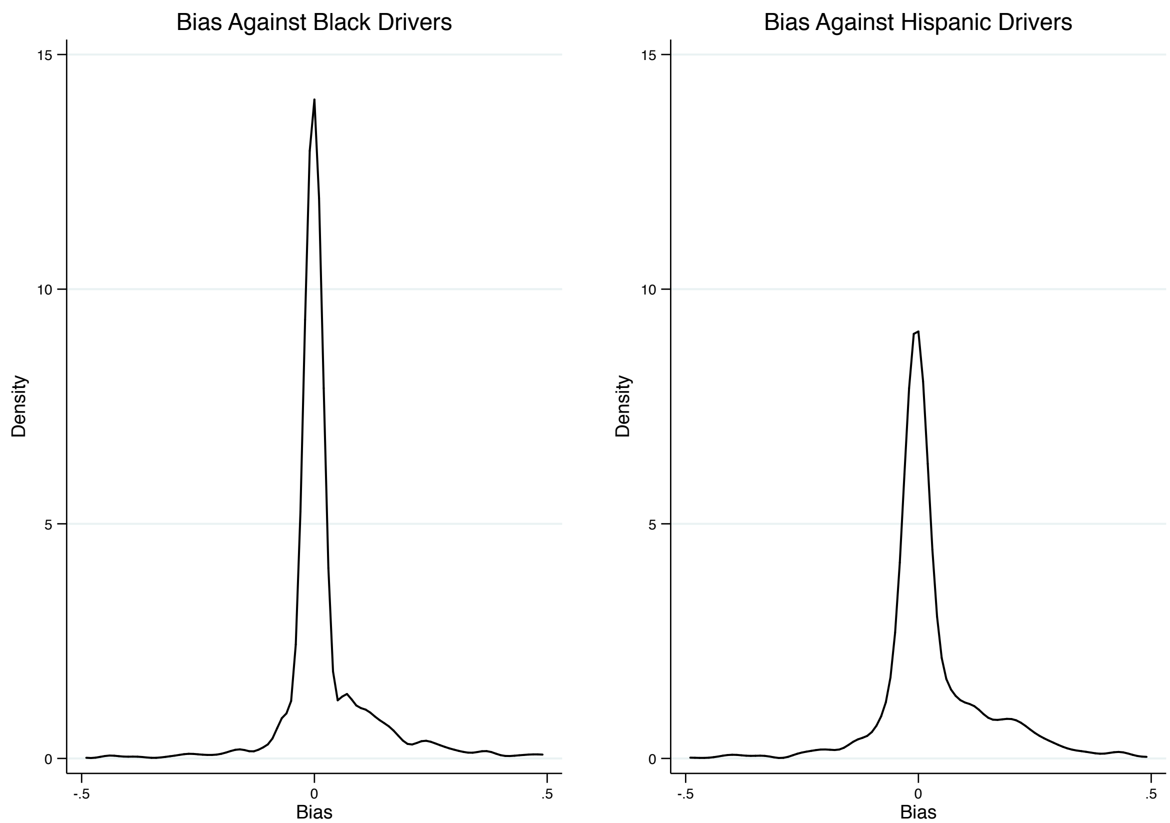
Notes: Figure plots location of data with GPS information overlaid on a roads shapefile provided by the Florida Department of Transportation.

Table A-1: Linear Probability Estimates with GPS Road Controls

	(1) Discount	(2) Discount	(3) Discount	(4) Discount	(5) Discount
Black	-0.0690***	-0.0675***	-0.0336***	-0.0351***	-0.0323***
	(0.0216)	(0.0207)	(0.00477)	(0.00451)	(0.0104)
Hispanic	-0.182***	-0.176***	-0.0511***	-0.0441***	-0.0423***
	(0.0294)	(0.0283)	(0.00861)	(0.00655)	(0.0155)
Driver Female		0.0368***	0.0184***	0.0172***	0.0188***
		(0.00588)	(0.00315)	(0.00251)	(0.00619)
Florida License		-0.0480*	0.0224***	0.0181***	0.0165
		(0.0279)	(0.00552)	(0.00507)	(0.0130)
Age		1.574	2.368***	2.654***	2.633
		(1.383)	(0.659)	(0.611)	(1.588)
Age Squared		-10.43	-13.74**	-16.67***	-19.54
		(16.13)	(6.699)	(5.842)	(16.94)
White Mean	.38	.38	.38	.38	.38
Zone X County FE			X		
Zone X County X Road FE				X	
Year X Month FE			X	X	
DOW X Hour FE			X	X	
Saturated FE					X
Observations	129732	129732	129732	129732	129732

Notes: County-level clustered standard errors in parentheses. Dependent variable is an indicator for charged speed equals 9 MPH above the limit. Age divided by 1000. Road information is taken from matches of GPS locations to road shape files from the Florida Department of Transportation. The final column using "Saturated FE" uses fixed effects at the Year X Month X Day-of-Week X Hour X Speed Limit X County X Road Segment level.

Figure A-4: Deconvolution of Officer Fixed Effects in GPS data



Notes: Figure plots the estimated distribution of bias across officers, where the regression controls for the road on which the driver is stopped.