# Variation in Racial Disparities in Police Use of Force*

Carl Lieberman†

October 20, 2020

**Abstract**

I examine racial disparities in police use of force using new data from New Jersey. Along the intensive margin of force, I find disparities that disfavor Black and Hispanic subjects and are larger at higher force levels, even after adjusting for incident-level factors and using new techniques to limit selection bias. I then extend empirical Bayes methods to estimate department-specific racial differences and document significant variation across and within 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.

*Keywords*: policing, police use of force, race

*JEL*: J15, K42.

*I am grateful to Jesse Bruhn, Leah Boustan, Janet Currie, Milena Djourelova, Thomas Fujiwara, Bo Honoré, Ilyana Kuziemko, David Lee, Alex Mas, Jonathan Mummolo, Amy Wickett, seminar participants at Princeton University and the Young Economists Symposium, 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.

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 the extent to which this problem varies. Optimal interventions may not be uniform for different departments or force levels, and if some departments have smaller or no 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 problem.

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

I answer these questions using new administrative data from New Jersey. The data are unique in their completeness, containing every use of force report by every officer in every municipal police department and the state police 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 overall 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 incident type and subject actions, do people of different races have different levels of force used against them? This parameter is empirically and politically relevant, but has not received much attention by researchers. Cases of police officers using force viewed as inordinate against people of color continue to occur, and the unexplained racial variation in police use of force after adjusting for incident factors corresponds with those perceived excesses. I find significant disparities in police use of force across races that are larger when considering more severe levels of 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. Additional analyses point to the importance of the department over the identity of the officer in these disparities.

To minimize the bias from 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, in particular the officer's decisions of whom to investigate or engage with and whether they should use force at all. These papers are built around 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 in which 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 should limit the role of race in the officer's decisions whether to engage with a subject or use force at all while preserving interactions between race and the intensity of force used. 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 explore how racial disparities vary across and within departments. To better conduct this analysis, I adapt empirical Bayes techniques to estimate departmental 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. A minority of more than 20% of departments have zero or negative racial differences for a 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 estimates. There is substantial variation in disparities within departments across force levels, and within-department correlations are near zero.

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, and these models cannot explain most of the variation in the data. When looking at the smaller subset of departments present in the 2016 Law Enforcement Management and Administrative Statistics (LEMAS) survey, the cultural and policy measures available there are more strongly correlated, but overall explanatory power is still low. Although harder-to-measure factors such as culture may play an important role, the variation across and within departments underlines the difficulty in addressing racial disparities in police use of force: there is no single factor that universally predicts the gaps.

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.[1] Many other papers explore related aspects of race and the criminal justice system.[2] This paper differs from prior work by focusing on *variation* in racial differences, specifically by force severity and departments, rather than treating race as having a single, homogeneous effect.

There is a small, highly interdisciplinary literature on variation in racial disparities that asks what can predict or explain the variation, offering different answers. 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 setting of an incident matters greatly and mediates 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 the 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 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

[1] Also see comments by Durlauf and Heckman (2020) and the response by Fryer (2020).

[2] 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), whether subjects are formally booked (Raphael and Rozo 2019), court decisions (Rehavi and Starr 2014; Arnold, Dobbie, and Yang 2018; Bielen, Marneffe, and Mocan 2019), and student discipline (Barrett et al. 2019).

appear to have racial differences against Blacks and Hispanics, but many more do, some very severely, and the identities of these departments change across force levels. Large amounts of unexplained variation in these differences, even with a rich set of covariates on the right-hand side, coupled with other estimates emphasizing the importance of the department, 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 planned central oversight never materialized. Third, although I use comprehensive data from New Jersey over a five-year period, my results are a result of who is (and is not) in that sample, that is, 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 on both the existence and variation of racial differences in police use of force.

# 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).[3]

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. The lowest level of force is compliance holds, such as arm bars and wrist locks. Next are unenhanced types of force: takedowns (forcing a subject to the ground), hands/fists (punches and slaps), and kicks/other leg strikes. Then there are enhanced force outcomes: pepper spray and other chemical agents, baton strikes, canines, stun guns (Tasers), and finally, discharging firearms. Constructive authority, the threat of force without its actual use, such as brandishing a firearm, is permitted, but warning shots are prohibited. 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, and canines are also uncommon, as not all departments have canine units. Police may very rarely employ nonlethal firearm rounds, such as beanbag rounds, in settings such as riots to incapacitate subjects, and I drop these incidents, as the situations in which they are used are not representative of typical police-civilian interactions.

## 1.2 Data

This project uses all known force reports from every municipal police department in New Jersey and the New Jersey State Police from 2012 through 2016. ProPublica, a nonprofit newsroom, and NJ Advance Media (NJAM), a news provider, obtained the reports through more than 500 public records requests and several legal threats. 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

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

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.[4] 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. Local variables come from the 2010 Census, 2012-2016 American Community Survey (ACS) five-year estimates, FBI's Uniform Crime Reporting (UCR) program, the New Jersey Division of Elections, and Project Implicit. Additional data on a smaller sample of departments comes from the 2016 LEMAS survey conducted by the Department of Justice (Bureau of Justice Statistics 2016).

## 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,

[4]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 a function of 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 (for example, after Officer A pepper sprays a subject, Officer B is able to place him in a compliance hold).

the lowest type of force available. In 25% of incidents, the most severe action officers take is striking subjects with their hands or fists, followed by 11% with pepper spray as their highest force level. All other types of force are relatively uncommon as maximums. 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 non-missing 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. 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.[5] 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 over-represented 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 is 31 years old.

Table A.1 presents summary statistics for the municipalities with their own police departments that are present in the cleaned data (some small municipalities lack dedicated police departments; the New Jersey State Police cover the state's highways and may also serve these towns). 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 reports are missing data in relevant variables.

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 high economic inequality as measured by the Gini coefficient relative 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 proxied 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. County-level Black-White implicit association test (IAT) *D*-scores from Project Implicit, where more positive values indicate stronger negative implicit biases against Blacks, show large variation: the standard deviation of 0.05 is approximately

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

equal to the difference in state-level means between Oregon and North Dakota.[6]

Table A.2 contains summary statistics for the police departments in the data. The median department has 23 full-time employees, 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):

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

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. I use four levels of force severity: compliance holds, unenhanced forced, enhanced force, and firing a weapon (which is a subset of enhanced force types).[7] For example, if a subject is struck with a baton (a type of enhanced force), the outcome would be 1 for at least compliance holds, unenhanced, and enhanced, but 0 for at fired weapons. I use this measure of force because it is the most intuitive way to interpret outcomes. 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 clear interpretations (Fryer 2019). The

[6] `https://github.com/lizredford/map-iat`

[7] Results in Appendix B use the full set of outcomes ordered by the NJ Attorney General's form and reporting by McCarthy and Nelson (2019): compliance holds, takedowns, hands/fists, leg strikes, pepper spray, batons, and firearms. I group canines and stun guns are with batons, the next most severe level of force, due to their rarity in the data.

coefficient of interest is $\beta$, 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 $\psi_p$ capture time-invariant aspects of each department's propensity to use higher levels of force, such as the severity of crimes on a department's beats. Time fixed effects $\nu_t$ adjust for year-month specific changes in overall force usage, capturing trends such as seasonality in crime. 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 variables, 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 at the officer level. These estimates allow me to investigate how disparities vary when adjusting for the officer's identity, which may be useful if there is significant heterogeneity in officer-level disparities within departments. 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. The officer-based models could hypothetically 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 one randomly chosen force report. However, this is an edge case, and results with a different draw are similar.

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

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

stratified by department. To prevent separation, I do not include officer fixed effects, use year fixed effects instead of year-month, use event type indicators for each individual event type rather than each combination of event types, and change the officer rank indicators to a dummy for the officer being a superior or not. By exponentiating $\beta$, I obtain odds 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 like 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 departments 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 and within departments. The simplest approach would be to make a slight modification to Equation 1 and estimate equations of the form

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

with the interest being in the distribution of $\beta_p$. Although these estimates may be unbiased and consistent, OLS tends to generate the most extreme estimates for departments with the fewest observations and does not distinguish between estimates based on departments with many observations and those from much smaller samples.

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, for example, 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 $\sigma_p^2 \equiv \text{Var}(u_{iopt}^{BH} - \varepsilon_{iopt}^{BH})$, the variance of the difference between residuals between Equations 3 and 4 using only Black and Hispanic observations rather than the full sample.[8] I then take the estimated racial disparities $\beta_p$ 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

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

are the departmental empirical Bayes weights, $\varepsilon_p^{BH}$ 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 $p$.

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

### 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.

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

$X_p$ 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, Mitt Romney's vote share in the 2012 presidential election, and county-level $D$-scores for the Black-White IAT from Project Implicit. I repeat this exercise on the non-random subset of departments in the 2016 LEMAS survey using additional measures of department policies and culture plausibly correlated with racial disparities: asset forfeiture, the use of a written aptitude test in selecting recruits, having a written community policing plan, formally surveying local residents to improve policing, having written policies on stop and frisk, foot pursuits, and unbiased policing, and whether the department's chief executive is female or non-Hispanic White. 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 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 plausibly 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, that is, in who has force used against them at all, poses one problem. 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.[9] 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 a particular 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, dropping incidents in which subjects only "resist." The former

[9]This concept is related to the more general idea of differences in the marginal subject across races, discussed, for example, by Becker (1957).

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 discrepancies in some reports, often around officer names, and the only missing reports uncovered are 70 from Jersey City (prior to cleaning, there are more than 1100 force reports from Jersey City in the data). 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 binary 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. These gaps increase with force severity, and their magnitudes are similar for Blacks and Hispanics within each level of force.

Relative to outcome means, disparities for Blacks and Hispanics compared to Whites slightly under 20% for at least unenhanced, and 36% for Blacks and 22% for Hispanics for at least enhanced. 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 over 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 are still present. For the models using department fixed effects and clustering, the disparities estimated for Black or Hispanic individuals for at least unenhanced, enhanced, and fired weapons are approximately 1.5, 2.8, and 0.1 percentage points, respectively, with all except the firearms level statistically significant at the 5% level. While the positive disparities for firing weapons have economically significant point estimates considering the rarity of the events, that rarity also greatly limits statistical power. Second, relative to the baseline level of each force type, racial disparities increase with the severity of the force type. In percentage terms, the department fixed effects-based disparities for Black or Hispanic subjects are 3.0%, 19.2%, and 25.0%, and this monotonicity is also present when using the full set of force levels in Appendix B. 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, a hypothesis I will explore more later in this paper.

Figures 3 and 4 and Table A.5 present the estimated racial differences from Equation 1 with indicators for each race. Breaking apart the Black/Hispanic dummy, 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 the previous models. In contrast, I find much smaller disparities for Hispanics. For Asians/Pacific Islanders, point estimates are small and mostly 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, suggesting that the results are not dependent on the usage of linear probability models. 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 unenhanced, enhanced, and fired weapons being 1.05, 1.25, and 1.44, respectively.

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 6.9% and 23.7% for at least unenhanced and enhanced force. These figures are similar to those using the full sample, though slightly larger. 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 fairly similar to the ones based on department fixed effects, but their standard errors are about twice as large. These estimates may also be more fragile from having to estimate officer fixed effects on such a reduced sample. Both sets of estimates largely exhibit the same pattern from the full sample where the relative disparities increase with the severity of the force (including the results with full set of outcomes in Appendix B), excepting firing weapons. 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.

There may be reasons to expect disparities to shrink over the course of the data, such as increased scrutiny towards police (the shooting of Michael Brown in Ferguson, Missouri occurred in 2014) incentivizing misreporting or departments improving through learning and reducing excessive force against Black and Hispanic subjects. Figure 7 presents point estimates from the full model for the subject being Black/Hispanic interacted with the year using 2012 as a reference to test this idea. There is no compelling evidence of changes in racial disparities over time, casting doubt on these hypotheses.

Although it is exceedingly difficult to identify causal mechanisms with observational police data, we may wonder whether these disparities are the result of taste-based or statistical discrimination, as the policy implications for treating each may be very different. Note that racially discriminatory policing is illegal in New Jersey and should not be considered justified, regardless of motivation. Statistical discrimination might manifest here due to a belief that, all else equal, Black or Hispanic subjects pose greater threats than subjects of other races, for example from aggressiveness or physical strength, prompting higher levels of force (these beliefs need not be accurate; see Bohren et al. 2020). Under the assumption that officers should not have this belief for female subjects, who tend to have lower levels of force used against them, interacting Black/Hispanic status with the female subject indicator can help to differentiate between channels of discrimination. A positive coefficient for the subject being Black/Hispanic is consistent with both statistical and taste-based discrimination. A negative coefficient on the interaction between Black/Hispanic and female would then suggest statistical discrimination, while a zero coefficient would be more consistent with taste-based discrimination. Table 2 shows that coefficients from this augmented full model on the subject being Black/Hispanic, the subject being female, and their interaction are positive, negative, and approximately zero, respectively, for both the at least unenhanced and enhanced models, supporting the taste-based discrimination hypothesis (I do not include the fired weapons outcome, as only five women are shot in my sample).

Given the similar results from models based on department and officer fixed effects, I now explore the relative importance of the department and officer more closely. On a set of 1041 incidents by 174 manually identified officers who switch departments, I fit Equation 1 with officer fixed effects and an additional indicator for the department in which an officer served having an above-median racial disparity for the relevant levels of force as estimated in Section 3.2.[10] Table 3 contains the results. For at least unenhanced force, the interaction between a subject being Black or Hispanic and the department having an above-median disparity is positive, large, and significant, supporting the idea that the department in which an officer serves is a larger determinant of racial disparities than the identity of the officer. For at least enhanced force, the interaction is 0, possibly because more severe force is less discretionary, leaving less room for the new department to affect an officer's force intensity.

## 3.2 Variation in Racial Disparities

In this section, I focus on how racial disparities vary with departments. Overall racial disparities treat racial differences as monolithic, while they may vary both across and within 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 $\beta_p$ come from the new empirical Bayes estimator in Equation 5. I leave results from the unshrunk OLS estimates to Appendix C for conciseness.

Figure 8 presents kernel density estimates of the empirical Bayes posterior departmental disparities, with summary statistics in Table 4 (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

[10] I do not analyze firearms here, as no switching officers use that level of force in my data. Additionally, I include year fixed effects instead of month-year due to the greatly reduced sample size.

"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 enhanced 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 $\text{Var}(\varepsilon_p^{BH})$ from Equation 5 is very small 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 sizable: about 6 percentage points for at least unenhanced, 4.5 percentage points for at least enhanced, and 0.6 percentage points for fired weapons. Comparing the dispersion of the estimates to the outcome means in Figure 8 reveals the large magnitude of the more extreme departmental disparities. Encouragingly, many departments do not seem to have racial disparities, at least for certain force outcomes. About 22% of departments have zero or negative racial disparities for at least unenhanced and enhanced, while the number is 39% for fired weapons.

I now use the multiple force outcomes to examine racial disparities within departments. Do departments that have greater racial disparities at one level of force also tend to have greater disparities at others? For example, do departments with larger disparities for at least unenhanced force typically to have larger disparities on the at least enhanced measure? Figure 9 plots the correlations of winsorized department-level disparities across force levels to address Perhaps surprisingly, I find essentially no correlations across force levels. Knowing that a department has a large, small, or no disparity at one force level tells us almost nothing about its racial differences at another level.

Both across and within departments, we see variation in racial disparities. This variation highlights the difficulties in identifying problematic departments and designing interventions targeting racial policing. It may be difficult to treat departments with such heterogeneous racial differences, and the variation in disparities even within a department further confounds efforts.

## 3.3 Predicting Departmental Racial Disparities

Having established the heterogeneity present in department-specific racial disparities, I turn to the question of what can predict these disparities. For example, plotting a heatmap of the disparities in Figure A.4 rules out geographic factors such as proximity to New York City or Philadelphia or clusters of departments with similar race gaps. I proceed by running regressions of the estimated departmental disparities from the winsorized empirical Bayes estimates from Equation 5 on an array of possible correlates (results using unshrunk OLS estimates from Equation 3 are in Appendix C). 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.

For ease of reading and interpretation, I first make two modifications to the data. First, 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. Second, following Gelman (2008), I divide non-binary variables by two times their standard deviations, so that all coefficients (including binary ones) are on approximately the same scale; coefficients on non-binary variables may be interpreted as the change in outcomes associated with moving from one standard deviation below the mean to one standard deviation above it.

I report the results of these regressions graphically in Figure 10 and numerically in Table 5. Despite the number of explanatory variables and the popular belief that at least some of them can affect racial policing, the models do a poor job of predicting the racial disparities (all $R^2$ values are at most 0.039), and only one can reject the null hypothesis of an $F$-test of joint significance for all covariates at the 5% level. Most variables' coefficients change greatly across models, both in magnitude and even sign. This may not be a problem, as we have already seen the weak correlations of within-department, across-outcome disparities. For example, departments with more Black or Hispanic officers could have smaller disparities on the at least unenhanced measure, as suggested by the model and consistent with works such as Wilkins and Williams (2008), Nicholson-Crotty, Nicholson-Crotty, and Fernandez (2017) and Ba et al. (2020), but diversity may not be a strong enough channel to impact officers' intensive margin decisions at the higher levels of force, hence the null coefficients there. Overall, however, this exercise underscores the difficulty in identifying potential causes of (and thus, solutions to) racial differences in policing.

With these observables unable to predict the disparities, the variation may be coming from variables I do not observe. Natural candidates include items that are difficult to obtain or measure such as department policies and intangibles like culture. To attempt to get at these factors, I use the 2016 LEMAS survey to acquire more detailed information on the subset of municipal departments surveyed in that year (this is a non-random sample, as the LEMAS uses a stratified sampling design at the national level based on the number of sworn personnel and agency type, and response rates, while high, are not 100%). From the survey, I add to the regressions a number of variables that reflect departments' policies and/or culture, such as whether they have written policies on unbiased policing, whether they formally survey local residents to obtain feedback and improve policing, whether they report positive asset forfeiture, and whether the chief executive of the department is female or non-Hispanic White.

The results from these regressions are in Figure 11 and Table 6. Comparing coefficients on variables from LEMAS and not, the at least enhanced and fired weapon models in particular show that the LEMAS-sourced variables on policy and culture have the largest correlation magnitudes. Mechanically, $R^2$ increases from the addition of regressors (which doubles to 20) and the reduction in sample size (454 to 92), but ranges from 0.18 to 0.26. For the purposes of fit comparison, Table A.10 presents regression results with the subset of departments present in the 2016 LEMAS but using only the non-LEMAS predictors and has $R^2$ values ranging from 0.05 to 0.13. Overall, it is clear that much of the variation is still coming from other sources. These may be other cultural or policy factors or department-specific idiosyncrasies, but the variation across and within departments makes clear the lack of a singular predictor of racial disparities in police use of force.

# 4 Conclusion

In this paper, I combine new analytical strategies with incident-level data on all recorded uses of force by municipal and state 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. The department seems to play a larger role in determining these disparities than the individuals officers. I then extend empirical Bayes methods and document substantial heterogeneity in these disparities across and within departments, finding some departments without disparities against Black and Hispanic subjects, but also a long tail that especially disfavors them, and no within-department correlations across force levels. Finally, I show that many commonly proposed factors do a poor job of explaining these departmental disparities. While the strongest evidence is for cultural and policy variables, the large amounts of unexplained variation suggest this is incomplete, at least for available measures. Although the intensive margin measure of racial differences at the core of this paper is not the only such measure, it is central to the discourse around race and policing and heretofore underexplored, broadening our understanding of the problems at the heart of one of the most important social issues today.

Much work remains to be done on race and police use of force, with policy and research closely intertwined. 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, and the difficulties in predicting departmental disparities using observational data make targeting reforms difficult. Police departments and public officials must ensure that data availability and transparency continue to improve to aid progress. 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: canine | 39,322 | 0.01 |
| Max force: taser | 39,322 | 0.002 |
| 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 Female Subject on Police Use of Force of At Least Specified Severity, Conditional on Force

| | Unenhanced | Enhanced |
|---|---|---|
| Subject Black/Hispanic | $0.014^{**}$ | $0.028^{***}$ |
| | (0.007) | (0.005) |
| Subject female | $-0.173^{***}$ | $-0.064^{***}$ |
| | (0.009) | (0.005) |
| Subject Black/Hispanic $\times$ female | 0.008 | 0.003 |
| | (0.011) | (0.008) |
| Fixed effects | Dept. | Dept. |
| Clustering | Dept. | Dept. |
| Outcome mean | 0.505 | 0.146 |
| $R^2$ | 0.180 | 0.118 |
| Num. obs. | 39184 | 39184 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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 interacted with 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 3: Effect of Being in Department with Above-Median Empirical Bayes Racial Disparity, Officers Switching Departments Only

| | Unenhanced | Enhanced |
|---|---|---|
| Subject Black/Hispanic | $-0.069$ | $0.001$ |
| | $(0.056)$ | $(0.032)$ |
| Department above median | $-0.076$ | $0.066$ |
| | $(0.063)$ | $(0.042)$ |
| Subject Black/Hispanic $\times$ department above median | $0.235^{***}$ | $-0.005$ |
| | $(0.070)$ | $(0.052)$ |
| Fixed effects | Off. | Off. |
| Clustering | Off. | Off. |
| $R^2$ | 0.443 | 0.297 |
| Num. obs. | 1099 | 1099 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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 department in which the officer served having above-median racial disparities from the empirical Bayes analysis. This regression only includes incidents from officers identified as switching departments.

Table 4: Summary Statistics for Empirical Bayes Department x Black/Hispanic Subject Interactions

| | Unenhanced | Enhanced | Fired Weapons |
|---|---|---|---|
| SD | 0.086 | 0.062 | 0.009 |
| SD (Winsorized) | 0.068 | 0.045 | 0.006 |
| Min | -0.412 | -0.237 | -0.127 |
| P01 | -0.181 | -0.178 | -0.025 |
| P05 | -0.053 | -0.086 | -0.007 |
| P25 | 0.004 | 0.006 | -0.001 |
| Median | 0.015 | 0.028 | 0.001 |
| P75 | 0.028 | 0.033 | 0.002 |
| P95 | 0.094 | 0.056 | 0.009 |
| P99 | 0.430 | 0.088 | 0.022 |
| Max | 0.778 | 0.895 | 0.038 |
| Mean | 0.021 | 0.014 | 0.000 |
| % $\leq 0$ | 0.223 | 0.225 | 0.386 |

*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 5: Predicting 100 x (Department x Black/Hispanic Winsorized Empirical Bayes Estimates), RHS Variables Normalized by 2x Standard Deviation

| | Unenhanced | Enhanced | Fired Weapons |
|---|---|---|---|
| Log median household income | 0.563 | −0.353 | 0.091 |
| | (0.782) | (0.539) | (0.077) |
| Gini coefficient | −0.266 | 0.502 | −0.068 |
| | (0.746) | (0.494) | (0.054) |
| Log population | 1.338 | 0.722 | −0.010 |
| | (1.440) | (1.105) | (0.134) |
| Log population per square mile | −0.005 | 0.580 | 0.129* |
| | (0.844) | (0.536) | (0.067) |
| Log number of police | −1.841 | −0.398 | −0.166 |
| | (1.421) | (1.099) | (0.155) |
| % officers not White or Asian/PI | −1.134** | 0.223 | 0.037 |
| | (0.455) | (0.396) | (0.060) |
| % population 18-65 not White or Asian/PI | −0.521 | −0.615 | 0.188 |
| | (0.904) | (0.784) | (0.115) |
| Violent crime rate | 0.679 | 0.913 | −0.033 |
| | (0.629) | (0.594) | (0.095) |
| 2012 presidential election Romney vote % | −0.027 | −0.629 | 0.115 |
| | (1.173) | (0.857) | (0.122) |
| County mean Black-White IAT *D*-score | −0.962 | 0.503 | 0.053 |
| | (0.672) | (0.577) | (0.072) |
| Prob > F | 0.437 | 0.045 | 0.179 |
| $R^2$ | 0.019 | 0.035 | 0.039 |
| Num. obs. | 454 | 454 | 454 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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. Each variable on the right-hand side of the regression has been divided by twice its standard deviation.

Table 6: Predicting 100 x (Department x Black/Hispanic Winsorized Empirical Bayes Estimates), RHS Numeric Variables Normalized by 2x Standard Deviation, 2016 LEMAS Departments Only

| | Unenhanced | Enhanced | Fired Weapons |
|---|---|---|---|
| Log median household income | 0.603 | −0.730 | −0.011 |
| | (1.150) | (1.105) | (0.130) |
| Gini coefficient | 1.442 | −0.460 | −0.103 |
| | (1.060) | (1.139) | (0.186) |
| Log population | 3.012 | 0.521 | −0.041 |
| | (2.314) | (1.946) | (0.456) |
| Log population per square mile | 1.316 | 0.048 | 0.027 |
| | (1.265) | (1.210) | (0.169) |
| Log number of police | −3.868 | −0.537 | −0.115 |
| | (2.471) | (2.052) | (0.483) |
| % officers not White or Asian/PI | −1.207 | 0.158 | 0.022 |
| | (0.817) | (0.881) | (0.156) |
| % population 18-65 not White or Asian/PI | 2.254 | 0.661 | 0.133 |
| | (1.869) | (1.584) | (0.226) |
| Violent crime rate | 0.680 | 0.127 | 0.080 |
| | (0.832) | (0.687) | (0.099) |
| 2012 presidential election Romney vote % | 0.704 | −0.330 | 0.069 |
| | (1.580) | (1.714) | (0.234) |
| County mean Black-White IAT *D*-score | −1.461 | 1.420 | 0.001 |
| | (0.898) | (0.887) | (0.151) |
| Dept. has nonzero asset forfeiture | −1.332 | −0.865 | 0.051 |
| | (1.550) | (1.504) | (0.205) |
| Dept. uses written aptitude test in selecting recruits | 0.466 | 1.893** | 0.050 |
| | (1.118) | (0.820) | (0.133) |
| Dept. maintains a written community policing plan | 1.172 | 0.985 | −0.074 |
| | (0.838) | (0.946) | (0.131) |
| Dept. formally surveys local residents | −2.942 | −0.604 | −0.004 |
| | (2.033) | (1.271) | (0.336) |
| Dept. has written policy on stop and frisk | 0.470 | −0.041 | −0.230 |
| | (1.393) | (1.630) | (0.193) |
| Dept. has written policy on foot pursuits | 1.823 | 0.903 | −0.123 |
| | (1.195) | (1.190) | (0.142) |
| Dept. has written policy on unbiased policing | −1.546 | −3.393*** | 0.229 |
| | (1.788) | (1.279) | (0.242) |
| Dept. chief executive is female | 0.228 | −1.578 | −0.893* |
| | (2.690) | (1.465) | (0.478) |
| Dept. chief executive is non-Hispanic White | −1.081 | −2.922*** | 0.054 |
| | (2.062) | (1.061) | (0.279) |
| Prob > F | 0.227 | 0.023 | 0.182 |
| $R^2$ | 0.246 | 0.197 | 0.203 |
| Num. obs. | 92 | 92 | 92 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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. Each non-binary variable on the right-hand side of the regression has been divided by twice its standard deviation.

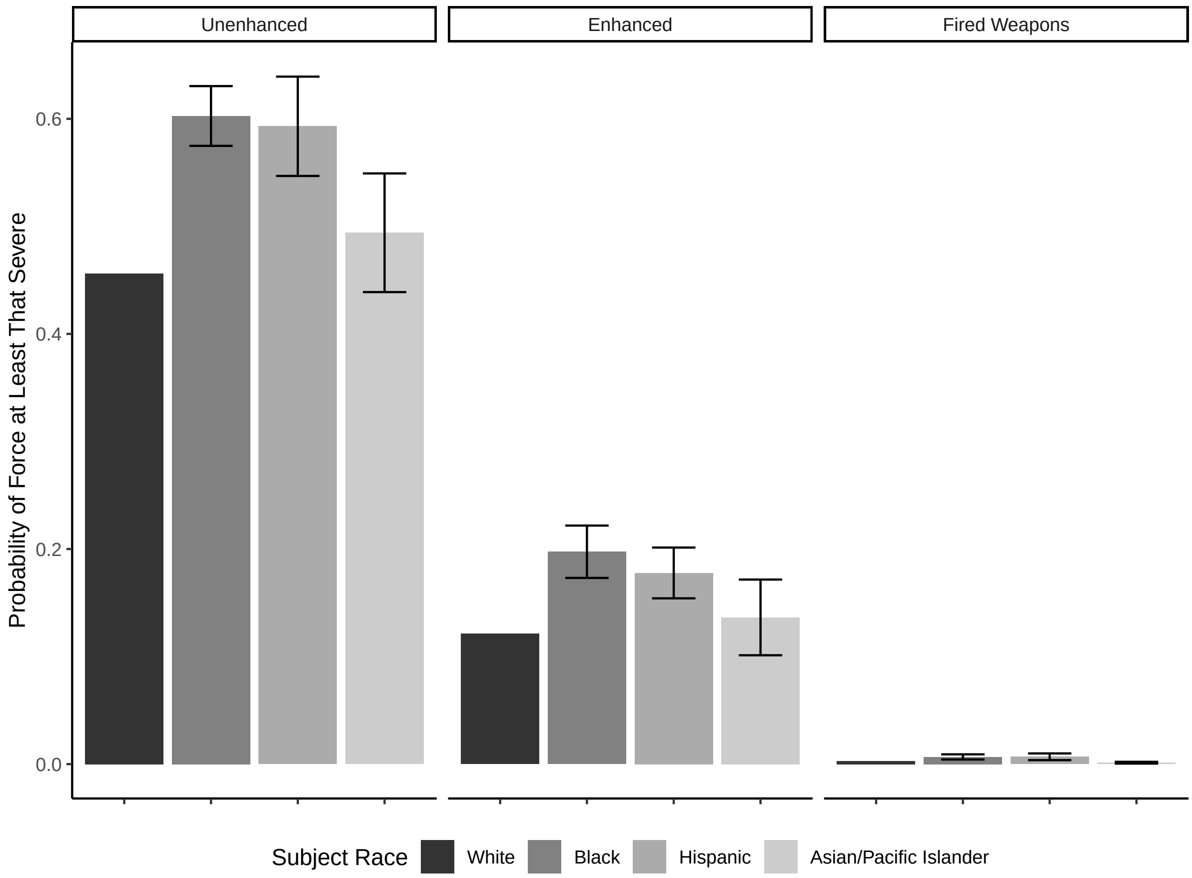


Figure 1: Overall Racial Disparities (No Controls)

*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.

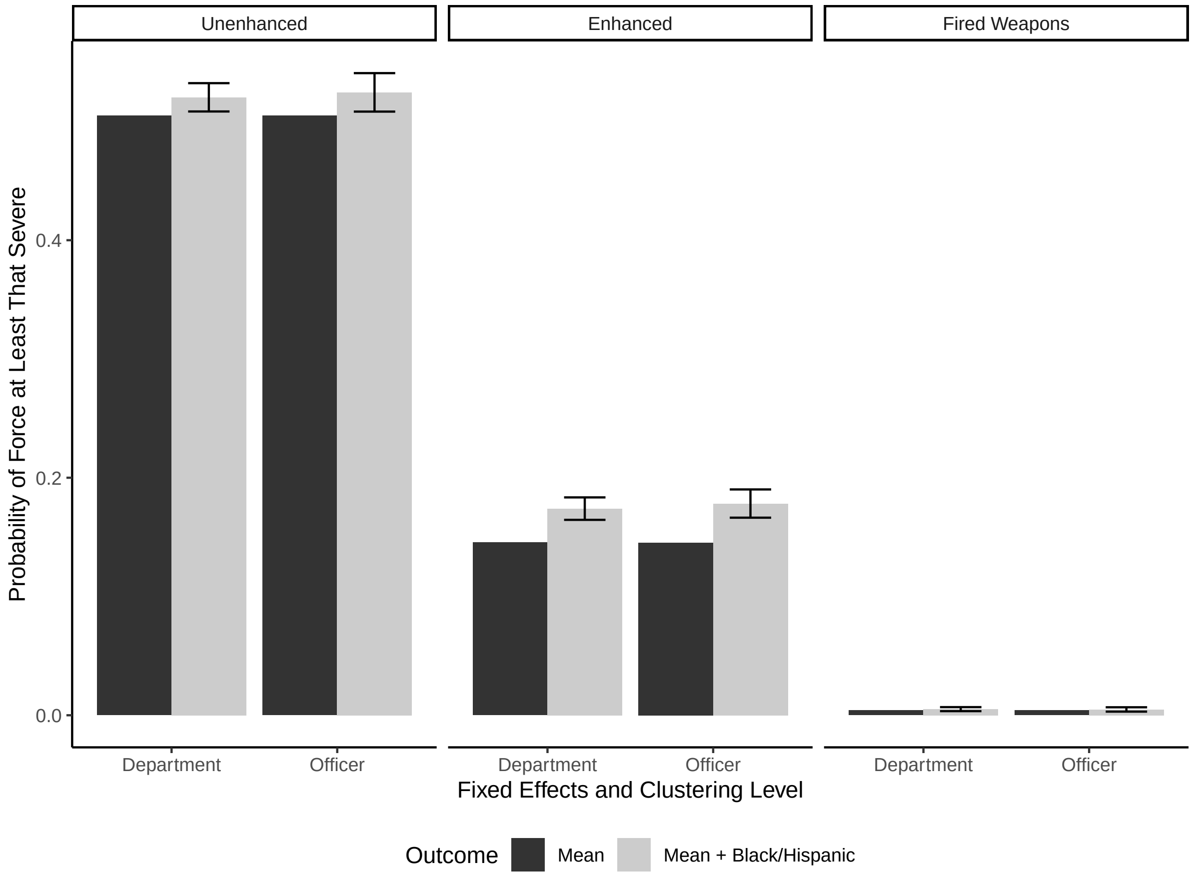


Figure 2: Overall Racial Disparities for Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity

*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.

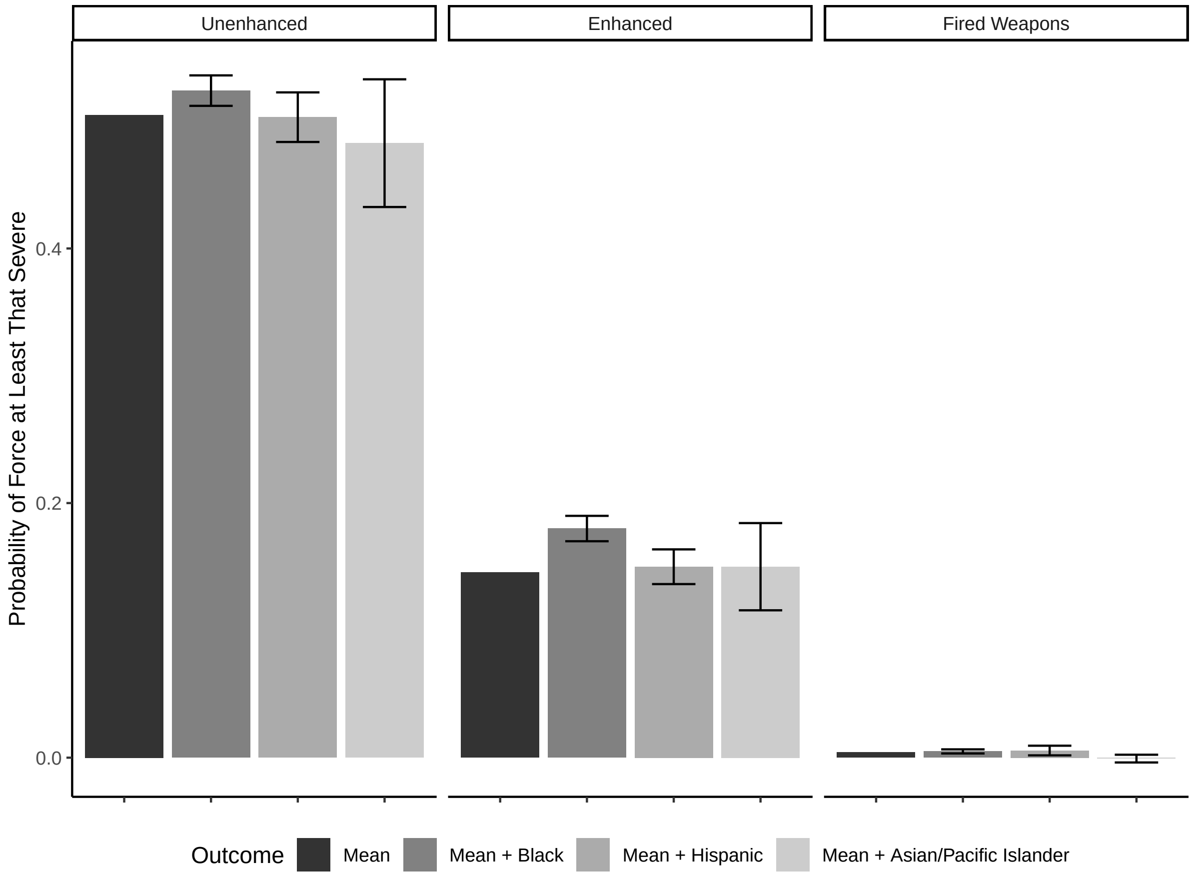


Figure 3: Overall Racial Disparities of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity, Full Race Dummies (Department Fixed Effects and Clustering)
*Notes:* Figure presents results from a series of OLS models fit via Equation 1. Each heading represents a different 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.

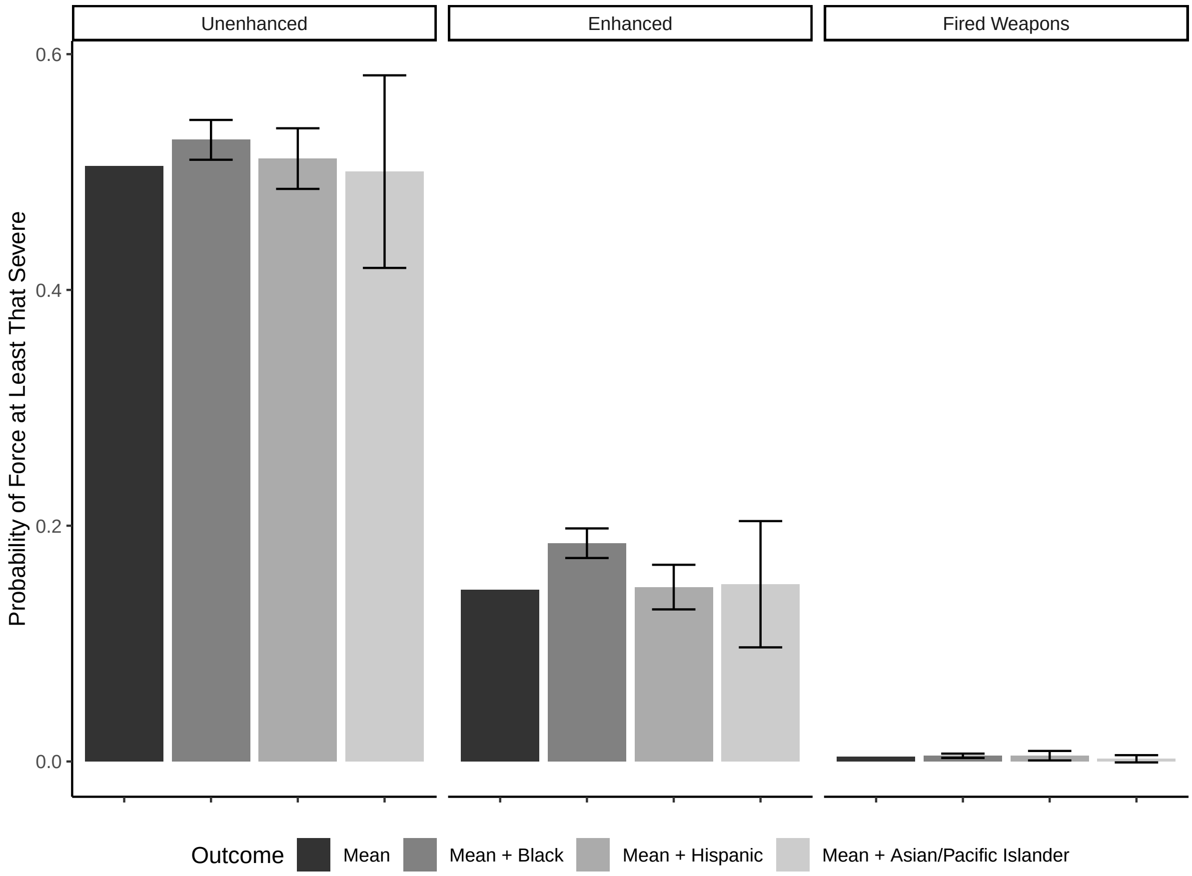


Figure 4: Overall Racial Disparities of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity, Full Race Dummies (Officer Fixed Effects and Clustering)
*Notes:* Figure presents results from a series of OLS models fit via Equation 1. Each heading represents a different outcome: 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.

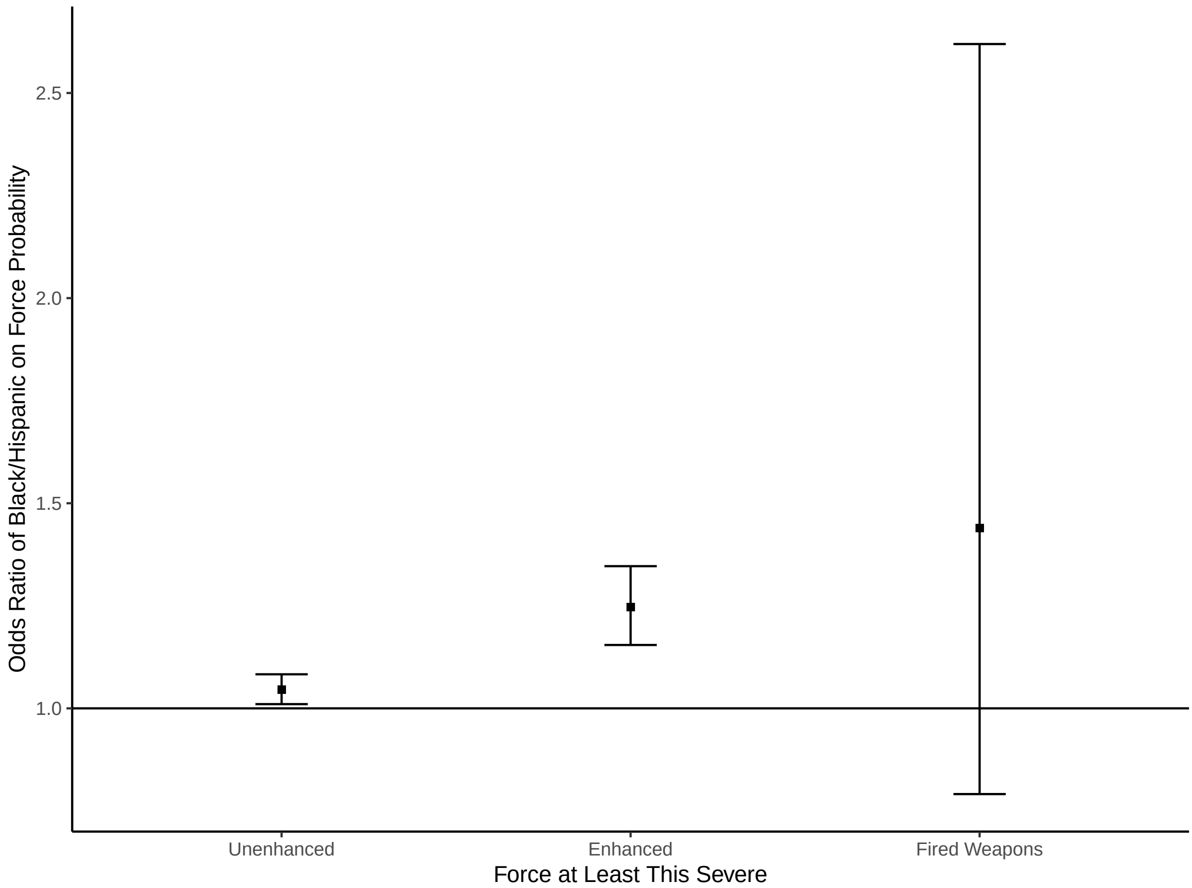


Figure 5: Conditional Logit Odds Ratios of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity

*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.

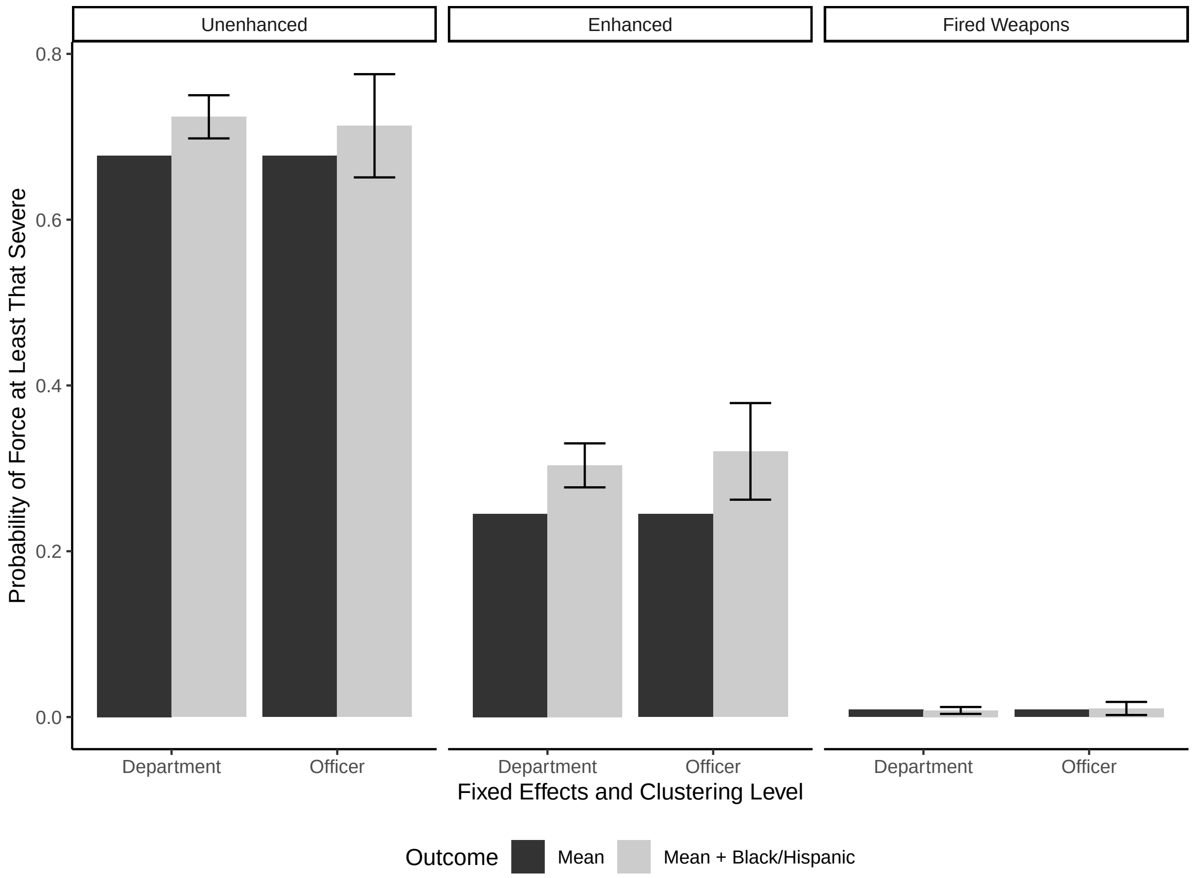


Figure 6: Overall Racial Disparities of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity (Subset Where Race is Unlikely to Affect Decision to Engage Subject and Subject at Least Physically Threatened/Attacked Officer or Another)

*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.

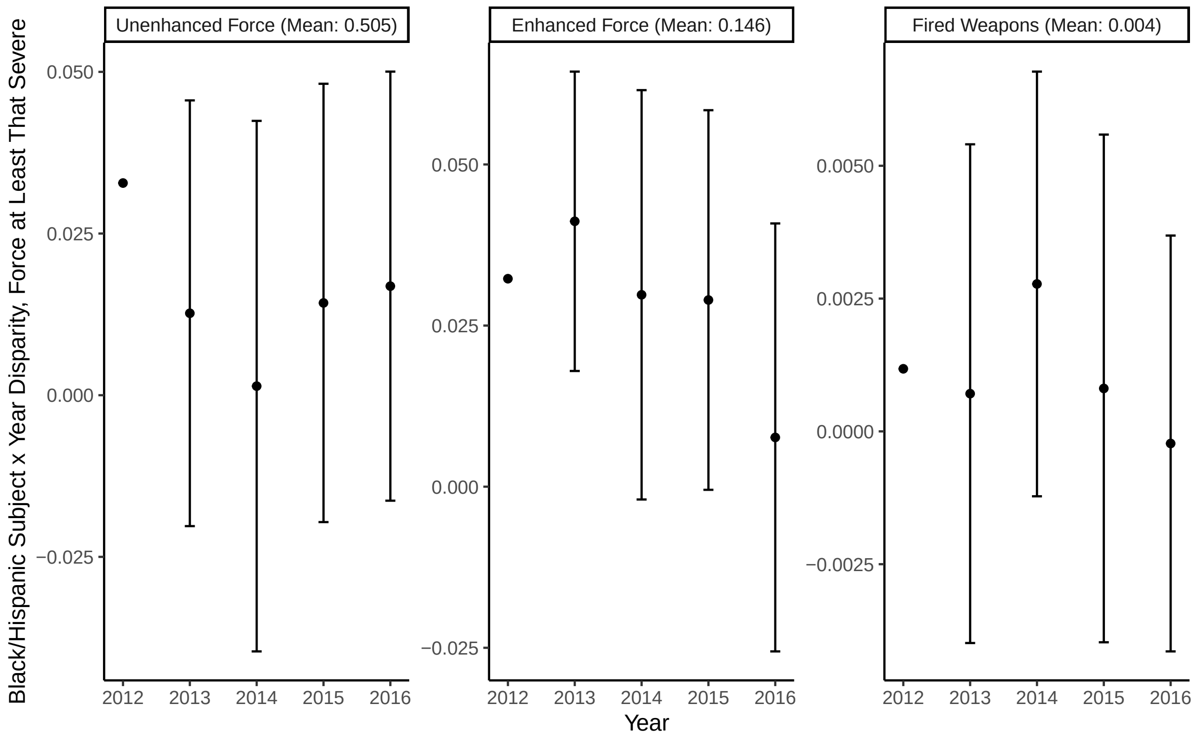


Figure 7: Overall Racial Disparities of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity by Year

*Notes:* Figure presents results from a series of OLS models fit via Equation 1 with the Black $\times$ Hispanic indicator interacted with year (2012 is omitted). Each heading represents a different outcome: whether, conditional on any force being used, force of at least the specified severity was used. 95% Confidence intervals are based on the corresponding year's coefficient. Standard errors are clustered at the department level.

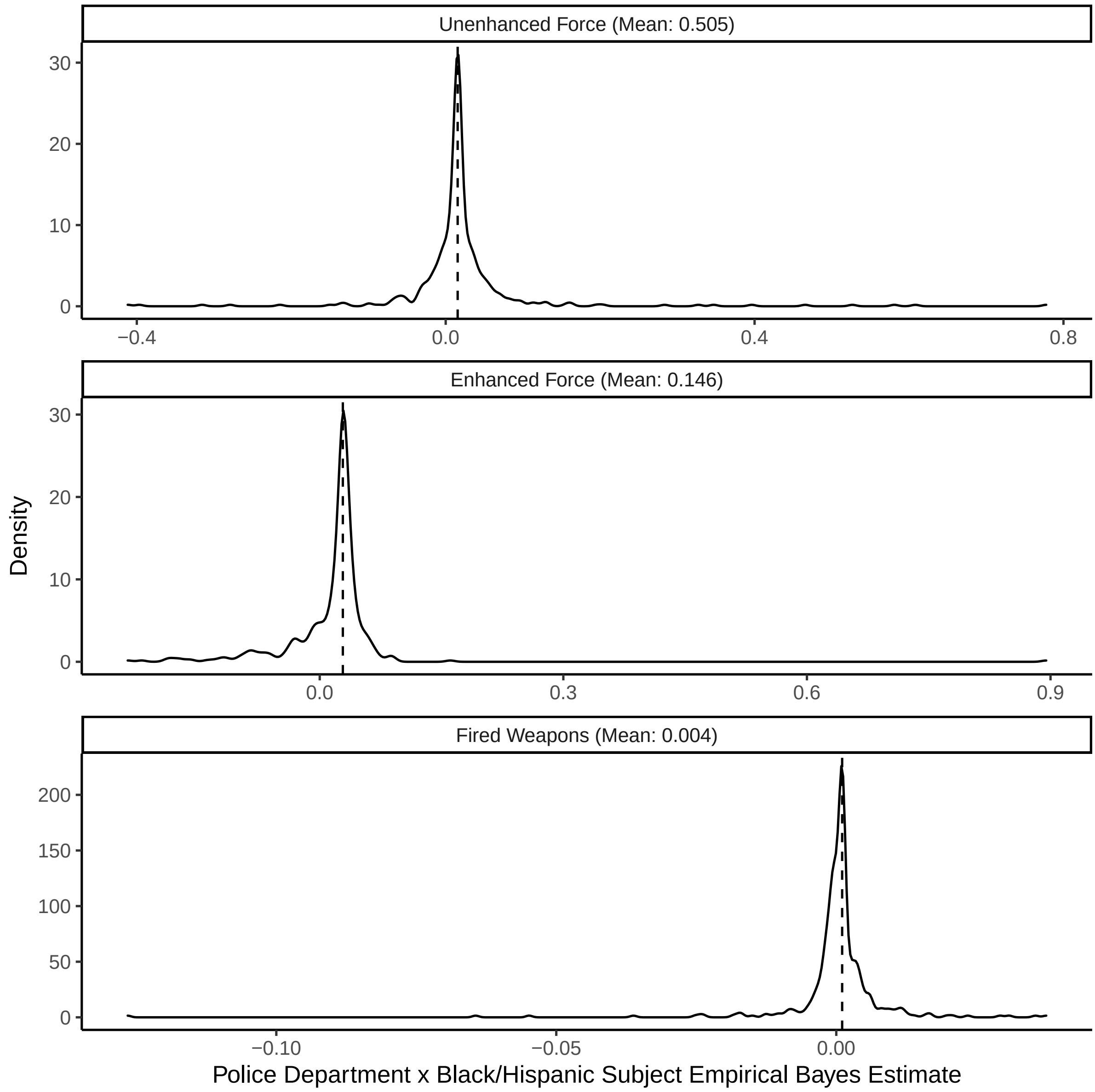


Figure 8: Distribution of Empirical Bayes Estimates of Department-Black/Hispanic Interactions

*Notes:* Figure presents kernel density estimates of department-specific racial disparities $\beta$ 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.

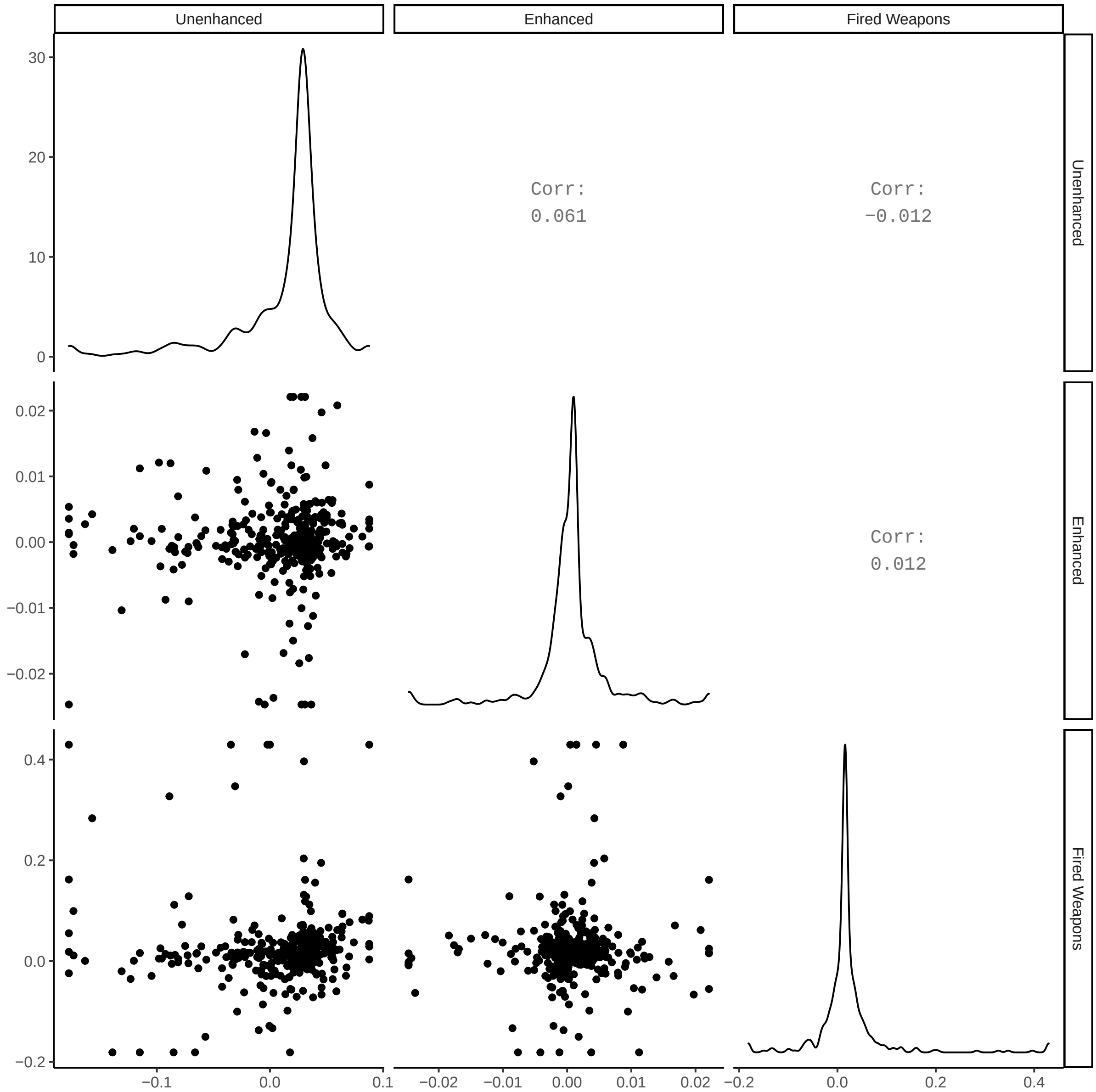


Figure 9: Within-Department Correlations of Winsorized Empirical Bayes Estimates of Department-Black/Hispanic Interactions Across Force Types

*Notes:* Figure presents the correlations across different force types of the winsorized department-specific racial disparities $\beta$ 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.

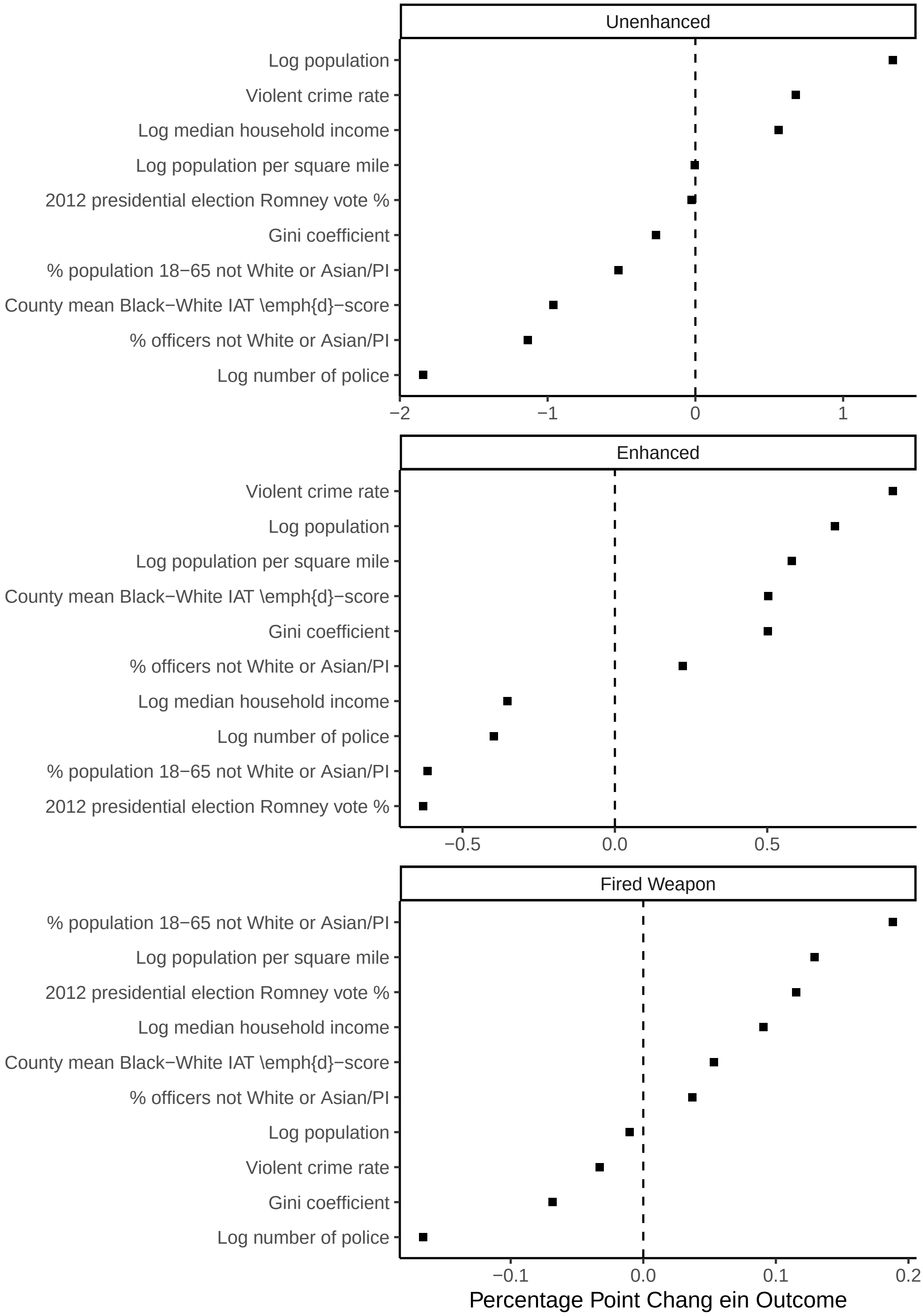


Figure 10: Coefficients from Regression of Empirical Bayes Estimates of Department-Black/Hispanic Interactions on Possible Correlates

*Notes:* Figure presents coefficients from a regression of winsorized empirical Bayes estimates of departmental disparities on the listed variables as described in Equation 6. Each variable on the right-hand side of the regression has been divided by twice its standard deviation to aid in interpretation.

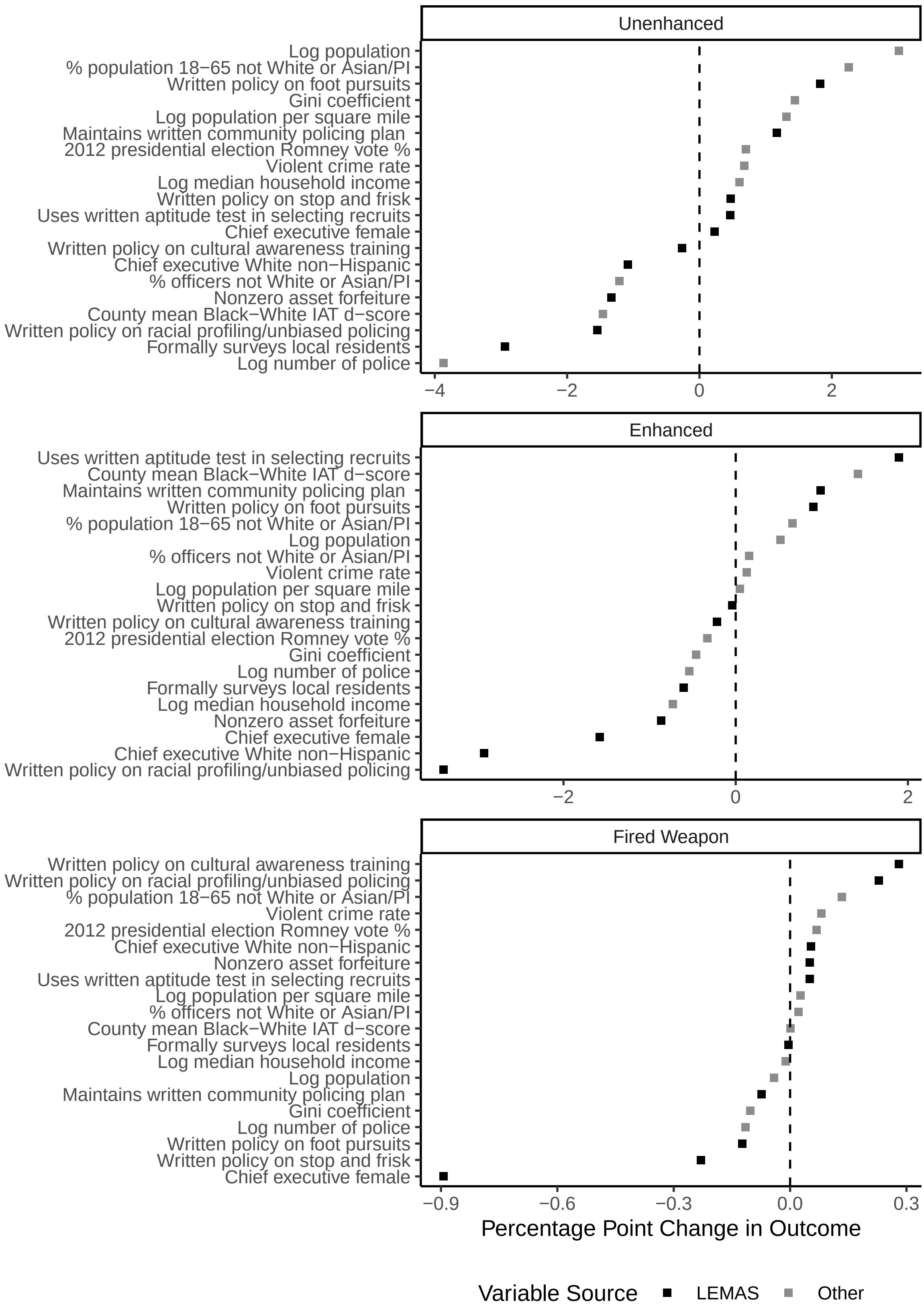


Figure 11: Coefficients from Regression of Empirical Bayes Estimates of Department-Black/Hispanic Interactions on Possible Correlates, Departments in 2016 LEMAS Only

*Notes:* Figure presents coefficients from a regression of winsorized empirical Bayes estimates of departmental disparities on the listed variables as described in Equation 6. Non-binary variables on the right-hand side of the regression has been divided by twice its standard deviation to aid in interpretation.

# 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.

Barrett, Nathan, et al. 2019. "Disparities and Discrimination in Student Discipline by Race and Family Income". *Journal of Human Resources*.

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.

Bohren, J. Aislinn, et al. 2020. *Inaccurate Statistical Discrimination: An Identification Problem*. Tech. rep. National Bureau of Economic Research.

Bureau of Justice Statistics. 2016. *Law Enforcement Management and Administrative Statistics (LEMAS)*. doi:10.3886/ICPSR37323.v1.

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 Roland G. Fryer. 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`.

Durlauf, Steven N., and James J. Heckman. 2020. "An Empirical Analysis of Racial Differences in Police Use of Force: A Comment". *Journal of Political Economy* 128 (10): 3998–4002.

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

— . 2020. "An Empirical Analysis of Racial Differences in Police Use of Force: A Response". *Journal of Political Economy* 128 (10): 4003–4008.

Gelman, Andrew. 2008. "Scaling Regression Inputs by Dividing by Two Standard Deviations". *Statistics in Medicine* 27 (15): 2865–2873.

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* 114 (3): 619–637.

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. http://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.

Raphael, Steven, and Sandra V. Rozo. 2019. "Racial Disparities in the Acquisition of Juvenile Arrest Records". *Journal of Labor Economics* 37 (S1): S125–S159.

Rehavi, M. Marit, and Sonja B. Starr. 2014. "Racial Disparity in Federal Criminal Sentences". *Journal of Political Economy* 122 (6): 1320–1354.

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 recorded, 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 (for example, "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, such 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 multiple types, which I allow, except for the "other" category.

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 more likely that the officer-stated reason is missing than nonexistent. I remove a handful of incidents involving nonlethal firearms ("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 | 10,373.00 | 296.00 | 277,140.00 |
| Population/square mile) | 454 | 4,020.84 | 5,616.57 | 2,612.12 | 39.13 | 55,880.00 |
| Median household income | 454 | 87,296.63 | 31,652.80 | 83,006.00 | 26,214.00 | 190,625.00 |
| 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 | 1.67 | 2.59 | 0.85 | 0.00 | 25.66 |
| Romney vote share 2012 presidential election | 454 | 45.20 | 14.79 | 47.74 | 1.31 | 81.82 |
| County mean Black-White IAT *D*-score | 21 | 0.35 | 0.05 | 0.35 | 0.24 | 0.41 |

*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, the New Jersey Division of Elections, and Project Implicit.

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 (No Controls)

| | Unenhanced | Enhanced | Fired Weapons |
|---|---|---|---|
| Intercept (White) | $0.456^{***}$ | $0.121^{***}$ | $0.003^{***}$ |
| | (0.014) | (0.007) | (0.000) |
| Subject Black | $0.098^{***}$ | $0.052^{***}$ | $0.003^{**}$ |
| | (0.014) | (0.012) | (0.001) |
| Subject Hispanic | $0.088^{***}$ | $0.032^{***}$ | $0.003^{*}$ |
| | (0.024) | (0.012) | (0.002) |
| Subject Asian/PI | $-0.011$ | $-0.009$ | $-0.003^{***}$ |
| | (0.028) | (0.018) | (0.000) |
| Clustering | Dept. | Dept. | Dept. |
| Outcome mean | 0.505 | 0.146 | 0.004 |
| $R^2$ | 0.009 | 0.005 | 0.000 |
| Num. obs. | 39322 | 39322 | 39322 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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

| | Unenhanced | | Enhanced | | Fired Weapons | |
|---|---|---|---|---|---|---|
| Subject Black/Hispanic | $0.015^{**}$ | $0.020^{**}$ | $0.028^{***}$ | $0.033^{***}$ | 0.001 | 0.001 |
| | (0.006) | (0.008) | (0.005) | (0.006) | (0.001) | (0.001) |
| Fixed effects | Dept. | Off. | Dept. | Off. | Dept. | Off. |
| Clustering | Dept. | Off. | Dept. | Off. | Dept. | Off. |
| Outcome mean | 0.505 | 0.505 | 0.146 | 0.145 | 0.004 | 0.004 |
| $R^2$ | 0.180 | 0.515 | 0.118 | 0.466 | 0.180 | 0.554 |
| Num. obs. | 39184 | 39133 | 39184 | 39133 | 39184 | 39133 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$ *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

| | Unenhanced | | Enhanced | | Fired Weapons | |
|---|---|---|---|---|---|---|
| Subject Black | $0.019^{***}$ | $0.022^{***}$ | $0.034^{***}$ | $0.040^{***}$ | 0.001 | 0.001 |
| | (0.006) | (0.009) | (0.005) | (0.006) | (0.001) | (0.001) |
| Subject Hispanic | −0.002 | 0.006 | 0.004 | 0.003 | 0.002 | 0.001 |
| | (0.010) | (0.013) | (0.007) | (0.010) | (0.002) | (0.002) |
| Subject Asian/PI | −0.022 | −0.005 | 0.004 | 0.005 | $-0.005^{***}$ | −0.002 |
| | (0.026) | (0.042) | (0.017) | (0.027) | (0.002) | (0.002) |
| Fixed effects | Dept. | Off. | Dept. | Off. | Dept. | Off. |
| Clustering | Dept. | Off. | Dept. | Off. | Dept. | Off. |
| Outcome mean | 0.505 | 0.505 | 0.146 | 0.145 | 0.004 | 0.004 |
| $R^2$ | 0.181 | 0.515 | 0.118 | 0.467 | 0.180 | 0.554 |
| Num. obs. | 39184 | 39133 | 39184 | 39133 | 39184 | 39133 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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

| | Unenhanced | Enhanced | Fired Weapons |
|---|---|---|---|
| Subject Black/Hispanic | $1.046^{*}$ | $1.247^{*}$ | 1.439 |
| | (1.010, 1.083) | (1.154, 1.347) | (0.791, 2.619) |
| Fixed effects | Dept. | Dept. | Dept. |
| Clustering | Dept. | Dept. | Dept. |
| Num. obs. | 39322 | 39322 | 39322 |

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

*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, Incidents where Race Likely Unrelated to Decision to Engage with Subject and Subject at Least Physically Threatened/Attacked Officer or Another

| | Unenhanced | | Enhanced | | Fired Weapons | |
|---|---|---|---|---|---|---|
| Subject Black/Hispanic | 0.047*** | 0.036 | 0.058*** | 0.076** | −0.001 | 0.001 |
| | (0.013) | (0.032) | (0.014) | (0.030) | (0.002) | (0.004) |
| Fixed effects | Dept. | Off. | Dept. | Off. | Dept. | Off. |
| Clustering | Dept. | Off. | Dept. | Off. | Dept. | Off. |
| Outcome mean | 0.677 | 0.677 | 0.245 | 0.245 | 0.009 | 0.009 |
| $R^2$ | 0.189 | 0.728 | 0.140 | 0.708 | 0.276 | 0.841 |
| Num. obs. | 7778 | 7770 | 7778 | 7770 | 7778 | 7770 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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, Incidents where Race Likely Unrelated to Decision to Engage with Subject

| | Unenhanced | | Enhanced | | Fired Weapons | |
|---|---|---|---|---|---|---|
| Subject Black/Hispanic | 0.026*** | 0.029** | 0.033*** | 0.044*** | 0.000 | −0.000 |
| | (0.009) | (0.014) | (0.007) | (0.011) | (0.001) | (0.002) |
| Fixed effects | Dept. | Off. | Dept. | Off. | Dept. | Off. |
| Clustering | Dept. | Off. | Dept. | Off. | Dept. | Off. |
| Outcome mean | 0.541 | 0.541 | 0.166 | 0.166 | 0.004 | 0.004 |
| $R^2$ | 0.187 | 0.603 | 0.132 | 0.559 | 0.215 | 0.672 |
| Num. obs. | 19860 | 19840 | 19860 | 19840 | 19860 | 19840 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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, Incidents where Subject at Least Physically Threatened/Attacked Officer or Another

| | Unenhanced | | Enhanced | | Fired Weapons | |
|---|---|---|---|---|---|---|
| Subject Black/Hispanic | $0.024^{**}$ | $0.031^{*}$ | $0.047^{***}$ | $0.058^{***}$ | 0.001 | 0.001 |
| | (0.010) | (0.018) | (0.010) | (0.017) | (0.002) | (0.003) |
| Fixed effects | Dept. | Off. | Dept. | Off. | Dept. | Off. |
| Clustering | Dept. | Off. | Dept. | Off. | Dept. | Off. |
| Outcome mean | 0.642 | 0.642 | 0.218 | 0.218 | 0.009 | 0.009 |
| $R^2$ | 0.174 | 0.665 | 0.125 | 0.627 | 0.227 | 0.733 |
| Num. obs. | 14580 | 14558 | 14580 | 14558 | 14580 | 14558 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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: Predicting 100 x (Department x Black/Hispanic Winsorized Empirical Bayes Estimates), RHS Numeric Variables Normalized by 2x Standard Deviation, 2016 LEMAS Departments Only

| | Unenhanced | Enhanced | Fired Weapons |
|---|---|---|---|
| Log median household income | 0.640 | −0.555 | 0.023 |
| | (0.998) | (1.062) | (0.139) |
| Gini coefficient | 1.435 | −0.789 | −0.113 |
| | (1.017) | (1.159) | (0.176) |
| Log population | $3.700^{*}$ | −0.732 | −0.407 |
| | (1.974) | (1.590) | (0.383) |
| Log population per square mile | 1.677 | 0.831 | 0.055 |
| | (1.242) | (1.166) | (0.192) |
| Log number of police | $-4.781^{**}$ | 0.313 | 0.197 |
| | (2.271) | (1.916) | (0.422) |
| % officers not White or Asian/PI | $-1.754^{**}$ | 0.194 | 0.051 |
| | (0.683) | (0.748) | (0.172) |
| % population 18-65 not White or Asian/PI | 1.006 | 0.214 | 0.086 |
| | (1.604) | (1.344) | (0.222) |
| Violent crime rate | 0.918 | 0.582 | 0.021 |
| | (0.756) | (0.923) | (0.107) |
| 2012 presidential election Romney vote % | 0.678 | −0.329 | −0.036 |
| | (1.506) | (1.598) | (0.218) |
| County mean Black-White IAT *D*-score | $-1.675^{*}$ | 1.489 | −0.032 |
| | (0.908) | (0.910) | (0.167) |
| Prob > F | 0.11 | 0.71 | 0.70 |
| $R^2$ | 0.134 | 0.069 | 0.045 |
| Num. obs. | 92 | 92 | 92 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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. Each non-binary variable on the right-hand side of the regression has been divided by twice its standard deviation.

**_____________________ 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<br>☐ 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<br>☐ 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.

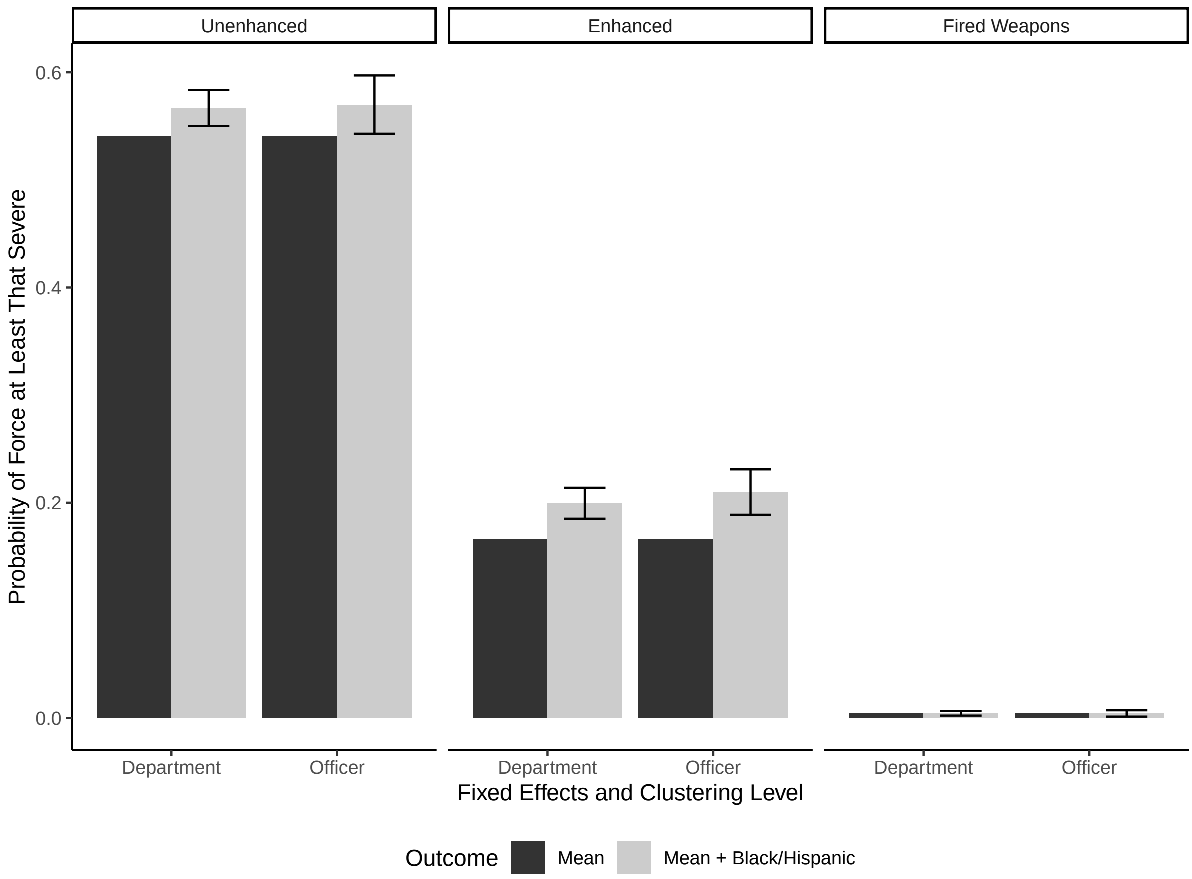


Figure A.2: Overall Racial Disparities of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity (Subset Where Race is Unlikely to Affect Decision to Engage Subject)

*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.

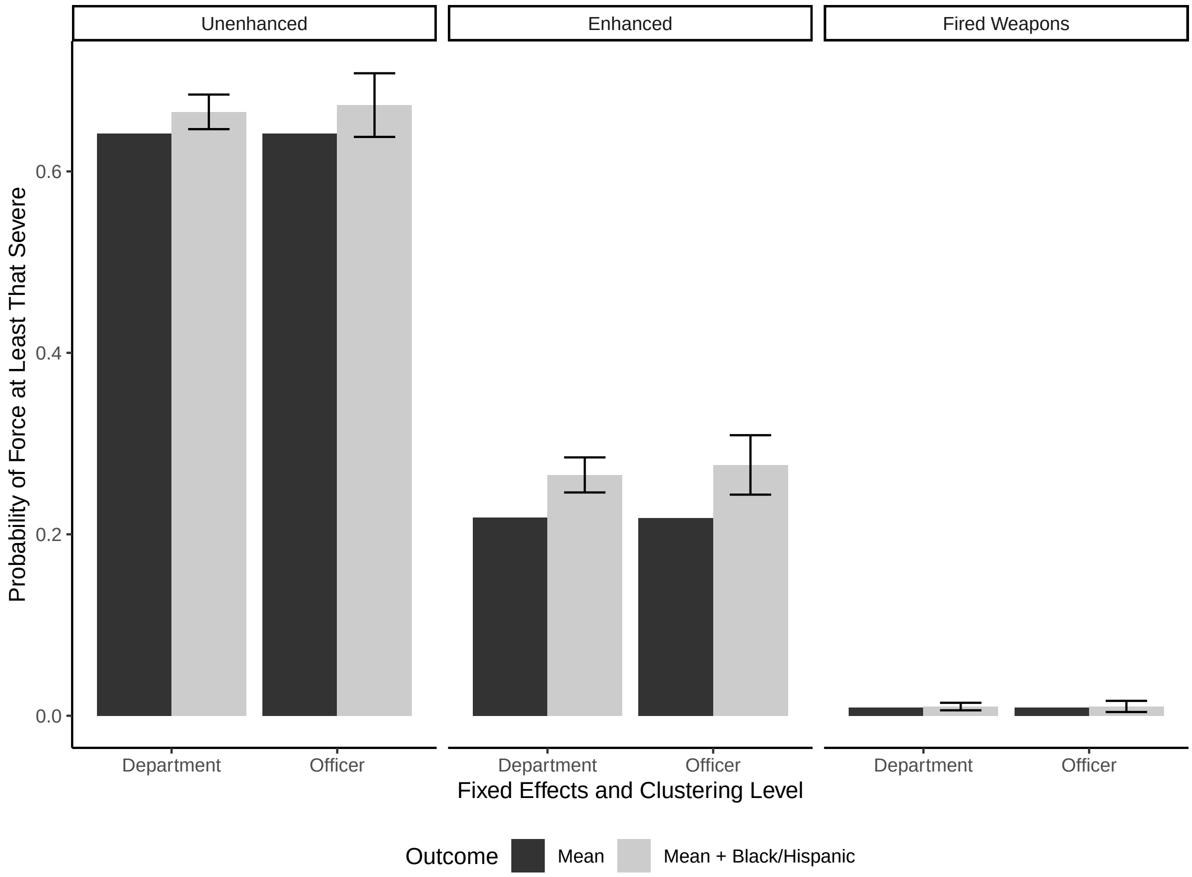


Figure A.3: Overall Racial Disparities of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity (Subset Where Subject at Least Physically Threatened/Attacked Officer or Another)

*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.

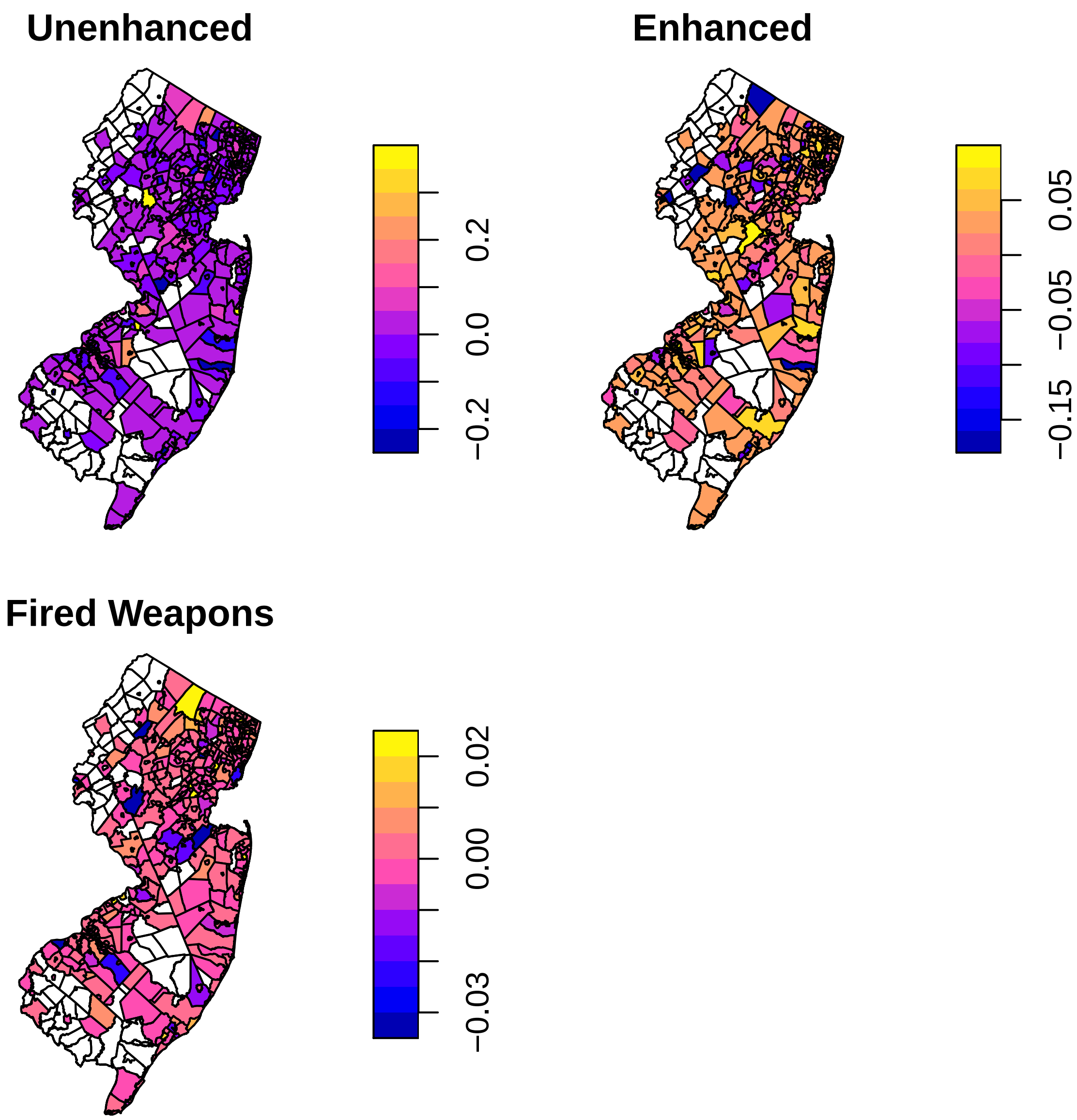


Figure A.4: Heatmap of of Winsorized Empirical Bayes Estimates of Department-Black/Hispanic Interactions

*Notes:* Figure presents heatmaps of department-specific racial disparities $\beta$ between White/Asian/Pacific Islander subjects and Black/Hispanic subjects as estimated from the empirical Bayes estimator in Equation 5. 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. Municipalities in white are not present in the data.

# B Results with Full Set of Force Outcomes

Table B.1: Racial Disparities by Police in Force of At Least Specified Severity, Conditional on Force (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 | 0.088*** | 0.078*** | 0.042*** | 0.032*** | 0.018*** | 0.003* |
| | (0.024) | (0.021) | (0.011) | (0.012) | (0.006) | (0.002) |
| Subject Asian/PI | −0.011 | −0.009 | −0.003 | −0.009 | 0.003 | −0.003*** |
| | (0.028) | (0.027) | (0.020) | (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 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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 B.2: Racial Disparities by Police in Force of At Least Specified Severity, Conditional on Force

| | Takedowns | | Hands/Fists | | Leg Strikes | | Pepper Spray | | Batons | | Fired Weapons | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Subject Black/Hispanic | $0.015^{**}$ | $0.020^{**}$ | $0.019^{***}$ | $0.024^{***}$ | $0.031^{***}$ | $0.038^{***}$ | $0.028^{***}$ | $0.033^{***}$ | $0.010^{***}$ | $0.010^{***}$ | 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 |
| $R^2$ | 0.180 | 0.515 | 0.177 | 0.521 | 0.114 | 0.452 | 0.118 | 0.466 | 0.075 | 0.422 | 0.180 | 0.554 |
| Num. obs. | 39184 | 39133 | 39184 | 39133 | 39184 | 39133 | 39184 | 39133 | 39184 | 39133 | 39184 | 39133 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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 B.3: Racial Disparities by Police in Force of At Least Specified Severity, Conditional on Force

| | Takedowns | | Hands/Fists | | Leg Strikes | | Pepper Spray | | Batons | | Fired Weapons | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Subject Black | $0.019^{***}$ | $0.022^{***}$ | $0.023^{***}$ | $0.026^{***}$ | $0.038^{***}$ | $0.045^{***}$ | $0.034^{***}$ | $0.040^{***}$ | $0.011^{***}$ | $0.012^{***}$ | 0.001 | 0.001 |
| | (0.006) | (0.009) | (0.006) | (0.009) | (0.006) | (0.007) | (0.005) | (0.006) | (0.003) | (0.003) | (0.001) | (0.001) |
| Subject Hispanic | −0.002 | 0.006 | 0.002 | 0.010 | 0.003 | 0.006 | 0.004 | 0.003 | 0.004 | −0.002 | 0.002 | 0.001 |
| | (0.010) | (0.013) | (0.010) | (0.013) | (0.008) | (0.011) | (0.007) | (0.010) | (0.004) | (0.006) | (0.002) | (0.002) |
| Subject Asian/PI | −0.022 | −0.005 | −0.022 | −0.012 | 0.010 | 0.007 | 0.004 | 0.005 | −0.005 | −0.002 | $-0.005^{***}$ | −0.002 |
| | (0.026) | (0.042) | (0.025) | (0.040) | (0.019) | (0.031) | (0.017) | (0.027) | (0.008) | (0.014) | (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 | 0.515 | 0.177 | 0.521 | 0.115 | 0.452 | 0.118 | 0.467 | 0.076 | 0.422 | 0.180 | 0.554 |
| Num. obs. | 39184 | 39133 | 39184 | 39133 | 39184 | 39133 | 39184 | 39133 | 39184 | 39133 | 39184 | 39133 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. *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 B.4: Racial Disparities by Police in Force of At Least Specified Severity, Conditional on Force, 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 | $0.047^{***}$ | 0.036 | $0.044^{***}$ | 0.035 | $0.055^{***}$ | $0.066^{**}$ | $0.058^{***}$ | $0.076^{**}$ | $0.024^{***}$ | $0.036^{**}$ | $-0.001$ | 0.001 |
| | (0.013) | (0.032) | (0.014) | (0.033) | (0.014) | (0.032) | (0.014) | (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 | 0.677 | 0.677 | 0.639 | 0.639 | 0.312 | 0.312 | 0.245 | 0.245 | 0.073 | 0.073 | 0.009 | 0.009 |
| $R^2$ | 0.189 | 0.728 | 0.184 | 0.730 | 0.136 | 0.694 | 0.140 | 0.708 | 0.133 | 0.708 | 0.276 | 0.841 |
| Num. obs. | 7778 | 7770 | 7778 | 7770 | 7778 | 7770 | 7778 | 7770 | 7778 | 7770 | 7778 | 7770 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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.

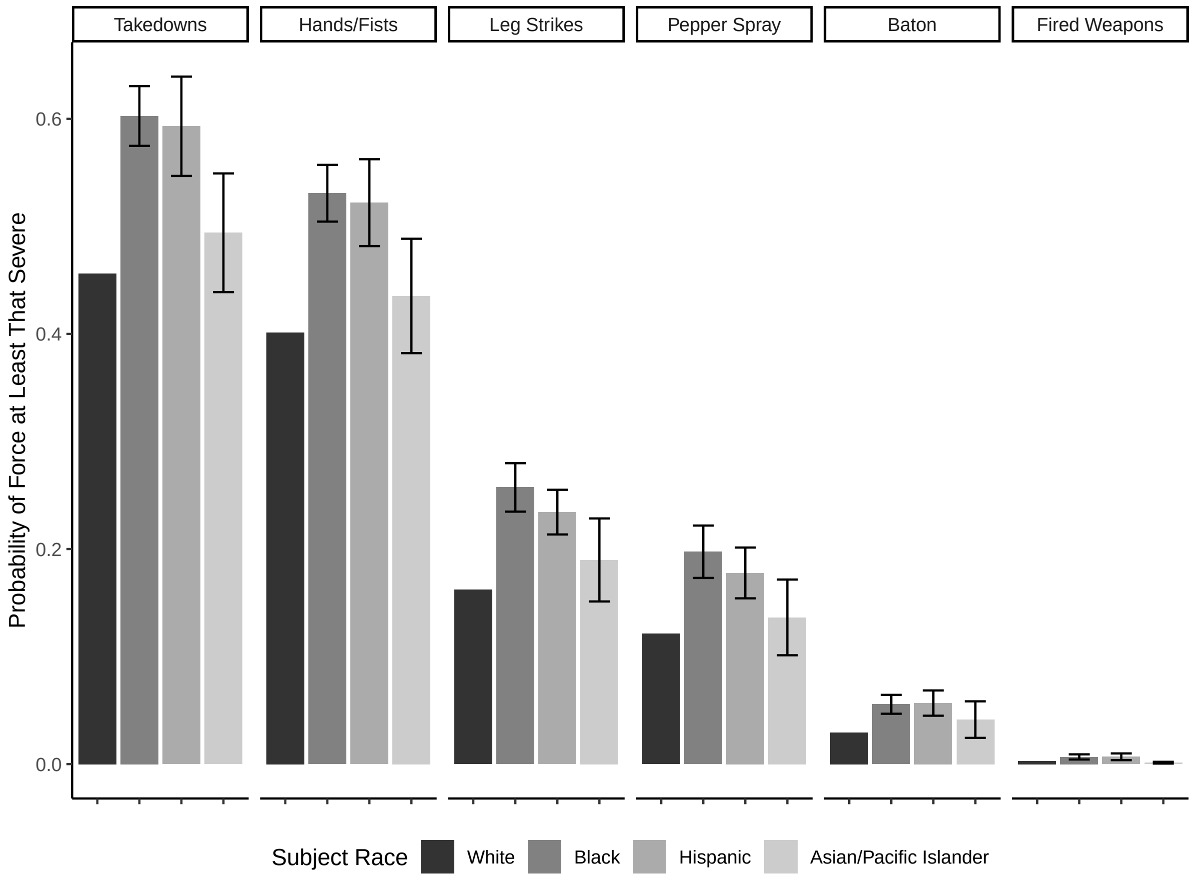


Figure B.1: Overall Racial Disparities (No Controls)

*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.

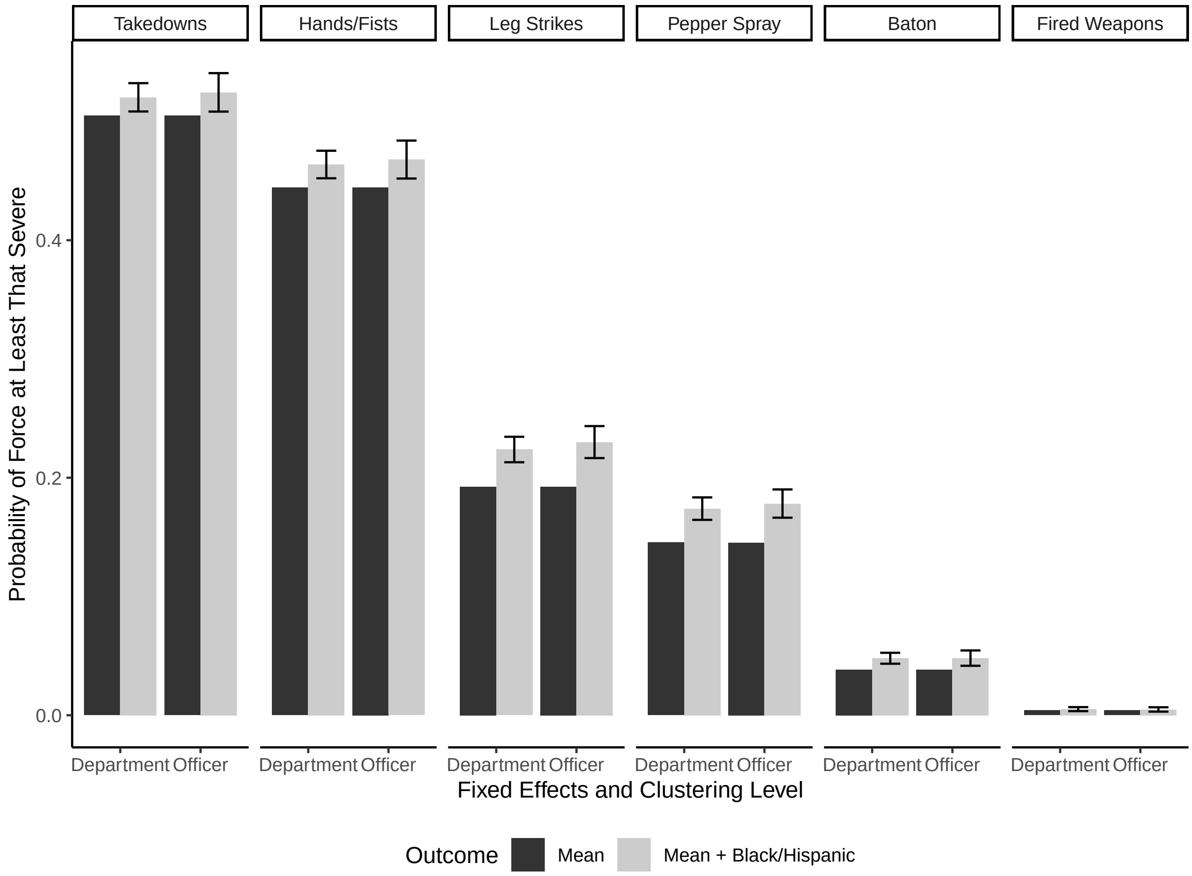


Figure B.2: Overall Racial Disparities for Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity

*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.

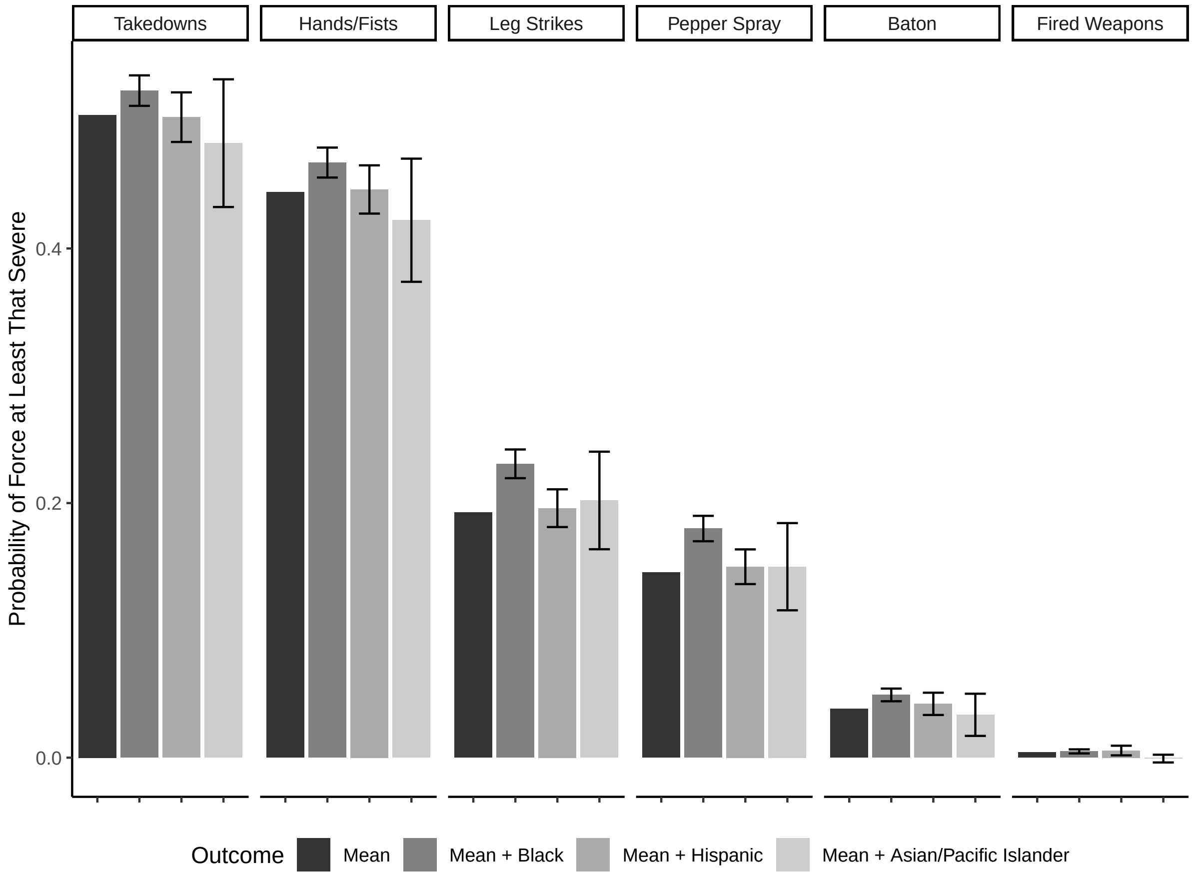


Figure B.3: Overall Racial Disparities of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity, Full Race Dummies (Department Fixed Effects and Clustering)
*Notes:* Figure presents results from a series of OLS models fit via Equation 1. Each heading represents a different 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.

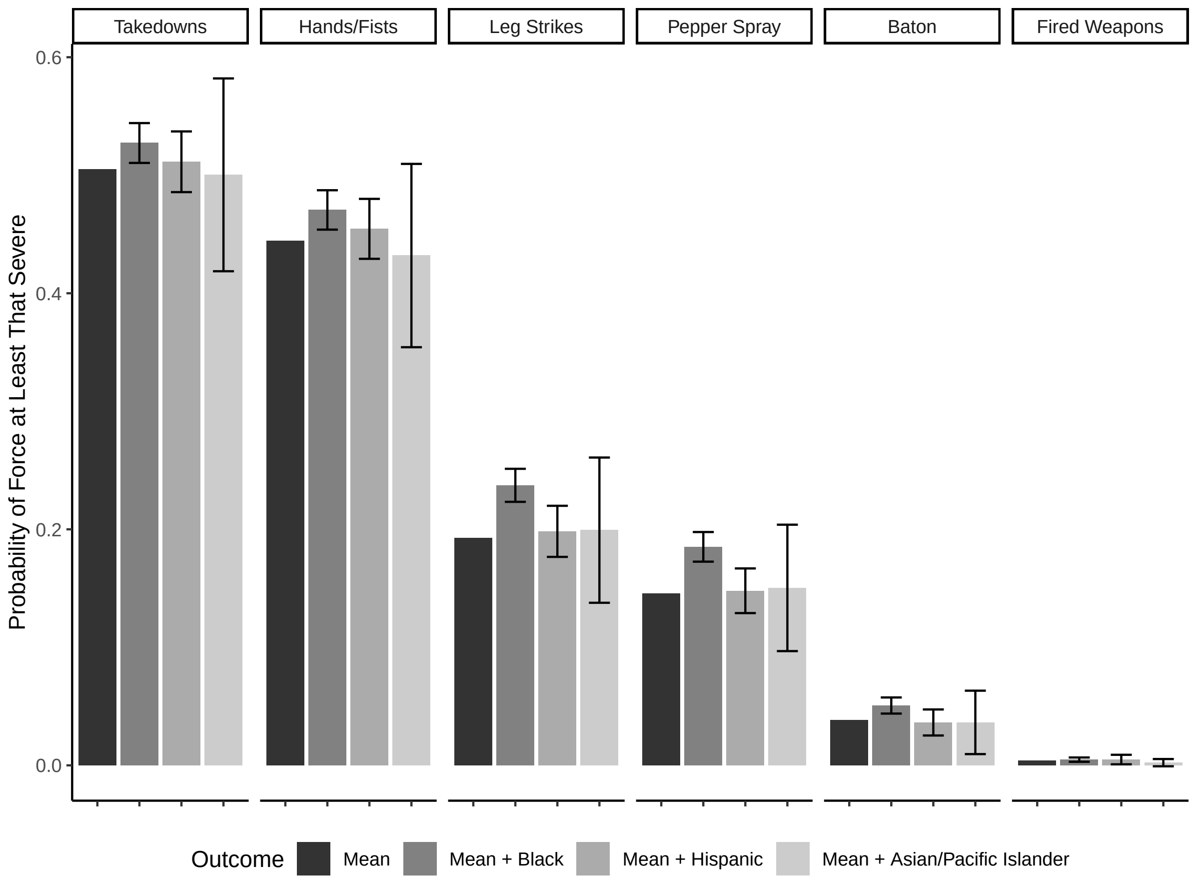


Figure B.4: Overall Racial Disparities of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity, Full Race Dummies (Officer Fixed Effects and Clustering)

*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.

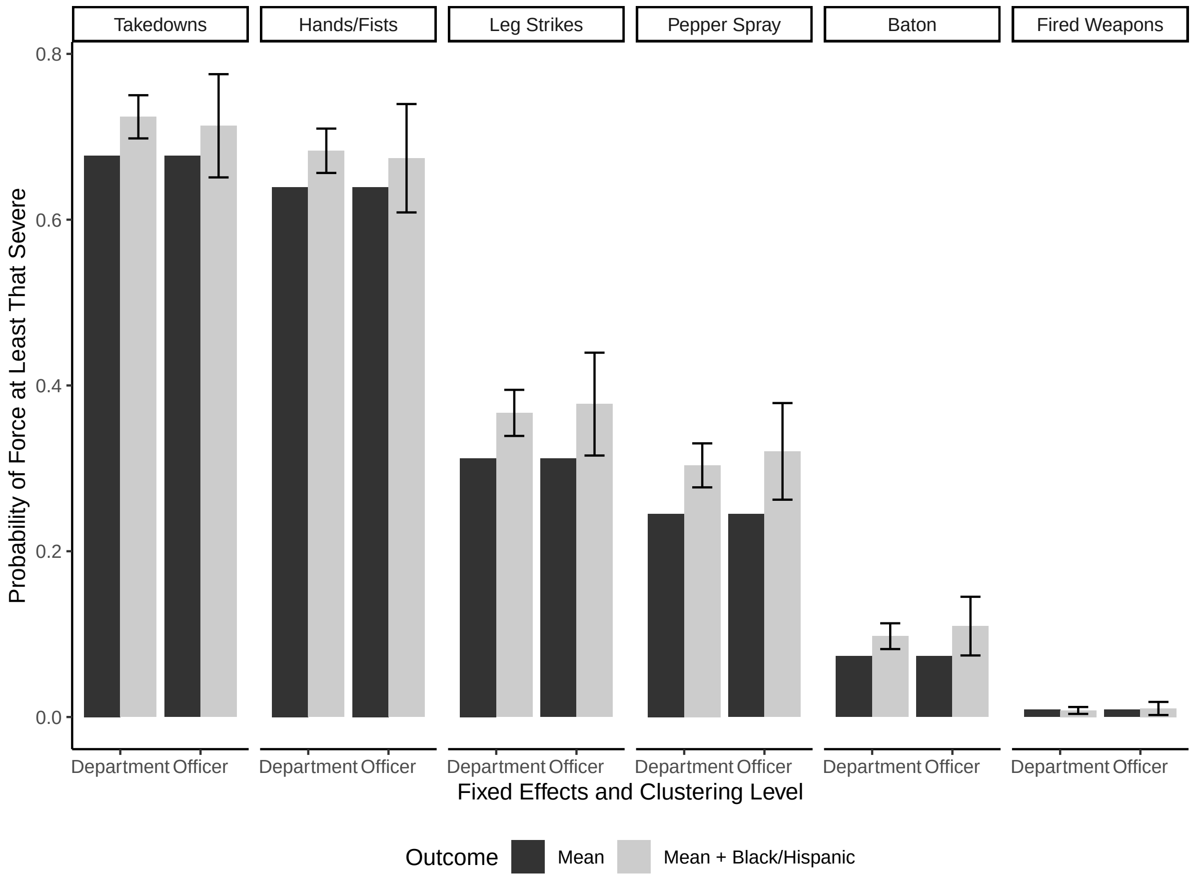


Figure B.5: Overall Racial Disparities of Subject Being Black/Hispanic on Probability of Force of at Least Specified Severity (Subset Where Race is Unlikely to Affect Decision to Engage Subject and Subject at Least Physically Threatened/Attacked Officer or Another)
*Notes:* Figure presents results from 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.

## C Results with OLS Estimates of Departmental Disparities

Table B.5: Summary Statistics for OLS Estimates of Department x Black/Hispanic Subject Interactions

| | Unenhanced | Enhanced | Fired Weapons |
|---|---|---|---|
| SD | 0.263 | 0.182 | 0.027 |
| Min | -0.968 | -0.800 | -0.215 |
| P01 | -0.518 | -0.355 | -0.070 |
| P05 | -0.359 | -0.220 | -0.020 |
| P25 | -0.094 | -0.063 | -0.002 |
| Median | 0.016 | 0.011 | 0.000 |
| P75 | 0.144 | 0.082 | 0.004 |
| P95 | 0.555 | 0.297 | 0.017 |
| P99 | 0.809 | 0.827 | 0.065 |
| Max | 1.090 | 1.034 | 0.276 |
| Mean | 0.042 | 0.023 | 0.001 |
| % $\leq 0$ | 0.450 | 0.463 | 0.488 |

*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 B.6: Predicting 100 x (Department x Black/Hispanic Interaction OLS Coefficients), RHS Variables Normalized by 2x Standard Deviation

| | Unenhanced | Enhanced | Fired Weapons |
|---|---|---|---|
| Log median household income | 1.899 | $-5.135^{**}$ | 0.244 |
| | (3.875) | (2.590) | (0.281) |
| Gini coefficient | 2.179 | 1.299 | $-0.191$ |
| | (3.590) | (2.642) | (0.277) |
| Log population | $-0.665$ | 1.041 | 0.348 |
| | (9.311) | (8.050) | (0.598) |
| Log population per square mile | $5.762^{*}$ | $4.127^{*}$ | $0.357^{*}$ |
| | (3.469) | (2.445) | (0.215) |
| Log number of police | $-2.870$ | $-0.002$ | $-0.389$ |
| | (8.928) | (7.445) | (0.586) |
| % officers not White or Asian/PI | 0.085 | 1.884 | 0.038 |
| | (2.794) | (2.354) | (0.162) |
| % population 18-65 not White or Asian/PI | 3.250 | $-2.748$ | $-0.689$ |
| | (4.354) | (3.066) | (0.480) |
| Violent crime rate | 2.195 | $-0.240$ | 0.035 |
| | (2.928) | (2.371) | (0.291) |
| 2012 presidential election Romney vote % | $11.241^{**}$ | 3.389 | $-0.746$ |
| | (5.670) | (4.198) | (0.686) |
| County mean Black-White IAT *D*-score | $-1.791$ | 0.768 | 0.054 |
| | (2.867) | (1.925) | (0.512) |
| Prob > F | 0.54 | 0.20 | 0.45 |
| $R^2$ | 0.024 | 0.023 | 0.015 |
| Num. obs. | 405 | 405 | 405 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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. Each variable on the right-hand side of the regression has been divided by twice its standard deviation.

Table B.7: Predicting 100 x (Department x Black/Hispanic Interaction OLS Coefficients), RHS Variables Normalized by 2x Standard Deviation

| | Unenhanced | Enhanced | Fired Weapons |
|---|---|---|---|
| Log median household income | $21.273^{**}$ | $-9.137$ | $-0.098$ |
| | (9.124) | (6.479) | (0.837) |
| Gini coefficient | $-7.978$ | $-6.949$ | $-1.362$ |
| | (6.105) | (6.863) | (1.193) |
| Log population | 13.507 | 2.103 | $-1.544$ |
| | (12.288) | (13.500) | (2.442) |
| Log population per square mile | 8.177 | 7.808 | $-0.030$ |
| | (6.405) | (6.307) | (0.604) |
| Log number of police | $-18.280$ | $-5.013$ | 0.712 |
| | (12.633) | (14.300) | (2.155) |
| % officers not White or Asian/PI | $-13.345^{**}$ | $-1.420$ | $-0.393$ |
| | (5.316) | (4.648) | (0.723) |
| % population 18-65 not White or Asian/PI | $14.858^{*}$ | $-1.228$ | $-1.384$ |
| | (8.539) | (7.204) | (1.594) |
| Violent crime rate | $10.006^{**}$ | 1.668 | 0.254 |
| | (4.861) | (2.496) | (0.386) |
| 2012 presidential election Romney vote % | 8.342 | 2.838 | $-2.075$ |
| | (8.271) | (5.805) | (2.102) |
| County mean Black-White IAT *D*-score | 3.123 | 1.684 | $-0.670$ |
| | (4.802) | (4.088) | (0.682) |
| Dept. has nonzero asset forfeiture | 2.889 | $-5.102$ | $-1.867$ |
| | (8.830) | (7.590) | (2.113) |
| Dept. uses written aptitude test in selecting recruits | $-2.332$ | 3.077 | 0.443 |
| | (6.187) | (4.144) | (0.578) |
| Dept. maintains a written community policing plan | 8.106 | 4.578 | $-0.303$ |
| | (5.718) | (3.733) | (0.626) |
| Dept. formally surveys local residents | 1.690 | $-4.152$ | 0.594 |
| | (7.716) | (3.739) | (0.941) |
| Dept. has written policy on stop and frisk | $-0.672$ | $-2.697$ | 0.728 |
| | (6.014) | (5.676) | (1.249) |
| Dept. has written policy on foot pursuits | 4.831 | $-1.573$ | $-0.648$ |
| | (5.204) | (4.205) | (0.811) |
| Dept. has written policy on unbiased policing | $-12.127$ | $-1.351$ | 1.771 |
| | (9.089) | (6.691) | (2.186) |
| Dept. chief executive is female | $-7.464$ | 0.399 | $-0.245$ |
| | (10.654) | (9.714) | (2.019) |
| Dept. chief executive is non-Hispanic White | 8.585 | $-1.983$ | 0.270 |
| | (11.985) | (4.686) | (0.805) |
| Prob > F | 0.36 | 0.26 | 0.68 |
| $R^2$ | 0.265 | 0.172 | 0.160 |
| Num. obs. | 83 | 83 | 83 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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. Each non-binary variable on the right-hand side of the regression has been divided by twice its standard deviation.

Table B.8: Predicting 100 x (Department x Black/Hispanic Interaction OLS Coefficients), RHS Variables Normalized by 2x Standard Deviation, 2016 LEMAS Departments Only

| | Unenhanced | Enhanced | Fired Weapons |
|---|---|---|---|
| Log median household income | $21.338^{**}$ | $-9.842^{*}$ | $-0.170$ |
| | (8.489) | (5.352) | (0.734) |
| Gini coefficient | $-4.501$ | $-5.705$ | $-1.426$ |
| | (6.161) | (6.021) | (1.166) |
| Log population | 15.334 | 2.742 | $-1.841$ |
| | (12.741) | (10.710) | (1.764) |
| Log population per square mile | $10.764^{**}$ | 8.297 | $-0.465$ |
| | (5.360) | (5.710) | (0.743) |
| Log number of police | $-20.995^{*}$ | $-7.563$ | 0.898 |
| | (12.523) | (10.728) | (1.404) |
| % officers not White or Asian/PI | $-13.466^{***}$ | $-0.607$ | $-0.168$ |
| | (4.859) | (4.137) | (0.520) |
| % population 18-65 not White or Asian/PI | $15.025^{**}$ | $-2.217$ | $-1.076$ |
| | (7.463) | (5.899) | (1.317) |
| Violent crime rate | $10.929^{**}$ | 1.129 | $-0.037$ |
| | (4.351) | (2.474) | (0.294) |
| 2012 presidential election Romney vote % | 9.431 | 2.061 | $-1.671$ |
| | (8.061) | (5.266) | (1.697) |
| County mean Black-White IAT *D*-score | 1.017 | 2.010 | $-0.701$ |
| | (3.747) | (3.391) | (0.547) |
| Prob > F | 0.19 | 0.58 | 0.89 |
| $R^2$ | 0.220 | 0.124 | 0.085 |
| Num. obs. | 83 | 83 | 83 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

*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. Each non-binary variable on the right-hand side of the regression has been divided by twice its standard deviation.

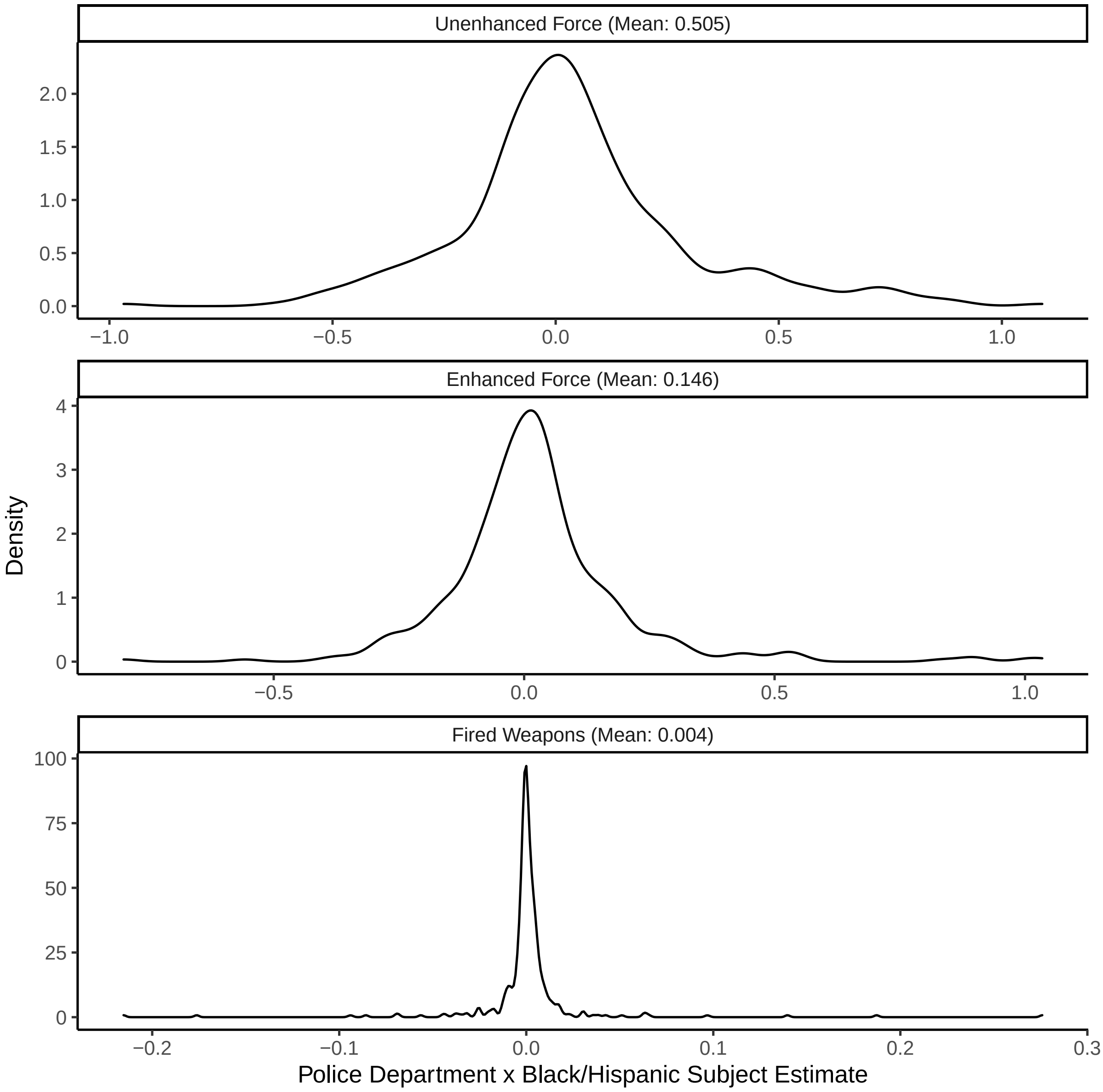


Figure C.1: Distribution of Unshrunk Estimates of Department-Black/Hispanic Interactions

*Notes:* Figure presents kernel density estimates of department-specific racial disparities $\beta$ 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.

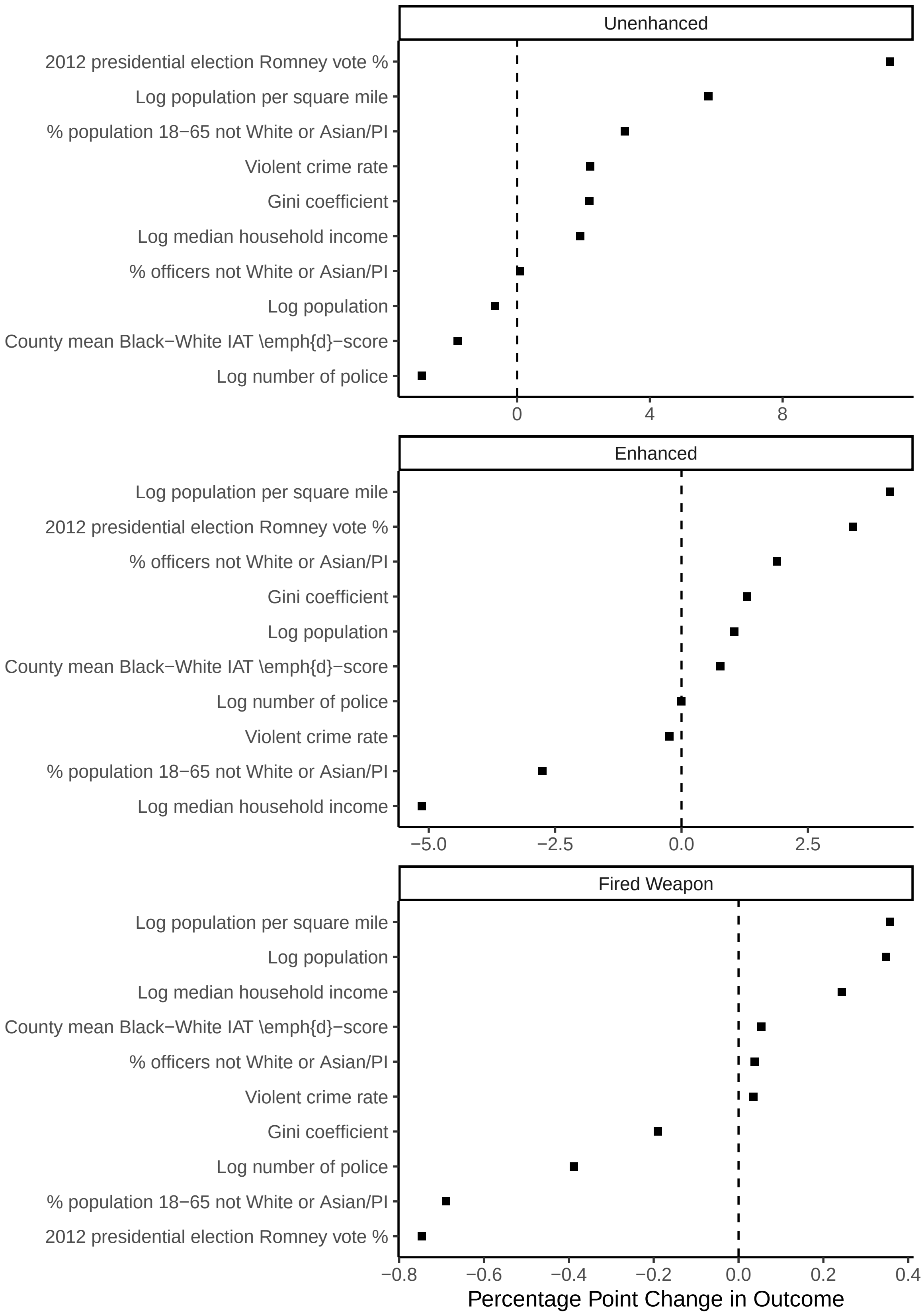


Figure C.2: Coefficients from Regression of OLS Estimates of Department-Black/Hispanic Interactions on Possible Correlates

*Notes:* Figure presents coefficients from a regression of OLS estimates of departmental disparities on the listed variables as described in Equation 6. Each variable on the right-hand side of the regression has been divided by twice its standard deviation to aid in interpretation.

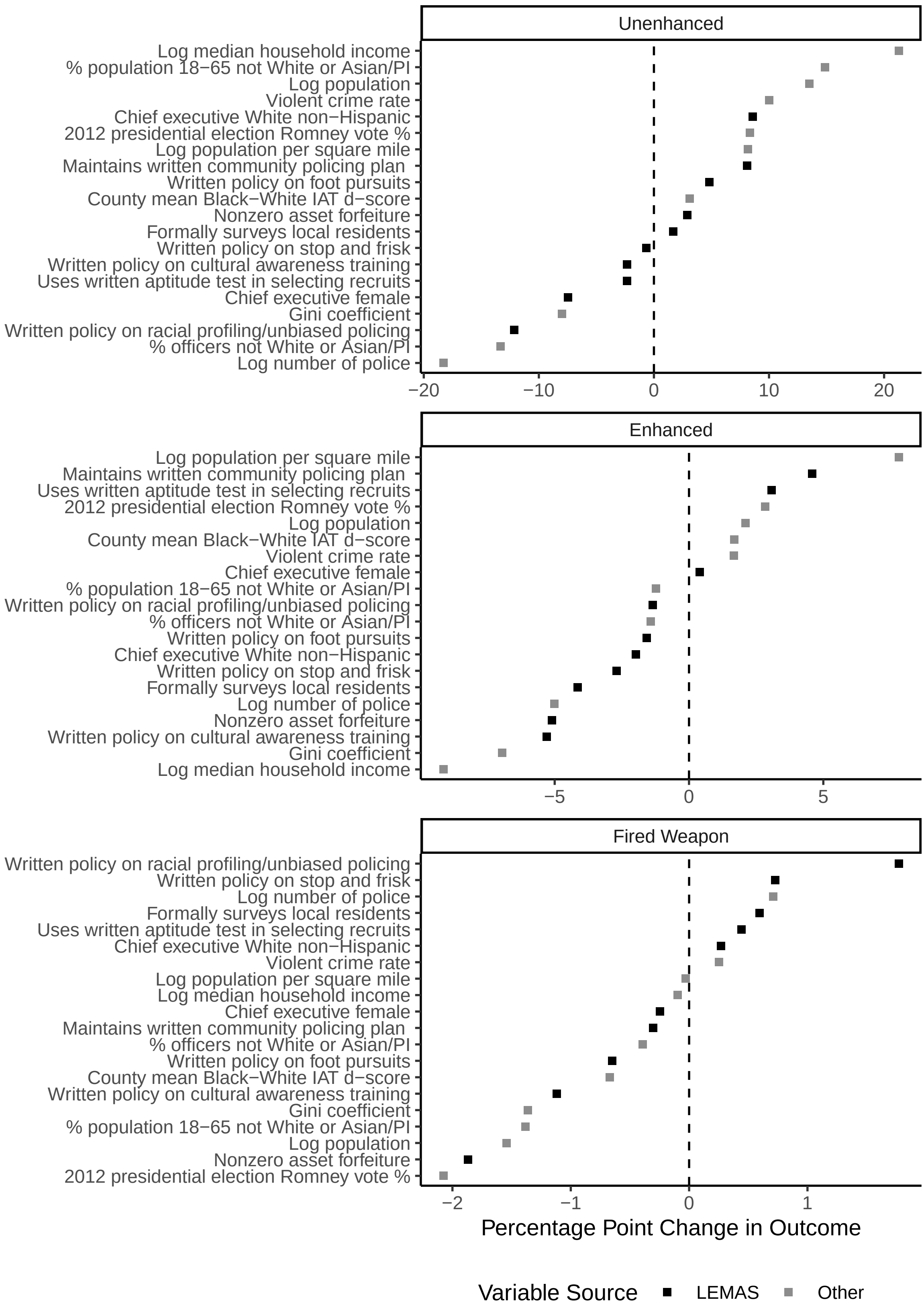


Figure C.3: Coefficients from Regression of OLS Estimates of Department-Black/Hispanic Interactions on Possible Correlates, Departments in 2016 LEMAS Only

*Notes:* Figure presents coefficients from a regression of OLS estimates of departmental disparities on the listed variables as described in Equation 6. Non-binary variables on the right-hand side of the regression has been divided by twice its standard deviation to aid in interpretation.