Race and the use of deadly force by police in America*

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Abstract

Police shootings kill a disproportionate number of minority males in the US. This, and the historically fraught role of police as enforcers of racial discrimination has led to calls for police reform. In this article, I study whether law enforcement are more likely to employ deadly force against minorities, everything else equal. To do so, I use as a proxy for the justifiable use of deadly force the predicted probability of aggravated assault against responding officers. I find that Black males have a *lower* likelihood of dying or being shot by police during an arrest attempt compared to risk-equivalent White males. This difference is unlikely to be explained by misreporting or geography. My findings suggest that the large number of Black males killed by police is explained by a higher probability of interaction and arrest (exposure), and not by a lower threshold for the use of deadly force conditional on arrest (extensive margin). I also fail to find evidence of higher *intensity* in the use of deadly force against Black or Hispanic individuals. I find some evidence of less leniency towards Hispanic males on the part of police, although I cannot reject that this is caused by language barriers.

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> We conclude that such [deadly] force may not be used unless it is necessary to prevent the escape and the officer has probable cause to believe that the suspect poses a significant threat of death or serious physical injury to the officer or others.
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> United States Court of Appeals for the Sixth Circuit, *Tennessee v. Garner, 471 U.S. 1 (1985)*

1 Introduction

Black individuals make up approximately 12.6% of the US population, but 27.3% of all fatalities in officer-involved shootings (OIS). This disproportionate number of fatalities, coupled with the historical role that police have played in enforcing racial discrimination has led to calls for police reform and increased accountability. While this subject has received considerable attention, the existing literature has failed to reach a consensus as to whether race plays a role in the use of deadly force, as result of lacking a unified conceptual framework, limited data, and methodological shortcomings.

Generally speaking, the lawful use of deadly force requires that officers have a *reasonable* belief that they, or a third party, are at *immediate* risk of death, serious injury, kidnap, or rape, and that it is *necessary* to use deadly force to repel the aggression. The Supreme Court has also established that the totality of circumstances as seen through the eyes of a hypothetical "reasonable" officer establishes the baseline that the justice system needs to consider when assigning legal liability. I rely on this notion of justice to analyze the behavior of officers during incidents in which civilians from different racial backgrounds were shot and killed.[1]

The legal framework referenced here can be re-framed to some extent as the legal right that officers have to use the highest level of force possible (lethal) to prevent an aggravated assault.[2] This offense is widely reported in official data, which allows me to study whether

[1] I use the terms "civilian", "citizen", "male" and "individual" interchangeably, although technically military personnel and undocumented immigrants may be part of the sample.

[2] In the state of Pennsylvania, for instance, §2702(a) defines this offense as: "attempts to cause serious bodily injury to another..." (paragraph 1), "attempts to cause or intentionally, knowingly or recklessly causes serious bodily injury to any of the officers..." (paragraph 2), and "attempts to cause or intentionally or know-

the decision by police to use deadly force against civilians is affected by race, once we control for risk of aggravated assault.

In the absence of racial bias (i.e., taste discrimination), the use of deadly force should be proportional to the risk posed by a civilian. To make this comparison, I first fit a function that estimates the probability that any responding officer would have suffered an aggravated assault from event and civilian characteristics. This probability is calculated using a random forest algorithm, that identifies incidents where police suffered aggravated rather than ordinary assault, using as a training set events where law-enforcement agencies reported an assault against a peace officer to the FBI through the National Incident-Based Reporting System (NIBRS).

I then project the risk of aggravated assault to officers (which I call *objective risk*) onto the set of deadly OIS, and on a 5% random sample of incidents where a civilian was arrested. I estimate the likelihood of dying conditional on arrest from the ratio of deaths to arrests for individuals with similar objective risk. While there is high-quality national data available for deadly police shootings, there is no such data-set that tracks non-deadly police shootings. To address this and estimate the conditional probability of being shot by police, I approximate the unobserved number of non-fatal OIS by dividing deaths by the race-specific likelihoods of surviving an OIS, as reported by 47 of the 50 largest police departments in the country.

Arrests and deadly police shootings are the result of three types of selection. For an arrest to occur, first, police need to interact with a civilian and, secondly, either have probable cause that he or she committed a crime, or have an outstanding arrest warrant. For a deadly shooting to occur, an officer needs to first, interact with a civilian, secondly, use deadly force, and third, the level of force used has to prove fatal. The data that I have access to captures event, civilian and, in some cases, officer characteristics for incidents that lead

ingly causes bodily injury to another with a deadly weapon" (paragraph 3. See Statue §2701 and 2702 of the state of Pennsylvania). An assault that otherwise doesn't meet the requirements set in §2701 is considered an ordinary assault to an arrest or a deadly shooting. Unfortunately, I do not observe incidents where a civilian interacted with police, but was not arrested, or "non-incidents" where the civilian didn't interact at all with police. While I fail to find substantive evidence of racial bias conditional on arrest or use of deadly force, my results are not informative of potential bias at earlier stages of a police-civilian interaction.

In addition to the aforementioned issues of selection, my analysis could be affected by misreporting. First, police could make "honest" mistakes when documenting a criminal incident. There's some evidence that this happens in NIBRS: Jarvis (2015) finds an unusually large number of reports in the last hours of a shit, which suggests that officers erroneously document the time when they filled a report, as opposed to the time where the event occurred. To limit this type of measurement error I omit from my analysis variables that Jarvis (2015) found problematic. Secondly, and perhaps more importantly, there could be intentional misreporting. Although insufficient to rule out false reports, we should note that unlike in other settings, falsely reporting on a police interaction could be considered obstruction of justice, a criminal offense that carries non-negligible consequences[3]. Still, my analysis will consider the potential impact of systemic misreporting on the empirical results.

My strategy to limit the effect of intentional misreporting is the following. First, I rely on event characteristics that are both unambiguous and hard to falsify: indicators for firearm, offensive use of a knife, car (i.e., trying to run over an officer), or blunt instrument, and the state where the event occurred. Secondly, while I use police reports from NIBRS to estimate the objective risk function, the projection step in my main exercise is done on the set of deadly police shootings reported by the Washington Post, an independent news outlet. The Post constructs these data by cross-referencing police reports, open-source media, news, and social media, and conducting its own investigations. Thus, the numerator in my

[3]Additionally, the FBI used to conduct Quality Assurance Reports (QAR) where a random sample of 500 incidents in a given state were audited by federal agents every three years. To the best of my knowledge, the FBI relayed these reports to state and local authorities who in some cases made those reports public.

estimate of the probability of death (shooting) conditional on arrest and objective risk likely suffers less measurement error than the denominator. I can't directly validate whether the event characteristics in arrest reports are intentionally misreported or the potential extent of misreporting. I can, however, run a series of robustness exercises that explore how sensitive my results are to it.

Before presenting my main results, consider a simple exercise in descriptive statistics that makes the identification strategy more transparent. Black civilians are reported to comprise 34% of all instances in which a civilian had a firearm during the commission of aggravated assault against a peace officer. The presence of firearms is itself a strong predictor of a deadly shooting: a firearm was retrieved in 3,374 (63%) of such incidents. Suppose that civilians who were killed would have been arrested had they survived their injuries, and that the conditional probability of being shot at by police when in possession of a firearm during the commission of aggravated assault on a peace officer was equal for every race. Based on these facts we would naively expect 1,143 deaths among Black males in such incidents between 2016 and 2020 (3,374 $\times$ 0.34), a figure higher than the 963 recorded deaths during that time period. A similar conclusion can be reached if we extend the comparison to every other weapon, except knives. On the contrary, based on the number of deadly shootings against unarmed civilians and the reported share of Black, unarmed males who committed aggravated assault against an officer, we would have expected to see 25 fewer fatalities in this group. Descriptive statistics thus suggest that "high-risk" Black males are being killed at a lower rate than predicted, and that "lower-risk" individuals from this group are dying at a higher rate.

My main analysis replicates this basic fact using a more comprehensive risk measure. Relative to my predictions, I find slightly more lower-risk Black individuals killed by police than expected, and substantially fewer high-risk casualties. Conditional on being arrested, Black civilians in the 90th percentile of risk experienced 1% less likelihood of death on average compared to equivalent White suspects, and approximately the same likelihood of being shot. These results persist when I use as predictive features only an indicator of firearm and state. Misreporting (intentional or not) about these features would be extremely unlikely, which suggests that my results are not driven by misreporting.[4]

Within the pool of civilians killed by police fire, I find similar average risk across all racial and ethnic groups. Results are similar if I restrict the sample to incidents where police had presumably more leeway to justify a shooting based on civilian behavior, as opposed to material evidence (i.e., incidents where the civilian exhibited signs of "mental illness," and critical events where no bodycam footage is available[5]).

I do observe some notable differences in the *intensive* margin. For every racial group, I find that approximately 1.5 officers responded on average to an incident that escalated to a shooting, and that these officers fired on average 6.5 rounds. White civilians, however, experience 17% higher mortality compared to Black individuals, conditional on being shot by police, and conditional on event and officer characteristics. Approximately one fourth of this difference is explained by Black civilians being younger on average. Still, there is a 12% gap in survival rates that I cannot account for. This is a topic for future research. In the same vein, White civilians pay a higher premium for being in possession of a firearm in terms of survival, and benefit the least from having responding officers of the same race as them (Hispanic males benefit the most, which could be explained by language barriers).

I use a simple discrete-choice model to rationalize the evidence of more "leniency" towards high-risk Black males with the perception, supported in some cases by bodycam footage, that a larger fraction of low-risk Black males are unjustifiably killed. In the model, officers choose whether to use lethal force on a suspect based on their perception of the

[4]An officer claiming that an arrestee had a firearm needs to produce said firearm. To illegally plant one, an officer would first need to procure a firearm that can't be traced back to him or her, manage to not be caught while in its possession, and then plant it without raising suspicion. The potential costs of being caught are extremely large, while any potential benefits to the officer would likely be minor. Furthermore, it would be much easier to incriminate an individual by planting illegal narcotics, for example, which are easy to acquire according to most D.E.A. field offices, and which are also much harder to trace.

[5]The policy of deploying bodycams has been found by Ariel et al. (2018) to reduce the number of assaults against officers, but they also offer some evidence of over-caution on the part of police which then led to more assaults.

risk posed by him and his racial identity. A fraction of officers are statistical discriminators in the sense that they overestimate the risk posed by Black males, while others are reverse taste discriminators who especially dislike shooting members of that demographic. Statistical discrimination could arise from the higher prevalence of handguns in aggravated assaults on officers committed by Black, relative to White males, while taste discrimination could occur if officers expect acute social repercussion from killing a Black male, or if they fear increased oversight and a higher probability of prosecution. The model predicts a larger share of low-risk Black civilians killed by police and fewer higher-risk fatalities than expected among this demographic.

Lastly, I estimate the amount of "excess deaths" by constructing a number of counterfactual scenarios. If every individual faced the same risk of death *ex ante* we would replicate the well established fact that Black civilians face 50% excess deaths. This difference cannot be accounted for by geography: i.e., results are not driven by Black people being overrepresented in places where there is a uniformly lower threshold for using deadly force. If instead, the counterfactual is based on the number of felonious killings of on-duty officers, the number of excess deaths of Black males flips sign: there are 627 *fewer* fatalities between 2016 and 2020 than expected. Strikingly, the difference in excess deaths calculated in this fashion and those constructed with my measure of objective risk is only 10% of the total number of Black citizens killed by police. I then show that 80% of this gap is accounted for by that group's higher survival rate. In other words, the total number of police shootings (deadly or not) involving Black civilians is in line with my estimates that account for risk of aggravated assault to officers. In order to overturn my main result (i.e., that the number of excess deaths of Black civilians is non-positive) police would need to overestimate on average the risk posed by Black males who were arrested by almost 30%.

Overall, my results suggest that the large number of Black males killed by police is explained by their higher likelihood of interaction and arrest (*exposure*), and not by officers holding a lower threshold for using deadly force against them conditional on exposure (*extensive margin*), or by a higher *intensity* in the use of lethal force.[6] On the contrary, I do observe some indications that Hispanic civilians enjoy less leniency from officers during arrest attempts. This could be partly explained by language barriers that could make it harder for members of that demographic to follow police commands. Thus, to limit the staggering and tragic loss of life among minorities, policies should be implemented that address the underlying forces that lead Black and Hispanic males to be arrested and interact with police at such high rates, including socio-economic inequality and, possibly, over-policing. It could also be worthwhile to teach officers basic commands in Spanish. While investing in more equitable treatment during interactions might yield some improvements, my work suggests that these gains are limited.

Previous literature, originally rooted in labor economics, has studied racial bias in police searches with mixed results.[7] Recent articles have started studying inequity at the highest level of force (see for example Hoekstra and Sloan (2022) and Fryer (2019)). This article is closest to Fryer (2019), with some important differences. First, while that article uses police reports from departments that voluntarily shared these data, I will consider all deadly shootings in the country and arrest reports from a much larger sample of jurisdictions covering 60% of the US population. Secondly, because I explicitly estimate the objective risk to officers I can detect heterogeneous differential effects of race on the use of deadly force. Third, this index allows me to match individual fatalities with comparable (in terms of objective risk) arrests, and thus to compute the likelihood of death (shooting) as a

[6]These results are consistent with our intuition. Consider that using deadly force carries extraordinary costs to an officer, even under the "best" of circumstances. For instance, officers may face psychological repercussions and social costs from this event, as well as criminal, and potentially even civil, liability. In that sense, deadly shootings would be the last place we would expect racial bias to manifest.

[7]Knowles, Persico and Todd (2001) developed a simple model that illustrates the role of discrimination during police searches for contraband, which is based on the probability of success in the search. Their original insight influenced much of the subsequent literature. In their application, they failed to find evidence of racial bias against Black, but not Hispanic motorists. Anwar and Fang (2006) extended their model to allow for different behavior by officer's race and relaxed the assumption that civilians of a given race carry contraband at the same rate. They also failed to find significant evidence of discrimination. On the contrary, Antonovics and Knight (2009) show that the patterns of searches on motorists can be explained by taste discrimination against certain minorities, but not by statistical discrimination. Fryer (2019) finds a higher likelihood of ordinary force against Black individuals, even in circumstances where officers reported compliance from them.

function of objective risk and race. Lastly, this article is also related to a smaller literature that has used shares of fatalities (relative to the population, or to the estimated criminal population). Compared to Ross, Winterhalder and McElreath (2021) and Cesario, Johnson and Terrill (2019) I am able to study the under or over-representation of civilians in terms of casualties across comparable risk brackets. Because the legal justification for using deadly force references risk to officers, this is likely a better comparison.

This article is divided as follows. In section 2 I discuss in detail the datasets used here. Section 3 describes how a typical OIS develops. Section 4 presents my empirical results. In section 5 I develop a simple model to explain some of the patterns observed in the data. Finally, section 6 offers some concluding remarks.

2 Data

I rely on micro-data at the incident level from the National Incident Based Reporting Systems (NIBRS). This FBI-led dataset "captures details on each single crime incident –as well as on separate offenses within the same incident –including information on victims, known offenders, relationships between victims and offenders, arrestees, and property involved in crimes.[8]". NIBRS was created to address known shortcomings from the Uniform Crime Reporting system (UCR), which is not currently able to provide adequate information on crime[9]. The incident-level structure of NIBRS, where individual events are uniquely codified for a given law-enforcement agency, allows me to match offenses to victims, offenders, arrestees and high-level information of the incident including the agency/ies involved, geographic coverage and date and time of the event.

Increasingly, law-enforcement agencies are transitioning to NIBRS to report data to the FBI. Table 1 describes the geographic coverage of NIBRS on an annual basis. The number of agencies in the program rose from 14,670 in 2016 to 16,781 in 2019, a 14.4% increase. The

[8] FBI. Consulted June 14, 2022.
[9] Multi-agency Letter in Support of the NIBRS Transition. Consulted June 14, 2022.

reduction observed in 2020 likely reflects the fact that some agencies did not submit records on time. Importantly, the population covered by agencies in the program increased 50.6% from 127.8 in 2016 to 192.5 million in 2020.

I also rely on data from the FBI's Law Enforcement Officers Killed and Assaulted program (LEOKA) to construct shares of felonious killings for racial and ethnic groups to serve as proxy for share of justifiable homicides in some of the exercises. The program captures aggregate data of incidents where a sworn, on-duty officer with full arrest powers, who was in possession of a badge and firearm died as a result of felonious injuries. Between 2011 and 2020 a total of 503 officers were killed in the line of duty by 502 known offenders.

Data on police shootings comes from the Washington Post, and comprises every on-duty OIS since 2016. It includes indicators for the race of the deceased, the presence of weapons, date, geo-location, circumstances, and an indicator for mental health crisis. The database is constructed from news reports, statements by law-enforcement, third-parties (such as *Killed by police* and *Fatal encounter*), as well as the Post's own investigation. The reader should note that the Post only tracks incidents where an on-duty officer killed a civilian. I present some descriptive statistics from both NIBRS and the Post's database in section 3. The data from the Post is broadly in line with other authors who have relied on vital data. Buehler (2017) reports that the number of deaths per million among non-Hispanic Black and Hispanic males are 2.8 and 1.7 times higher, respectively, compared to non-Hispanic White males. Using data on the number of killed between 2016-2019 from the Washington Post and total number of males from the census I calculate that non-Hispanic Black males experience 11.34 police deaths per million, compared to 5.38 for Hispanic and 4.3 for non-Hispanic White individuals. Thus, similar to Buehler (2017) I find that Black and Hispanic males face 2.64 and 1.25 times higher mortality.

I rely on "Shot by Cops" from Vice News to study the lethality of critical incidents as a function of event characteristics and race. Vice News constructed this database from information voluntarily submitted by 47 out of the 50 largest police departments in the country and covers 2010 through 2016. Crucially, it includes both lethal and non-lethal critical incidents involving police. In addition to the typical event characteristics, it also attaches a brief description of each incident and information on the race and number of responding officers. Lastly, population figures for the racial and ethnic groups considered here comes from the Census Bureau. I use these data for some of the counterfactual exercises.

3 Assaults on police and a typical OIS

While each individual OIS is unique, some patterns emerge by studying a large collection of cases. This section intends to provide the reader an understanding of the individuals involved, their behavior, the role of weapons, and general details about the incidents.

A natural place to start the discussion are assaults on officers, as they are integral to classifying an otherwise second-degree homicide or manslaughter (felony) as a justifiable homicide (not a felony). The number of assaults on officers throughout the day follows a U-shape with a maximum at midnight and a minimum at 6 hours. This pattern roughly holds for both ordinary and aggravated assaults, which exhibit approximately the same 3:1 ratio throughout the day (figure 1). The distribution of OIS is similar in that it reaches a minimum at 6 hours. However, the maximum number of deadly incidents occurs between 16 to 18 hours in the afternoon (figure 2).

Assaults on officers are mostly carried-out by males, who also constitute the overwhelming majority of those killed by police. Figure 3 shows that for every ordinary assault involving a female there were almost two and a half times as many involving males. The ratio is almost 1:4 among aggravated assaults, and even more extreme for deadly OIS, where almost every recorded case involves a male. There is little difference in the ratio of males in assaults on police (71-77%) and deadly OIS (94-97%). Because the drivers of these incidents might differ between genders and the ratios are unbalanced, I concentrate the rest of the analysis on this demographic.

Table 2 shows basic descriptive statistics in incidents of ordinary, aggravated assault, and deadly shootings. In terms of the distribution of assaults and deadly shootings, White civilians carry-out the majority of aggravated assaults (60%) and constitute the majority of those killed by officers (51%), followed by Black (27.3%) and Hispanic individuals (9.1 and 19.1%).

White offenders who commit assault on police are considerable older than their Black and Hispanic counterparts (34.8 years vs 30.3 and 30 years, respectively). A similar pattern can be seen among deadly OIS, where White civilians are 6.2-7.5 years older on average. This difference is the result of a large fraction of young individuals from minority groups among those who commit assaults on law-enforcement and who are killed in OIS (figure 4).

Handguns are the primary firearm present in aggravated assaults: Black suspects carry them in 16.4% of cases compared to 8.9 and 7.3% for Hispanic and White individuals. Long guns (i.e., shotguns and riffles) are much less common than handguns, and it is mostly White individuals who carry them. Importantly, long guns are significantly over-represented among felonious killings of on duty-officers: riffles alone contribute to 19.6% of all fatalities, while shotguns cause 4.3% of deaths[10]. The Washington Post does not make a distinction between long and handguns, which forces me to classify any such weapon system simply as a "firearm". As one might expect, firearms are notably more common among deadly shootings with 65.6, 64.4 and 56.5% of all Black, White and Hispanic individuals carrying them. Lastly, I do not observe significant differences in the share of suspects who were in possession of a replica gun: less than 0.2% of Black and Hispanics killed by police had one, compared to twice that fraction among White suspects[11]. Notably, I do observe a higher fraction of unarmed Black and Hispanic civilians killed by police (16.5%) compared to White individuals (14%).

Police registers the offensive use of knives at lower rates than hand-guns in aggravated

[10]Source: FBI, Law enforcement officers killed & assaulted (LEOKA), Figure 5, accessed June 28, 2022.

[11]While this could be interpreted as evidence consistent with limited or no racial bias, I would caution the reader against drawing conclusions in any direction. In the state of Pennsylvania, for instance, the "stand your ground" statue explicitly mentions replica guns as one of the possible requirements for the statue to apply, alongside actual firearms (§505(b)).

assaults on law-enforcement[12], particularly among Black suspects. Knives also account for less than 1% of all officer fatalities[13]. A reasonable fear is that police would miss-classify inconspicuous items as "blunt weapons", or report the offensive use of a car more often among minority suspects if a fraction of officers are racially biased. The evidence, however, is ambiguous in this respect: Hispanic males reportedly use blunt weapons more often than White males during aggravated assaults and deadly shootings, while Black males use a car offensively more often than White males in both types of events. Cars are used more often during aggravated assaults than firearms, while blunt weapons appear half as often. In the case of deadly shootings, however, firearms are one order of magnitude more common than either type of improvised weapon. This could indicate that officers leverage the increased discretionary time they get when dealing with these improvised, close contact weapons, to secure a peaceful surrender or rely on less lethal means to subdue a suspect.

Table 6 provides descriptive statistics on fatal and non-fatal shootings that were recorded and then voluntarily shared to Vice News by 47 out of the 50 largest police departments in the country. During critical incidents involving a single male, Black individuals experience the lowest mortality rate of any racial and ethnic group. 30.9% of males involved die as a result of their injuries, while Hispanic and White civilians die in 40 and 54.3% of critical incidents, respectively. There is little difference in the average number of responding officers (approximately 1.5), or the number of rounds fired by law enforcement (approximately 6.5).

According to the Post (table 2), Whites were more likely to exhibit signs of a mental health crisis during the course of an OIS than minorities (almost, twice as often as Black

[12]The FBI instructs law-enforcement agencies to only report the presence of a knife if it is used offensively, since these are also commonly used tools. The Washington Post does not make that distinction. Knives are relatively more rare in shootings partly due to specific rules of operation of certain police departments. For instance, in this particular incident, a San Diego PD officer initially fires a shotgun loaded with bean-bags as ammunition (less lethal) at close quarters against a woman brandishing a chef's knife (a lethal weapon). Officers only open fire with live rounds after the woman lounges towards the officers and manages to stab one of them in the chest. The woman who was shot died from her injuries, while the on-duty LEO was subsequently discharged from hospital.

[13]See footnote 10.

people). White suspects actively attacked police at a similar rate compared to Black suspects (67%). Table 3 presents descriptive statics on behavior exhibited during a deadly OIS. White suspects are *more* likely to be killed while attacking an officer, while exhibiting signs of mental distress compared to Black and Hispanic suspects. A similar pattern can be observed in the number of civilians killed who exhibited mental distress, and among those who in addition to this did not possess a weapon. Thus, the descriptive facts do not suggest that officers rely more often on claims of "aggressive" behavior to justify deadly fire against minority suspects. In terms of accountability, the presence of bodycams (which critically could hide unjustified use of force) is *more* common in shootings of Black and Hispanic, rather than White individuals.

4 Empirical results

4.1 A model of objective risk to officers

I explicitly estimate the objective risk of aggravated assault to officers, as a means of anchoring the analysis on the legal justification for using deadly force. To do so I consider records from NIBRS where an officer suffered either an aggravated or an ordinary assault in the line of duty (96,299 incidents in total). To avoid ambiguity I limit the analysis to events that involved a single, male offender. This reduces the number of observations to 62,345 (64.7% of total).

To estimate the model of objective risk I train a random forest algorithm to distinguish between aggravated and ordinary assault. In section 4.2 I project the estimated risk of aggravated assault (*objective risk*) on events that became a deadly police shooting (as reported by the Post). I then look at differences in the distribution of objective risk across racial groups, in order to investigate potential different thresholds for the use of deadly force. In section 4.3 I rely on a 5% random sample of arrest from NIBRS to project the risk metric. There, I estimate differences in mortality and likelihood of OIS for individuals of different races, but with similarly high objective risk. My goal is to determine whether police avoids escalating to deadly force in interaction with non-minority individuals at greater rates. In section 4.4 I look at the factors that affect civilian survival during an OIS. Lastly, in section 4.5 I construct counterfactual scenarios using some of the results from previous sections to estimate the number of *excess deaths*.

4.2 Analysis of deadly OIS

I project my measure of *objective-risk to officers* discussed previously onto the Washington Post database on deadly OIS. The latter records the deaths of 6,333 males and 298 females (4.5% of the total) by police between 2016 and 2020. I use only records belonging to males throughout the analysis, as I have less power to identify the potentially different dynamics of female deadly OIS.

The parameters of the model used for projection were selected through 10-fold stratified cross-validation[14]. I then chose the model with the highest out-of-sample average balanced accuracy[15]. Note that this model is constrained by the set of variables that are observed both in NIBRS, and in the Washington Post database, which are: indicators of firearm, knife, blunt weapon, explosives, offensive use of a car, age of the individual killed, date of the event, and the state where the incident took place. My selected model, which I call **Model I**, fits 500 trees[16] using as inputs: indicators for firearm, knife, blunt weapon, offensive use of a car, and state[17].

Table 16 presents the confusion matrix of a randomly chosen fold. Tables 17 through 19 show these matrices for the subset of Black, Hispanic and White individuals. I report out-

[14]Stratified cross-validation is necessary due to the unbalanced distribution of labels: there are 44,275 incidents of ordinary assault compared to only 18,070 aggravated assaults.

[15]Balanced accuracy is defined as the arithmetic mean accuracy across categories (i.e., ordinary and aggravated assaults).

[16]Splits in this model are selected to minimize entropy, subject to the requirement that each node has at least 12 records.

[17]I also estimated a parsimonious model, which should be less affected by intentional misreporting in which I only use an indicator of firearm and the state of occurrence. This model has an average, out-of-sample balanced accuracy of 0.66.

of-sample performance in table 7. The model exhibits a balanced accuracy of 0.77 with little heterogeneity across groups, with the exception of Hispanics. For this sub-set balanced accuracy is 2% lower, on account of worse-than-average specificity and precision.

Figure 5 depicts the corresponding distribution of objective risk by racial group among deadly OIS. I find a slightly larger proportion of Black males among those that presented less risk to officers, relative to White and Hispanic males (e.g., the cumulative fraction of Black males with an associated probability of aggravated assault below 0.5 is higher than that of other groups). The fraction of low-risk individuals is smallest for White civilians after controlling for state fixed effects (figure 6).

Table 10 shows the point estimates of risk as a function of racial identifiers. I find negative, statistically significant point estimates for Black males in every specification that does not control for state fixed effects (columns 1, 2, 4). My preferred specification includes state fixed effects (column 5) to account for differences in access to firearms and trauma centers which have been shown to influence the number of fatalities (Nagin (2020)). Using that specification, I fail to find differences in the average risk posed by civilians of any race.

Table 11 runs similar regressions as that in column 4 separately across more homogeneous sub-sets of individuals, using my preferred specification. Column 1 restricts the sample to incidents where the Washington Post reported signs of mental illness of the civilian killed. Column 2 includes only individuals who were in possession of a firearm. This is possibly the most homogeneous group of all[18]. Column 3 shows point estimates in incidents where no bodycam was present. I do not find significant differences among Black and Hispanic, relative to White individuals. My results thus suggest that the distribution of risk among civilians killed is similar across races, although there is some evidence that minorities are over-represented in the lower end of the risk spectrum. I fail to observe evidence of police strategically withholding bodycam footage to cover unlawful uses of force against minorities, or officers deciding to not turn on their body-cams in critical incidents

[18] This goes back to the concept of firearms as force multipliers that level the playing field. As the old saying goes: *God created men equal. Colonel Colt made them equal.* (Smithsonian Magazine)

where they expect to use excessive force against minorities.

4.3 Analysis of arrests

Similar to Fryer (2019) I also analyze high-risk interactions that did not escalate to the use of deadly force. My goal is to test whether police systematically decides against using deadly force on non-minority suspects more often, even if they would have been justified in doing so (in other words, I investigate if White civilians enjoy more leniency from law enforcement). To do so I take a 5% random sample of incidents from NIBRS where an individual was either arrested on site or placed under police custody. I project onto these data the objective risk of aggravated assault to officers, as estimated from a random forest model (see section 4.2).

Using NIBRS for both training and projection[19] allows me to consider a richer model, than the one used for OIS. Notably, the resulting **Model II** differs only in the inclusion of an indicator of severe injury of LEO as control. The corresponding confusion matrix for a randomly selected fold of the stratified cross-validation is presented in table 20. Tables 21 through 23 show confusion matrices by racial groups. As before, table 7 summarizes the performance of the models. Similar to Model I, I find equivalent out-of-sample performance for White and Black civilians, whereas balanced accuracy is 2% lower than average for Hispanic males.

Figure 10 shows the likelihood of death for civilians who were arrested by law enforcement. The assumption here, and throughout the analysis of arrests, is that civilians who were killed would have been arrested otherwise. As we would expect, mortality is fairly limited for lower-risk arrestees (there is however, a spike for Black males with associated risk of $[0.2, 0.3)$ and for Hispanic civilians with risk of $[0.4, 5)$). The probability of death increases sharply at around 70-80% chance of aggravated assault and reaches its maximum for every group at 80-90%. Surprisingly, mortality in the cell with the highest

[19] Projections used in my analysis are always strictly out-of-sample.

risk is moderate. Black civilians experience the lowest mortality of any group at 80-100% risk.

Figure 8 shows the cumulative distribution of objective risk to officers among those arrested, by race. Above 0.7, the distribution of Black arrestees dominates that of Hispanic males, which in turn dominates the distribution of White suspects. In other words, the right tail in the distribution of risk for Black civilians includes more mass than that of the other two racial and ethnic groups. Figure 9 shows the fraction of arrests of Black, White and Hispanic individuals for the 25, 50, 75, 90, 95 and 99 percentile of arrests by objective risk (the average risk of aggravated assault to officers increases as we move from left to right). The dotted lines in figure 9 denote the relative shares among those killed by police. If LEO's are agnostic with respect to race we would expect the shares for any given racial and ethinic group and to approach those observed among deadly shootings as we consider groups of individuals that presented more risk to officers. From the 90th. percentile onward Hispanic individuals are under-represented, while White and Black civilians are exactly and over-represented, respectively.

Table 8 shows point estimates for a linear probability model of the likelihood of being killed (shot) during an arrest among civilians in the 50th, 75th and 90th percentile of risk. White individuals at the 75th and 90th percentile experience approximately 1% higher likelihood of death and arrest compared to Black civilians, the omitted category. This result holds if we consider a predictive model of aggravated assault that only considers the state where the events occurred, and the presence of a firearm. Furthermore, all coefficient estimates are statistically significant at 5%. Hispanic males experience approximately similar mortality than their Black counterparts. In some specifications Hispanic ethnicity is associated with a higher likelihood of being shot, and in others with a lower probability. Point estimates for Hispanic are approximately half in magnitude compared to White.

The evidence from arrests thus suggests that for the most part police does not differentially use deadly force against minorities in similarly risky scenarios. I fail to find evidence that there is a lower threshold for using deadly force against minorities or that White civilians receive more leniency. This however, masks some incidents where low-risk Black and Hispanic civilians appear to have been shot at higher rates than their White counterparts. Lastly, the evidence also suggests that high-risk Black arrestees face a lower probability of death or lethal force than comparable White offenders.

4.4 Surviving an OIS

An unfortunate aspect of the current available data is that it mostly centers around incident where a civilian died as a result of injuries sustained. A notable exception is the "Shot by Cops" database produced by Vice News. As previously discussed, it includes 47 out of the 50 largest police departments that agreed to share these data, and hence is not nationally representative. In this section I discuss which factors contribute to the deadliness of an OIS from the perspective of the civilian involved. Note however, that the relationship between the level of deadly force that officers attempt to use and the ultimate outcome is far from clear: a LEO who is being chased by a knife-wielding attacker and who is in great fear for their life might shoot more rounds than an officer who faces less fear (perhaps because there is more distance to the attacker). While it's true that *ceteribus paribus* more bullet impacts would reduce the chance of surviving, it's also the case that there is a trade-off between accuracy and speed of fire, which means that shooting more rounds could paradoxically lead to fewer hits or hits to less anatomically relevant parts of the body.

Notwithstanding, I estimated the likelihood of dying during the course of an OIS as a function of event, civilian and responding officer(s) characteristics. Table 12 shows point estimates for a logit regression where the dependent variable is an indicator for fatal shooting. Relative to Black, the omitted category, White individuals face higher risk of death, although the point estimate is not significant when including age fixed effects. Figure 12 shows the average marginal effects of several components in a shooting. I measure no increase in lethality from being in possession of a firearm for Black males, while the increase is similar for Hispanic and White individuals. Using a knife offensively also yields large increases in mortality. The marginal increase is largest for Hispanic and lowest for White citizens, perhaps on account of a much higher baseline mortality. Hispanic individuals seem to benefit the most from having a responding officer of the same ethnicity as them, which could be explained by language barriers. White civilians benefit the least from this. Lastly, as expected, I observe increases in lethality as the number of responding officers increase, possibly due to more rounds being fired. Facing 3 or more responding officers dramatically reduces the chance of survival, especially for Hispanic and Black individuals.

Table 13 shows the average marginal effect of race and ethnicity on the chances of surviving an OIS. Hispanic individuals do not appear to pay a "premium" relative to Black citizens (the omitted category), whereas White males face 17% fewer chances of survival in the model without age fixed effects. This difference is reduced by one quarter when including them, which likely stems from the fact that White suspects tend to be much older than the comparison group, and potentially less physically resilient. Still, I'm not able to explain why White individuals have 12.6% more chances of dying from police fire. This is a topic for future research.

4.5 Counterfactuals

In this section I calculate the expected number of civilians killed and shot by police under various assumptions. First, I investigate whether the patterns in the data can be explained by the geographic distribution of people: for instance, minorities could be concentrated in areas where there is a uniformly lower threshold for using deadly force. Next, I look at whether the distribution of risk among individuals arrested is able to account for these stylized facts. In order to do that, I initially construct estimates of the risk of deadly OIS based on group's share in felonious killings of officers. Lastly, I divide the sample of individuals placed in custody into non-overlapping cells based on objective risk and compute the likelihood of deadly OIS for each cell. I do this in order to account for the different distributions of risk across racial and ethnic groups. I summarize these counterfactuals by computing the number of *excess deaths*, which are defined as the difference between the observed and the projected number of deaths for each group.

I rely on the US Census[20] to compute counterfactuals based on population shares. For the purpose of this exercise I consider only individuals who are White, Black and Hispanic. Together, these groups constitute 90.1% of the entire US population and 88.6% of all individuals killed by police. Table 9 shows that, nationally, 595 Black men were killed *in excess* between 2016 and 2020. This figure represents 49.6% of all Black men killed by police. Hispanic individuals are only slightly over-represented in this metric with 41 excess deaths (4.8% of all cases). White individuals are under-represented by 27.5%, which translates into 636 fewer deaths than what we would have expected. Importantly, a similar pattern can be seen if we impute the likelihood at the state[21] or geographic region level[22]. While this simple exercise in descriptive statistics does not prove by itself racial bias on the part of police, it suggest that the patterns that we observe cannot be accounted for by the distribution of individuals in space.

Next, I construct a measure of excess deaths by using the shares by race and ethnicity observed during felonious killings of on-duty officers. Because Black individuals account for 37.1% of those felonies and 22.9% of those killed by police the number of excess deaths for this group is -627 (i.e., we would expect more Black males to be killed by police than what we observe). This specific metric has the desirable property that it naturally links to existing laws of self defense: by definition, officers would have been legally allowed to open fire on anyone who ended killing a LEO. It requires, however, the assumption that the shares of felonious killings are proportional to the number of incidents where law enforcement would have been justified in using deadly force. As I explain in table 9 the FBI

[20] Annual County Resident Population Estimates by Age, Sex, Race, and Hispanic Origin. Accessed June 24, 2022. Because Hispanic origin is considered an ethnicity and not a race, some White and Black individuals are also counted as Hispanic. I explicitly define a Hispanic individual as one who self identifies as one. I then denote Black and White individuals as those who identify as such, and who are *not* Hispanic.

[21] See table 14

[22] Regions as defined in the FBI's NIBRS documentation. See table 15

considers “Hispanic” an ethnicity and not a race. Thus, some Black and White individuals are assigned both labels. I attempt to correct this by imputing the shares of White-Hispanics and Black-Hispanics reported in NIBRS’ arrest tables. This correction only changes the number of excess deaths for Black people from -627 to -605, but is able to account for 3/4 of White excess deaths.

In the last two rows of table 9 I leverage the predictions from Model I (section 4.2) to assign arrested and killed individuals to cells based on their respective objective risk. Cell $k = 1$ includes individuals with estimated risk of aggravated assault of $[0, 10\%)$, cell $k = 2$ with $[10, 20\%)$, etc. Within a cell and race I then compute the hazard rate by dividing the number of civilians killed between 2016 and 2020 by the number of individuals arrested during the same time period. To construct the denominator I scale the number of arrests in NIBRS with the inverse of the sampled fraction (0.05) and with the inverse of the population covered by NIBRS-reporting agencies relative to the US population. My last exercise (“Risk-adjusted mortality”) is in the spirit of the “population shares” literature. I calculate the hazard for a given cell by pooling all the arrests and fatalities from every race. Then I construct my counterfactual number of deaths by multiplying the number of individuals of each race with the respective hazard of a given cell. Strikingly, excess deaths for Black citizens, -615, are off by 2% relative to the counterfactual using felonious killings of on-duty officers as basis, and 1% off when we correct for Hispanic ethnicity. In this counterfactual it is White (9.9% of deaths), and especially Hispanic (33.4% of deaths) people the ones who are over-represented in deadly OIS.

In the lower panel of table 9 I replicate the same set of counterfactual scenarios, but now using the number of OIS, as opposed to fatalities. Because there is no reliable data on non-fatal shootings, I re-scale the number of deadly OIS by the inverse of the mortality rate for a given group. For Black civilians who experience 30% mortality one death corresponds then to 3.3 shootings, whereas for White civilians with 54% mortality the figure would be 1.85. This re-scaling naturally has the effect of further increasing the overrepresentation of

Black males relative to their share in the population. Interestingly, the number of excess shootings for Black civilians is -283 when I consider as basis that group's share in felonious killings of officer and when I adjust for Hispanic ethnicity. Observed and predicted shootings under that counterfactual are only 9% apart, an 80% reduction relative to when I considered fatalities. Lastly, the counterfactual scenario relying on risk-adjusted mortality diverges somewhat from the latter one (I record -18.7% excess shootings). Still, taking into account survival rates and risk to officer is able to account for more than half of the excess previously recorded.

5 A model of police behavior

In this section I develop a simple discrete choice model to explain some of the seemingly contradictory findings that I have reported so far. First, let's consider an officer who engages a civilian who might kill him or her with probability Ψ. In this setup there is a continuum of officers with measure 1 and a fraction λ of them are racially biased ($\theta = 1$) against Black people (B). Civilians who are not B are W. After observing the civilian's racial identity and having estimated the risk posed, officers decide whether to use deadly force ($h = 1$) or not ($h = 0$). Lastly, our agent can survive or not the interaction. If he or she uses deadly force, then the probability of surviving is 1, and otherwise assumes a subjective probability of survival of p, which is composed of the true likelihood Ψ and an overestimation v_3 of the risk posed by B for type $\theta = 1$ officers. In this simple model agents dislike dying and using deadly force, especially against B among $\theta = 0$ officers. The pay-offs are described by

$$U = (1 - h)\left[p \times u(dead) + (1 - p) \times u(alive)\right] + h\left[u(alive) - v_1 - v_2(1 - \theta) \times B\right] \tag{1}$$

$$p = \Psi + v_3\theta \times B$$

After normalizing $u(dead) = 0$ and $u(alive) = \kappa > 0$ we can simplify

$$\begin{aligned} U &= (1-p)\kappa + p \times h \times \kappa - v_1 \times h - v_2(1-\theta)h \times B \\ p &= \Psi + v_3\theta \times B \end{aligned} \tag{2}$$

Let's denote by U^h the utility when using deadly force, and U^o otherwise

$$U^h = \kappa - v_1 - v_2(1-\theta) \times B \tag{3}$$

$$U^o = (1 - \psi - v_3 \times \theta \times B)\kappa \tag{4}$$

An officer uses deadly force if and only if:

$$U^h \geq U^o \tag{5}$$

$$\kappa - v_1 - v_2(1-\theta) \times B \geq \kappa - \Psi \times \kappa - v_3\theta \times B \times \kappa \tag{6}$$

$$\Psi \geq \frac{v_1 + (v_2(1-\theta) - v_3\theta \times \kappa)\, B}{\kappa} \tag{7}$$

The likelihood of using deadly force is the same for either type of θ whenever the suspect is not B:

$$\Psi \geq \frac{v_1}{\kappa} \tag{8}$$

The likelihood of h for a $\theta = 0$ officer paired with a subject B is *lower* compared to subjects W:

$$\Psi \geq \frac{v_1 + v_2}{\kappa} \geq \frac{v_1}{\kappa} \tag{9}$$

Lastly, the probability of deadly force for $\theta = 1$ officer who is paired with a Black individual is

$$\Psi \geq \frac{v_1 - v_3\kappa}{\kappa} \tag{10}$$

From this we can construct the response function of both types of officers. The table below summarizes these insights.

Risk	Action by $\theta = 1$ officer	Action by $\theta = 0$ officer
$[0, \frac{v_1 - v_3\kappa}{\kappa}) \equiv R_1$	$h = 0$	$h = 0$
$[\frac{v_1 - v_3\kappa}{\kappa}, \frac{v_1}{\kappa}) \equiv R_2$	$h = 1$ iff $B = 1$	$h = 0$
$[\frac{v_1}{\kappa}, \frac{v_1 + v_2}{\kappa}) \equiv R_3$	$h = 1$	$h = 1$ iff $B = 0$
$[\frac{v_1 + v_2}{\kappa}, 1] \equiv R_4$	$h = 1$	$h = 1$

Let's assume now that there is a measure 1 of civilians in this population who are randomly paired with officers (one can think of this population as individuals who are placed in custody). A share $s^B = 1 - s^W$ of these civilians are Black. The likelihood of a Black civilian being killed is:

$$P(h|B = 1) = \chi\left[\Psi \in R_2, R_3\right]\lambda + \chi\left[\Psi \in R_4\right] \tag{11}$$

where χ denotes the indicator function. The conditional likelihood of being killed for a White citizen is

$$P(h|B=0) = \chi\left[\Psi \in R_3, R_4\right] \tag{12}$$

From this we can derive some implications of the model

1. A fraction λ of moderate-risk (R_2) civilians are killed, but only if they are Black
2. A fraction λ of higher-risk (R_3) Black civilians are killed, whereas all White individuals with the same risk profile are shot
3. All citizens that present a high risk (R_4) are killed

The model thus implies a higher share of lower-risk, and a lower share of higher-risk Black citizens killed. Whether ex-ante B types face more hazard depends on the respective distributions of Ψ, and the fraction of $\theta = 1$ officers.

The number of felonious killings of officers is affected by racial bias through two channels:

1. $\lambda \times G_2 \times s^b$ *fewer* officers are killed by lower-risk Black civilians, where $G_2 \equiv F\left(\frac{v_1}{\kappa}\right) - F\left(\frac{v_1 - v_3\kappa}{\kappa}\right)$ and $F(\cdot)$ denotes the cumulative density of risk to officers when paired with B.
2. Higher-risk Black civilians kill officers in excess at a rate of $(1-\lambda) \times G_3 \times s^b$, where $G_3 \equiv F\left(\frac{v_1 + v_2}{\kappa}\right) - F\left(\frac{v_1}{\kappa}\right)$.

Racial bias leads to more officers killed whenever the increase in casualties due to bias exceeds its associated reduction. In other words, whenever

$$(1-\lambda)\times G_3\times s^b > \lambda\times G_2\times s^b \tag{13}$$

$$(1-\lambda)\times\left[F\left(\frac{v_1+v_2}{\kappa}\right)-F\left(\frac{v_1}{\kappa}\right)\right] > \lambda\times\left[F\left(\frac{v_1}{\kappa}\right)-F\left(\frac{v_1-v_3\kappa}{\kappa}\right)\right] \tag{14}$$

$$F\left(\frac{v_1+v_2}{\kappa}\right) > \frac{F\left(\frac{v_1}{\kappa}\right)-\lambda F\left(\frac{v_1-v_3\kappa}{\kappa}\right)}{1-\lambda} \tag{15}$$

Note that the numerator on the right is positive. It follows then that for any values of v_1, v_2, v_3 and for any underlying distribution with can find λ close to 1 such that 15 is violated, i.e., for a sufficiently large fraction of statistical discriminators racial bias reduces the number of officers killed (at the expense of more casualties among Black citizens). Conversely, for $v_2 > 0$ and λ sufficiently low 15 will hold. In other words, given enough reverse-taste discriminators racial bias will increase the number of officers killed.

6 Concluding remarks

In this paper I lay out a novel identification strategy anchored on the laws of self defense, which are used to assign criminal liability to officers involved in an OIS when appropriate. In doing so, I analyze these critical events from the perspective of first responders, which is what the Supreme Court mandates in this type of litigation.

I believe there are four fundamental questions that we need to answer to understand the use of lethal force by law enforcement: *are laws of self defense too strong or weak in the United States? Are minorities over-policed on account of race or ethnic background? Do non-minorities experience a lower likelihood of facing lethal force, ceteribus paribus?, and, is there a lower threshold for using deadly force against minorities?* Here, I attempt to answer the last two.

My results suggest that Black, Hispanic and White individuals represent on average the same risk to officers at the time of their deaths. Furthermore, I do not find differences in the intensity of force used: approximately the same number of officers respond to incidents and fire a similar number of rounds at civilians on average. During the course of the incident, White suspects pay a higher premium from being in possession of a firearm and die at higher rates compared to minorities. The latter difference cannot be accounted for by measured event, officer or civilian characteristics. This has the implication that only analyzing fatal outcomes underestimates the proportion of critical incidents involving minorities. I do not find evidence that police use hard-to-verify claims, such as mental state or aggressive predisposition, to try to justify shooting minority suspects at higher rates.

I do observe a lower likelihood that law enforcement escalates to using deadly force against Black males relative to similarly dangerous Hispanic or White suspects. This finding is quantitatively and qualitatively similar to what we would have learned from the share of felonious killings of on-duty LEO's: Black males constitute 23% of those killed by law enforcement and take part in 37% of felonious killings. It also matches our intuition if we consider the share of Black males who were in possession of a firearm during the course of an aggravated assault on a peace officer.

I rationalize the perception, often backed by bodycam footage, that police is sometimes more willing to open fire on lower-risk Black civilians with my findings of more leniency towards high-risk Black suspects through a discrete choice model where officers decide whether to use deadly based on perceived risk, race of the suspect, and whether they are statistical or reverse taste discriminators. Statistical discrimination might arise by the expectation that a Black male would be armed, based on the higher prevalence of handguns involved in assaults on officers among this demographic. On the other hand, some LEO's could be reverse taste discriminator in the sense that they especially dislike shooting Black civilians, perhaps out of fear of social costs, or increased scrutiny by a district attorney, who may ultimately face political pressure to levy felony charges. This simple framework is able to explain why we would expect to see more low-risk and less high-risk Black males killed by police, and how that group could be over represented in felonious killings of officers.

Overall, my findings suggest that in order to decrease the tragic loss of life among males from minority groups during police encounters we must first look at the *exposure* to policing. Policies that address systematic economic or social inequality among these groups have the potential to save more lives than strategies focused on the *extensive* margin, such as racial-awareness training in police departments. Reducing the likelihood that responding officers suffer an aggravated assault (for example, through effective gun control or by equipping them with retention holsters that make it harder for an attacker to steal an officer's gun) could also lead to fewer incidents in which deadly force is required.

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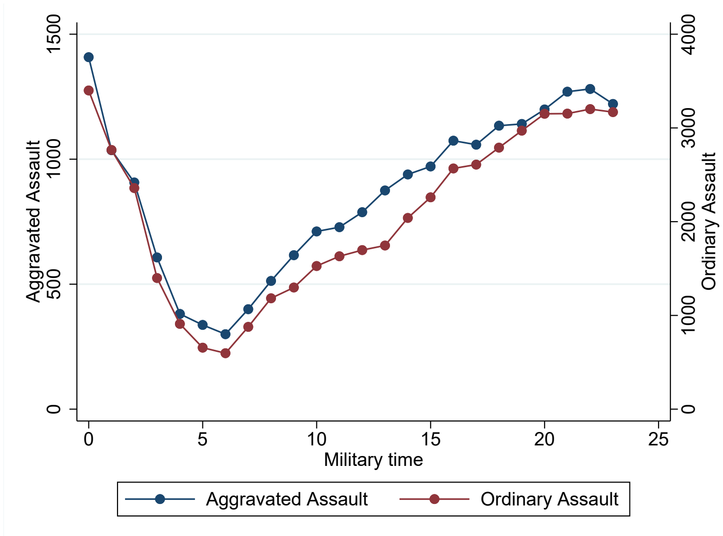
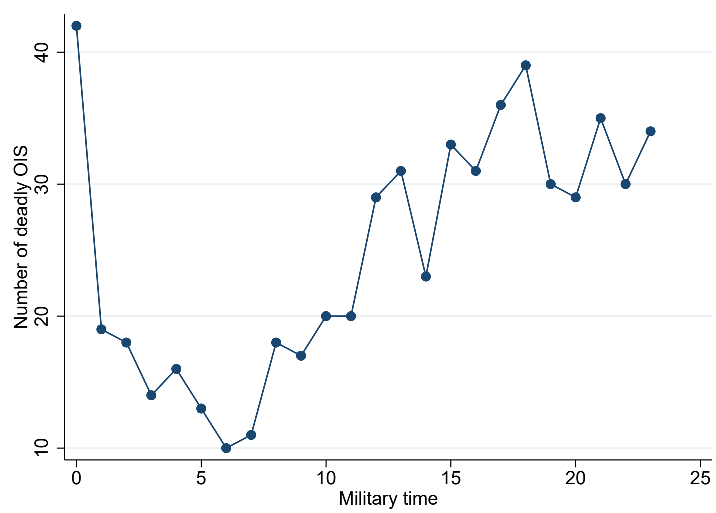
7 Figures and Tables

Figure 1: Timing of assaults against LEO's



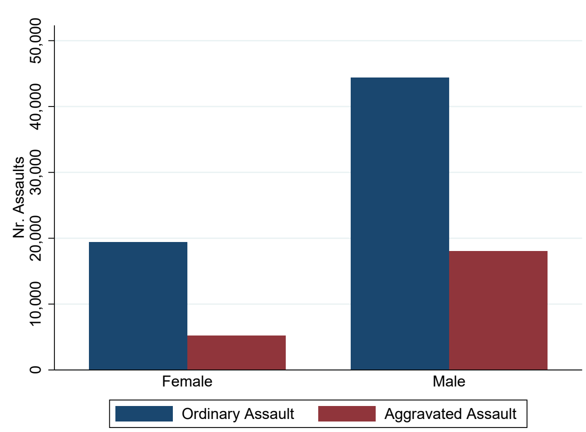
Note: This figure presents the number of reported assaults suffered by on-duty LEO's throughout the day. Own construction using data from 2016-2020 from the National Incidence Based Reporting System (NIBRS).

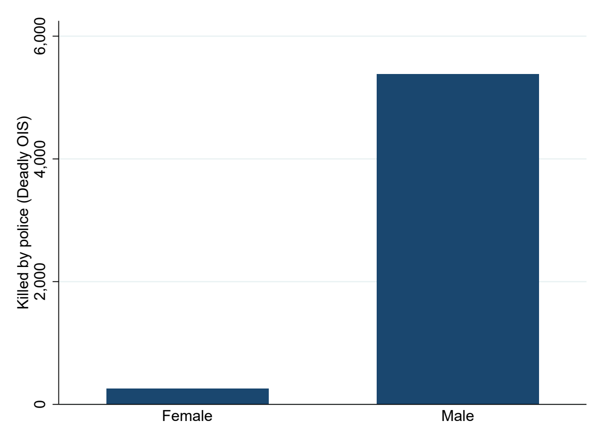
Figure 2: Timing of deadly OIS



Note: This figure presents the number of reported justifiable homicides committed by on-duty LEO's. Own construction using data from 2016-2020 from the National Incidence Based Reporting System (NIBRS). Note that the number of OIS reported in NIBRS is significantly smaller than the Washington Post database on deadly OIS. The latter, however, does not report the hour when the incident occurred.

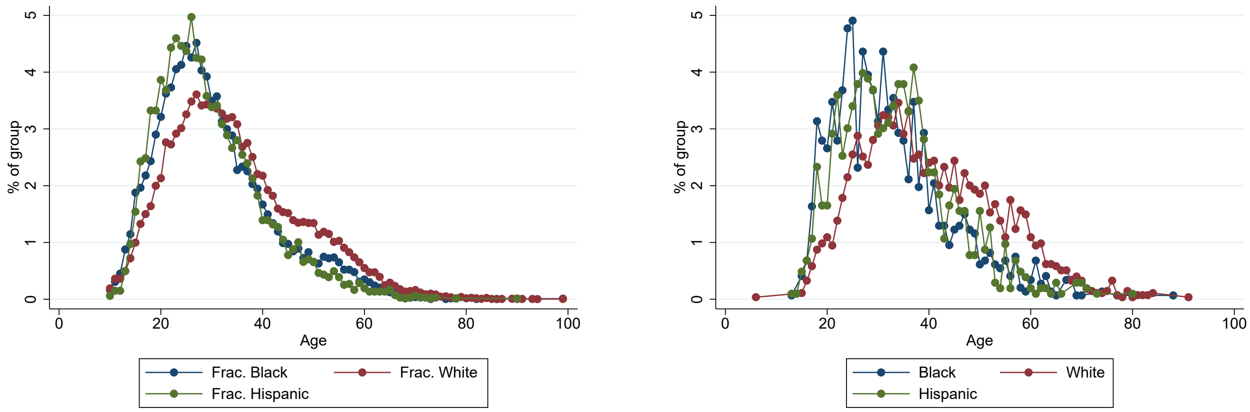
Figure 3: Gender and assaults on police/OIS





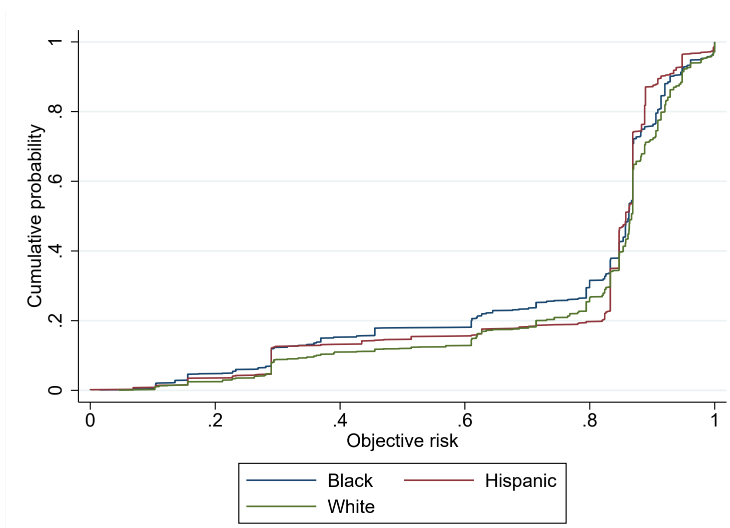
Note: Panel *a* shows the number of assaults on police by gender, from NIBRS (2016-2020). Panel *b* depicts the number of deadly OIS by gender, from the Washington Post database on deadly OIS (2016-2020).

Figure 4: Age distribution in assaults on police/OIS



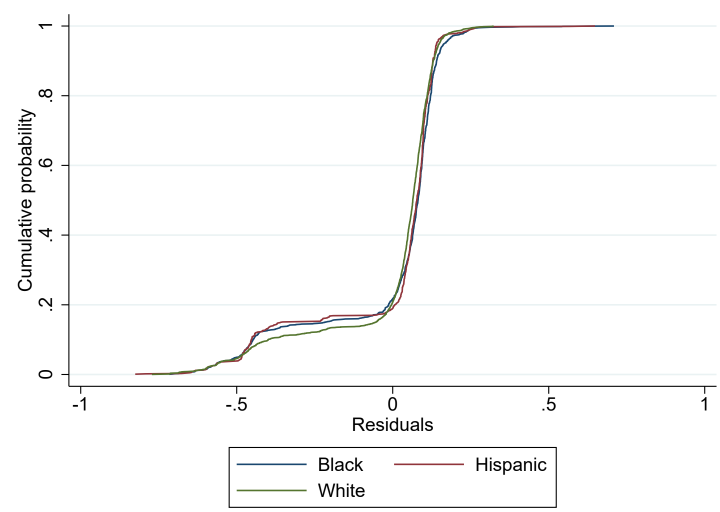
Note: Panel *a* shows the age distribution of perpetrator's of assaults on police by the perpetrator's race, using NIBRS data from 2016 to 2020. Panel *b* shows the corresponding figure for deadly OIS by race, from the Washington Post database on deadly OIS (2016-2020).

Figure 5: Objective risk to officer during OIS



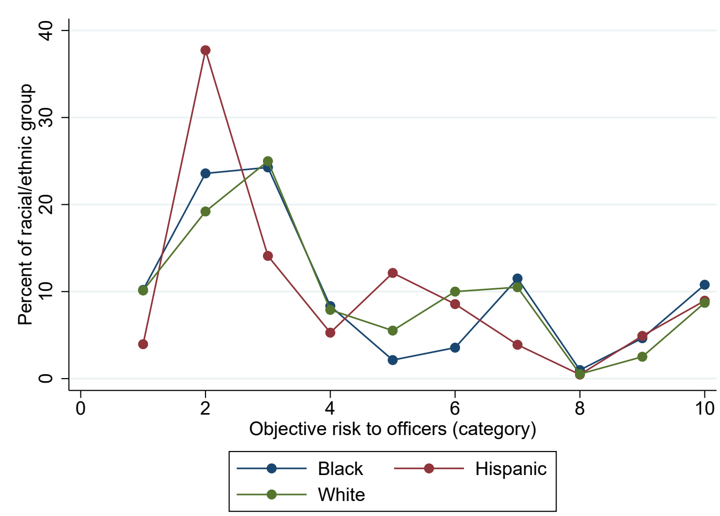
Note: This figure presents the CDF of objective risk among all deadly OIS recorded by the Washington Post. Predictive Model I is used to construct these estimates (see section 4.2).

Figure 6: Objective risk to officer during OIS



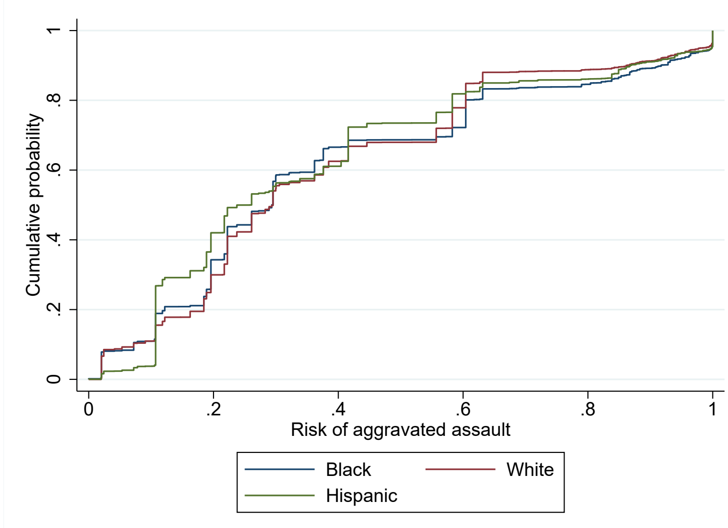
Note: This figure presents the CDF of objective risk among all deadly OIS recorded by the Washington Post. Predictive Model I is used to construct these estimates (see section 4.2).

Figure 7: Distribution of risk (arrests)



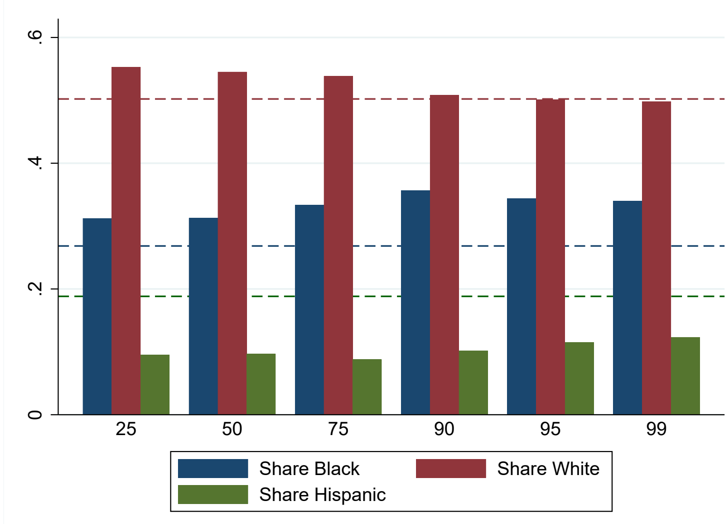
Note: This figure presents the PDF of objective risk among a 5% randomly selected sample of incidents from NIBRS where an individual was either arrested on site or placed in custody by law enforcement. Categories are defined in 0.1 increments starting from 0, i.e., category 1 includes individuals that presented 0-10% risk of aggravated assault, etc. Predictive Model II is used to construct these estimates (see section 4.3).

Figure 8: Cumulative distribution of risk (arrests)



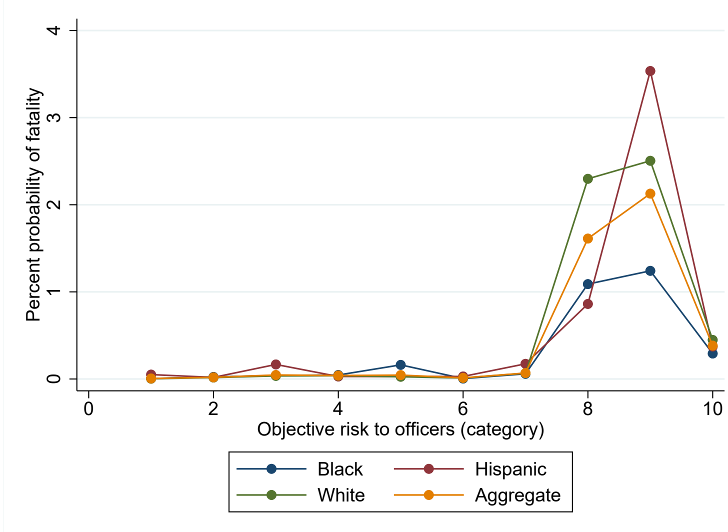
Note: This figure presents the CDF of objective risk among a 5% randomly selected sample of incidents from NIBRS where an individual was either arrested on site or placed in custody by law enforcement. Predictive Model II is used to construct these estimates (see section 4.3).

Figure 9: Racial composition by risk-level of arrest



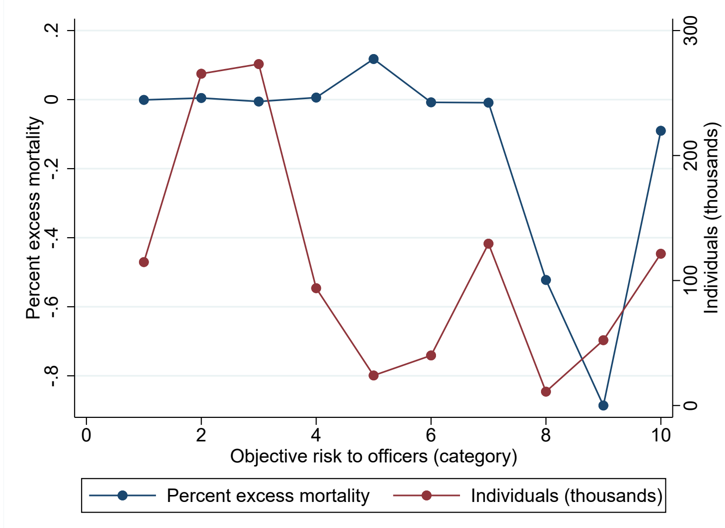
Note: This figure presents the relative racial composition of arrests by risk level based on percentiles of the objective risk distribution. For example, the first three columns describe the shares of arrests among the 75% most dangerous arrests (i.e., 25 percentile) for Black, White and Hispanic individuals, respectively. Columns for any given percentile do not add up to 1, because a small percentage of individuals not belonging to those three racial and ethnic groups was ignored. The dotted lines indicate the shares by racial and ethnic groups among those killed by police.

Figure 10: Probability of death as function of objective risk



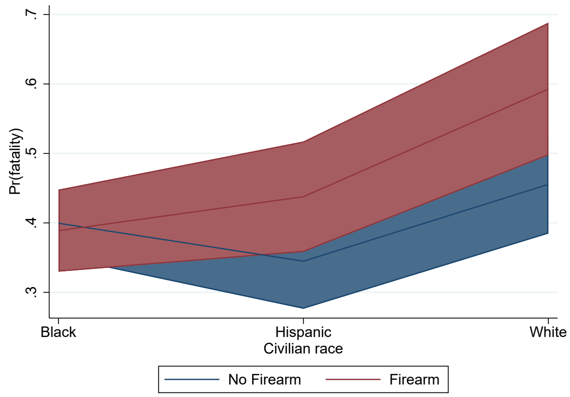
Note: This figure presents the percent estimated mortality across objective risk categories. This probability was constructed by dividing the number of individuals with associated risk category $k = \{1, 2, \cdots, 10\}$ who were killed by the number of individuals from the same category that were arrested on site or placed in custody. The underlying assumption is that individuals who were killed by police would have been arrested had they not been killed. Deaths are reported by the Washington Post and are nationally representative, while number of arrests comes from a 5% random sample of reports from agencies that submit these data to the FBI (see table 1). To scale the latter appropriately I multiplied arrests by $\frac{1}{5\%} \times \frac{\text{US population}}{\text{NIBRS population}}$.

Figure 11: Break-down of risk-adjusted excess Black mortality

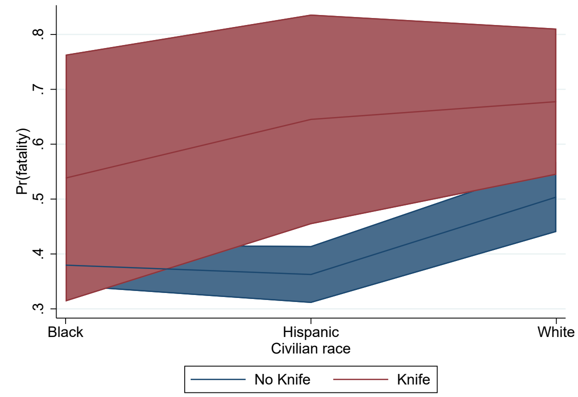


Note: This figure presents the percent estimated mortality across objective risk categories. This probability was constructed by dividing the number of individuals with associated risk category $k = \{1, 2, \cdots, 10\}$ who were killed by the number of individuals from the same category that were arrested on site or placed in custody. The underlying assumption is that individuals who were killed by police would have been arrested had they not been killed. Deaths are reported by the Washington Post and are nationally representative, while number of arrests comes from a 5% random sample of reports from agencies that submit these data to the FBI (see table 1). To scale the latter appropriately I multiplied arrests by $\frac{1}{5\%} \times \frac{\text{US population}}{\text{NIBRS population}}$.

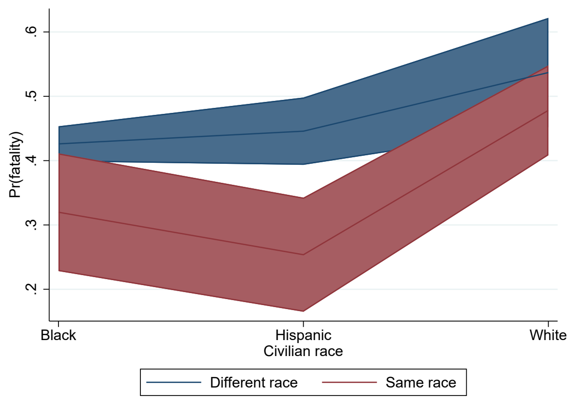
Figure 12: Marginal effects on civilian mortality



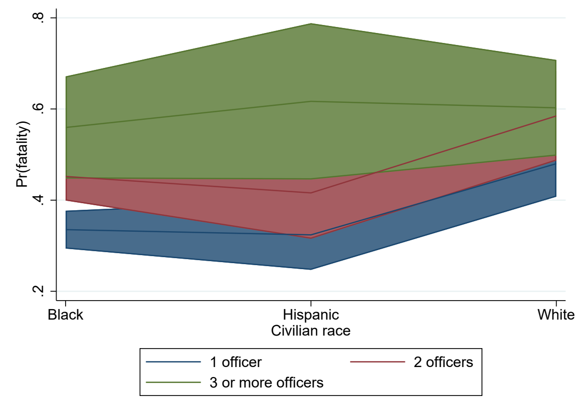
(a) Firearm



(b) Knife



(c) Same race officer and civilian



(d) Nr. of officers

Note: These figures show the marginal effect on the likelihood that a civilian dies during an OIS. I consider event characteristics from OIS (deadly or not) as reported by Vice News in the database "Shot by Police". Point estimates are the mean marginal effect calculated from a logit model (see column (2) of table 12). Standard errors were calculated via the Delta Method.

Table 1: Geographic reach of NIBRS

	2016	2017	2018	2019	2020
Originating agency	14670	16781	16782	16781	15252
Cities	7803	15566	15588	15588	14968
FBI field office	56	56	56	56	55
Judicial district	91	91	91	91	91
MSA	389	390	391	391	385
State	51	51	51	51	51
Population (millions)	127.8	160.3	161.5	156.9	192.5

Note: This table only includes observations from law-enforcement agencies that either submitted records to NIBRS, or that relied on another agency to submit them. *Originating agency* refers to the agency that submitted a record to NIBRS. *Cities* denotes the city where the law-enforcement agency is headquartered. The figures for *population* describe the estimated number of people covered by the agencies referred here.

Table 2: Descriptive statistics: assaults and deadly shootings

N=44378	Assault on officer (ordinary)							
	Black		Hispanic		White		Other	
Fraction	0.311	(0.46)	0.109	(0.31)	0.541	(0.50)	0.039	(0.19)
Age	30.392	(11.45)	29.330	(10.30)	33.973	(12.79)	31.476	(11.17)
Hand gun	0.027	(0.16)	0.015	(0.12)	0.009	(0.10)	0.004	(0.06)
Long gun	0.002	(0.04)	0.001	(0.04)	0.002	(0.05)	0.001	(0.03)
Knife	0.013	(0.11)	0.020	(0.14)	0.012	(0.11)	0.013	(0.11)
Blunt weapon	0.004	(0.06)	0.008	(0.09)	0.006	(0.08)	0.006	(0.08)
Car as weapon	0.001	(0.02)	0.002	(0.05)	0.002	(0.04)	0.002	(0.05)
Explosives	0.000	(0.01)	0.000	(0.00)	0.000	(0.01)	0.000	(0.00)
No weapon	0.959	(0.20)	0.959	(0.20)	0.972	(0.16)	0.977	(0.15)
N=18005	Assault on officer (aggravated)							
	Black		Hispanic		White		Other	
Fraction	0.273	(0.45)	0.091	(0.29)	0.602	(0.49)	0.034	(0.18)
Age	30.270	(11.52)	30.078	(10.34)	34.883	(12.79)	32.485	(11.27)
Hand gun	0.164	(0.37)	0.089	(0.28)	0.110	(0.31)	0.073	(0.26)
Long gun	0.016	(0.13)	0.015	(0.12)	0.041	(0.20)	0.026	(0.16)
Knife	0.058	(0.23)	0.104	(0.31)	0.092	(0.29)	0.117	(0.32)
Blunt weapon	0.045	(0.21)	0.076	(0.26)	0.060	(0.24)	0.068	(0.25)
Car as weapon	0.253	(0.43)	0.194	(0.40)	0.212	(0.41)	0.146	(0.35)
Explosives	0.007	(0.08)	0.002	(0.05)	0.005	(0.07)	0.008	(0.09)
No weapon	0.488	(0.50)	0.542	(0.50)	0.507	(0.50)	0.588	(0.49)
N=5383	Deadly OIS							
	Black		Hispanic		White		Other	
Fraction	0.273	(0.45)	0.191	(0.39)	0.510	(0.50)	0.026	(0.16)
Age	32.590	(11.27)	33.777	(10.88)	40.062	(13.28)	35.237	(11.82)
Body-cam	0.196	(0.40)	0.141	(0.35)	0.107	(0.31)	0.190	(0.39)
Mental illness	0.155	(0.36)	0.174	(0.38)	0.291	(0.45)	0.239	(0.43)
Attack	0.673	(0.47)	0.590	(0.49)	0.661	(0.47)	0.563	(0.50)
Firearm	0.656	(0.48)	0.565	(0.50)	0.644	(0.48)	0.430	(0.50)
Knife	0.136	(0.34)	0.216	(0.41)	0.177	(0.38)	0.338	(0.47)
Blunt weapon	0.014	(0.12)	0.029	(0.17)	0.015	(0.12)	0.007	(0.08)
Car as weapon	0.031	(0.17)	0.023	(0.15)	0.024	(0.15)	0.021	(0.14)
Explosives	0.000	(0.00)	0.002	(0.04)	0.001	(0.03)	0.007	(0.08)
Replica gun	0.002	(0.05)	0.001	(0.03)	0.004	(0.06)	0.000	(0.00)
No weapon	0.164	(0.37)	0.165	(0.37)	0.140	(0.35)	0.197	(0.40)

Note: This table presents descriptive statistics on assaults (ordinary and aggravated) against peace officers (top and middle section, respectively), and on deadly OIS (bottom). Data on assaults comes from the National Incidence Based Reporting System (NIBRS) from the FBI, and that of deadly shootings from the Washington Post. I define an individual with "no weapon" as someone who did not have a firearm, knife, blunt instrument or explosive, and who did not use his or her car as a weapon.

Table 3: Descriptive statistics: behavior in an OIS

	Black (N=1467)		Hispanic (N=1029)		White (N=2745)		Other (N=142)	
Attack	0.673	(0.47)	0.590	(0.49)	0.661	(0.47)	0.563	(0.50)
Attack & mental health	0.098	(0.30)	0.087	(0.28)	0.187	(0.39)	0.141	(0.35)
Attack & No weapon	0.070	(0.26)	0.049	(0.22)	0.057	(0.23)	0.056	(0.23)
Attack & mental health & No weapon	0.012	(0.11)	0.004	(0.06)	0.014	(0.12)	0.014	(0.12)
Mental health	0.155	(0.36)	0.174	(0.38)	0.291	(0.45)	0.239	(0.43)
Mental health & no weapon	0.022	(0.15)	0.021	(0.14)	0.029	(0.17)	0.042	(0.20)
No weapon	0.164	(0.37)	0.165	(0.37)	0.140	(0.35)	0.197	(0.40)

Note: This table presents the group shares killed by police that fit a certain characteristic (e.g., exhibited signs of mental health crisis), as reported by the Washington Post database on police killings.

Table 4: Predicted Black civilian deaths from weapon presence

	Deadly OIS			Aggravated Assault			Exp. Black killed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total	Black	Frac. Black	Total	Black	Frac. Black	(1) $\times$ (6)
Firearm	3374	963	0.285	967	328	0.339	1143
Knife	954	199	0.209	1527	285	0.187	178
Blunt weapon	93	21	0.226	1038	221	0.213	19
Car as weapon	138	45	0.326	3953	1242	0.314	43
Explosives	5	0	0.000	97	34	0.351	1
No weapon	821	240	0.292	9149	2397	0.262	215

Note: This table presents the group shares killed by police that fit a certain characteristic (e.g., exhibited signs of mental health crisis), as reported by the Washington Post database on police killings.

Table 5: Descriptive statistics: felonious killings of LEO's

(N=537)	Black		Hispanic		White	
Fraction	0.371	(0.02)	0.143	(0.02)	0.564	(0.02)
Fraction (non-Hispanic)	0.359	(0.02)			0.445	(0.02)

Note: This table presents descriptive statistics on the criminal killings of on-duty officers, based on data from the FBI's Law Enforcement Officers Feloniously Killed (LEOKA), for 2010-2019 (table 42). The FBI considers "Hispanic" to be an ethnicity and not a race, which implies that White or Black individuals can also be Hispanic. This inevitably means that Hispanic suspects are double counted. "Felonious kills (non-Hispanic)", tries to mitigate this by estimating the number of Black and White non-Hispanic individuals who feloniously killed an on-duty officer based on the shares of non-Hispanic Black and White offenders who assaulted officers, as reported in the FBI's NIBRS database. 1.2% and 11.9% of Black and White individuals are assumed to be Hispanic, respectively.

Table 6: Descriptive statistics: civilian mortality during an OIS

	Black (N=1229)		Hispanic (N=563)		White (N=565)	
Fatal shooting	0.309	(0.46)	0.400	(0.49)	0.543	(0.50)
Armed	0.388	(0.49)	0.414	(0.49)	0.453	(0.50)
Firearm	0.388	(0.49)	0.414	(0.49)	0.453	(0.50)
Knife	0.043	(0.20)	0.071	(0.26)	0.142	(0.35)
Replica firearm	0.074	(0.26)	0.078	(0.27)	0.083	(0.28)
Unarmed	0.117	(0.32)	0.146	(0.35)	0.136	(0.34)
Nr. responding officers	1.554	(1.29)	1.698	(1.56)	1.679	(1.34)
Nr. rounds fired	6.615	(9.60)	7.025	(8.67)	6.469	(9.33)
Fraction White officers	0.412	(0.47)	0.371	(0.45)	0.547	(0.47)
Age	28.685	(10.19)	30.815	(10.09)	36.736	(13.13)

Note: This table is based on incident-level data voluntarily shared to Vice News by 47 out of the 50 largest police departments. The data presented here covers critical incidents involving a single male between 2010 to 2016.

Table 7: Performance of predictive models

	N	sensitivity	specificity	precision	neg. prediction	bal. accuracy
			Deadly OIS (Model I)			
All	6886	0.72	0.82	0.63	0.88	0.77
Black	2272	0.70	0.85	0.64	0.89	0.77
Hispanic	591	0.72	0.78	0.54	0.89	0.75
White	3813	0.74	0.80	0.63	0.87	0.77
			Arrests (Model II)			
All	6309	0.73	0.87	0.70	0.89	0.80
Black	1869	0.74	0.88	0.68	0.91	0.81
Hispanic	666	0.70	0.87	0.65	0.89	0.78
White	3492	0.72	0.87	0.71	0.87	0.79

Note: based on the out-of-sample selection made by a random forest algorithm, which was tasked with identifying aggravated assaults against on-duty officers from ordinary assaults from NIBRS. Variable and parameter selection was made using 10-fold stratified cross validation.

Table 8: Likelihood of death/shooting given arrest

Prob. Death	Baseline model			Minimal model		
Risk percentile	50th	75th	90th	50th	75th	90th
White	0.006	0.013	0.010	0.009	0.014	0.016
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Hispanic	-0.000	0.003	0.004	0.001	0.005	0.007
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Other	-0.001	0.000	0.001	0.003	0.004	0.004
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)
Prob. Shooting	Baseline model			Minimal model		
Risk percentile	50th	75th	90th	50th	75th	90th
White	-0.001	0.008	0.009	0.006	0.014	0.017
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Hispanic	-0.009	-0.002	0.005	-0.004	0.005	0.011
	(0.005)	(0.005)	(0.006)	(0.003)	(0.005)	(0.006)
Other	-0.024	-0.027	-0.022	-0.012	-0.014	-0.020
	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.005)

Note: This table shows the likelihood of death and officer-involved shooting among civilians in the 50, 75 and 90th percentile of objective risk who were arrested on site or placed in custody. The omitted category is Black. The baseline model is described in section 4.2. The minimal model predicts aggravated assault to officers using as features only the presence of a firearm and the state where the incident happened.

Table 9: Counterfactual/excess deaths and OIS

	Excess deaths			% of total killed		
	Black	Hispanic	White	Black	Hispanic	White
National	595	41	-636	49.6	4.8	27.5
State	630	-52	-577	52.5	6.1	25.0
Division	626	-67	-560	52.2	7.9	24.2
Felonious kills	-627	146	-465	52.3	17.2	20.1
Felonious kills (non-Hispanic)	-605		-135	50.4		5.8
Risk-adjusted mortality	-615	344	271	41.9	33.4	9.9
	Excess OIS			% of OIS		
	Black	Hispanic	White	Black	Hispanic	White
National	1840	273	-2113	58.8	13.6	50.5
State	1896	42	-1937	60.6	2.1	46.3
Felonious kills	-324	668	-1072	10.4	33.4	25.6
Felonious kills (non-Hispanic)	-283		-447	9.0		10.7
Risk-adjusted mortality	-676	927	-251	18.7	39.5	5.2

Note: *Excess deaths* are defined as the difference between the number of individuals of a given race or ethnicity that would have been killed by police if each group had the same event likelihood, and the actual number of individuals killed. The rows corresponding to "National", "State" and "Division" calculate excess deaths based on the rates of police killings observed at the national, state and FBI-defined division level, respectively, and the group's population share at that specific geographic level. "Felonious kills" uses as basis to construct predicted number of killed by race the share of that group observed in felonious killings of on-duty officers between 2010 and 2019, as reported by FBI's LEOKA project. Because the FBI considers "Hispanic" an ethnicity and not a race, some Black and White individuals might be double counted. The next row, "Felonious kills (non-Hispanic)", tries to mitigate this by estimating the number of Black and White non-Hispanic individuals who feloniously killed an on-duty officer based on the shares of non-Hispanic Black and White offenders who assaulted officers, as reported in the FBI's NIBRS database. 1.2% and 11.9% of Black and White individuals are assumed to be Hispanic, respectively.

Table 10: Objective risk during deadly OIS

	(1)	(2)	(3)	(4)	(5)
Black=1	-0.036**	-0.029*	-0.012	-0.030**	-0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Asian=1	-0.011	-0.002	-0.014	-0.004	-0.008
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Hispanic=1	-0.018*	-0.014	-0.016**	-0.013	-0.011
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	6,333	6,030	6,333	6,030	6,030
stateFE			Yes		Yes
monthFE				Yes	Yes
ageFE		Yes		Yes	Yes
r2	0.005	0.018	0.142	0.046	0.181

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows point estimates of objective risk posed to officers during deadly OIS on racial identifiers. Lower values are consistent with a reduced threshold for using deadly force compared to White individuals.

Table 11: Objective risk during deadly OIS (alternative specification)

	(1)	(2)	(3)
	Mentall illness	Firearm	No bodycam
Black=1	-0.023	0.000***	-0.001
	(0.01)	(0.00)	(0.01)
Asian=1	-0.025	0.000***	0.006
	(0.06)	(0.00)	(0.02)
Hispanic=1	0.003	0.000***	-0.011
	(0.01)	(0.00)	(0.01)
N	1,359	3,797	5,180
stateFE	Yes	Yes	Yes
monthFE	Yes	Yes	Yes
ageFE	Yes	Yes	Yes
r2	0.307	1.000	0.167

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows point estimates of objective risk posed to officers during deadly OIS on racial identifiers. Lower values are consistent with a reduced threshold for using deadly force compared to White individuals.

Table 12: Civilian mortality as a function of event characteristics

	(1)		(2)	
Fatal shooting				
Hispanic	1.019	(0.22)	0.776	(0.19)
White	1.957***	(0.35)	1.316	(0.39)
Firearm=1 × Black	1.334	(0.25)	0.950	(0.22)
Firearm=1 × Hispanic	1.451*	(0.31)	1.612*	(0.47)
Firearm=1 × White	2.069***	(0.43)	1.871**	(0.52)
Knife=1 × Black	4.426***	(1.74)	2.088	(1.23)
Knife=1 × Hispanic	4.471***	(1.43)	3.997***	(2.06)
Knife=1 × White	2.488***	(0.68)	2.277**	(0.84)
One officer is same race as civilian=1 × Black	0.660**	(0.14)	0.590*	(0.17)
One officer is same race as civilian=1 × Hispanic	0.430***	(0.10)	0.353***	(0.11)
One officer is same race as civilian=1 × White	0.758	(0.16)	0.763	(0.22)
2 officers × Black	1.798***	(0.27)	1.734***	(0.31)
2 officers × Hispanic	2.327***	(0.43)	1.587	(0.53)
2 officers × White	1.780***	(0.36)	1.607*	(0.40)
More than 2 officers × Black	3.321***	(0.81)	2.809***	(0.85)
More than 2 officers × Hispanic	4.280***	(1.31)	4.095***	(2.24)
More than 2 officers × White	2.156***	(0.62)	1.745**	(0.44)
Female officer=1	1.013	(0.18)	1.056	(0.20)
Constant	0.627***	(0.09)	0.787	(0.62)
N	2,357		1,515	
cityFE	Yes		Yes	
ageFE	No		Yes	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows point estimates of objective risk posed to officers during deadly OIS on racial identifiers. Lower values are consistent with a reduced threshold for using deadly force compared to White individuals.

Table 13: Marginal effect of race on mortality during an OIS

	(1)	(2)
Hispanic	0.010	-0.005
	(0.03)	(0.03)
White	0.168***	0.126***
	(0.03)	(0.04)
N	2,357	1,515
cityFE	Yes	Yes
ageFE	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows the average marginal effect of race on civilian mortality. I consider event characteristics from OIS (deadly or not) as reported by Vice News in the database "Shot by Police". The coefficients reported here correspond to column (1) of table 12.

A Tables and figures

Table 14: Excess deaths by state

	Deaths per 100,000				Excess deaths		
State	All	Black	Hispanic	White	Black	Hispanic	White
AK	0.8	2.4	0.0	0.8	2.0	-1.5	-0.5
AL	0.4	0.4	0.1	0.3	5.4	-2.4	-3.0
AR	0.4	1.0	0.0	0.4	11.6	-4.7	-6.9
AZ	0.6	1.1	0.8	0.5	6.5	14.4	-20.9
CA	0.4	1.1	0.4	0.3	76.0	11.7	-87.7
CO	0.6	1.3	0.9	0.4	8.8	16.7	-25.5
CT	0.1	0.1	0.2	0.1	0.4	1.6	-1.9
DC	0.4	0.8	0.0	0.1	5.6	-1.4	-4.2
DE	0.2	0.4	0.0	0.2	1.9	-0.8	-1.1
FL	0.3	0.6	0.2	0.3	48.7	-27.0	-21.7
GA	0.3	0.4	0.2	0.3	13.2	-4.0	-9.2
HI	0.3	0.7	0.4	0.2	0.7	0.3	-0.9
IA	0.2	1.0	0.0	0.2	4.9	-1.7	-3.2
ID	0.4	1.6	0.5	0.4	0.7	0.8	-1.5
IL	0.2	0.6	0.1	0.1	41.2	-4.9	-36.3
IN	0.3	0.8	0.2	0.2	16.7	-1.7	-15.0
KS	0.3	0.8	0.4	0.3	4.1	1.6	-5.7
KY	0.4	0.7	0.4	0.3	6.2	0.1	-6.3
LA	0.4	0.8	0.1	0.3	25.0	-3.7	-21.4
MA	0.1	0.3	0.2	0.1	5.7	3.5	-9.2
MD	0.3	0.5	0.1	0.1	21.2	-4.0	-17.2

Table 14: Excess deaths by state

	Deaths per 100,000				Excess deaths		
State	All	Black	Hispanic	White	Black	Hispanic	White
ME	0.3	1.0	1.0	0.2	0.7	0.7	-1.5
MI	0.1	0.3	0.1	0.1	13.0	-1.4	-11.6
MN	0.2	0.6	0.2	0.2	7.6	0.5	-8.1
MO	0.4	1.3	0.3	0.3	31.9	-1.6	-30.4
MS	0.4	0.4	0.2	0.4	-0.4	-0.7	1.1
MT	0.5	0.0	0.0	0.5	-0.1	-0.8	0.9
NC	0.3	0.4	0.2	0.2	17.7	-4.0	-13.7
ND	0.1	0.0	0.0	0.2	-0.2	-0.2	0.3
NE	0.2	1.1	0.2	0.2	3.9	-0.2	-3.7
NH	0.2	0.0	0.0	0.2	-0.2	-0.4	0.6
NJ	0.1	0.5	0.1	0.1	18.9	-3.8	-15.0
NM	1.0	0.5	1.3	0.7	-0.9	13.4	-12.5
NV	0.6	0.9	0.7	0.4	4.6	5.3	-9.9
NY	0.1	0.3	0.0	0.1	27.4	-8.1	-19.3
OH	0.2	0.7	0.0	0.2	34.0	-4.0	-30.1
OK	0.8	2.1	0.5	0.7	19.1	-6.4	-12.7
OR	0.4	1.8	0.2	0.4	5.5	-4.0	-1.5
PA	0.1	0.6	0.1	0.1	28.7	-0.2	-28.5
RI	0.1	0.6	0.1	0.0	1.7	0.4	-2.1
SC	0.3	0.3	0.2	0.3	2.6	-2.0	-0.6
SD	0.3	0.0	0.0	0.3	-0.3	-0.4	0.6
TN	0.4	0.5	0.2	0.3	9.3	-3.1	-6.2
TX	0.3	0.5	0.2	0.3	40.3	-30.2	-10.0
UT	0.4	3.5	0.5	0.3	5.4	3.0	-8.3

Table 14: Excess deaths by state

	Deaths per 100,000				Excess deaths		
State	All	Black	Hispanic	White	Black	Hispanic	White
VA	0.2	0.5	0.1	0.2	19.5	-3.8	-15.7
VT	0.3	0.0	0.0	0.3	-0.1	-0.1	0.2
WA	0.3	1.3	0.5	0.2	14.3	6.5	-20.8
WI	0.3	1.0	0.3	0.2	12.9	0.0	-12.9
WV	0.5	2.5	0.0	0.4	6.4	-0.7	-5.7
WY	0.4	0.0	0.8	0.4	-0.1	1.0	-0.8

Note: *Excess deaths* are defined as the difference between the number of individuals of a given race or ethnicity that would have been killed by police if each group had the same hazard rate within the same state, and the actual number of individuals killed. *Deaths per 100,000* are defined as *excess deaths* per 100,000 individuals within a state.

Table 15: Excess deaths by division

State	Deaths per 100,000				Excess deaths		
	All	Black	Hispanic	White	Black	Hispanic	White
New England	0.1	0.3	0.2	0.1	7	4	-11
Middle-Atlantic	0.1	0.4	0.1	0.1	74	-14	-60
East North Central	0.2	0.6	0.1	0.2	115	-15	-100
West North Central	0.3	1.0	0.2	0.2	54	-2	-52
South Atlantic	0.3	0.5	0.2	0.2	134	-49	-86
East South Central	0.4	0.5	0.2	0.3	21	-6	-15
West South Central	0.4	0.7	0.2	0.4	96	-75	-21
Mountain	0.6	1.1	0.8	0.4	26	72	-98
Pacific	0.4	1.1	0.4	0.3	99	18	-117

Note: *Excess deaths* are defined as the difference between the number of individuals of a given race or ethnicity that would have been killed by police if each group had the same hazard rate within a division, and the actual number of individuals killed. *Deaths per 100,000* are defined as *excess deaths* per 100,000 individuals within a division.

Table 16: Predictive model I: confusion matrix (All)

		Prediction outcome		
		HR= 0	**HR**= 1	**total**
Actual value	**HR**= 0	3979	879	4858
	HR= 1	563	1465	2028
	total	4542	2344	

Note: based on the popularity contest produced by predictive model I (see sub-section 4.2). The underlying random forest algorithm was tasked with identifying aggravated assaults against on-duty officers from ordinary assaults using data from NIBRS. Features and parameters were selected using 10-fold stratified cross validation. The values from this table correspond to the confusion matrix of a randomly selected fold from the cross-validation selection step.

Table 17: Predictive model I: confusion matrix (Black individuals)

		Prediction outcome		
		HR= 0	**HR**= 1	**total**
Actual value	**HR**= 0	1419	242	1661
	HR= 1	182	429	611
	total	1601	671	

Note: based on the popularity contest produced by predictive model I (see sub-section 4.2). The underlying random forest algorithm was tasked with identifying aggravated assaults against on-duty officers from ordinary assaults using data from NIBRS. Features and parameters were selected using 10-fold stratified cross validation. The values from this table correspond to the confusion matrix of a randomly selected fold from the cross-validation selection step.

Table 18: Predictive model I: confusion matrix (Hispanic individuals)

		Prediction outcome		
		HR= 0	**HR**= 1	**total**
Actual value	**HR**= 0	343	94	437
	HR= 1	43	111	154
	total	386	205	

Note: based on the popularity contest produced by predictive model I (see sub-section 4.2). The underlying random forest algorithm was tasked with identifying aggravated assaults against on-duty officers from ordinary assaults using data from NIBRS. Features and parameters were selected using 10-fold stratified cross validation. The values from this table correspond to the confusion matrix of a randomly selected fold from the cross-validation selection step.

Table 19: Predictive model I: confusion matrix (White individuals)

		Prediction outcome		
		HR= 0	**HR**= 1	**total**
Actual value	**HR**= 0	2098	517	2615
	HR= 1	315	883	1198
	total	2413	1400	

Note: based on the popularity contest produced by predictive model I (see sub-section 4.2). The underlying random forest algorithm was tasked with identifying aggravated assaults against on-duty officers from ordinary assaults using data from NIBRS. Features and parameters were selected using 10-fold stratified cross validation. The values from this table correspond to the confusion matrix of a randomly selected fold from the cross-validation selection step.

Table 20: Predictive model II: confusion matrix (All)

		Prediction outcome		
		HR= 0	**HR**= 1	**total**
Actual value	**HR**= 0	3909	575	4484
	HR= 1	501	1324	1825
	total	4410	1899	

Note: based on the popularity contest produced by predictive model II (see sub-section 4.3). The underlying random forest algorithm was tasked with identifying aggravated assaults against on-duty officers from ordinary assaults using data from NIBRS. Features and parameters were selected using 10-fold stratified cross validation. The values from this table correspond to the confusion matrix of a randomly selected fold from the cross-validation selection step.

Table 21: Predictive model II: confusion matrix (Black individuals)

		Prediction outcome		
		HR= 0	**HR**= 1	**total**
Actual value	**HR**= 0	1246	162	1408
	HR= 1	122	339	461
	total	1368	501	

Note: based on the popularity contest produced by predictive model II (see sub-section 4.3). The underlying random forest algorithm was tasked with identifying aggravated assaults against on-duty officers from ordinary assaults using data from NIBRS. Features and parameters were selected using 10-fold stratified cross validation. The values from this table correspond to the confusion matrix of a randomly selected fold from the cross-validation selection step.

Table 22: Predictive model II: confusion matrix (Hispanic individuals)

		Prediction outcome		
		HR= 0	**HR**= 1	**total**
Actual value	**HR**= 0	428	66	494
	HR= 1	52	120	172
	total	480	186	

Note: based on the popularity contest produced by predictive model II (see sub-section 4.3). The underlying random forest algorithm was tasked with identifying aggravated assaults against on-duty officers from ordinary assaults using data from NIBRS. Features and parameters were selected using 10-fold stratified cross validation. The values from this table correspond to the confusion matrix of a randomly selected fold from the cross-validation selection step.

Table 23: Predictive model II: confusion matrix (White individuals)

		Prediction outcome		
		HR$=0$	**HR**$=1$	**total**
Actual value	**HR**$=0$	2061	321	2382
	HR$=1$	308	802	1110
	total	2369	1123	

Note: based on the popularity contest produced by predictive model II (see sub-section 4.3). The underlying random forest algorithm was tasked with identifying aggravated assaults against on-duty officers from ordinary assaults using data from NIBRS. Features and parameters were selected using 10-fold stratified cross validation. The values from this table correspond to the confusion matrix of a randomly selected fold from the cross-validation selection step.