Variation in Racial Disparities in Police Use of Force*

Carl Lieberman†

June 14, 2020

Abstract

I examine racial disparities in police use of force using new data from New Jersey. Looking at the intensive margin of force, I find large disparities that disfavor black and Hispanic subjects and increase with force severity, even after adjusting for comprehensive incident-level factors and using new methods to limit selection bias. I then extend empirical Bayes methods to estimate department-specific racial differences and document significant variation across New Jersey's hundreds of departments. Finally, I observe that these departmental disparities are difficult to predict, which may suggest intangibles such as culture may play a large role in racial policing. (*JEL* J15, K42)

Racial inequality in police use of force is among the most important policy issues in the United States, and calls for reform grow louder with each unarmed person of color killed by police. As society seeks to address these race gaps, it is paramount that we know how the extent of this problem varies. Optimal interventions may not be uniform, and if some departments have smaller or nonexistent racial differences, they may provide insights on how to improve the others. Unfortunately, data and analytical limitations often require researchers to treat racial disparities as homogeneous in their analyses, limiting our understanding of the problems we face.

In this paper, I explore three aspects of how racial disparities in police use of force vary. First, how do racial disparities in use of force change along the spectrum of force severity? Second, how do these racial differences vary across departments? And third, what predicts department-level racial disparities?

I answer these questions using new administrative data from New Jersey. The data are unique in their completeness, containing every recorded use of force by every officer

*I am grateful to Jesse Bruhn, Leah Boustan, Janet Currie, Thomas Fujiwara, Bo Honoré, Ilyana Kuziemko, David Lee, Alex Mas, Jonathan Mummolo, Amy Wickett, seminar participants at Princeton University, and members of the Princeton Police Department for helpful comments. The Princeton University Industrial Relations Section provided generous financial support.

†Industrial Relations Section, Princeton University, Princeton, NJ 08544. carll@princeton.edu. https://carl.ac.

in every police department in the state over five years. Notably, they include the entire force spectrum, from placing the subject in a compliance hold to discharging a firearm. Further, because the data cover the entire state, they feature substantial variation in locations, with more than 450 police departments serving over 550 municipalities ranging from small, racially homogeneous towns to dense, diverse cities.

For the question of how racial disparities vary over the force spectrum, I focus on the intensive margin of force: conditional on force being used and adjusting for event-level observables such as the subject's actions and incident setting, do people of different races have different levels of force used against them? I find significant disparities in police use of force across races that increase with the severity of the force. Compared to outcome means, blacks and Hispanics are about 3% more likely than whites and Asians/Pacific Islanders to have force more severe than compliance holds, the lowest level of force, used against them, while they are about 19% more likely when looking at enhanced types of force: pepper spray, batons, canines, stun guns, and firearms. These gaps are driven primarily by large disparities that disfavor blacks.

To minimize the role of selection into my data as I address this question, I build on the techniques of Grogger and Ridgeway (2006) and Horrace and Rohlin (2016) in identifying a set of incidents that plausibly reduces the effects of race outside of the decision of what level of force to use. These papers use the "veil of darkness" hypothesis, arguing that in poor lighting (such as nighttime traffic stops), a subject's race is harder to observe, and hence less likely to factor into the officer's decision to stop a vehicle. I extend this method by restricting the dataset to "always stop" incidents, those where the subject likely would have been stopped regardless of their race (crimes in progress, disputes, and traffic stops at night), and incidents where the subject at least physically threatened or attacked an officer or another individual, where the outside option of not using any force is less viable. Both of these restrictions limit the role of race in the officer's decisions whether to engage with a subject or use force at all. The results from this analysis are similar to the full-sample estimates, suggesting that selection bias prior to observation may not be a major problem in my setting and bolstering my estimates.

Next, I leverage New Jersey's large number of police departments to analyze how racial disparities vary across departments. To better conduct this cross-department analysis, I adapt empirical Bayes techniques to estimate heterogeneous group-specific differences. Using this new estimator, I find that the overall disparities mask large variation in these disparities across departments that often dwarfs the overall estimated magnitudes. About 20-30% of departments have zero or negative racial differences for any given force level, but there is also a long right tail of departments where black and Hispanic subjects face disparities significantly larger than the overall average estimates. Within-department correlations of these estimates across force levels suggest that departments with large racial differences at one level are more likely to have similar disparities at other close force levels, though these correlations are weaker for force levels further apart on the spectrum.

Finally, I treat the estimated departmental disparities as the quantities of interest themselves and explore whether departmental or municipality characteristics such as officer diversity, economic inequality, violent crime rates, and political preferences are able to predict these racial gaps through a "horse race" analysis. I find that commonly proposed factors such as racial diversity do not correlate with the disparities. The most suggestive evidence is in favor of areas that are poorer and have greater economic inequality having larger racial disparities. However, the low predictive power of these models may indicate that intangibles such as department culture play a large role.

Although there is relatively little work about variation in racial differences in police use of force compared to overall gaps, economists and other social scientists have long grappled with the question of how race interacts with the criminal justice system. Recent efforts have made progress on this methodologically thorny issue using new data or empirical strategies to obtain better estimates. Nix et al. (2017) examine fatal police shootings using novel data collected by *The Washington Post* and find racial differences in whether a shot subject was attacking the officer and whether they were armed. Weisburst (2019) uses data from the Dallas Police Department and finds that black civilians are disproportionately likely to be involved in an incident involving any level of force, stemming from differences in likelihood of arrest. Fryer (2019) estimates overall disparities by combining several different data sources, including New York City's Stop, Question, and Frisk program and officer-involved shootings from 16 police departments. He finds racial disparities in police use of force for blacks relative to whites to be consistent over the nonlethal force spectrum with odds ratios of around 1.2, while Hispanic-white disparities decrease as the force level increases; he also finds no disparities for police shootings. Knox, Lowe, and Mummolo (2020) argue that the estimates from Fryer (2019) understate the causal effect of race by not accounting for racial differences in police-civilian interactions prior to the encounter, such as patrolling habits and the decision of whether to stop a subject. Many other papers explore related aspects of race and the criminal justice system.[1] This paper differs from prior work by focusing on *variation* in racial differences, across force severity and departments, rather than treating race as having a single, homogeneous effect.

A separate and highly interdisciplinary literature asks what can predict or explain the variation in these disparities, offering varying explanations. Terrill and Reisig (2003), for example, use data collected on police ride-alongs to explore how "neighborhood context" (such as economic status and homicide rate) affects police use of force and find that the

[1]Examples include police stops and searches (Knowles, Persico, and Todd 2001; Anwar and Fang 2006; Persico and Todd 2006; Antonovics and Knight 2009; Coviello and Persico 2015; West 2018), speeding tickets (Goncalves and Mello 2017), police reform after racially unjust incidents (Heaton 2010; Devi and Fryer 2020; Luh 2020), and court decisions (Arnold, Dobbie, and Yang 2018; Bielen, Marneffe, and Mocan 2019).

setting of an incident matters greatly and can mediate the overall effect of a subject's race. Ross (2015), in the project most similar to this aspect of my work, conducts an analysis of county-level police shootings with local racial populations as the benchmark, finding significant variation in risk ratios at this level of aggregation associated with "larger metropolitan counties with low median incomes and a sizable portion of black residents, especially when there is high financial inequality." Hoekstra and Sloan (2020) exploit plausibly exogenous variation from 911 dispatch assignment rules from two cities and observe that white officers increase their use of force more when dispatched to more minority neighborhoods than minority officers do, also finding that racial differences are more severe for firearms than other force types. The variation present in my setting and new empirical Bayes estimator are key to this paper's value-added, as they allow me to explore how racial differences vary in a unified, expansive setting with detailed microdata on every level of force and hundreds of police departments.

In identifying these variations in racial disparities, I move forward our understanding of race and policing. Beyond simply observing heterogeneity in police use of force, the variation present in department-level disparities underscores the difficulties in remedying the differences and how a one-size-fits-all intervention may not be appropriate. Some departments do not appear to have racial differences against blacks and Hispanics, but many more do, some very severely, and the identities of these departments can change across force levels. Large amounts of unexplained variation in these differences, even with a rich set of covariates on the right-hand side, may also suggest that difficult-to-measure factors such as department cultures play an important role in determining how race and police use of force interact.

My results offer new insights to the literature on racial differences in policing, but it is worth noting several caveats. First, I examine the intensive margin of force: whether, conditional on force being used, subjects of certain races have more severe types of force used against them. As in many studies, the extensive margin of whether force is used at all cannot be analyzed without implausibly strong assumptions about how race affects the number and type of police-civilian interactions (such as assuming that it does not). Second, the data I analyze come from the police themselves, and it is conceivable that some reports are withheld or contain misinformation. I discuss this concern in detail when outlining my analytical strategy, noting in particular that crowdsourcing efforts have not indicated widespread suppression of incidents and that incentives for misreporting were hugely diminished by the fact that the planned central oversight never came about. Third, although I use the entire universe of force reports in New Jersey over a five-year period, my results are a result of who is (and is not) in that sample, i.e., who has force used against them at all. I take steps to minimize selection bias, but as I discuss later, depending on how cases are selected, one could find different results. Nevertheless, the patterns I do find are clear evidence of both the existence and variation of racial differences in police use of force, and these insights inform the literature more broadly.

1 Institutional Background and Data

1.1 Use of Force and Force Reporting in New Jersey

In 2001, the New Jersey Attorney General's Office began to require that police officers document all uses of force in the line of duty. Figure A.1 shows a model form for these force reports. Although not every department seems to follow this template exactly, the information gathered is largely the same across departments. Plans for a centralized system for analysis and oversight by the state never materialized, and most of these reports ended up in storage, unused and inaccessible by the public (NJ Advance Media 2019).[2]

Police in New Jersey are authorized to use several types of force in the line of duty. These standard force types police use can be ordered along a spectrum of severity (McCarthy and Nelson 2019). The lowest level of force is compliance holds, such as arm bars and wrist locks, followed by takedowns (forcing a subject to the ground), hands/fists (punches and slaps), kicks and other leg strikes, pepper spray and other chemical agents, baton strikes, canines, stun guns, and discharging firearms. Constructive authority, the threat of force without its actual use, such as brandishing a firearm, is permitted, but warning shots are prohibited. Not all departments have canine units. Stun guns are mostly absent from the data due to state regulations against their use, though departments began rolling them out after a change in the law in 2016. Because canines and stun guns are not always available to officers and are rare in the data, I group them with batons, the next most severe level of non-firearm mechanical force. Police may very rarely employ nonlethal firearm rounds, such as beanbag rounds, in settings such as riots to incapacitate subjects. I drop these incidents, as the situations in which they are used are not representative of typical police-civilian interactions. A conversation with an active police officer in New Jersey indicates that the level of force used in an incident should be the minimum necessary to gain control over the situation. Put differently, police officers should minimize force used subject to the constraint that the threat posed by the suspect is neutralized.

1.2 Data

This project uses all known force reports made in every police department in New Jersey from 2012 through 2016. ProPublica, a nonprofit newsroom, and NJ Advance Media (NJAM), a news provider, obtained the reports through 506 public records requests and

[2] In the wake of the killing of George Floyd, the New Jersey Attorney General announced that a statewide use of force portal would be ready later in 2020.

several legal threats. These records represent the universe of force used by police officers in New Jersey over that time. Following substantial data entry and cleaning, ProPublica and NJAM made the resulting dataset available for purchase in January 2019.

These reports contain rich incident-level information. Among other variables, the reports record the time, date, and location of the incident, the nature of the incident (such as a crime in progress or traffic stop), the officer(s) involved, the subject(s) involved and their actions that led to force being used, officer identities and demographics, the types of force an officer used against the subject, and whether an officer or subject was injured or killed.

Despite the efforts by ProPublica, NJAM, and their partner data entry firm, the final dataset required additional processing before I could use it in my analysis. For example, some types of force used by police are not neatly categorized, and instead consist of irregular descriptions such as "grabbed rock out of her hand" or "in foot pursuit grabbed suspect left hand." Appendix A documents how I clean and process the data. I structure the data so that each observation represents one subject who had force used against them by one officer in an incident. For cases where multiple officers use force against a single subject, I keep the officer who uses the greatest level of force, choosing randomly in the event of ties.[3] I remove 44 subjects whose indicated races do not fall within the categories of white, black, Hispanic, or Asian/Pacific Islander, such as people marked as "mixed." After cleaning, there are 39,322 incidents that I use in my analysis.

I supplement the force reports with information on New Jersey's police departments and municipalities. Characteristics of the police departments themselves, such as racial diversity, are from ProPublica and NJAM. Municipality variables come from the 2010 Census, 2012-2016 American Community Survey (ACS) five-year estimates, FBI's Uniform Crime Reporting (UCR) program, and New Jersey Division of Elections.

1.3 Summary Statistics

Table 1 presents summary statistics for the force reports in the dataset after cleaning. It includes the most extreme type of force used in each incident, the most extreme action the subject took that may have prompted the force, whether an officer was injured, the type of incident, and subject demographics. In 50% of incidents in the sample, officers use only compliance holds, the lowest type of force available. In 25% of incidents, the most severe action officers take is striking subjects with their hands or fists, and 11% of incidents have pepper spray as their highest force level. All other types of force are

[3]There are several justifiable ways to structure the data. I choose this format, as it is most natural for my empirical strategy in which the outcome of each incident is the greatest level of force used. When multiple officers use force, it is then sensible to keep the officer who used the greatest level of force, especially because other officers may only able to use lower levels of force because another officer used a more severe type (e.g., after Officer A pepper sprays a subject, Officer B is able to place him in a compliance hold).

relatively uncommon as maxima. Officers discharge firearms in under half a percent of observations, representing over 160 shootings between 2012 and 2016.

Subject actions are concentrated on the lower end of the spectrum. Resisting an officer, which I also use as a catchall for nonmissing behaviors that do not fit elsewhere, is the most extreme behavior in 63% of incidents. Physically threatening or attacking an officer, for example punching, kicking, or spitting, follows with 34% of observations. The remaining 3% of the data is divided approximately evenly between blunt weapon, knife, and vehicle threats/attacks, as well as threats with firearms. Only 0.1% of incidents involve a subject actually discharging a firearm. 10% of force reports indicate that an officer was injured.

Incident types are varied. I follow the model force report from the New Jersey Attorney General and include indicators for crimes in progress, domestic disputes, other disputes, suspicious persons, traffic stops, and other incidents. An incident may have multiple types, except for the "other" category, which I reserve for incidents that are not classified as belonging to any other category (including incidents originally marked as "other," when applicable). Consistent with the sample being only incidents in which officers used force, the most common incident classification is crime in progress, making up more than a quarter of the data. Domestic disputes are the next most frequent at 13% of the sample. Other disputes and suspicious persons are each 11% of the sample, traffic stops are 9%, and 33% of incidents fall into the "other" category.

Subject demographics are not representative of New Jersey's population. 48% of the subjects in the sample are white, 41% are black, 10% are Hispanic, and 1% are Asian/Pacific Islander. From the ACS five-year estimates for 2012-2016, 57% of the state's population at the time was non-Hispanic white and 9% was non-Hispanic Asian/Pacific Islander, making these two groups underrepresented in the force reports. Blacks are severely overrepresented, with non-Hispanic blacks comprising only 13% of the population. Due to data limitations, I treat Hispanic status as a distinct racial category; one cannot be Hispanic and another race in the data.[4] Note that officers use their own judgment when recording a subject's race. 19% of the state population was Hispanic of any race, but it is impossible to know whether they are overrepresented or underrepresented in the force data, as the criteria used to classify individuals as Hispanic in the force reports are not the same as those used in the ACS. Only 20% of subjects are female. The average subject in the data is 31 years old,

Table A.1 presents summary statistics for the municipalities whose police departments are present in the data. Note that this does not include municipalities served by the New Jersey State Police (NJSP), which is responsible for highways and some small towns

[4] Some departments' force reports do distinguish between a subject's race and Hispanic origins, but many do not. The cleaned version of the racial variable in the dataset made available to researchers treats Hispanic status as a race.

which lack a dedicated police force. For New Jersey's approximately 565 municipalities, 461 police departments are present in the raw data. A handful of small municipalities with a combined 58 force reports do not appear in my subsequent analyses because their force reports are missing data in relevant covariates.

New Jersey's hundreds of municipalities offer significant heterogeneity over margins such as race, income, size, and political preferences over which policing might vary. Populations for municipalities in the sample range from hundreds to hundreds of thousands. As of the 2010 Census, New Jersey has seven of the 10 densest incorporated places in the United States, and it is overall the densest state in the country, though this too varies greatly within the state. New Jersey is among the richest states by median income, but there are significant areas of poverty and it has relatively high economic inequality as measured by the Gini coefficient compared to other states. The adjusted population figures shown in Table A.1 are for the population ages 18 through 65 in each municipality. Although New Jersey is mostly white, many areas have barely any whites while others are almost exclusively white. Violent crime rates range from 0.03 to 55 crimes per 1000 people. Political preferences, as measured by Mitt Romney's share of the vote in the 2012 presidential election, are consistent with the state leaning Democratic overall despite the presence of more conservative areas.

Table A.2 contains summary statistics for the police departments in the data. The median department has 23 full-time employees, while the average is almost 43 and the maximum is over 1,000. Racial diversity on the whole is poor: the median department's officers are more than 90% white, 0% black, 0% Hispanic, and 0% Asian/Pacific Islander (not all departments' racial breakdowns sum to 100% due to inconsistencies in reporting).

2 Empirical Strategy

2.1 Specifications

2.1.1 Overall Disparities

For the question of overall racial disparities, my primary econometric specification estimates the following equation via ordinary least squares (OLS):

$$Force_{iopt} = \beta \cdot \mathrm{BH}_i + X'_{iopt}\gamma + \psi_p + \nu_t + \epsilon_{iopt} \tag{1}$$

where subscripts i, o, p, and t denote the incident, officer, department, and year, respectively. $Force$ is a binary "at least this severe" measure of the extent of the force used in an incident. For example, if a subject is punched, then the outcome would be 1 for at least compliance holds, takedowns, and hands/fists, but 0 for at least leg strikes, pepper spray, batons, and fired weapons. I use this measure of force because it is the most intuitive way to interpret outcomes.[5] Alternative parameterizations such as the maximum or minimum force level used incompletely describe an event, and analyzing every force level separately can result in estimates without obvious interpretations (Fryer 2019). The coefficient of interest is β, the difference in the observed probabilities of black or Hispanic (BH) subjects having more severe types of force used against them conditional on any force relative to the reference group (whites and Asians/Pacific Islanders). I primarily use a binary race indicator for a subject being black or Hispanic to improve statistical power, but also estimate models with a full set of race indicators. X is a vector of incident-level characteristics including time, type of incident, officer rank, subject behaviors, subject sex, and a quadratic of the subject's age. Because incidents may have multiple types, I include indicators for each unique combination of types rather than each individual type; the effect of an incident that is a crime in progress and a traffic stop is not the same as the sum of the crime in progress and traffic stop effects. Department fixed effects ψ_p capture time-invariant aspects of each department's propensity to use higher levels of force, such as the overall crime level on a department's beats. Time fixed effects ν_t adjust for year-specific changes in overall force usage, such as from changes in crime rates. I cluster standard errors at the department level.

Although I am able identify many department and officer fixed effects simultaneously due to officers switching departments, including officer fixed effects requires dropping many coefficients, which will be important for later analyses. Instead, I estimate an additional series of models using officer fixed effects instead of department fixed effects with clustering done at the officer level. These estimates allow me to investigate how disparities vary when adjusting for the officer identity, which may be useful if there is significant heterogeneity in officer-level disparities within a department. Further, comparing these results to the ones using department fixed effects allows me to observe the role of the individual officer as opposed to the department. Note that the officer-based models may be sensitive to the data cleaning process in which, for each incident where multiple officers use the most severe level of force in that incident, I keep only one randomly chosen force report. This is an edge case, however, and results with a different draw appear similar.

As a robustness check, in addition to the OLS estimates from Equation 1, I estimate conditional logit models of the following form:

$$\ln\left(\frac{Pr(Force_{iopt}=1)}{1-Pr(Force_{iopt}=1)}\right) = \beta\cdot \mathrm{BH}_i + X'_{iopt}\gamma + \psi_p + \nu_t + \epsilon_{iopt} \tag{2}$$

stratified by department. There are too few observations per officer for conditional logit to provide reliable results when stratifying by officer. By exponentiating β, I obtain odds

[5] Of particular note is the "at least pepper spray" outcome, which is especially straightforward. Positive outcomes are all mechanically or chemically enhanced types of force: pepper spray, batons, canines, stun guns, and firearms. Negative outcomes are compliance holds, takedowns, hands/fists, and leg strikes.

ratios for black and Hispanic subjects compared to white and Asian/Pacific Islander ones. Logit-based estimators offer several advantages over OLS, in particular probabilities bounded between 0 and 1, useful for rare events such as shootings, and conditional logit further addresses issues surrounding the inconsistency of logit with numerous fixed effects. However, as I move up the force spectrum, separation becomes a larger concern. More municipalities will have only zeros in the outcome, and these observations must be completely dropped from the analysis.

2.1.2 Department-Specific Disparities

Next, I examine variation in racial disparities across departments. The simplest approach would be to make a slight modification to Equation 1 and estimate equations of the form

$$\text{Force}_{iopt} = \beta_p \cdot \text{BH}_i \times \text{Department}_p + X'_{iopt}\gamma + \psi_p + \nu_t + \epsilon_{iopt} \tag{3}$$

with the interest being in the distribution of β_p. Although these estimates may be unbiased and consistent, OLS estimates tend to generate the most extreme estimates for departments with the fewest observations, a problem I do observe in my data.

To improve upon OLS for identifying these hundreds of related disparities, I modify empirical Bayes estimators, such as those commonly used in estimating teacher value-added (see, e.g., Kane and Staiger 2008; Chetty, Friedman, and Rockoff 2014), to estimate these group-specific differences for each department. Empirical Bayes estimators use the overall distribution of estimates to inform each individual point estimate. Although these general techniques are not new (Morris 1983), there is almost no work on extending this estimator to a setting where we are interested in estimates of a "treatment" on only a subset of the population, like a department's propensity to use more intense force against black and Hispanic subjects relative to white and Asian/Pacific Islander ones, as opposed to overall effects (see related work by Kline and Walters 2019 in the context of audit studies of discrimination).

As is standard practice, I fit a normal distribution for the prior and apply Bayesian updating to obtain a posterior distribution for each department's estimate. Less reliable estimates, such as those from departments with few observations, are shifted towards the population mean, resulting in a "shrinkage" estimator. After updating, I record the centers of the posterior distributions and use them as the estimates.

For each level of force, I begin by estimating the following "pooled" regression:

$$\text{Force}_{iopt} = \beta_0 \cdot \text{BH}_i + X'_{iopt}\gamma + \psi_p + \nu_t + u_{iopt} \tag{4}$$

I subsequently use the following distribution as the prior

$$\beta_p \sim N(\hat{\beta}_0, \sigma_p^2)$$

where $\sigma_p^2 \equiv \mathrm{Var}(u_{iopt}^{BH} - \epsilon_{iopt}^{BH})$, the variance of the difference between residuals between Equations 3 and 4 using only black and Hispanic observations rather than the full sample.[6] I then take the estimated racial disparities β_p from Equation 3 and compute the empirical Bayes estimates

$$\hat{\beta}_{p,EB} = w_p \cdot \hat{\beta}_p + (1 - w_p) \cdot \hat{\beta}_0 \tag{5}$$

where

$$w_p \equiv \frac{\sigma_p^2}{\sigma_p^2 + \mathrm{Var}(\epsilon_p^{BH})/n_p^{BH}}$$

are the departmental empirical Bayes weights, ϵ_p^{BH} is the residual for an observation with a black or Hispanic subject in department p (residuals for other subjects are omitted), and n_p^{BH} is the number of observations with black or Hispanic subjects for department p.

2.1.3 Predicting Department-Specific Disparities

In this exercise, I treat the estimated department-specific disparities as the outcomes of interest and regress them on variables describing both the departments and the municipalities they serve.

$$\hat{\beta}_{p,EB} = X_p' \alpha + \epsilon_p \tag{6}$$

X_p is a vector of department/municipality-level characteristics: log median household income, Gini coefficient, log population, log population density, log number of police, the percentage of officers who are not white or Asian/Pacific Islander, the percentage of the population ages 18 to 65 that are not white or Asian/Pacific Islander, the violent crime rate, and Mitt Romney's vote share in the 2012 presidential election. I also report results using the OLS estimates of β_p as the outcome. These regressions provide suggestive results for some of the commonly hypothesized contributors to police violence or bias.

2.2 Identification and Limitations

I estimate disparities in the intensity of police use of force experienced by subjects of different races conditional on force and after adjusting for incident characteristics and subject behaviors. Here I discuss this parameter and outline the efforts I take to limit the effects of confounding factors in my analysis.

Every incident in the data in this paper undergoes two "treatments" prior to the officer's decision of what level of force to use. First is the decision to engage with a

[6] One could instead estimate σ_p^2 as $\mathrm{Var}(u_{iopt}^{BH}) - \mathrm{Var}(\epsilon_{iopt}^{BH})$, but this may result in negative estimated variances. It does not in my case, and the results with either method are nearly identical.

subject, such as whether to stop someone on the street or pull over a vehicle. Second is the extensive margin of whether to use force at all. Each of these treatments is likely affected by race, and there is evidence from similar settings that they may be (Gelman, Fagan, and Kiss 2007; Fryer 2019). Because my incidents take place after these decisions, selection bias in who is in the sample, i.e. in who has force used against them at all, poses one problem. As explained by Fryer (2019), analysis conditional on force being used may be biased if an officer's decision to use force is dependent on a subject's race. Conditional on force, one might find no marginal effect of race, but that neglects to account for varying probabilities across race of interactions with police.

If officers engage with civilians of different races at different rates, this could affect force rates, and depending on the nature of the interactions, also the severity of force used.[7] If officers are overly suspicious of blacks, there could be many unwarranted stops that end without force or with only compliance holds, of which only the latter would appear in my data. If whites are then only stopped for committing violent offenses that require high levels of force from officers, my empirical strategy could be biased towards a disparity that disfavors *whites*. Or it could be that officers patrol in a manner that makes them more likely to engage with blacks committing violent crimes and whites committing nonviolent offenses, which could threaten my results in the opposite direction. These problems are complicated by the presence of the second pre-observation treatment in my setting: the extensive margin of whether to use force at all.

Although it is impossible to determine ex post whether an individual stop or decision to use force was motivated by a subject's race, under milder assumptions, I can limit the role of racial disparities prior to the intensive margin of force severity. Using information on incident characteristics and subject actions, I repeat my analysis of overall disparities on a subset of observations where the subject's race was less likely to factor into the decisions whether to investigate and whether to use force. Specifically, I use the intersection of two subsets of the data, building on the ideas of Grogger and Ridgeway (2006) and Horrace and Rohlin (2016). First, I take crimes in progress, disputes, and traffic stops at night (8:00 PM through 5:59 AM), discarding suspicious person incidents, daytime traffic stops, and "other" incidents. Second, I restrict the sample to incidents where the subject at least physically threatened or attacked an officer or another individual, i.e. I drop incidents where subjects only "resisted." The former set should contain fewer racial stops and the latter should be missing fewer incidents where no force was used, limiting correlations between race and the error term and improving my estimates.

A final concern is that the data I use come from the police themselves, and officers could withhold or misreport information. NJAM has attempted to solve any such problems through a crowdsourcing effort (McCarthy 2019). This has uncovered minor

[7]This concept is related to the more general idea of differences in the marginal subject across races, discussed, e.g., in Becker (1957).

discrepancies in some reports, often around officer names, and the only missing reports identified are 70 from Jersey City (excluding these reports and prior to cleaning, the data contain 996 reports from Jersey City). Reporting by NJAM's NJ.com and a discussion with an active New Jersey police officer also indicate that there is some disagreement about when officers are required to fill out force reports. Because my coefficient of interest is the racial disparity after adjusting for incident characteristics, errors in the data such as missing reports would only bias my estimates if they are correlated with the subject's race. If officers misreport black or Hispanic subjects as posing greater threats than they actually do in incidents, this would cause me to underestimate racial disparities. Note that incentives to misreport are greatly diminished by the lack of central oversight over this time period. Force reports existed mostly as physical copies, many only at the departments themselves despite guidelines that all force should be reported to county prosecutors, making external monitoring difficult (Nelson 2019; McCarthy and Stirling 2019).

3 Results

3.1 Overall Racial Disparities

Before estimating the full model, it is helpful to understand the racial disparities that exist without adjusting for any covariates. Figure 1 plots the disparities from regressing indicator variables for the force used being at least as severe as the stated level on a set of indicators for the subject being black, Hispanic, or Asian/Pacific Islander on top of the intercept (the mean for whites). Table A.3 contains the corresponding regression results. Black and Hispanic subjects are much more likely to have higher levels of force used against them. The magnitudes of these disparities are similar for blacks and Hispanics within each level of force. These gaps increase with force severity. Relative to outcome means, the disparities for blacks and Hispanics compared to whites are about 20% for at least takedowns and hands/fists for both groups, around 33% for blacks and 22% for Hispanics for at least leg strikes and pepper spray, and around 45% for both for at least batons. Estimates in the fired weapons category are positive and small in absolute terms, but large when considering the rarity of these events. This result contrasts with those from Fryer (2019), who does not find racial disparities against blacks and Hispanics even in the raw data. Asians/Pacific Islanders are somewhat less likely to have more severe force types used against them than people of other races, though these differences tend to be much smaller in magnitude than the ones for blacks and Hispanics.

Next, I estimate racial disparities in the full model defined by Equation 1. Both sets of models treat race as a binary variable where the reference group is whites and Asians/Pacific Islanders and the alternative group contains blacks and Hispanics. Figure

2 plots the estimated racial disparities overlaid on outcome means, with the corresponding regression results in Table A.4.

Examining these racial disparities reveals several patterns. First, the racial differences are diminished compared to the previous models that do not adjust for incident observables, though they remain present. For the models using department fixed effects and clustering, the disparities estimated for black or Hispanic individuals for at least takedowns, hands/fists, leg strikes, pepper spray, batons, and fired weapons are approximately 1.5, 1.9, 3.1, 2.8, 0.9, and 0.1 percentage points, respectively. These gaps for all levels below fired weapons are statistically significant at the 5% level. I estimate positive but statistically insignificant disparities for firing weapons, but these events are so rare that precision is low. Second, relative to the baseline level of each force type, racial disparities increase with the severity of the force type until the maximum level, firing weapons. In percentage terms, the department fixed effects-based disparities for black or Hispanic subjects are 3.0%, 4.3%, 16.1%, 19.2%, 23.7%, and 25.0%. Finally, the results are similar for models using department and officer fixed effects and clustering. Estimates from the latter tend to be slightly larger, with marginally less precision. The similarities of both models provide suggestive evidence that the department or municipality is a more important factor than the identify of the officer in the incident.

Figures 3 and 4 and Table A.5 present the estimated racial differences from Equation 1 with indicators for every race. When including separate dummies for blacks and Hispanics, it becomes clear that the previous disparities are largely driven by blacks. The coefficient on being black in each regression is similar to but slightly larger than the black or Hispanic estimates from Table A.4. In contrast, I find much smaller disparities for Hispanics, sometimes near 0, especially for the models with department fixed effects. For Asians/Pacific Islanders, point estimates are small and almost always negative. The group's point estimate of -0.5 percentage points for having a weapon fired at them with department fixed effects is enormous considering that only 0.4% of all incidents involve police shootings.

Figure 5 and Table A.6 show the odds ratios from the conditional logit models in Equation 2. The results are qualitatively similar to the OLS ones. Point estimates are positive and small at the lower levels of force, and they increase with the severity of the force, with the odds ratios for at least takedowns, hands/fists, leg strikes, pepper spray, baton, and fired weapons being 1.05, 1.06, 1.21, 1.25, 1.30, and 1.36, respectively. Although the odds ratio for firing weapons is comparable in magnitude to those for other high levels of force, the associated standard errors are large and I cannot reject the null hypothesis of no racial difference.

As described in Section 2.2, to limit the role of racial differences in the unobserved decisions to stop a subject and use force against them, I estimate Equation 1 on the intersection of two subsets of the data. This new sample consists of incidents where a subject's race was less likely to affect the officer's decision whether to engage with the subject and incidents where the outside option of not using force was less feasible and contains about 7,800 incidents.

Figure 6 and Table A.7 contain the results from regressions with this new sample. Note that although the point estimates are larger in magnitude than their full sample analogs, outcome means are naturally higher here than in the full sample, as these incidents tend to be more severe than the dropped ones, necessitating higher levels of force. Relative to the new outcome means, the estimated racial disparities using department fixed effects represent increases of about 6.2%, 6.0%, 17.0%, 22.5%, and 31.5% for at least takedowns, hands/fists, leg strikes, pepper spray, and batons. These figures are similar to those using the full sample, though slightly larger at the lowest and highest levels of nonlethal force. The point estimate for fired weapons is approximately 0. Standard errors increase severalfold due to the decreased sample size. The estimates using officer fixed effects are smaller than the ones based on department fixed effects at the lower force levels and similar at higher ones, and their standard errors are about twice as large. These estimates may be more fragile from having to estimate officer fixed effects on such a reduced sample. Both sets of estimates exhibit the same qualitative pattern as those from the full sample where the relative disparities increase with the severity of the force, excepting lethal force. Figures A.2 and A.3 and Tables A.8 and A.9 contain estimates from each subset individually instead of their intersection, which remain similar. Overall, the similarities of these estimates using the subsetted data to their full data counterparts support the use of the entire dataset for subsequent exercises and may indicate that racial differences in events leading to the officer's decision about the intensive margin of force do not have large effects in this setting.

As a test for possible mechanisms, I look at whether there is a negative effect on force when the subject and officer are the same race. A negative coefficient (i.e., officers being more likely to use more severe force when the subject is a different race) may be consistent with taste-based discrimination. Table 2 shows the coefficients from an indicator for same-race subject and officer added to Equation 1. The signs are positive, indicating increased propensity to use greater levels of force when the subject and officer are of the same race, which is evidence against taste-based discrimination. However, factors such as departmental norms or the beats to which individual officers are assigned may distort or mask own-race preferences. Note that racially discriminatory policing is illegal in New Jersey and should never be considered justified, regardless of motivation.

3.2 Variation in Racial Disparities

In this section, I focus on how racial disparities vary across departments. Overall racial disparities treat racial differences as monolithic, while they likely vary across departments. Furthermore, overall estimates place the most weight on the places with the most incidents, typically large, urban areas. As explained in Section 2, my preferred estimates of department-level racial disparities β_p come from the new empirical Bayes estimator in Equation 5.

Figure 7 presents kernel density estimates of the empirical Bayes posterior departmental disparities, with summary statistics in Table 3 (recall that the estimates are calculated without a main coefficient on race, and are centered at the overall racial disparity, not 0). The distributions have long tails that often dwarf the overall racial disparities estimated before. As the level of force increases, the distributions get tighter due to the events becoming rarer, and thus the "confidence" in each point estimate is lower and the estimates are shrunk more towards the grand mean. There are some clear outliers, which are a small sample problem. In the pepper spray subplot, for example, the point around 0.9 corresponds to Point Pleasant, which used force against only two black or Hispanic individuals in my sample. These observations were part of the same incident on subjects with nearly identical demographic variables and same type of force used against them, so $\text{Var}(\epsilon_p^{BH})$ from Equation 5 is approximately 0 and the OLS estimate is barely shrunk. To prevent these estimates from receiving undue weight, I winsorize the distributions at the 1% and 99% levels.

The winsorized standard deviations of these estimates are about 6 percentage points for at least takedowns and hands/fists, 4.5 percentage points for at least leg strikes and pepper spray, 2.3 percentage points for at least batons, and 0.6 percentage points for fired weapons. Distributions for all levels of force have long tails. The distributions for the lowest levels of force are slightly right-skewed, with more departments having large disparities that disfavor black or Hispanic individuals, while the higher levels are more left-skewed. About 20% to 30% of departments have zero or negative racial disparities for each level of force except for fired weapons. Comparing the dispersion of the estimates to the outcome means in Figure 7 reveals the large magnitude of the more extreme departmental disparities.

I plot the distribution of OLS-based unshrunk estimates in Figure A.4. These estimates are naturally much more spread out than the empirical Bayes ones, but the negative correlation between the number of observations and the magnitude of the estimate makes them unreliable.

To address the question of whether departments that have greater racial disparities at one level of force tend to have greater disparities at others, Figure A.5 displays the correlation of winsorized department-level disparities across force levels. I find modest positive correlations. For adjacent levels of force, correlations range from 0.17 to 0.86, while for levels one apart, values range from 0.03 to 0.36. Correlations are approximately 0 beyond that point. Some of this is mechanical (by using the "at least this severe" measure of force, adjacent force types will have similar outcomes, particularly when one is fairly rare as a maximum), but there does seem to be a link, though it does not span the full spectrum.

3.3 Predicting Departmental Racial Disparities

Having established the heterogeneity present in department-specific racial disparities, I turn to the question of what predicts these disparities. I proceed by running regressions of the estimated departmental disparities from the winsorized empirical Bayes estimates from Equation 5 and the OLS estimates from Equation 3 on an array of possible correlates. I do not winsorize the OLS estimates, which have more extreme distributions by nature. Because the mapping from police departments to their municipalities is almost one-to-one, I include regressors based on both the police departments themselves and the municipalities they serve. Doing so requires dropping the New Jersey State Police, as that department covers state highways and some municipalities that lack their own department.

My preferred estimates for this exercise are those based on the at least pepper spray outcome. This outcomes constitutes a well-defined group (all mechanically or chemically enhanced force types) that appears frequently in the data, being usable by the officer in many situations, including both when the officer is in arm's reach of a subject and at range.

I report the results of these regressions with the empirical Bayes estimates as the dependent variable in Table 4. For ease of reading, I multiply the outcome by 100, so that, for example, a coefficient of 0.2 corresponds with an increase in the outcome of 0.2 percentage points, not 20 percentage points. Despite the number of explanatory variables and the belief that they can affect racial policing, the models do a poor job of predicting the racial disparities in each department (all R^2 values are at most 0.037), and only the at least batons model can reject the null hypothesis of an F-test of joint significance for all covariates at the 5% level (at least leg strikes, pepper spray, and fired weapons all have p-values of around 0.1). The precise zero effects for the diversity of officers, including the squared term to allow a "tipping point," contrast with the results of works such as Wilkins and Williams (2008), Nicholson-Crotty, Nicholson-Crotty, and Fernandez (2017) and Ba et al. (2020), which all find effects of officer race on racial policing. Although most variables' coefficients flip signs across models, given the magnitude of the correlations of the disparities for dissimilar force levels, this may not inherently be a problem. For example, larger municipalities may tend to have larger disparities for lower levels of force, but have smaller disparities at highest levels. I report the results from the regressions using unshrunk OLS estimates in Table A.11. These models have similarly poor predictive power and suffer from the presence of outlier estimates.

Within my preferred model, at least pepper spray, the economic variables, log median household income and municipality Gini coefficient, appear most promising. A 100% increase in a municipality's median household income is associated with about a 0.77 percentage point decline in absolute disparities, while an increase in the Gini coefficient of 0.1 correlates with a small increase of around 0.67 percentage points. These variables have significant variation across the state: the greatest median household income in a municipality is more than seven times that of the least, and municipality-level Gini coefficients range from about 0.3 to 0.6 in New Jersey. The signs on these variables are concordant with Ross (2015)'s results on police shootings at the county level. Given the corresponding overall racial disparity of 2.8 percentage points in Table A.4, the correlations with these economic variables are quite large. Despite the economic significance of the point estimates, however, they are not statistically significant, and the model as a whole still does not explain the variation in the point estimates well, suggesting that there may be other unobserved and/or intangible factors that drive most of the variation, like department culture.

4 Conclusion

In this paper, I combine new analytical strategies with incident-level data on all recorded uses of force by police in New Jersey between 2012 and 2016 to estimate racial differences in the severity of force used on a subject, conditional on force. This rich dataset allows me to adjust for factors such as the type of incident or the subject's actions to reduce the role of selection into the dataset and better examine the role of race in police violence. I present evidence of large disparities across races, in particular for blacks, in police use of force that increase along the spectrum of force severity. I then extend empirical Bayes methods and document substantial heterogeneity in these disparities across departments, finding some departments without disparities against black and Hispanic subjects, but also a long tail that especially disfavors them. Finally, I show that many commonly proposed factors do a poor job of explaining these departmental disparities. There is limited evidence for municipality-level economic variables and none for racial or ethnic diversity of the department or local population, and the amount of unexplained variation may suggest that harder-to-measure factors such as department culture may play a large role.

Much work remains to be done on race and police use of force, with policy and research closely intertwined. Having identified this variation in racial disparities in police use of force, it is imperative that we identify why these gaps exist and what separates the departments without apparent racial differences from those with them. This analysis may be difficult, and if the source is indeed intangibles like culture, new analyses and data may be necessary. The presence of departments without estimated racial disparities is a promising sign that progress is possible, but this variation may also mean that a uniform treatment is sub-optimal. Note also that the margin on which I look for racial differences, the intensity of force conditional on force, is not the only such measure, and more work is needed to improve our understanding of why and how an officer uses force from start to finish, including why an officer engages with a given subject and the extensive margin of who has force used against them at all. Police departments and public officials must additionally ensure that data availability and transparency continue to improve. Initiatives such as New Jersey's new statewide data portal combined with its mandatory force reporting and the FBI's National Use-of-Force Data Collection will hopefully facilitate future research on how race and policing interact. These problems cannot be solved without close collaboration of researchers and policymakers, and better data give both the tools needed to move forward.

Table 1: Summary Statistics for Force Reports

Statistic	N	Mean
Max force: compliance hold	39,322	0.50
Max force: takedown	39,322	0.06
Max force: hands/fists	39,322	0.25
Max force: leg strike	39,322	0.05
Max force: pepper spray	39,322	0.11
Max force: baton	39,322	0.03
Max force: fired weapon	39,322	0.004
Max subject action: resisted	39,322	0.63
Max subject action: physical threat/attack	39,322	0.34
Max subject action: blunt weapon threat/attack	39,322	0.01
Max subject action: knife threat/attack	39,322	0.01
Max subject action: vehicular threat/attack	39,322	0.01
Max subject action: firearm threat	39,322	0.01
Max subject action: fired weapon	39,322	0.001
Officer injured	39,322	0.10
Incident: crime in progress	39,322	0.27
Incident: domestic dispute	39,322	0.13
Incident: other dispute	39,322	0.11
Incident: suspicious person	39,322	0.11
Incident: traffic stop	39,322	0.09
Incident: other	39,322	0.33
Subject: white	39,322	0.48
Subject: black	39,322	0.41
Subject: Hispanic	39,322	0.10
Subject: Asian/Pacific Islander	39,322	0.01
Subject: female	39,322	0.20
Subject: age	39,322	31.09

Notes: Data cover all police departments in New Jersey from 2012 through 2016. Data have been restructured so that each observation is a subject who had force used against them by police and cleaned as described in Appendix A. "Max force" refers to the highest level of force used in an incident; lower levels of force are not reported. "Max subject action" indicates the most severe action a subject took that could justify an office using force. Force used and subject actions are ordered from least severe to most severe. Incidents may have multiple types.

Table 2: Effect of Same-Race Officer and Subject on Police Use of Force of At Least Specified Severity, Conditional on Force Used, Incidents with Nonmissing Officer Race Only

	Takedowns	Hands/Fists	Leg Strikes	Pepper Spray	Batons	Fired Weapons
Officer and subject same race	0.013	0.026	0.021	0.023	0.012	0.003
	(0.009)	(0.011)	(0.009)	(0.008)	(0.003)	(0.002)
Fixed effects	*Dept.*	*Dept.*	*Dept.*	*Dept.*	*Dept.*	*Dept.*
Clustering	*Dept.*	*Dept.*	*Dept.*	*Dept.*	*Dept.*	*Dept.*
Outcome mean	0.490	0.441	0.189	0.140	0.037	0.004
R^2	0.181	0.184	0.124	0.125	0.082	0.213
Num. obs.	28637	28637	28637	28637	28637	28637

Notes: Table reports OLS estimates from Equation 1, which regresses a binary measure of whether police used force of at least the specified severity on indicators for the subject's race, an indicator for the subject being female, a quadratic of the subject's age, time of day fixed effects, indicators for the subject's actions, an indicator for whether an officer was harmed, an indicator for whether the subject was an emotionally disturbed person, indicators for the officer's rank, year fixed effects, department fixed effects, and an indicator for the subject and officer being of the same race.

Table 3: Summary Statistics for Empirical Bayes Department x Black/Hispanic Subject Interactions

	Takedown	Hands/Fists	Leg Strikes	Pepper Spray	Batons	Fired Weapons
SD	0.084	0.089	0.067	0.063	0.025	0.009
SD (Winsorized)	0.064	0.061	0.047	0.045	0.023	0.006
Min	-0.400	-0.347	-0.439	-0.300	-0.200	-0.125
P01	-0.207	-0.238	-0.175	-0.180	-0.106	-0.031
P05	-0.052	-0.059	-0.097	-0.087	-0.043	-0.008
P25	0.004	0.007	0.009	0.005	-0.003	-0.001
Median	0.015	0.019	0.031	0.028	0.009	0.001
P75	0.027	0.031	0.036	0.032	0.011	0.002
P95	0.085	0.080	0.064	0.058	0.022	0.009
P99	0.386	0.366	0.097	0.087	0.036	0.023
Max	0.777	0.851	0.913	0.906	0.061	0.034
Mean	0.020	0.021	0.017	0.014	0.000	0.000
$\% \leq 0$	0.220	0.193	0.207	0.226	0.295	0.391

Notes: Table reports empirical Bayes estimates of departmental racial disparities from Equation 5, which regresses a binary measure of whether police used force of at least the specified severity on indicators for the subject's race interacted with a department indicator, an indicator for the subject being female, a quadratic of the subject's age, time of day fixed effects, indicators for the subject's actions, an indicator for whether an officer was harmed, an indicator for whether the subject was an emotionally disturbed person, indicators for the officer's rank, year fixed effects, and department fixed effects. Winsorization is done at the 1st and 99th percentiles.

Table 4: Predicting 100 x (Department x Non-White/Asian/Pacific Islander Winsorized Empirical Bayes Estimates)

	Takedowns	Hands/Fists	Leg Strikes	Pepper Spray	Batons	Fired Weapons
Log median household income	0.585	0.553	−0.865	−0.768	0.194	0.107
	(0.921)	(0.876)	(0.713)	(0.697)	(0.361)	(0.094)
Gini coefficient	−3.267	3.772	6.594	6.656	0.482	−0.291
	(6.860)	(6.820)	(5.556)	(4.904)	(2.543)	(0.635)
Log population	−0.019	0.332	0.182	0.192	−0.361	0.023
	(0.652)	(0.726)	(0.607)	(0.528)	(0.255)	(0.077)
Log population per square mile	−0.076	−0.042	0.225	0.184	0.080	0.077
	(0.342)	(0.333)	(0.253)	(0.242)	(0.124)	(0.031)
Log number of police	−0.635	−0.893	−0.132	0.067	0.320	−0.126
	(0.721)	(0.772)	(0.702)	(0.639)	(0.316)	(0.091)
% officers not white or Asian/PI	0.046	0.007	−0.002	−0.028	−0.018	−0.004
	(0.035)	(0.031)	(0.028)	(0.028)	(0.013)	(0.004)
Squared % officers not white or Asian/PI	−0.001	−0.000	−0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% population 18-65 not white or Asian/PI	−0.024	−0.013	−0.044	−0.037	−0.031	0.002
	(0.050)	(0.048)	(0.036)	(0.033)	(0.020)	(0.006)
Squared % population 18-65 not white or Asian/PI	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Log violent crimes per 1000	−0.379	−0.236	−0.023	0.103	−0.065	−0.001
	(0.311)	(0.320)	(0.224)	(0.217)	(0.103)	(0.028)
2012 presidential election Romney vote %	−0.028	−0.039	−0.038	−0.025	−0.003	0.006
	(0.036)	(0.035)	(0.025)	(0.026)	(0.015)	(0.004)
Prob > F	0.233	0.299	0.113	0.135	0.017	0.136
R^2	0.021	0.016	0.032	0.027	0.028	0.037
Num. obs.	455	455	455	455	455	455

Notes: Table reports coefficients from a regression of winsorized empirical Bayes estimates of the department-specific racial disparities $\beta_{p,EB}$ for black/Hispanic subjects on municipal/departmental-level covariates as shown in Equation 6. Winsorized is done at the 1% and 99% levels. Each column corresponds to a regression with the outcome being whether, conditional on force being used, force of at least the specified severity was used.

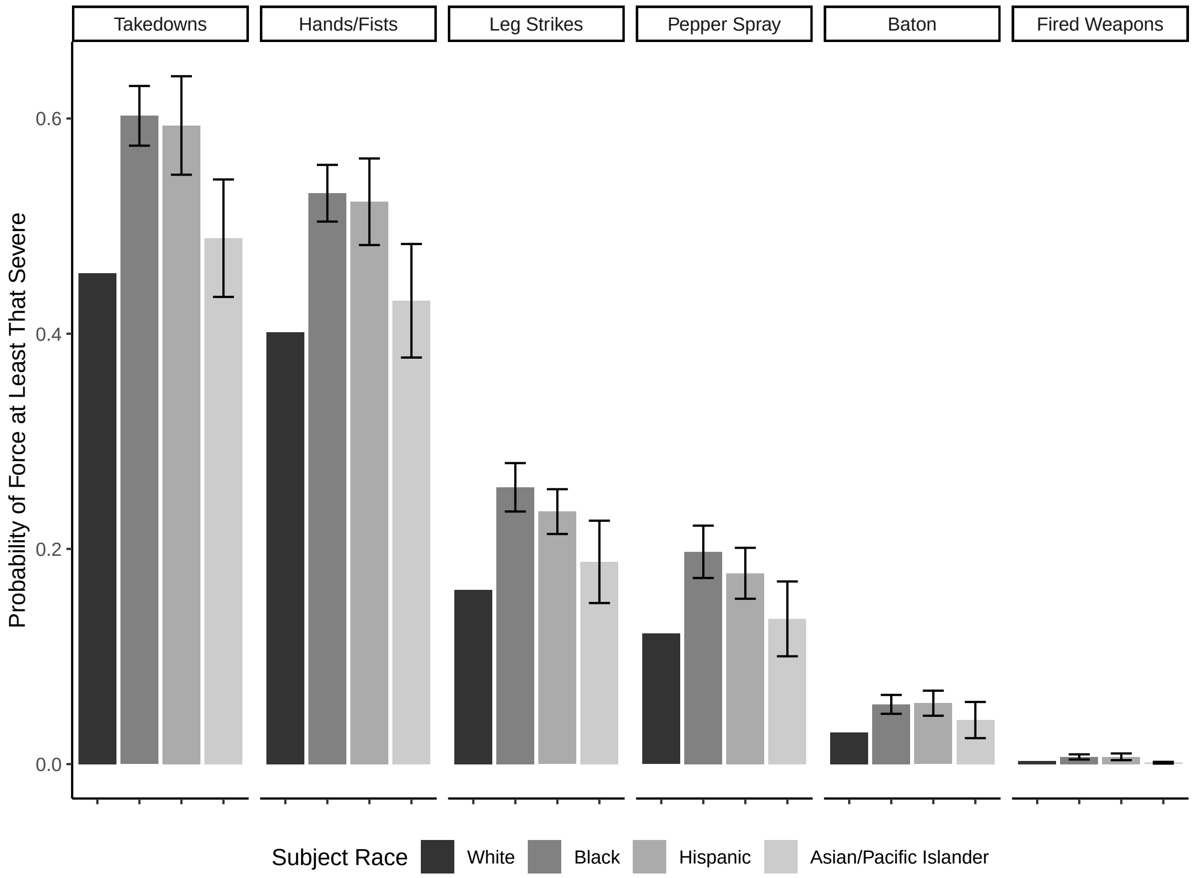

Figure 1: Overall Racial Disparities (No Controls)

Notes: Figure presents results from a series of OLS models regressing outcomes on a full set of racial dummies. Each heading represents a different outcome: whether, conditional on any force being used, force of at least the specified severity was used. Non-white bars are obtained by taking the intercept (whites) and adding the coefficient on that race. Confidence intervals are based on the corresponding race coefficient. Standard errors are clustered at the department level.

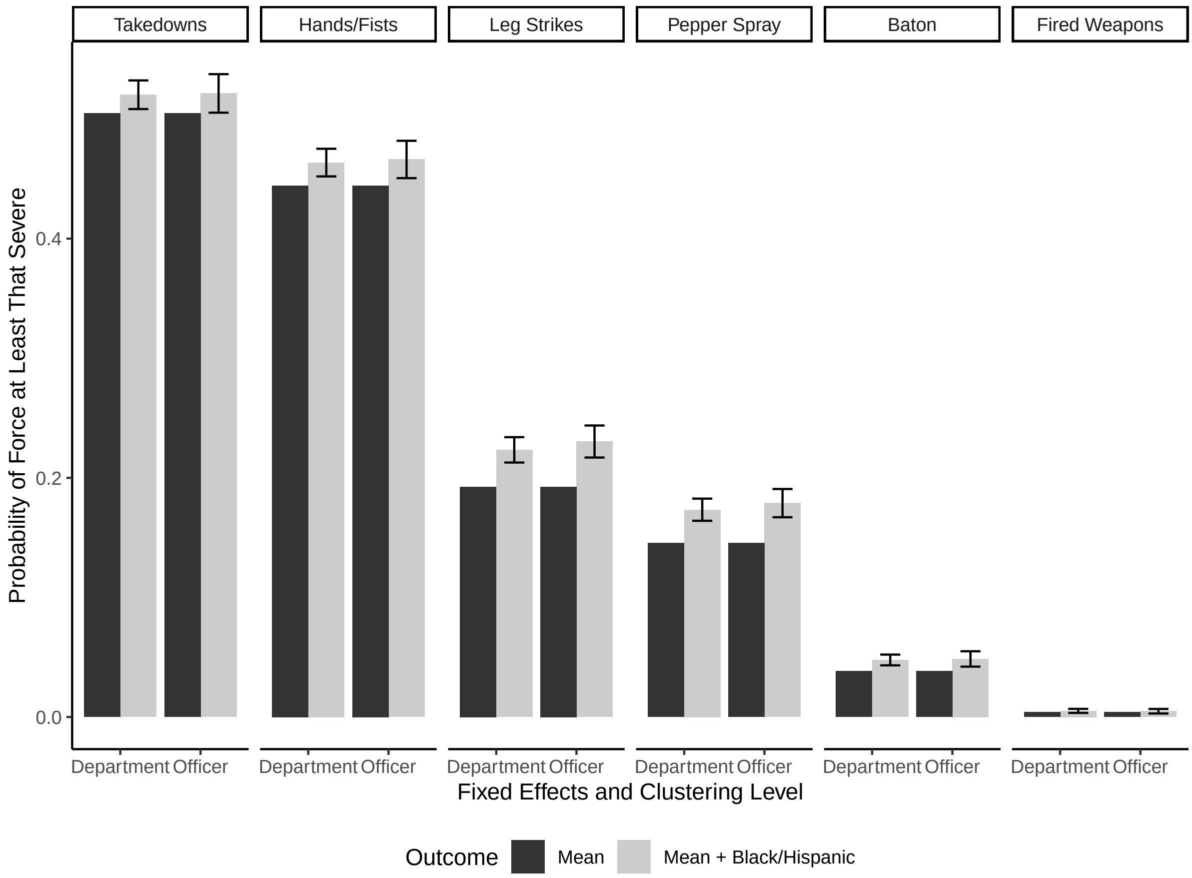

Figure 2: Overall Racial Disparities for Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity

Notes: Figure presents results from a series of OLS models fit via Equation 1. Each heading represents a different outcome: whether, conditional on any force being used, force of at least the specified severity was used. Bars labeled "Department" include department fixed effects, and bars labeled "Officer" instead include officer fixed effects. Confidence intervals are based on the black/Hispanic coefficient.

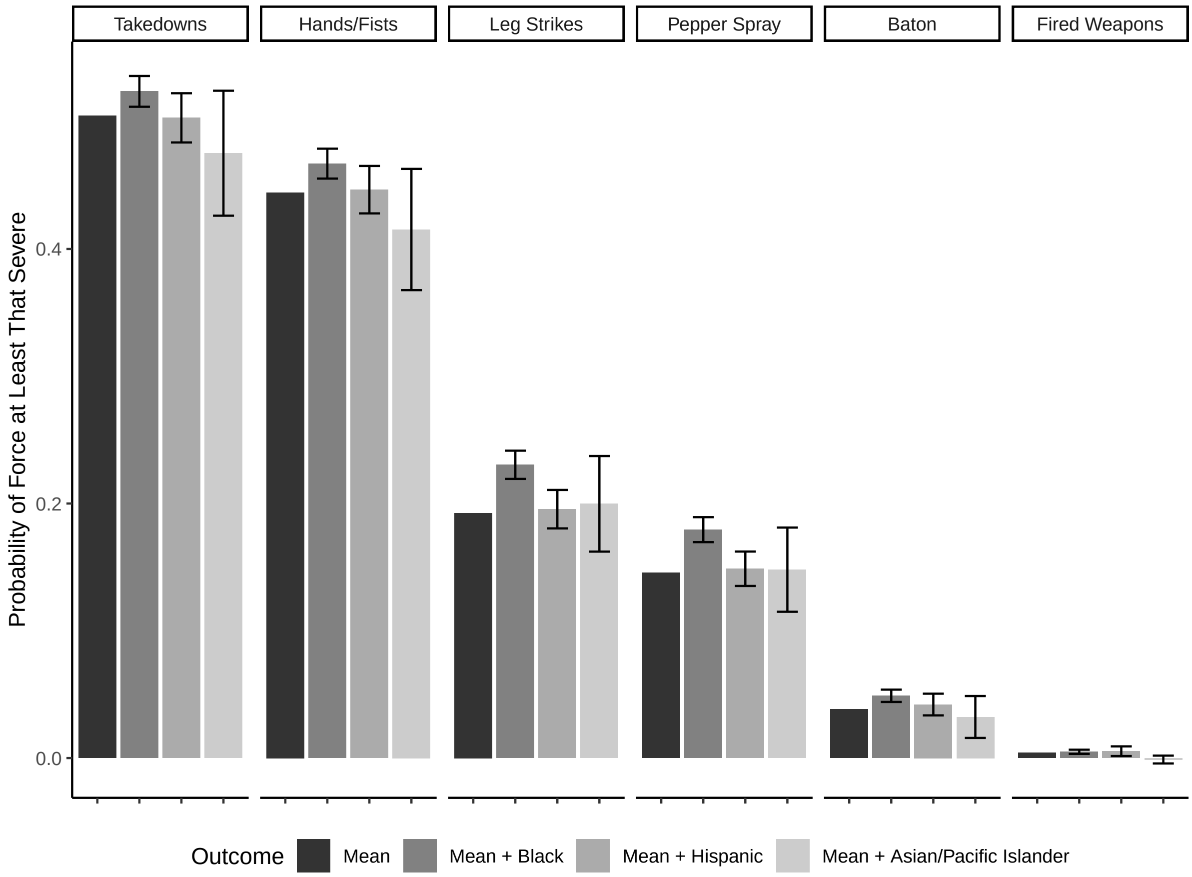

Figure 3: Overall Racial Disparities of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity, Full Race Dummies (Department Fixed Effects and Clustering)

Notes: Figure presents results from a series of OLS models fit via Equation 1. Each heading represents a different outcome: whether, conditional on any force being used, force of at least the specified severity was used. Confidence intervals are based on the corresponding race coefficient. Standard errors are clustered at the department level.

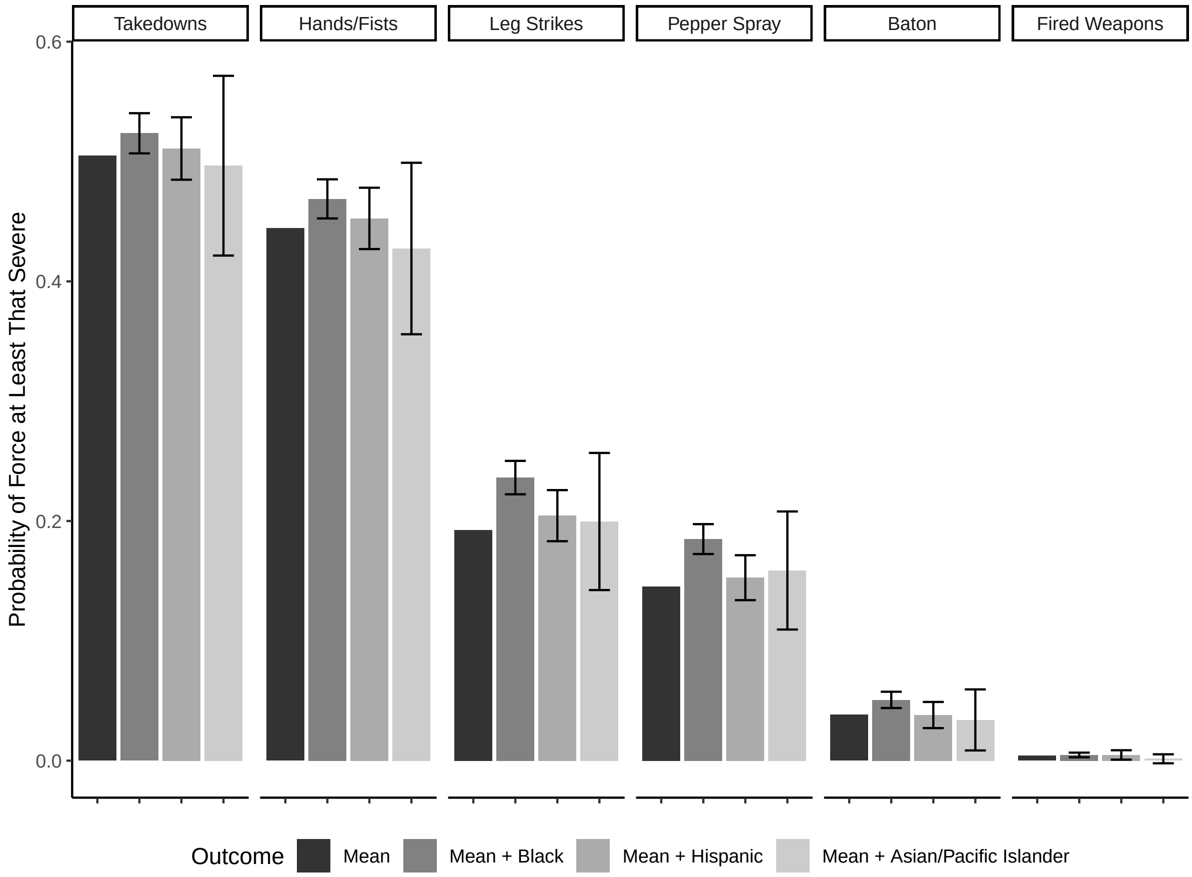

Figure 4: Overall Racial Disparities of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity, Full Race Dummies (Officer Fixed Effects and Clustering)

Notes: Figure presents results from a series of OLS models fit via Equation 1. Each heading represents a different outcome: whether, conditional on any force being used, force of at least the specified severity was used. Confidence intervals are based on the corresponding race coefficient. Standard errors are clustered at the officer level.

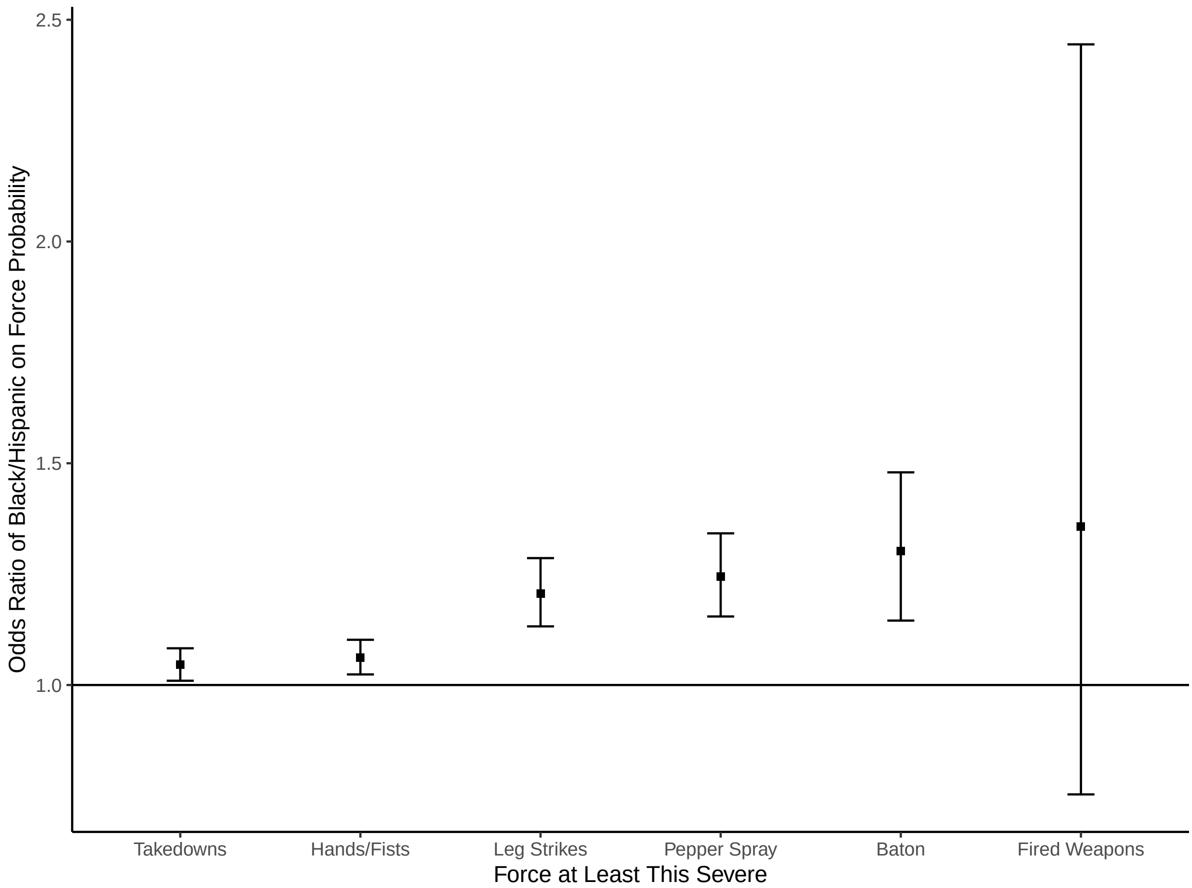

Figure 5: Conditional Logit Odds Ratios of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity

Notes: Figure presents results from a series of conditional logit models fit via Equation 2. Each heading represents a different outcome: whether, conditional on any force being used, force of at least the specified severity was used. Points indicate the odds ratio of a black/Hispanic subject. Confidence intervals clustered at the department level are obtained by exponentiating the logit coefficients from the regression and are asymmetric.

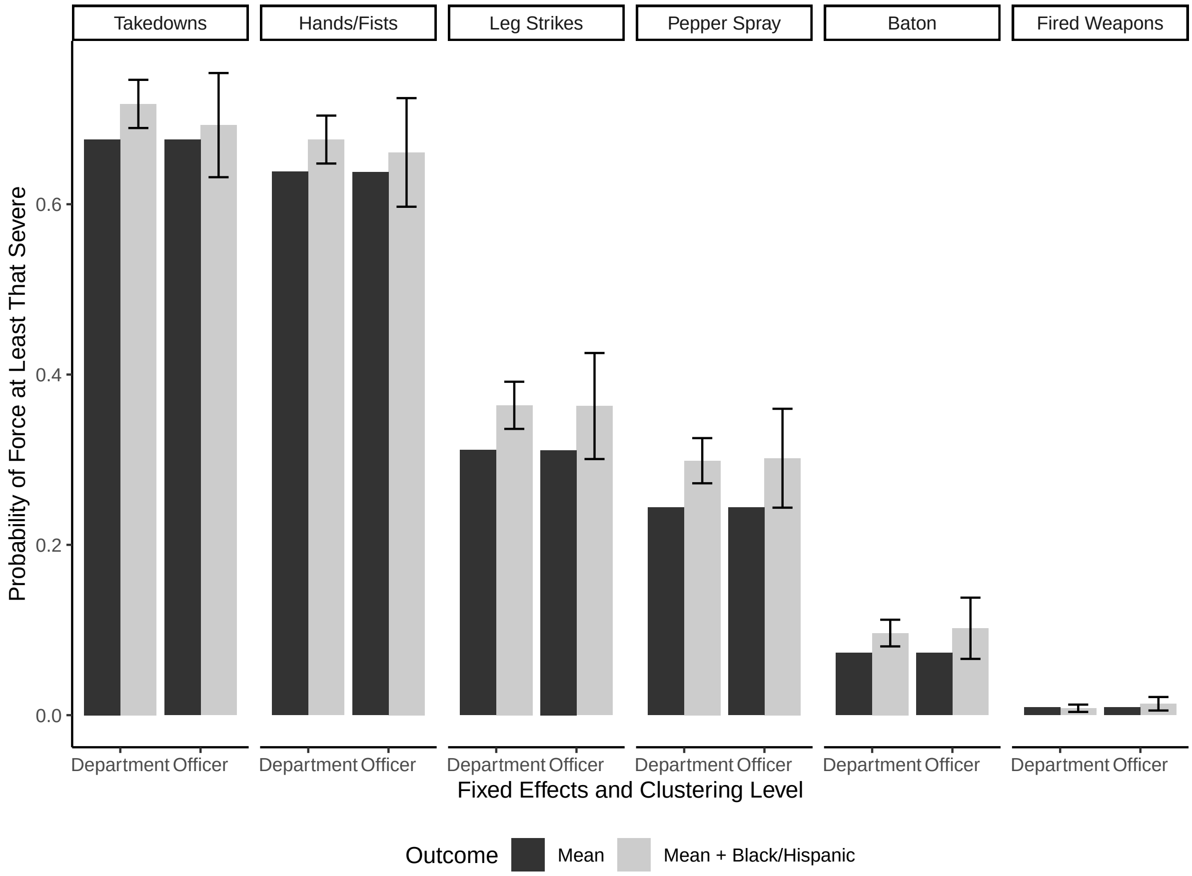

Figure 6: Overall Racial Disparities of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity (Subset Where Race is Unlikely to Affect Decision to Engage Subject and Subject at Least Physically Threatened/Attacked Officer or Another)
Notes: Figure presents results from a series of OLS models estimated on the subset of the data where a subject's race was less likely to have influenced the officer's decision to engage with the subject: crimes in progress, disputes, and traffic stops at night, and where the subject at least physically threatened or attacked an officer or another. The latter restriction is equivalent to dropping observations where the most severe actions by the subject was resisting. Regressions are fit via Equation 1. Each heading represents a different outcome: whether, conditional on any force being used, force of at least the specified severity was used. Bars labeled "Department" include department fixed effects, and bars labeled "Officer" instead include officer fixed effects. Confidence intervals are based on the black/Hispanic coefficient.

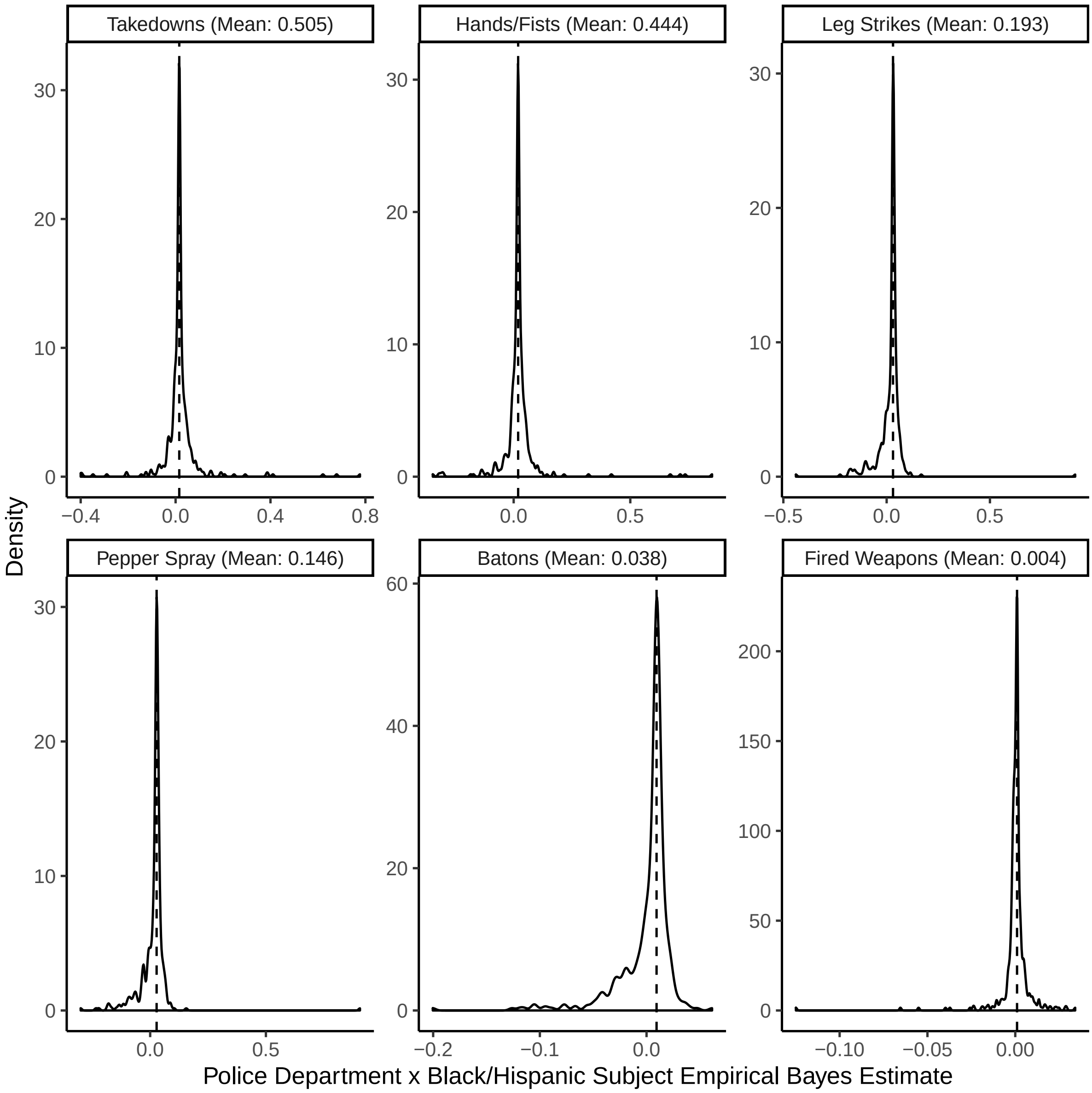

Figure 7: Distribution of Empirical Bayes Estimates of Department-Black/Hispanic Interactions

Notes: Figure presents kernel density estimates of department-specific racial disparities β between white/Asian/Pacific Islander subjects and black/Hispanic subjects as estimated from the empirical Bayes estimator in Equation 5 with Gaussian kernels and the Silverman (1986) rule-of-thumb bandwidth. Each subgraph shows results from regressions with the specified outcome outcome: whether, conditional on any force being used, force of at least the specified severity was used. The dashed line indicates the mean of the prior.

References

Antonovics, Kate, and Brian G Knight. 2009. “A New Look at Racial Profiling: Evidence from the Boston Police Department”. *The Review of Economics and Statistics* 91 (1): 163–177.

Anwar, Shamena, and Hanming Fang. 2006. “An Alternative Test of Racial Prejudice in Motor Vehicle Searches: Theory and Evidence”. *American Economic Review* 96 (1): 127–151.

Arnold, David, Will Dobbie, and Crystal S. Yang. 2018. “Racial Bias in Bail Decisions”. *The Quarterly Journal of Economics* 133 (4): 1885–1932.

Ba, Bocar, et al. 2020. *The Impact of Racial and Ethnic Diversity in Policing*. Tech. rep. Visited on 04/03/2020. `https://scholar.princeton.edu/sites/default/files/jmummolo/files/bkmr_racialethnicdiversitypolicing.pdf`.

Becker, Gary S. 1957. *The economics of discrimination*. University of Chicago press.

Bielen, Samantha, Wim Marneffe, and Naci H. Mocan. 2019. *Racial Bias and In-group Bias In Judicial Decisions: Evidence from Virtual Reality Courtrooms*. Working Paper, Working Paper Series 25355. National Bureau of Economic Research. `http://www.nber.org/papers/w25355`.

Chetty, Raj, John N. Friedman, and Jonah E. Rockoff. 2014. “Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates”. *American Economic Review* 104 (9): 2593–2632.

Coviello, Decio, and Nicola Persico. 2015. “An Economic Analysis of Black-White Disparities in the New York Police Department’s Stop-and-Frisk Program”. *The Journal of Legal Studies* 44 (2): 315–360.

Devi, Tanaya, and Jr Fryer Roland G. 2020. *Policing the Police: The Impact of ”Pattern-or-Practice” Investigations on Crime*. Working Paper, Working Paper Series 27324. National Bureau of Economic Research. `http://www.nber.org/papers/w27324`.

Fryer, Roland G. 2019. “An Empirical Analysis of Racial Differences in Police Use of Force”. *Journal of Political Economy* 127 (3): 1210–1261.

Gelman, Andrew, Jeffrey Fagan, and Alex Kiss. 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.

Goncalves, Felipe, and Steven Mello. 2017. *A Few Bad Apples? Racial Bias in Policing*. Working Papers 608. Princeton University, Department of Economics, Industrial Relations Section. `https://ideas.repec.org/p/pri/indrel/608.html`.

Grogger, Jeffrey, and Greg Ridgeway. 2006. "Testing for Racial Profiling in Traffic Stops from Behind a Veil of Darkness". *Journal of the American Statistical Association* 101 (475): 878–887.

Heaton, Paul. 2010. "Understanding the Effects of Antiprofiling Policies". *The Journal of Law and Economics* 53 (1): 29–64.

Hoekstra, Mark, and CarlyWill Sloan. 2020. *Does Race Matter for Police Use of Force? Evidence from 911 Calls*. Working Paper, Working Paper Series 26774. National Bureau of Economic Research. `http://www.nber.org/papers/w26774`.

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

Kane, Thomas J., and Douglas O. Staiger. 2008. "Estimating Teacher Impacts on Student Achievement: An Experimental Evaluation". National Bureau of Economic Research working paper 14607.

Kline, Patrick, and Christopher Walters. 2019. *Audits as Evidence: Experiments, Ensembles, and Enforcement*. Tech. rep. `https://arxiv.org/abs/1907.06622`.

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

Knox, Dean, Will Lowe, and Jonathan Mummolo. 2020. "Administrative Records Mask Racially Biased Policing". *American Political Science Review*: 1–19.

Luh, Elizabeth. 2020. *Not So Black and White: Uncovering Racial Bias from Systematically Misreported Trooper Reports*. Tech. rep. Visited on 06/06/2020. `https://elizluh.github.io/files/highwaybias.pdf`.

McCarthy, Craig. 2019. *Help us continue to improve N.J's first statewide database of police use of force*. Visited on 06/01/2019. `https://www.nj.com/news/2018/12/help-us-continue-to-improve-njs-first-statewide-database-of-police-use-of-force.html`.

McCarthy, Craig, and Blake Nelson. 2019. *Every way a police officer is legally allowed to harm another person, ranked*. Visited on 06/01/2019. `https://www.nj.com/news/2018/11/every_way_a_police_officer_is_legally_allowed_to_harm_another_person_from_a_to_z.html`.

McCarthy, Craig, and Stephen Stirling. 2019. *How we built the most comprehensive statewide database of police force in the United States*. Visited on 06/01/2019. `https://www.nj.com/news/2018/11/how_we_built_the_most_comprehensive_statewide_database_of_police_force_in_the_us.html`.

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

Nelson, Blake. 2019. *Frequently asked questions about The Force Report.* Visited on 06/01/2019. https://www.nj.com/news/2018/11/frequently_asked_questions_about_the_force_report.html.

Nicholson-Crotty, Sean, Jill Nicholson-Crotty, and Sergio Fernandez. 2017. "Will More Black Cops Matter? Officer Race and Police-Involved Homicides of Black Citizens". *Public Administration Review* 77 (2): 206–216.

Nix, Justin, et al. 2017. "A Bird's Eye View of Civilians Killed by Police in 2015: Further Evidence of Implicit Bias". *Criminology & Public Policy* 16 (1): 309–340.

NJ Advance Media. 2019. *The Force Report.* Visited on 06/01/2019. force.nj.com.

Persico, Nicola, and Petra Todd. 2006. "Generalising the Hit Rates Test for Racial Bias in Law Enforcement, with an Application to Vehicle Searches in Wichita". *The Economic Journal* 116 (515): F351–F367.

Ross, Cody T. 2015. "A Multi-Level Bayesian Analysis of Racial Bias in Police Shootings at the County-Level in the United States, 2011–2014". *PLoS One* 10 (11): e0141854.

Silverman, Bernard W. 1986. *Density estimation for statistics and data analysis.* Vol. 26. CRC press.

Terrill, William, and Michael D. Reisig. 2003. "Neighborhood Context and Police Use of Force". *Journal of Research in Crime and Delinquency* 40 (3): 291–321.

Weisburst, Emily K. 2019. "Police Use of Force as an Extension of Arrests: Examining Disparities across Civilian and Officer Race". *AEA Papers and Proceedings* 109:152–56.

West, Jeremy. 2018. *Racial Bias in Police Investigations.* Tech. rep. Visited on 06/07/2019. https://people.ucsc.edu/~jwest1/articles/West_RacialBiasPolice.pdf.

Wilkins, Vicky M., and Brian N. Williams. 2008. "Black or Blue: Racial Profiling and Representative Bureaucracy". *Public Administration Review* 68 (4): 654–664.

Appendix (For Online Publication Only)

A Data Cleaning

Despite the substantial efforts by the teams at ProPublica and NJ Advance Media, the use of force dataset requires additional processing to be used for analysis. Here I outline the changes I make to the data.

The structure of each department's force reports and how many officers or subjects can be put on a single report vary. For consistency, I structure the data so that every observation is one subject who had force used against them by one officer. When there are multiple force reports for a single subject in an incident, I identify duplicates by computing similarity scores based on the Levenshtein distance between subject names, preventing situations such as a missing middle initial in one report or typos from creating repeat incidents. When officers from different departments use force against the same subject in the same incident as identified by the subject identifier and time of the incident, I continue to keep only the highest use of force from *any* department. For 167 force reports where multiple officers are record, I use the first officer listed. Because my empirical strategies are based on the most severe level of force used against a subject, for incidents where multiple officers use force against a single subject, I keep the officer who uses the greatest level of force, choosing randomly in the event of ties.

Besides restructuring, the most significant modifications I make are for the types of force used. These are text strings and contain many irregularities. Some have typos, some do not directly correspond with force categories (e.g., "Grabbed Gardening Tool Out Of Her Hand"), and some forms, notably from the New Jersey State Police, have their own names for force levels, such as "physical" and "mechanical." In keeping with my empirical strategy, I map these force levels to the highest type of force used in each incident.

Many force classifications require subjective judgments, outlined below. These decisions are further informed by officer narratives whenever possible. For instances where an officer uses a firearm as a blunt weapon ("pistol whipping"), I mark this as a use of a baton, the most similar type of force. Similarly, when blunt objects such as flashlights are used to strike a subject, I record them as batons. When batons are used for leverage in compliance holds, I count these incidents as compliance holds. I do not count restraints such as handcuffs or "the wrap" as force, but maneuvers to facilitate them may be, such as forcing one's arms behind their back. Unless there is an indication that a subject was punched, slapped, or otherwise struck, I classify hands on the subject as compliance holds rather than the hands/fists level. If an officer pushes a subject to get them to move, such as pushing them into a police vehicle, I classify it as a compliance hold. When the pushing is done to incapacitate a subject, such as pushing them off of a bicycle, I classify it as a use of hands/fists. I classify forcibly moving actively resisting subjects as compliance holds, but do not count moving passively resisting subjects, as when a subject sits down and does not move.

Two other variables require manual cleaning: the unique officer identifier and the actions of the subject. The officer identifier present in the dataset does not track officers as they move across departments. Using available information on race, experience, rank, and geographic location, I manually create an officer identifier variable that follows officers across departments. The subject actions variable is structured in the same manner as the force used variable and suffers from the same inconsistency problems. Again I manually map this variable to the "maximum" action a subject took that justified force. The lowest category is resisting, which includes physically resisting an officer's control, fleeing officer apprehension, and other actions that do not fit into another category. The next categories, physical, blunt, knife, and vehicle, cover both attacks and threats of attack. I split incidents involving firearms into threats with firearms and actually firing the weapons. I only count subject actions directed at humans, ignoring behaviors such as subjects attempting to kick out the windows of the police vehicle in which they are being held. I consider flailing and spitting or using other bodily fluids as projectiles to be a physical attack. When a subject attempts to disarm an officer, I mark it as a physical attack.

For the incident type variable, I use the categories present on the New Jersey Attorney General model form (Figure A.1): crime in progress, domestic, other dispute, suspicious person, and other, reserving "other" for incidents that do not fit into another category. Some incidents have multiply types, which I allow.

I remove a small number of irregular or non-representative observations from the data. I drop 963 observations (over 600 of them would have been dropped anyway due to other missing variables) where no reason for the force was given, as it is likelier that the officer-stated reason is missing than nonexistent. I remove a handful of incidents involving nonlethal firearms (i.e. "riot guns"), as these are not standard police carry. I do not include the constructive authority category of force, incidents where a firearm or stun gun is drawn but not fired to induce compliant behavior, as no physical force is used in these situations. I remove 44 individuals whose indicated races do not fall within the categories of white, black, Hispanic, or Asian/Pacific Islander, such as people marked as "mixed."

Table A.1: Summary Statistics for Municipalities Represented in Use of Force Data

Statistic	N	Mean	St. Dev.	Median	Min	Max
Population	454	18,424.43	25,402.93	10,373	296	277,140
Population/square mile)	454	4,020.84	5,616.57	2,612.1	39	55,880
Median household income	454	87,296.63	31,652.80	83,006	26,214	190,625
Gini coefficient	454	0.43	0.05	0.43	0.33	0.60
Land area (sq. miles)	454	11.16	16.50	3.67	0.10	111.13
Adjusted pop. % white	454	68.52	22.53	74.44	1.82	99.29
Adjusted Pop. % black	454	8.41	12.17	3.87	0.00	88.77
Adjusted Pop. % Hispanic	454	14.16	14.30	9.19	0.00	82.94
Adjusted Pop. % Asian/PI	454	7.66	9.15	4.51	0.00	58.60
Violent crimes per 1000	454	5.95	8.09	3.01	0.03	54.97
Romney vote share 2012 presidential election	454	45.23	14.81	47.74	1.31	81.82

Notes: Data cover all municipalities present in the force reports after cleaning and processing that are served by their own police department in the force reports data, i.e. not those served by New Jersey State Police. Data have been cleaned as described in Appendix A. Data come from the 2010 Census, 2012-2016 American Community Survey five-year estimates, FBI's Uniform Crime Reporting program, and the New Jersey Division of Elections.

Table A.2: Summary Statistics for Police Departments Represented in Use of Force Data

Statistic	N	Mean	St. Dev.	Median	Min	Max
Avg. num. full-time police employees	455	42.75	76.41	23	0	1,088
% officers white	455	72.42	35.01	90.58	0.00	100.00
% officers black	455	2.64	6.80	0.00	0.00	78
% officers Hispanic	455	2.04	5.69	0.00	0.00	53.49
% officers Asian/Pacific Islander	455	0.53	2.13	0.00	0.00	30

Notes: Data cover all police departments in New Jersey from 2012 through 2016 with force reports after cleaning and processing. Not all departments' racial breakdowns sum to 100%. Data from ProPublica and NJ Advance Media.

Table A.3: Racial Disparities by Police in Force of At Least Specified Severity, Conditional on Force Used (No Controls)

	Takedowns	Hands/Fists	Leg Strikes	Pepper Spray	Batons	Fired Weapons
Intercept (white)	0.456	0.401	0.162	0.121	0.029	0.003
	(0.014)	(0.012)	(0.007)	(0.007)	(0.002)	(0.000)
Subject black	0.098	0.086	0.065	0.052	0.017	0.003
	(0.014)	(0.013)	(0.011)	(0.012)	(0.004)	(0.001)
Subject Hispanic	0.089	0.078	0.042	0.032	0.018	0.003
	(0.023)	(0.020)	(0.011)	(0.012)	(0.006)	(0.002)
Subject Asian/PI	−0.016	−0.014	−0.005	−0.011	0.003	−0.003
	(0.028)	(0.027)	(0.019)	(0.018)	(0.009)	(0.000)
Clustering	*Dept.*	*Dept.*	*Dept.*	*Dept.*	*Dept.*	*Dept.*
Outcome mean	0.505	0.444	0.193	0.146	0.038	0.004
R^2	0.009	0.007	0.006	0.005	0.002	0.000
Num. obs.	39322	39322	39322	39322	39322	39322

Notes: Table reports OLS estimates from regressions where the outcome is a binary measure of whether police used force of at least the specified severity on indicators for subject race with no other covariates.

Table A.4: Racial Disparities by Police in Force of At Least Specified Severity, Conditional on Force Used

	Takedowns		Hands/Fists		Leg Strikes		Pepper Spray		Batons		Fired Weapons	
Subject black/Hispanic	0.015	0.017	0.019	0.022	0.031	0.038	0.028	0.033	0.009	0.010	0.001	0.001
	(0.006)	(0.008)	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.006)	(0.002)	(0.003)	(0.001)	(0.001)
Fixed effects	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*
Clustering	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*
Outcome mean	0.505	0.505	0.444	0.444	0.193	0.192	0.146	0.145	0.038	0.038	0.004	0.004
R^2	0.181	0.511	0.177	0.518	0.114	0.451	0.116	0.465	0.074	0.415	0.184	0.533
Num. obs.	39322	39266	39322	39266	39322	39266	39322	39266	39322	39266	39322	39266

Notes: Table reports OLS estimates from Equation 1, which regresses a binary measure of whether police used force of at least the specified severity on indicators for the subject's race, an indicator for the subject being female, a quadratic of the subject's age, time of day fixed effects, indicators for the subject's actions, an indicator for whether an officer was harmed, an indicator for whether the subject was an emotionally disturbed person, indicators for the officer's rank, year fixed effects, and department or officer fixed effects.

Table A.5: Racial Disparities by Police in Force of At Least Specified Severity, Conditional on Force Used

	Takedowns		Hands/Fists		Leg Strikes		Pepper Spray		Batons		Fired Weapons	
Subject black	0.019	0.019	0.023	0.025	0.038	0.044	0.034	0.039	0.011	0.012	0.001	0.001
	(0.006)	(0.009)	(0.006)	(0.008)	(0.006)	(0.007)	(0.005)	(0.006)	(0.002)	(0.003)	(0.001)	(0.001)
Subject Hispanic	−0.002	0.006	0.002	0.008	0.003	0.012	0.003	0.007	0.004	−0.000	0.001	0.001
	(0.010)	(0.013)	(0.009)	(0.013)	(0.008)	(0.011)	(0.007)	(0.010)	(0.004)	(0.006)	(0.002)	(0.002)
Subject Asian/PI	−0.030	−0.008	−0.029	−0.017	0.007	0.007	0.003	0.013	−0.006	−0.004	−0.005	−0.003
	(0.025)	(0.038)	(0.024)	(0.037)	(0.019)	(0.029)	(0.017)	(0.025)	(0.008)	(0.013)	(0.002)	(0.002)
Fixed effects	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*
Clustering	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*
Outcome mean	0.505	0.505	0.444	0.444	0.193	0.192	0.146	0.145	0.038	0.038	0.004	0.004
R^2	0.181	0.512	0.177	0.518	0.114	0.452	0.117	0.466	0.075	0.415	0.184	0.533
Num. obs.	39322	39266	39322	39266	39322	39266	39322	39266	39322	39266	39322	39266

Notes: Table reports OLS estimates from Equation 1, which regresses a binary measure of whether police used force of at least the specified severity on indicators for the subject's race, an indicator for the subject being female, a quadratic of the subject's age, time of day fixed effects, indicators for the subject's actions, an indicator for whether an officer was harmed, an indicator for whether the subject was an emotionally disturbed person, indicators for the officer's rank, year fixed effects, and department or officer fixed effects.

Table A.6: Conditional Logit Odds Ratios on Race in Intensity of Force Used Conditional on Force

	Takedowns	Hands/Fists	Leg Strikes	Pepper Spray	Batons	Fired Weapons
Subject black/Hispanic	1.046	1.062	1.207	1.245	1.302	1.357
	(1.010, 1.083)	(1.024, 1.102)	(1.132, 1.286)	(1.154, 1.342)	(1.145, 1.479)	(0.753, 2.445)
Fixed effects	*Dept.*	*Dept.*	*Dept.*	*Dept.*	*Dept.*	*Dept.*
Clustering	*Dept.*	*Dept.*	*Dept.*	*Dept.*	*Dept.*	*Dept.*
Num. obs.	39322	39322	39322	39322	39322	39322

Notes: Table reports conditional logit estimates from Equation 2, which regresses a binary measure of whether police used force of at least the specified severity on indicators for the subject's race, an indicator for the subject being female, a quadratic of the subject's age, time of day fixed effects, indicators for the subject's actions, an indicator for whether an officer was harmed, an indicator for whether the subject was an emotionally disturbed person, indicators for the officer's rank, and year fixed effects, stratified by department. Asymmetric 95% confidence intervals with clustering at the department level based on exponentiating the log odds confidence interval are in parentheses.

Table A.7: Racial Disparities by Police in Force of At Least Specified Severity, Conditional on Force Used, Incidents where Race Likely Unrelated to Decision to Engage with Subject and Subject at Least Physically Threatened/Attacked Officer or Another

	Takedowns		Hands/Fists		Leg Strikes		Pepper Spray		Batons		Fired Weapons	
Subject black/Hispanic	0.042	0.017	0.038	0.023	0.053	0.052	0.055	0.058	0.023	0.029	−0.001	0.004
	(0.014)	(0.031)	(0.014)	(0.033)	(0.014)	(0.032)	(0.013)	(0.030)	(0.008)	(0.018)	(0.002)	(0.004)
Fixed effects	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*
Clustering	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*
Outcome mean	0.676	0.676	0.638	0.638	0.311	0.311	0.244	0.244	0.073	0.073	0.009	0.009
R^2	0.185	0.731	0.180	0.731	0.131	0.695	0.132	0.711	0.128	0.707	0.272	0.841
Num. obs.	7806	7795	7806	7795	7806	7795	7806	7795	7806	7795	7806	7795

Notes: Table reports OLS estimates from Equation 1, which regresses a binary measure of whether police used force of at least the specified severity on indicators for the subject's race, an indicator for the subject being female, a quadratic of the subject's age, time of day fixed effects, indicators for the subject's actions, an indicator for whether an officer was harmed, an indicator for whether the subject was an emotionally disturbed person, indicators for the officer's rank, year fixed effects, and department or officer fixed effects. These regressions are run on a subset of the data where the following two conditions hold. 1) The subject at least physically threatened or attacked an officer or another person. 2) The incident's type is one where the subject's race was less likely to have influenced the officer's decision to engage with the subject: crimes in progress, disputes, and traffic stops at night.

Table A.8: Racial Disparities by Police in Force of At Least Specified Severity, Conditional on Force Used, Incidents where Race Likely Unrelated to Decision to Engage with Subject

	Takedowns		Hands/Fists		Leg Strikes		Pepper Spray		Batons		Fired Weapons	
Subject black/Hispanic	0.025	0.025	0.028	0.030	0.037	0.048	0.033	0.043	0.012	0.014	0.000	−0.000
	(0.009)	(0.013)	(0.009)	(0.013)	(0.007)	(0.012)	(0.007)	(0.011)	(0.003)	(0.006)	(0.001)	(0.002)
Fixed effects	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*
Clustering	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*
Outcome mean	0.541	0.541	0.481	0.481	0.217	0.217	0.166	0.166	0.046	0.046	0.004	0.004
R^2	0.185	0.603	0.184	0.607	0.126	0.547	0.129	0.561	0.087	0.535	0.216	0.654
Num. obs.	19924	19900	19924	19900	19924	19900	19924	19900	19924	19900	19924	19900

Notes: Table reports OLS estimates from Equation 1, which regresses a binary measure of whether police used force of at least the specified severity on indicators for the subject's race, an indicator for the subject being female, a quadratic of the subject's age, time of day fixed effects, indicators for the subject's actions, an indicator for whether an officer was harmed, an indicator for whether the subject was an emotionally disturbed person, indicators for the officer's rank, year fixed effects, and department or officer fixed effects. These regressions are run on a subset of the data where a subject's race was less likely to have influenced the officer's decision to engage with the subject: crimes in progress, disputes, and traffic stops at night.

Table A.9: Racial Disparities by Police in Force of At Least Specified Severity, Conditional on Force Used, Incidents where Subject at Least Physically Threatened/Attacked Officer or Another

	Takedowns		Hands/Fists		Leg Strikes		Pepper Spray		Batons		Fired Weapons	
Subject black/Hispanic	0.022	0.026	0.023	0.031	0.042	0.058	0.046	0.059	0.017	0.030	0.001	0.002
	(0.010)	(0.018)	(0.010)	(0.019)	(0.010)	(0.018)	(0.010)	(0.017)	(0.005)	(0.010)	(0.002)	(0.003)
Fixed effects	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*
Clustering	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*	*Dept.*	*Off.*
Outcome mean	0.642	0.642	0.603	0.603	0.282	0.281	0.218	0.218	0.063	0.063	0.009	0.009
R^2	0.171	0.663	0.166	0.665	0.116	0.616	0.121	0.628	0.106	0.595	0.229	0.715
Num. obs.	14639	14615	14639	14615	14639	14615	14639	14615	14639	14615	14639	14615

Notes: Table reports OLS estimates from Equation 1, which regresses a binary measure of whether police used force of at least the specified severity on indicators for the subject's race, an indicator for the subject being female, a quadratic of the subject's age, time of day fixed effects, indicators for the subject's actions, an indicator for whether an officer was harmed, an indicator for whether the subject was an emotionally disturbed person, indicators for the officer's rank, year fixed effects, and department or officer fixed effects. These regressions are run on a subset of the data where the subject at least physically threatened or attacked an officer or another person.

Table A.10: Summary Statistics for OLS Estimates of Department x Black/Hispanic Subject Interactions

	Takedown	Hands/Fists	Leg Strikes	Pepper Spray	Batons	Fired Weapons
SD	0.261	0.265	0.202	0.186	0.083	0.027
Min	-0.920	-0.998	-0.795	-0.830	-0.197	-0.198
P01	-0.477	-0.542	-0.480	-0.403	-0.141	-0.071
P05	-0.325	-0.347	-0.293	-0.281	-0.073	-0.020
P25	-0.048	-0.098	-0.128	-0.108	-0.002	-0.001
Median	0.058	0.007	-0.041	-0.041	0.022	0.001
P75	0.182	0.143	0.034	0.036	0.042	0.004
P95	0.586	0.528	0.292	0.265	0.144	0.018
P99	0.852	0.845	0.785	0.780	0.267	0.066
Max	1.144	1.150	0.991	0.993	1.050	0.278
Mean	0.084	0.036	-0.030	-0.022	0.028	0.001
$\% \leq 0$	0.368	0.483	0.627	0.654	0.266	0.413

Notes: Table reports OLS estimates of departmental racial disparities from Equation 3, which regresses a binary measure of whether police used force of at least the specified severity on indicators for the subject's race interacted with a department indicator, an indicator for the subject being female, a quadratic of the subject's age, time of day fixed effects, indicators for the subject's actions, an indicator for whether an officer was harmed, an indicator for whether the subject was an emotionally disturbed person, indicators for the officer's rank, year fixed effects, and department fixed effects.

Table A.11: Predicting 100 x (Department x Non-White/Asian/Pacific Islander Interaction Coefficients)

	Takedowns	Hands/Fists	Leg Strikes	Pepper Spray	Batons	Fired Weapons
Log median household income	0.402	1.493	−5.958	−7.005	0.022	0.160
	(4.433)	(4.471)	(3.506)	(3.115)	(1.103)	(0.306)
Gini coefficient	11.128	20.735	27.455	14.313	4.831	−1.445
	(35.413)	(36.508)	(31.181)	(25.875)	(11.866)	(3.020)
Log population	−2.390	−0.258	0.057	0.357	−2.143	0.141
	(4.286)	(4.491)	(3.924)	(3.802)	(2.999)	(0.271)
Log population per square mile	2.004	2.426	2.677	2.222	−0.357	0.167
	(1.536)	(1.525)	(1.237)	(1.130)	(0.462)	(0.099)
Log number of police	−1.504	−2.486	0.004	0.606	2.729	−0.324
	(4.854)	(5.005)	(4.191)	(3.994)	(3.023)	(0.325)
% officers not white or Asian/PI	0.244	0.131	−0.150	−0.208	−0.028	0.003
	(0.162)	(0.158)	(0.116)	(0.107)	(0.059)	(0.026)
Squared % officers not white or Asian/PI	−0.003	−0.001	0.002	0.002	0.000	−0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
% population 18-65 not white or Asian/PI	−0.196	−0.341	−0.180	−0.086	−0.026	−0.044
	(0.226)	(0.226)	(0.177)	(0.163)	(0.062)	(0.022)
Squared % population 18-65 not white or Asian/PI	0.003	0.004	0.001	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)
Log violent crimes per 1000	−2.692	−0.655	−0.365	0.045	0.315	−0.149
	(1.592)	(1.584)	(1.186)	(1.061)	(0.430)	(0.133)
2012 presidential election Romney vote %	0.259	0.206	0.141	0.131	−0.026	−0.027
	(0.172)	(0.170)	(0.141)	(0.130)	(0.053)	(0.018)
Prob > F	0.24	0.44	0.41	0.24	0.75	0.64
R^2	0.041	0.032	0.030	0.034	0.021	0.021
Num. obs.	402	402	402	402	402	402

Notes: Table reports coefficients from a regression of the department-specific racial disparities $\beta_{p,OLS}$ for black/Hispanic subjects on municipal/departmental-level covariates as estimated by Equation 3. Each column corresponds to a regression with the outcome being whether, conditional on force being used, force of at least the specified severity was used.

____________________ POLICE DEPARTMENT

USE OF FORCE REPORT

A. Incident Information

Date	Time	Day of Week	Location	**INCIDENT NUMBER**

Type of Incident
☐ Crime in progress ☐ Domestic ☐ Other dispute ☐ Suspicious person ☐ Traffic stop
☐ Other (specify)

B. Officer Information

Name (Last, First, Middle)		Badge #	Sex	Race	Age	Injured Y / N	Killed Y / N
Rank	Duty assignment	Years of service		On-Duty Y / N		Uniform Y / N	

C1. Subject 1 (List only the person who was the subject of the use of force by the officer listed in Section B.)

Name (Last, First, Middle)	Sex	Race	Age	Weapon Y / N	Injured Y / N	Killed Y / N
☐ Under the influence ☐ Other unusual condition (specify)	Arrested Y / N		Charges			

Subject's actions (check all that apply)
☐ Resisted police officer control
☐ Physical threat/attack on officer or another
☐ Threatened/attacked officer or another with blunt object
☐ Threatened/attacked officer or another with knife/cutting object
☐ Threatened/attacked officer or another with motor vehicle
☐ Threatened officer or another with firearm
☐ Fired at officer or another
☐ Other (specify)

Officer's use of force toward this subject (check all that apply)
☐ Compliance hold
☐ Hands/fists
☐ Kicks/feet
☐ Chemical/natural agent
☐ Strike/use baton or other object
☐ Canine
☐ Other (specify)

Firearms Discharge
☐ Intentional
☐ Accidental

Number of Shots Fired ____
Number of Hits ____
[Use 'UNK' if unknown]

C2. Subject 2 (List only the person who was the subject of the use of force by the officer listed in Section B.)

Name (Last, First, Middle)	Sex	Race	Age	Weapon Y / N	Injured Y / N	Killed Y / N
☐ Under the influence ☐ Other unusual condition (specify)	Arrested Y / N		Charges			

Subject's actions (check all that apply)
☐ Resisted police officer control
☐ Physical threat/attack on officer or another
☐ Threatened/attacked officer or another with blunt object
☐ Threatened/attacked officer or another with knife/cutting object
☐ Threatened/attacked officer or another with motor vehicle
☐ Threatened officer or another with firearm
☐ Fired at officer or another
☐ Other (specify)

Officer's use of force toward this subject (check all that apply)
☐ Compliance hold
☐ Hands/fists
☐ Kicks/feet
☐ Chemical/natural agent
☐ Strike/use baton or other object
☐ Canine
☐ Other (specify)

Firearms Discharge
☐ Intentional
☐ Accidental

Number of Shots Fired ____
Number of Hits ____
[Use 'UNK' if unknown]

➤ If this officer used force against more than two subjects in this incident, attach additional USE OF FORCE REPORTS.

Signature:	Date:
Print Supervisor Name:	Supervisor Signature:

7/2001

Figure A.1: New Jersey Model Use of Force Report

Notes: Figure obtained from the website of the New Jersey Attorney General.

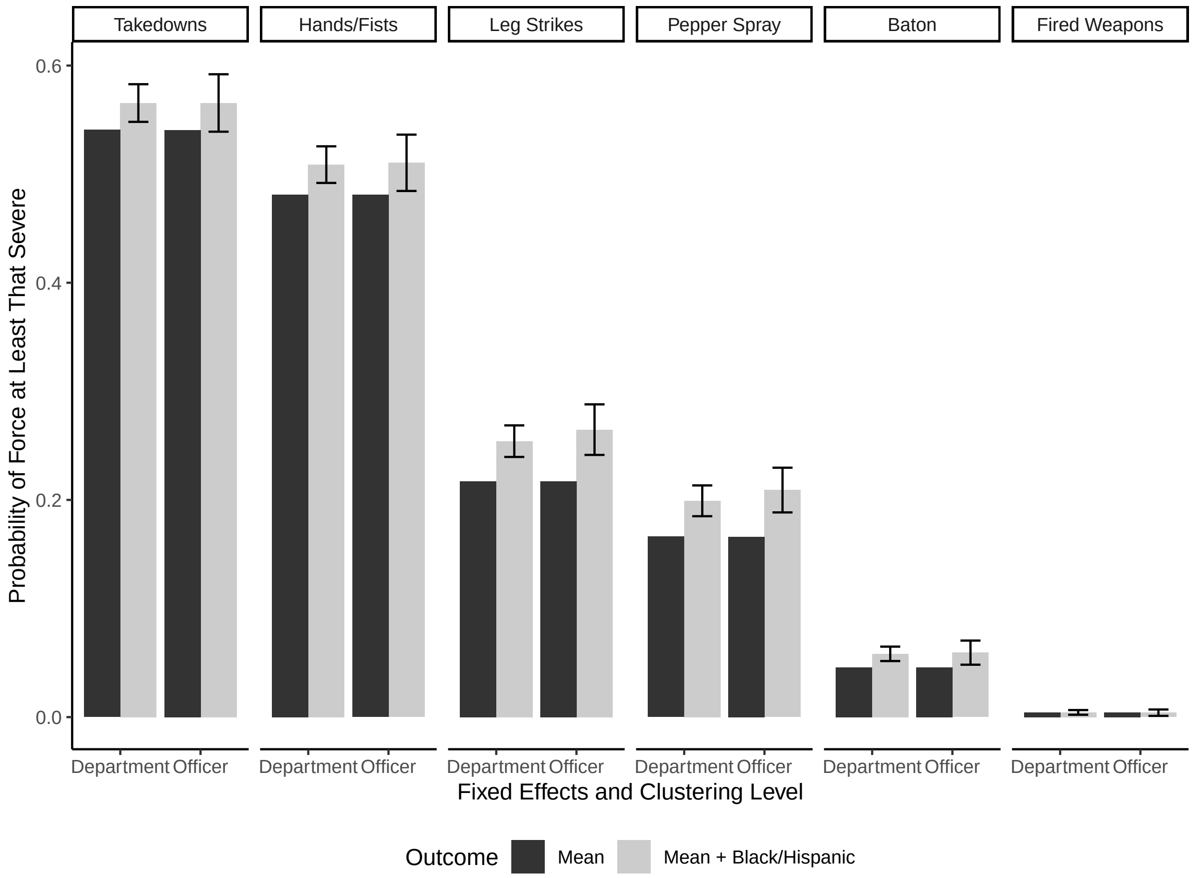

Figure A.2: Overall Racial Disparities of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity (Subset Where Race is Unlikely to Affect Decision to Engage Subject)

Notes: Figure presents results from a series of OLS models estimated on the subset of the data where a subject's race was less likely to have influenced the officer's decision to engage with the subject: crimes in progress, disputes, and traffic stops at night. Regressions are fit via Equation 1. Each heading represents a different outcome: whether, conditional on any force being used, force of at least the specified severity was used. Bars labeled "Department" include department fixed effects, and bars labeled "Officer" instead include officer fixed effects. Confidence intervals are based on the black/Hispanic coefficient.

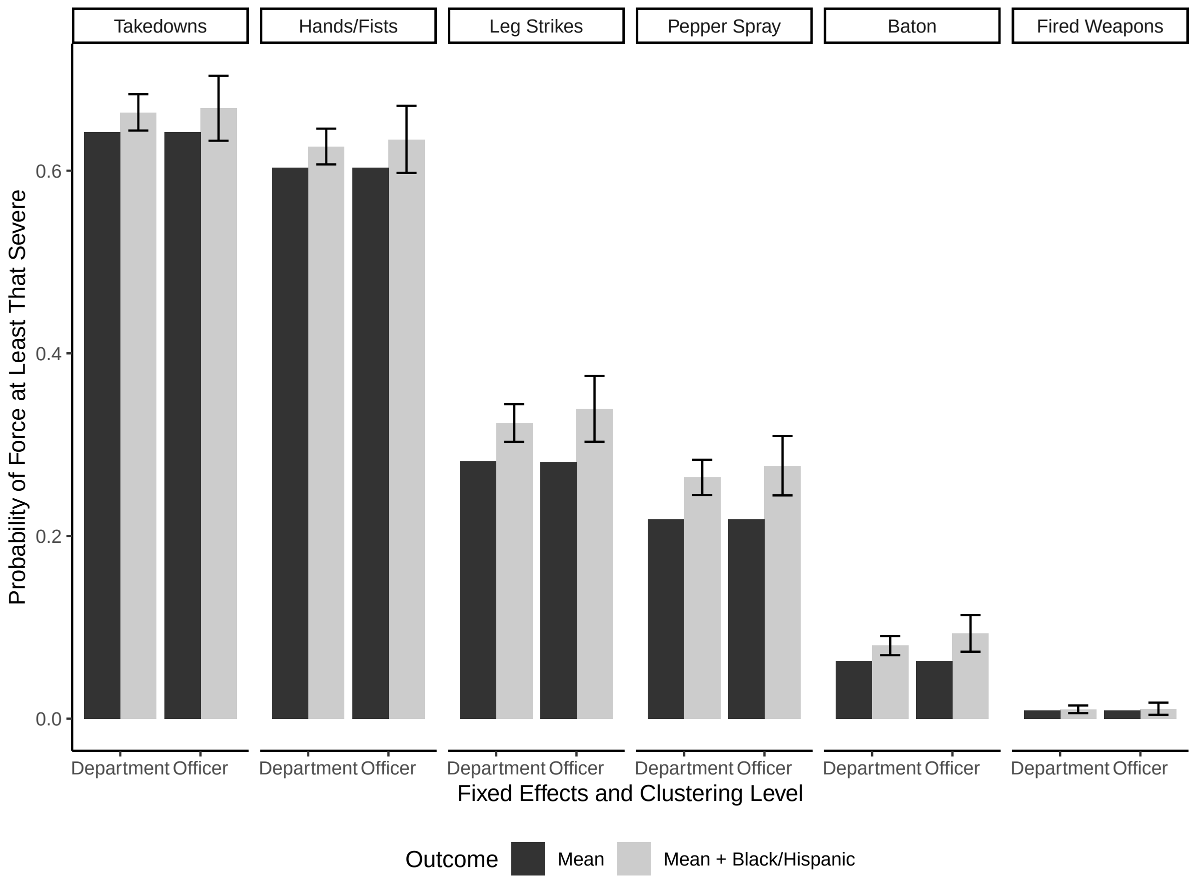

Figure A.3: Overall Racial Disparities of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity (Subset Where Subject at Least Physically Threatened/Attacked Officer or Another)

Notes: Figure presents results from a series of OLS models estimated on the subset of the data where the subject at least physically threatened or attacked an officer or another. Regressions are fit via Equation 1. Each heading represents a different outcome: whether, conditional on any force being used, force of at least the specified severity was used. Bars labeled "Department" include department fixed effects, and bars labeled "Officer" instead include officer fixed effects. Confidence intervals are based on the black/Hispanic coefficient.

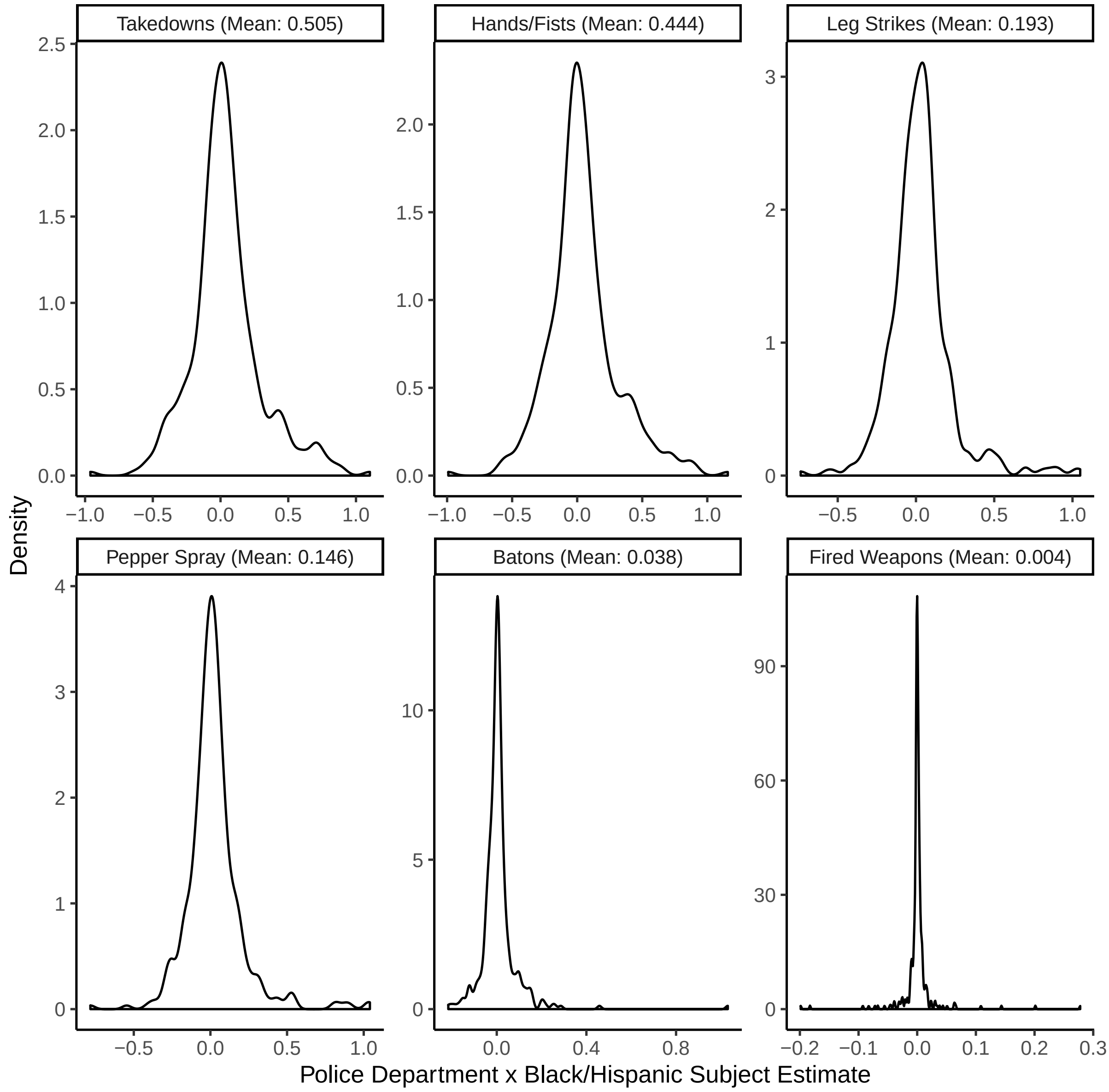

Figure A.4: Distribution of Unshrunk Estimates of Department-Black/Hispanic Interactions

Notes: Figure presents kernel density estimates of department-specific racial disparities β between white/Asian/Pacific Islander subjects and black/Hispanic subjects as estimated from the regression in Equation 3 with Gaussian kernels and the Silverman (1986) rule-of-thumb bandwidth. Each subgraph shows results from regressions with the specified outcome: whether, conditional on any force being used, force of at least the specified severity was used.

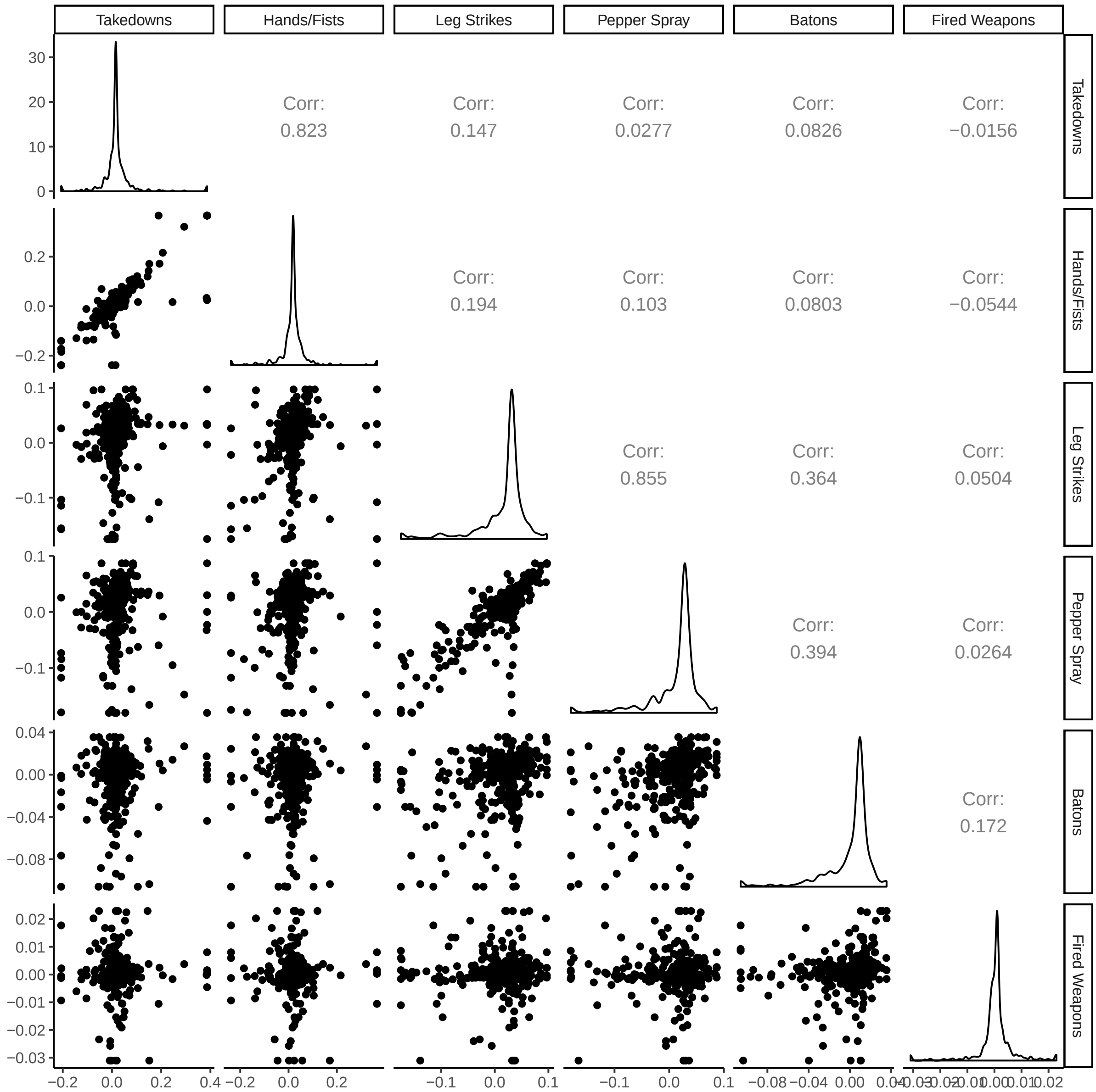

Figure A.5: Intra-Department Correlations of Winsorized Empirical Bayes Estimates of Department-Black/Hispanic Interactions Across Force Types

Notes: Figure presents the correlations across different force types of the winsorized department-specific racial disparities β between white/Asian/Pacific Islander subjects and black/Hispanic subjects as estimated from the empirical Bayes estimator in Equation 5. Winsorization is done at the 1st and 99th percentiles. Every level of force includes all types of force at least that severe. The bottom left triangle depicts scatterplots of the estimates for each department for the force types in the corresponding column and row. The diagonal shows a histogram of the distribution of department-specific estimates. The upper triangle presents the correlation coefficient for the estimates of the corresponding force types.