THE ECONOMIC JOURNAL

The Economic Journal, 1–16 https://doi.org/10.1093/ej/uead043
Advance Access Publication Date: 26 June 2023

A BEHAVIOURAL THEORY OF DISCRIMINATION IN POLICING*

Ryan Hübert and Andrew T. Little

A large economic literature studies whether racial disparities in policing are explained by animus or by beliefs about group crime rates. But what if these beliefs are incorrect? We analyse a model where officers form beliefs using crime statistics, but do not properly account for the fact that they will detect more crime in more heavily policed communities. This creates a feedback loop where officers over-police groups that they (incorrectly) believe exhibit high crime rates. This inferential mistake can exacerbate discrimination even among officers with no animus and who sincerely believe that disparities are driven by real differences in crime rates.

Racial disparities in policing are pervasive (see, for example, Epp *et al.*, 2014; Ghandnoosh, 2015; Goel *et al.*, 2016). There are two standard theoretical explanations for these disparities, one driven by preferences and one driven by beliefs. In a purely preference-driven account—often called taste-based discrimination—officers intrinsically like being punitive towards some groups, or dislike being punitive towards others. The second explanation—typically called statistical discrimination—is that there are real differences in the rates of criminal behaviour across groups. Knowing this, police allocate more time policing members of groups with higher crime rates, or at least in geographical areas where those groups are concentrated.

Another explanation for policing disparities sits uncomfortably between these two standard explanations. What if officers police a certain group more intensely because they believe that the group has a relatively high crime rate, but this belief is incorrect, or at least exaggerated?[1] In a proximate sense, this is discrimination driven by beliefs. But we might suspect that such inaccurate beliefs are more likely to be held by those with an intrinsic dislike of the group. If so, the traditional distinction between statistical and taste-based discrimination may not be as neat as is often presumed.

This is not just a hypothetical. Even when highly trained researchers use administrative data, it is difficult to correct for—or even know the extent of—statistical problems (Heckman and Durlauf, 2020; Knox *et al.*, 2020; Knox and Mummolo, 2020). There is no obvious reason to think that police decision-makers will generally do better when interpreting crime statistics (see,

* Corresponding author: Ryan Hübert, Department of Political Science, University of California, Davis, 469 Kerr Hall, One Shields Avenue, Davis, CA 95616, USA. Email: rhubert@ucdavis.edu

This paper was received on 13 August 2021 and accepted on 9 June 2023. The Editor was Steffen Huck.

Authors are listed in alphabetical order. Many thanks to Katie Angell, Aislinn Bohren, Tony Carey, Tom Clark, Brandon Davis, Peter Enns, Jack Glaser, Becca Goldstein, Anna Harvey, Peter Hull, Alex Imas, Kris Kanthak, Brad Leveck, Philip Marx, Meg Meyer, Conrad Miller, Emily Nix, Kyle Peyton, Tessa Provins, Gwen Prowse, Marcel Roman, Will Spaniel, Allison Stashko, Jeff Staton, Kalinda Ukanwa, Emily West, Michelle Wier, Jon Woon and audience members at the 2019 Political Economy and Public Law Conference, APSA 2019, SPSA 2020, the 2021 Conference on New Approaches to Discrimination Research, Berkeley, Chicago, Oxford, Pittsburg, Stanford, Washington University and USC for helpful comments.

[1] As discussed in more detail below, several recent papers consider this possibility and provide empirical tests, though not in the context of policing (Bohren *et al.*, 2019a,b; Mengel and Campos Mercade, 2021).

e.g., Glaser, 2015 for an overview). Police officials typically need to make decisions under time pressure without the benefit of the kind of statistical expertise that would enable high-quality assessments about crime across communities. If departments rely on bad data or do not interpret it correctly, this can perpetuate disparities (see, for example, Harcourt, 2007 and Lum and Isaac, 2016). Even the federal courts have weighed in to criticise flawed data analysis by police (e.g., *Floyd v. New York*, 959 F. Supp. 2d 540, S.D.N.Y. 2013).

A growing theoretical literature on agents with 'misspecified models' provides a natural way to explore the implications of police officers not interpreting data correctly (Bohren, 2016; Esponda and Pouzo, 2016; Heidhues *et al.*, 2018). We build on a strand within this literature on how incorrect beliefs and behaviour can interact (see Esponda and Pouzo, 2016 for a general analysis of such games). These interactions can lead to persistent incorrect beliefs in domains like education (Levy and Razin, 2017; Chauvin, 2018), labour markets, overconfidence and beliefs about the ability of others (Heidhues *et al.*, 2018; 2020) and political competition (Levy *et al.*, 2022). In a companion paper, we analyse a related model of discriminatory policing in which officers' policing choices are influenced by incorrect beliefs about crime that result from them conflating experiences of crime at work and experiences of crime in their social lives (Hübert and Little, 2022).

We develop a model of policing where officers do not fully account for the fact that more crimes are detected among members of groups that they police more intensely. Following Koehler and Mercer (2009) and Jehiel (2018), we call this bias *selection neglect* (see also Eyster and Rabin, 2005 and Esponda, 2008 for general analysis of models where individuals do not account for earlier selection problems related to others' actions).

The model also allows for police officers to have racial animus, and for crime rates to be different across groups. In the special case where officers form correct beliefs, these two mechanisms independently affect policing disparities, as in the standard accounts. However, once officers exhibit any selection neglect, a feedback loop begins where groups who are policed more intensely are viewed as having higher crime rates than they really do. This feedback loop amplifies whatever policing disparities would exist in the absence of selection neglect. A taste for discrimination causes inaccurate statistical discrimination. As crime data are the product of choices made by many individuals, this can cause discriminatory behaviour to spill over across officers.

We focus on policing since it is an important area of public policy in which faulty data analysis is widely believed to affect decision-making (see, for example, Glaser, 2015; Lum and Isaac, 2016 and Collins, 2018). However, the notion that selection neglect can cause inaccurate statistical discrimination is relevant to many other contexts, like labour markets and education, which we discuss in more detail in the conclusion. Regardless of the context, however, our analysis bolsters an emerging literature suggesting that it is more difficult to empirically distinguish taste-based and statistical discrimination than standard approaches would imply (e.g., Bohren *et al.*, 2019b; Hull, 2021).

1. Policing with Full Information

We study a model of a single police officer (pronoun 'he'), who we primarily interpret as a high-level official who makes decisions for the department as a whole, such as the chief of police. (At the end of Section 2, we discuss an extension with multiple officers, which we formally analyse in Online Appendix E.) Our model is intended to study discrimination arising from decisions about how to allocate police department resources, rather than individual decisions of officers to initiate an interaction with a citizen or escalate to using force (e.g., Knowles *et al.*, 2001; Hull, 2021; Feigenberg and Miller, 2022). More specifically, the officer makes a choice about how to allocate resources toward policing two groups, A and B. To avoid having to make normalisations by group size, assume that the two groups are equal in size.

The officer has a unit of resources, which we primarily interpret as time, to allocate between policing the two groups. Let w_A represent the share of time spent policing group A, with $w_B = 1 - w_A$ left for group B. We assume that the officer can choose to allocate his time evenly between the two groups, but can also choose to police one group more than the other. However, the officer cannot choose to allocate *all* of his time to one group or the other. Formally, the officer chooses $w_A \in [\underline{w}, \overline{w}]$, where $0 < \underline{w} \leq 1/2 \leq \overline{w} < 1$.

In the United States, it is typically illegal for governments (including police departments) to target individuals solely on the basis of their social grouping, such as their race, religion, gender, etc. Thus, one way to think about the choice in our model is that the police department decides to target resources toward different geographical locations, which due to residential segregation, have different proportions of the two groups. In Online Appendix B, we provide a microfoundation for the officer's choice in which the officer decides how to allocate time between neighbourhoods, and not between social groups.

We assume that the allocation of policing effort, w_A, affects the detection of crime. As a result, ours is a model of 'proactive policing' and not 'reactive policing' where officers respond to reports of crimes in progress or which have already occurred (e.g., via 911 calls). The model is also less applicable for crimes that are universally (or near universally) reported, such as murder. More generally, what matters for our argument is that police detect more crime among groups that commit crimes at a higher rate, and where they spend more resources policing.

Formally, we let the amount of crime caught among members of group J to be $c_J = p_J w_J$, where $p_J > 0$. The simplest way to interpret this is that p_J represents the average number of crimes committed by members of group J per unit of time, and w_J represents how much time is spent policing this group. These are the data that the officer uses to determine how to allocate effort.

While this formulation will prove particularly tractable, in the Online Appendix we consider two important extensions. First, in Online Appendix C, policing has a deterrent effect where the group crime rate decreases in the amount of time spent policing that group. This does not fundamentally change our argument. In Online Appendix D, we consider a more general version of the crime detection function that is increasing, but potentially non-linear in $p_J w_J$. A natural extension of selection neglect to this setting is that the officer may not know the shape of the crime detection function. If crime detection exhibits diminishing returns, but the officer is unaware of this fact, policing a group more intensely can lead the officer to *underestimate* that group's baseline crime rate (see Rambachan and Roth, 2019 for a related argument). Future work could explore the magnitude of this effect relative to the effects we study. In any case, we do not see it as fundamentally challenging our results since recent empirical research provides justification for a linear crime detection function (Feigenberg and Miller, 2022).

1.1. *Preferences*

We assume that the objective of the officer is to catch crimes. To capture the notion that the officer might have a taste for discrimination, we allow him to prefer catching crimes among one group or the other. We also assume that there are diminishing returns to the amount of crime caught within each group. This is a reduced-form way to capture the notion that some crimes are 'more important' to detect than others, and that the officer will first dedicate time to detecting the more important crimes (within each group). In addition to these key assumptions, we impose several technical assumptions on the officer utility.

ASSUMPTION 1. *The officer utility is $u(t_A c_A, t_B c_B)$, where $t_J > 0$, and the utility function $u(x_1, x_2)$ is*

(*i*) *symmetric in the two arguments ($u(x_1, x_2) = u(x_2, x_1)$),*
(*ii*) *continuously differentiable,*
(*iii*) *strictly increasing and concave in both arguments ($u_1 > 0$, $u_{11} < 0$, $u_2 > 0$, $u_{22} < 0$),*
(*iv*) *additively separable ($u_{12} = 0$).*

We interpret the t_A and t_B terms as the officer's 'taste' for catching crimes among groups A and B, respectively. Part (*i*) implies that this and the crime rates are the only relevant differences between the groups. Parts (*ii*) and (*iii*) of the assumption ensure that there is a maximiser and that higher values of t_J and p_J will make the officer value catching crimes among group J more. Part (*iv*) of the assumption allows us to set aside indirect effects where allocating effort toward one group lowers the marginal return to policing the other group. (We also show in the proof of Lemma 1 below that it is sufficient that the cross-partial not be too positive or too negative relative to the concavity in each argument.)

If the officer has correct beliefs about the crime rates (the p_J parameters) then the optimal allocation of policing effort is a straightforward maximisation of his utility function. When the officer has correct beliefs, we say that he has *full information*. Before we turn to the officer's optimisation problem, we make the following technical assumption about the utility function.

ASSUMPTION 2. *The officer utility is homogeneous with positive degree.*

Assumption 2 has two key implications. First, it ensures that the marginal return to policing group J is increasing in t_J and p_J, meaning that these parameters capture the standard intuitions about taste-based and statistical discrimination, respectively. Second, it allows us to focus our analysis on the way the optimal policing allocation changes in response to the *relative* taste for catching crime $r_t = t_A/t_B$ and the *relative* crime rate $r_p = p_A/p_B$. In Online Appendix A, we discuss how a weaker version of Assumption 2 generates less tidy, but qualitatively identical results.

LEMMA 1. *Given Assumption 1, there is a unique allocation w_A that maximises $u(t_A c_A, t_B c_B)$. Given Assumption 2, this optimal allocation depends only on $r_t r_p$, so we write it as a function: $w_A^{br}(r_t r_p)$. The optimal allocation has the following properties:*

(*i*) *$w_A^{br}(r_t r_p)$ is increasing in $r_t r_p$, and where $w_A^{br}(r_t r_p)$ is interior, it is strictly increasing,*
(*ii*) *$w_A^{br}(1) = 1/2$.*

PROOF. Using part (*ii*) of Assumption 1, u is continuously differentiable and any interior solution will be characterised by the following first-order condition (FOC):

$$\frac{\partial u}{\partial w_A} = t_A p_A u_1(t_A p_A w_A, t_B p_B(1 - w_A)) - t_B p_B u_2(t_A p_A w_A, t_B p_B(1 - w_A)) = 0.$$

To verify that the FOC characterises a maximum, consider the second derivative

$$\frac{\partial^2 u}{\partial w_A^2} = (t_A p_A)^2 u_{11}(t_A p_A w_A, t_B p_B(1-w_A)) + (t_B p_B)^2 u_{22}(t_A p_A w_A, t_B p_B(1-w_A)) \\ - 2 t_A p_A t_B p_B u_{12}(t_A p_A w_A, t_B p_B(1-w_A)).$$

By part (*iii*) of Assumption 1, u_{11} and u_{22} are both strictly negative and, by part (*iv*) of Assumption 1, u_{12} equals zero.[2] Therefore, u is strictly concave, and since it is continuous on a compact set, it must have a unique maximiser.

We now show that the optimal allocation given by the FOC is only a function of $r_t r_p$. First, multiply both sides of the FOC by $(t_B p_B)^{-(k-1)}$:

$$(t_B p_B)^{-(k-1)} r_t r_p u_1(t_A p_A w_A, t_B p_B(1-w_A)) - (t_B p_B)^{-(k-1)} u_2(t_A p_A w_A, t_B p_B(1-w_A)) = 0.$$

Since u is homogeneous with positive degree,[3] then u_1 and u_2 are both homogeneous degree $k-1$. We can simplify the equation above to

$$r_t r_p u_1(r_t r_p w_A, 1-w_A) - u_2(r_t r_p w_A, 1-w_A) = 0. \qquad (1)$$

The unique optimal allocation is the solution to (1), which depends only on $r_t r_p$. We accordingly write this solution as $w_A^{\text{br}}(r_t r_p)$.

To prove part (*i*) of the lemma, the homogeneity of u means that we can rewrite the first term of the FOC as

$$G(r_t r_p, w_A) = (r_t r_p)^k u_1(w_A, (r_t r_p)^{-1}(1-w_A)) - u_2(r_t r_p w_A, 1-w_A) = 0,$$

where w_A^{br} is interior and the change with respect to $r_t r_p$ is given by implicitly differentiating G, which means that the sign of $\partial w_A^{\text{br}}/\partial r_t r_p$ is equal to the sign of $\partial G/\partial r_t r_p$, which is given by

$$\frac{\partial G}{\partial r_t r_p} = k(r_t r_p)^{k-1} u_1(w_A, (r_t r_p)^{-1}(1-w_A)) \\ - (r_t r_p)^{k-2}(1-w_A) u_{12}(w_A, (r_t r_p)^{-1}(1-w_A)) - w_A u_{12}(r_t r_p w_A, 1-w_A).$$

Using Assumption 1, the first term is strictly positive and the remaining terms drop out since $u_{12} = 0$. So, at any interior solution, the optimal allocation is strictly increasing in $r_t r_p$, and since the FOC is strictly increasing in $r_t r_p$, the optimiser is weakly increasing in $r_t r_p$.

Finally, we prove part (*ii*) of the lemma. Substituting $r_t r_p = 1$ into the FOC gives $u_1(w_A, 1 - w_A) - u_2(w_A, 1-w_A) = 0$. Then, from part (*i*) of Assumption 1, the solution to this is equation is $w_A^{\text{br}}(r_t r_p = 1) = 1/2$. □

The two main parameters of interest in the previous result—r_t and r_p—have clear substantive interpretations. Since t_A and t_B capture the officer's taste for catching crimes among members of groups A and B, respectively, then if $r_t > 1$ (i.e., $t_A > t_B$), we say that the officer has *animus* towards group A. On the other hand, if $r_t < 1$ (i.e., $t_A < t_B$) then we say that the officer has animus towards group B. Similarly, when $r_p > 1$ (i.e., $p_A > p_B$), the crime rate among members of group A is higher than the crime rate among members of group B, and if $r_p < 1$ (i.e., $p_A < p_B$),

[2] If we relax part (*iv*) of Assumption 1, so that $u_{12} \neq 0$, then the second derivative is strictly negative as long as the cross-partial derivative is not too negative (relative to the u_{11} and u_{22} terms).

[3] Recall that $u(t_A c_A, t_B c_B)$ is homogeneous with positive degree if and only if, for any scalar a, there exists a $k > 0$ such that $u(a t_A c_A, a t_B c_B) = a^k u(t_A c_A, t_B c_B)$.

the opposite is true. These two parameters are the driving forces behind taste-based and statistical discrimination in our model.

All of our following results will hold for any utility function with the properties of Lemma 1. So, for example, the officer does not necessarily need to be motivated by maximising the amount of crime caught; he could also care about preventing crime from happening in the first place (for an approach to disentangling these motives, see Stashko, 2020). What really matters is that he wants to allocate more time to policing groups with higher crime rates, as well as groups against which he has animus.

One of our main goals in the analysis is to compare the disparities arising under full information with the disparities arising when the officer has incorrect beliefs. However, if the officer is policing at a corner with full information (i.e., $w^{\text{br}}(r_t r_p) \in \{\overline{w}, \underline{w}\}$) then there will (trivially) be no scope for increased discrimination when the officer has incorrect beliefs. To avoid this, we make one additional assumption.

ASSUMPTION 3. *It holds that*

$$\frac{u_2(\underline{w}, 1-\underline{w})}{u_1(1-\underline{w}, \underline{w})} < r_t r_p < \frac{u_2(\overline{w}, 1-\overline{w})}{u_1(1-\overline{w}, \overline{w})}.$$

This assumption implies the following result.

LEMMA 2. *Given Assumptions 1–3, the full information policing allocation is interior:* $w_A^{br}(r_t r_p) \in (\underline{w}, \overline{w})$.

PROOF. The proof of Lemma 1 shows that the first derivative of the objective function is continuous and strictly decreasing in w_A. So, there will be an interior solution if and only if it is strictly positive at $w_A = \underline{w}$ and strictly negative at $w_A = \overline{w}$. The first condition requires

$$r_t r_p u_1(r_t r_p \underline{w}, 1-\underline{w}) > u_2(r_t r_p \underline{w}, 1-\underline{w}),$$

$$\implies \quad r_t r_p > \frac{u_2(r_t r_p \underline{w}, 1-\underline{w})}{u_1(r_t r_p \underline{w}, 1-\underline{w})}.$$

Similarly, the second condition requires

$$r_t r_p < \frac{u_2(r_t r_p \overline{w}, 1-\overline{w})}{u_1(r_t r_p \overline{w}, 1-\overline{w})}.$$

Combining these requirements gives the result. □

1.1.1. *Main example*

For illustrations, we use the following utility function that meets Assumptions 1 and 2:

$$u(c_A, c_B) = \sqrt{t_A c_A} + \sqrt{t_B c_B} = \sqrt{t_A p_A w_A} + \sqrt{t_B p_B (1-w_A)}. \tag{2}$$

With this utility, the officer optimal allocation as a function of r_t and r_p is

$$w_A^{\text{br}}(r_t r_p) = \frac{r_t r_p}{1 + r_t r_p}.$$

Note that, since $r_t > 0$ and $r_p > 0$, this is always strictly between 0 and 1. As long as $\underline{w}$ and $\overline{w}$ are sufficiently close to 0 and 1, then $w_A^{\text{br}}(r_t r_p)$ is also interior.

1.1.2. *Disparities*

Going forward, we now label the officer's optimal allocation with full information as $w_A^{\dagger} = w_A^{\text{br}}(r_t r_p)$. Then, whenever the officer polices one group more than the other group, there is a *policing disparity*, given by

$$\Delta^{\dagger} \equiv |w_A^{\dagger} - 1/2|.$$

Since our model allows for both taste-based and statistical discrimination (via parameters r_t and r_p), $\Delta^{\dagger}$ can be decomposed into two component parts. Formally, define $w_A^{\text{stat}} = w_A^{\text{br}}(r_p)$ to be the 'statistical policing' allocation, which reflects what an officer does if he has no animus toward either group ($r_t = 1$), but statistically discriminates based on differences in the (true) crime rates. Following Bohren *et al.* (2019a), we refer to $w_A^{\text{stat}} - 1/2$ as 'traditional statistical discrimination', which will contrast with 'inaccurate statistical discrimination' that arises when the officer does not know r_p. The difference between what the officer chooses and this statistical benchmark, $w_A^{\dagger} - w_A^{\text{stat}}$, represents taste-based discrimination. Taken together, the policing disparity when the officer has full information can be decomposed as[4]

$$\Delta^{\dagger} = |\underbrace{(w_A^{\dagger} - w_A^{\text{stat}})}_{\substack{\text{taste-based}\\ \text{discrimination}}} + \underbrace{(w_A^{\text{stat}} - 1/2)}_{\substack{\text{traditional statistical}\\ \text{discrimination}}}| = |w_A^{\dagger} - 1/2|.$$

2. Policing with a Misspecified Model

Now we consider a situation in which the officer does not know the relative crime rates of the two groups (r_p), and forms this belief based on data generated by his policing choices. We assume that the data the officer uses are entirely driven by the crime detected as a result of his policing choices. However, in Online Appendix E, we explore the consequences of officers making choices based on data generated by *other* officers' choices as well.

We assume that the officer may use a misspecified model of crime prevalence when forming his beliefs about relative crime rates such that he misunderstands how policing allocations affect the crime detected.[5] In the extreme, the officer might infer that the relative number of crimes caught among the two groups is the same as the relative crime rates. As this involves the officer forming a posterior belief without taking into account the effect of his action on whether crimes make it into the data, following Koehler and Mercer (2009) and Jehiel (2018), we call this selection neglect.

We pick a particular form of this bias that leads to clear calculations; see Online Appendix F for a more general analysis. Suppose that the officer forms beliefs about the crime rates as if the crime prevalence is given by

$$\tilde{c}(w_J, p_J) = (1 - \nu) p_J w_J + \nu p_J$$

[4] Note that taste-based and statistical discrimination may yield discrimination against different groups. In this case, the policing disparity under full information will be closer to zero than the disparities generated by either kind of discrimination on its own.

[5] Coffman *et al.* (2019) studied a related source of bias in the context of gender stereotypes, where 'stereotype congruent' information is incorporated more than non-congruent information. If we interpret this as congruence changing whether a piece of information gets 'sampled' when forming beliefs, this can also be viewed as a version of selection neglect.

for $\nu \in [0, 1]$. If $\nu = 0$, this is the correct function for the amount of crime the officer detects. If $\nu = 1$, the officer believes that the crime he detects is equal to the crime rate p_J, and does not depend on w_J.

If the officer has this model of crime detection in his head then after observing a crime rate c_J and his own policing intensity w_J, his (possibly distorted) belief $\tilde{p}_J$ solves

$$c_J = (1-\nu)\tilde{p}_J w_J + \nu \tilde{p}_J.$$

Since $c_J = c(w_J, p_J) = w_J p_J$, we can substitute and rearrange:

$$\tilde{p}_J = \frac{w_J p_J}{(1-\nu)w_J + \nu}.$$

If $\nu = 0$, this simplifies to p_J, and is unaffected by w_J. However, for any $\nu > 0$, the belief will increase in w_J.[6]

Combining the group ratios, the belief about the ratio is[7]

$$\begin{aligned}\tilde{r}_p(w_A) &= \frac{p_A w_A/[\nu + (1-\nu)w_A]}{p_B(1-w_A)/[\nu + (1-\nu)(1-w_A)]} \\ &= r_p\left(\frac{w_A(\nu + (1-\nu)(1-w_A))}{(1-w_A)(\nu + (1-\nu)w_A)}\right). \qquad (3)\end{aligned}$$

As ν approaches zero, the officer's belief about crime, $\tilde{r}_p$, becomes more accurate (i.e., approaches r_p). As ν approaches one, $\tilde{r}_p$ approaches the belief formed by the most extreme selection neglect. More generally, as ν increases, the officer makes a more severe inferential mistake.

Why study this particular bias in policing? First, recent experimental studies provide strong causal evidence that subjects neglect selection effects and thus make faulty inferences about a state of the world (e.g., Esponda and Vespa, 2018; Barron *et al.*, 2019; Enke, 2020). Other experimental work demonstrates that discrimination in other contexts is partly driven by incorrect beliefs (Bohren *et al.*, 2019b; Barron *et al.*, 2020).

Second, several examples suggest that the phenomenon extends to the real-world context of policing. Using a case study of drug arrests in Oakland, California, Lum and Isaac (2016) demonstrated that data used in predictive policing algorithms perpetuate policing disparities since they are generated from past policing patterns and do not appear to reflect *actual* drug use patterns. In her opinion in *Floyd v. New York*, U.S. District Judge Scheindlin wrote 'The City [of New York] and its highest officials believe that blacks and Hispanics should be stopped at the same rate as their proportion of the local criminal suspect population' (p. 9). This is a prime example of selection neglect, which is precisely what Judge Scheindlin finds troubling: 'Instead, I conclude that the benchmark used by plaintiffs' expert—a combination of local population demographics and local crime rates (*to account for police deployment*) is the most sensible' (p. 9, emphasis added). Finally, Glaser (2015) recounted a particularly clear example of selection neglect when a former Los Angeles police chief told a reporter: 'if officers are looking for criminal activity,

[6] Given this crime belief function, it is always the case that $\tilde{p}_J \leq p_J$ because $w_J < 1$. However, a simple generalisation of the crime belief function is to write it as $\tilde{c}_J = \beta((1-\nu)p_J w_J + \nu p_J)$, where $\beta > 0$ scales whether the officer generally over- or under-estimates the prevalence of crime in each group. The resulting belief about crime rates is then $\tilde{p}_J = w_J p_J/(\beta((1-\nu)w_J + \nu))$. Scaling the crime belief function in this way does not affect the ratio $\tilde{r}_p$; hence, it would not affect the equilibrium policing allocation we derive below.

[7] Algebraically, our bias ends up resembling a technology used in Benabou and Tirole (2006), who used it to model how individuals bias their future beliefs by limiting recall of particular kinds of information and not fully adjusting for this limited recall.

they're going to look at the kind of people who are listed on crime reports' (p. 96). Of course, the 'kinds of people who are listed on crime reports' will be disproportionately from highly policed communities and not necessarily representative of those who are prone to commit crimes.

2.1. *Equilibrium*

So far, we have characterised how the officer's beliefs respond to his actions and how his actions respond to his beliefs. This suggests a natural equilibrium definition.

DEFINITION 1. *An* **equilibrium** *is a policing allocation* w_A^* *and a belief about crime rates* $\tilde{r}_p^*$, *where*

(*i*) w_A^* solves $w_A^* = w_A^{\text{br}}(r_t\tilde{r}_p^*)$ and
(*ii*) $\tilde{r}_p^* = \tilde{r}_p(w_A^*)$.

If $(\partial w_A^{br}/\partial w_A)|_{w_A=w_A^*} < 1$, *the equilibrium is* **stable**.

This is similar to what Esponda and Pouzo (2016) call a 'Berk Nash equilibrium'. Much of the theoretical literature on misspecified models provides general conditions under which beliefs and behaviour do in fact converge to such a stable point (Bohren, 2016; Esponda and Pouzo, 2016; Levy *et al.*, 2022). To keep the focus on our application, we analyse behaviour at a stable point.

PROPOSITION 1. *A stable equilibrium exists in the single officer model. If* ν *is sufficiently small, the equilibrium is unique.*

PROOF. If $w_A^{\text{br}}(r_t\tilde{r}_p(\underline{w}+\epsilon)) = \underline{w}$ for some $\epsilon > 0$ or $w_A^{\text{br}}(r_t\tilde{r}_p(\overline{w}-\epsilon)) = \overline{w}$ for some $\epsilon > 0$ then there is a stable corner equilibrium allocation.

We next show that if neither of these hold, there is an interior equilibrium. Let $F(w_A) = w_A^{\text{br}}(r_t\tilde{r}_p(w_A)) - w_A$. That is, $F(w_A)$ represents how the officer would change his allocation if starting from w_A. Accordingly, an equilibrium occurs where $F(w_A^*) = 0$.

If there is no stable corner solution then it must be the case that $w_A^{\text{br}}(r_t\tilde{r}_p(\underline{w}+\underline{\epsilon})) > \underline{w}$ for some small $\underline{\epsilon} \in (0, 1/2)$, and hence $F(\underline{w}+\underline{\epsilon}) > 0$. There must also be a $\overline{\epsilon} \in (0, 1/2)$ such that $w_A^{\text{br}}(r_t\tilde{r}_p(\overline{w}-\overline{\epsilon})) < \overline{w}$ and, similarly, $F(\overline{w}-\overline{\epsilon}) < 0$. By the continuity of w_A^{br} in $\tilde{r}_p$ and the continuity of $\tilde{r}_p$ in w_A, F is continuous in w_A, and so the intermediate value theorem implies that there must be a $w_A^* \in (\underline{\epsilon}, \overline{\epsilon})$ such that $F(w_A^*) = 0$, where $F'(w_A^*) < 0$. Finally, since $F'(w_A) = \partial w_A^{\text{br}}/\partial w_A - 1$, then

$$F'(w_A^*) < 0 \quad \Longleftrightarrow \quad \left.\frac{\partial w_A^{\text{br}}}{\partial w_A}\right|_{w_A=w_A^*} < 1,$$

and w_A^* is stable.

Finally, recall that there is a unique equilibrium when $\nu = 0$ by Lemma 1, and that it is interior by Lemma 2. By the continuity of w_A^{br} in $\tilde{r}_p$ and the continuity of $\tilde{r}_p$ in ν, there must exist some $\hat{\nu} > 0$ such that, for all $\nu < \hat{\nu}$, there is a unique equilibrium. □

The condition on ν in Proposition 1 is not always required for uniqueness. Consider the following utility function that satisfies our assumptions: $(t_A c_A)^\alpha + (t_B c_B)^\alpha$ with $\alpha \in (0, 1)$ capturing 'how concave' the utility function is in w_A. In Lemma A.2 of Online Appendix A, we show that there is a unique equilibrium for all ν as long as this utility function is sufficiently concave (sufficiently small α). To allow for clean statements about how inaccurate beliefs affect equilibrium behaviour, our remaining technical results (and illustrations) focus on cases where there is a unique equilibrium.

2.1.1. *Main example (continued)*

For our main example with a utility function given by (2), there is a unique equilibrium for any $\nu \in (0, 1]$ in which the officer chooses a policing allocation

$$w_A^* = \begin{cases} \underline{w} & \text{if } \widehat{w}_A < \underline{w}, \\ \widehat{w}_A & \text{if } \widehat{w}_A \in [\underline{w}, \overline{w}], \\ \overline{w} & \text{if } \widehat{w}_A > \overline{w}, \end{cases}$$

where

$$\widehat{w}_A = w_A^\dagger + \frac{\nu(r_t r_p - 1)}{(1-\nu)(1 + r_t r_p)}.$$

This is because there is a unique solution to $w_A = r_t \tilde{r}_p(w_A)/[1 + r_t \tilde{r}_p(w_A)]$ given by $\widehat{w}_A$. If $\widehat{w}_A$ lies in $[\underline{w}, \overline{w}]$ then it corresponds to an equilibrium allocation. Whenever $\widehat{w}_A$ does not lie in $[\underline{w}, \overline{w}]$, then there is an equilibrium at a corner solution. (See Proposition A.1 in Online Appendix A.)

2.1.2. *Illustrations*

In each panel of Figure 1, we illustrate the fixed point analysis for the officer's decision problem, using different values of r_t and r_p and assuming a utility function given by (2). The black curves trace out $w_A^{\text{br}}(r_t \tilde{r}_p(w_A))$ as a function of w_A. An equilibrium allocation lies at an intersection of the black curve and the 45° line.

The top left panel depicts a scenario with equal crime rates and no officer animus, $r_p = r_t = 1$. In this situation, despite making inferential mistakes, the officer's policing allocation is equal, $w_A^* = 1/2$. If the officer were to police group A more or less, there would be 'self-correction': he would move back towards the equilibrium with equal policing.

However, equal policing is fragile to changes in the exogenous parameters r_t and r_p. The bottom left panel demonstrates a situation with equal crime rates, but where the officer has animus toward group A. Without making an inferential mistake, the officer's animus toward group A causes him to engage in taste-based discrimination against group A so that $w_A^\dagger > 1/2$ (and thus $\Delta^\dagger > 0$). However, selection neglect causes him to police group A even more than he would due to his animus alone, $w_A^* > w_A^\dagger$.

Formally, if the officer chooses a policing allocation w_A^* in an equilibrium then we define the policing disparity relative to the full information benchmark as

$$\Delta^* \equiv |w_A^* - w_A^\dagger|.$$

This is the 'excess disparity' caused by the fact that the officer makes an inferential mistake when forming his belief about the two crime rates. Following Bohren *et al.* (2019a), we refer to it as *inaccurate statistical discrimination*. We show below that inaccurate statistical discrimination always goes in the same direction as the disparity caused by the standard explanations (and represented by $\Delta^\dagger$). We can therefore denote total discrimination as $\Delta = \Delta^\dagger + \Delta^*$. Returning to

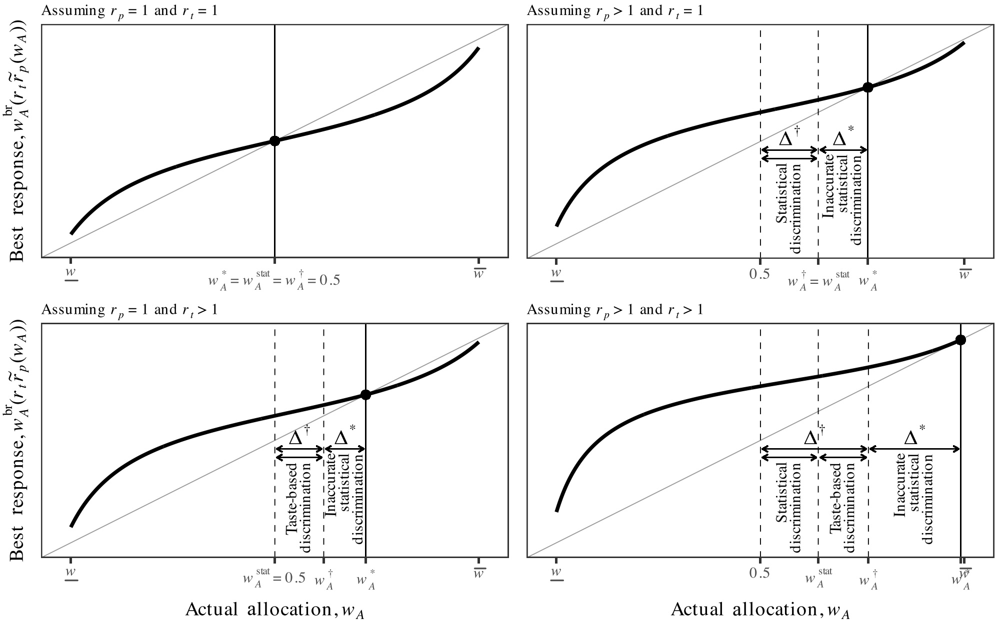

Fig. 1. *The Officer's Best Response.*
Notes: In each panel, we plot the officer's best response $w_A^{\text{br}}(r_t \tilde{r}_p(w_A))$ as a function of his actual policing allocation w_A. An equilibrium of the model occurs where $w_A^{\text{br}}(r_t \tilde{r}_p(w_A))$ intersects the diagonal line—i.e., at a fixed point, denoted by a large dot. Each panel depicts equilibria for different parameter values. We also depict the disparities caused by statistical, taste-based and inaccurate statistical discrimination in each equilibrium. For the left panels, crime rates are equal ($r_p = 1$) and, for the right panels, group A's crime rate is higher ($r_p > 1$). For the top panels, the officer has no animus ($r_t = 1$) and, for the bottom panels, the officer has animus against A ($r_t > 1$).

the bottom left panel of Figure 1, in this equilibrium about half of the officer's discrimination is driven by animus, and about half is driven by selection neglect.

Inaccurate statistical discrimination can also occur in the absence of officer animus. The top right panel indicates a case where $r_t = 1$, but $r_p > 1$. So, some of the disproportionate policing of group A is explained by different crime rates (again $w_A^\dagger > 1/2$, and $\Delta^\dagger > 0$), but the officer believes that these differences are bigger than they really are. As with the illustration of taste-based discrimination, this roughly doubles the policing disparity relative to the full information benchmark. Even though this is 'all statistical discrimination', roughly half of it is driven by incorrect beliefs.

Finally, the bottom right panel shows a case where group A has a higher crime rate and the officer has animus towards this group. In this case, no matter what feasible allocation he chooses, he would always like to police group A even more. This leads to a corner solution even though his policing allocation would be interior if he had full information.

For an officer with selection neglect, taste-based and statistical discrimination are no longer two mutually exclusive channels through which policing disparities emerge. When conceptualised in this way, our model shows that taste-based discrimination can *cause* (inaccurate) statistical discrimination. And since an officer's animus can cause distorted beliefs about crime rates, our model maps into an intuition in the academic literature (and in popular discourse) that the empirical phenomenon of prejudice will typically involve both racial animus and incorrect beliefs.

To be more concrete about how this works in our model, consider the following. First, the officer's animus causes him to allocate more policing effort toward one group. Then, since he spends more time policing that group, he sees more crimes among members of that group. Finally, selection neglect causes him to infer that the increased number of crimes he observes is an indication that the crime rate among members of that group is higher than it actually is. As a result (and notwithstanding his animus), his selection neglect causes him to *sincerely believe* that some (or even most) of his over-policing of one group is justified by the prevalence of crime among members of that group. As Gelman *et al.* (2007) pointed out: 'Police often point to the high rates of seizures of contraband, weapons, and fugitives in such stops, and also to a reduction of crime, to justify such aggressive policing' (p. 814).

The next proposition states exactly when policing with the misspecified model we study ends up amplifying policing disparities caused by taste-based and/or statistical discrimination.

PROPOSITION 2. *For any* $\nu \in (0, 1)$, *the following statements hold.*

(*i*) *If* $r_t r_p = 1$ *then there is an equilibrium with no policing disparity* (*since* $w_A^* = w_A^\dagger = 1/2$), *and the officer has correct beliefs about crime,* $\tilde{r}_p^* = r_p$.

(*ii*) *If* $r_t r_p \neq 1$, *and the equilibrium is unique, then selection neglect amplifies existing disparities:* $w_A^* > w_A^\dagger > 1/2$ *if* $r_t r_p > 1$ *and* $w_A^* < w_A^\dagger < 1/2$ *if* $r_t r_p < 1$ (*alternatively,* $\Delta^* > 0$), *and the officer has incorrect beliefs,* $\tilde{r}_p^* \neq r_p$.

PROOF. Part (*i*) immediately follows from the facts that $\tilde{r}_p(1/2) = 1$ (using (3)) and $w_A^{\text{br}}(1) = 1/2$ (from Lemma 1).

For part (*ii*), as in the proof of Proposition 1, let $F(w_A) = w_A^{\text{br}}(r_t \tilde{r}_p(w_A)) - w_A$. If the equilibrium is unique, it must be stable by Proposition 1. And so if w_A^* is the equilibrium, it must be the case that $F(w_A) > 0$ if and only if $w_A < w_A^*$ and $F(w_A) < 0$ if and only if $w_A > w_A^*$.

From Lemma 1, if $r_t r_p < 1$ then $w_A^\dagger < 1/2$, and so $\tilde{r}_p(w_A^\dagger) < r_p$, and so $w_A^{\text{br}}(r_t r_p) > w_A^{\text{br}}(r_t \tilde{r}_p(w_A^\dagger))$, and $F(w_A^\dagger) < 0$. Therefore, $w_A^\dagger > w_A^*$, and $\tilde{r}_p(w_A^*) < r_p$. The proof for $r_t r_p > 1$ follows an identical logic. □

If the officer's policing allocation is not at a corner ($\underline{w}$ or $\overline{w}$) then the disparity caused by inaccurate statistical discrimination is strictly positive as $r_t r_p$ moves away from 1. Figure 2 illustrates. In the left panel, we plot policing disparities as a function of the (true) relative crime rate, r_p. In the right panel, we plot policing disparities as a function of the officer's animus, r_t. In each panel, the grey line depicts the policing disparity caused by statistical and taste-based discrimination and the black line depicts the entire policing disparity. Note that in either panel, as long as $r_t r_p \neq 1$, then inaccurate statistical discrimination causes the policing disparity to be higher than it otherwise would have been with only taste-based and statistical discrimination.

As raised at several points above, we also analyse several extensions and variants of the model in the Online Appendix. In particular, we explore what happens in our model when (1) the officer chooses to allocate effort across neighbourhoods instead of groups (Online Appendix B); (2) crime rates endogenously respond (i.e., decrease) in response to policing (Online Appendix C); (3) there are non-linear returns to policing effort (Online Appendix D) and (4) the officer's beliefs are misspecified in a more general way (Online Appendix F). These extensions largely demonstrate

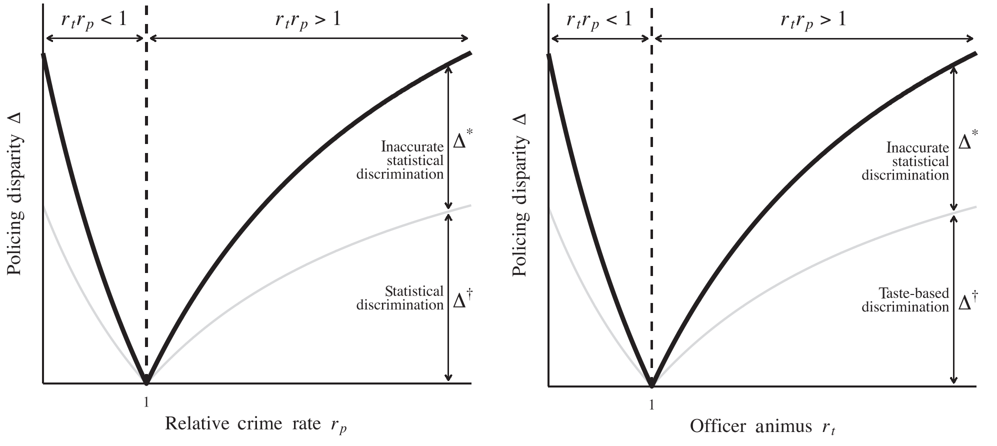

Fig. 2. *Policing Disparities.*

Notes: In each panel, we plot the policing disparity that emerges in an interior equilibrium of the model, as a function of the true relative crime rate (left panel) and the officer's animus toward group *A* (right panel). As long as $r_t r_p \neq 1$, the officer always engages in either statistical or taste-based discrimination, as well as inaccurate statistical discrimination.

that our core findings hold in a wide range of settings beyond the parsimonious one we study in the main text.

In Online Appendix E, we analyse an extension of our model in which there are multiple officers, each of whom learns about crime from their own policing efforts and from other officers.[8] The officers can differ with respect to their taste for policing the two groups (the t_J parameters) and the severity of their selection neglect (the ν parameters). As in the single officer case, feedback loops generating 'excess disparities' still arise. Moreover, they spill-over across officers: one officer's excessive policing of a group (due to their animus or their selection neglect) causes other officers to discriminate more than they would if they were policing alone. In this multi-officer setting with selection neglect, discrimination and inferential mistakes are both contagious across officers, lending credence to the old adage that a bad apple can spoil the bunch.

2.1.3. *Empirical and policy implications*

Empirically identifying the likely cause of policing disparities is important for policy-makers seeking to reduce them. But the possibility of inaccurate statistical discrimination creates an identification problem for researchers relying on standard hit-rate tests (see Bohren *et al.*, 2019a). An important empirical implication of our model is that simply giving officers accurate, external and trustworthy information about crime rates should reduce discrimination whenever there is selection neglect (see Proposition 2). If it does not then this rules out (genuinely held) inaccurate beliefs as a cause of discrimination.

The model also provides a policy rationale for the legal doctrine of disparate impact. By the logic of our model, disparities will always be 'excessive' with selection neglect, regardless

[8] Our analysis focuses on the case with two officers, but the arguments would naturally extend to a larger number.

of their root cause. Simply requiring a police department to reduce policing disparities (e.g., through a consent decree) can cause police officers to form more accurate beliefs about crime on the ground, all else equal.

A more normative concern one might raise is that the distinction between taste-based and inaccurate statistical discrimination is irrelevant insofar as they both generate 'inefficient' discrimination. However, to the extent that selection neglect plays a role in discriminatory policing, *even officers with animus* would willingly reduce their discriminatory behaviour if they had access to better information. Given that the evidence on the effectiveness of interventions to reduce animus is relatively weak (see Paluck *et al.*, 2021), policy-makers may be able to make progress with simpler interventions aimed at improving statistical reasoning about crime rates.

3. Conclusion

This paper studies how discrimination can be exacerbated when decision-makers do not account for the selection bias in data they observe. This phenomenon is acutely relevant for understanding the nature of racial discrimination in policing, as we have demonstrated with our substantive focus on this application. However, some of the core mechanics of our model could be applied to other topics, and have been in recent and contemporaneous work.

Another natural domain for these ideas is labour markets. If firms form beliefs about who will be productive based on those they hire, past discrimination will influence the sample of employees they have to learn from.[9] In this context it is possible to have a 'bias reversal' (Rambachan and Roth, 2019) if the only people to get hired from a group facing discrimination are particularly high ability. On the other hand, a potential source of positive feedback arises if employers and other advisors/mentors invest in individuals they expect will perform well (Chauvin, 2018).

Chauvin (2018) also applied this idea to the domain of education. In a related paper, Levy and Razin (2017) studied how labour market discrimination against those attending public schools and incorrect beliefs about the productivity of those attending public school can co-evolve when those who attend private schools tend to be systematically pessimistic about public schools and do not adjust for this fact when learning from each other.

As these examples illustrate, different situations may result in either negative or positive feedback depending on the circumstances. Pinning down exactly when one or the other arises is a promising direction for future theoretical work.

University of California, Davis, USA
University of California, Berkeley, USA

Additional Supporting Information may be found in the online version of this article:

Online Appendix

References

Barron, K., Ditlmann, R., Gehrig, S. and Schweighofer-Kodritsch, S. (2020). 'Explicit and implicit belief-based gender discrimination: A hiring experiment', Discussion Paper SP II 2020-306, WZB Berlin Social Science Center.

[9] Lepage (2020) showed that selection problems can lead to discrimination in hiring even if employers form beliefs by Bayes' rule, as selection can create skew in the beliefs about ability.

Barron, K., Huck, S. and Jehiel, P. (2019). 'Everyday econometricians: Selection neglect and overoptimism when learning from others', Discussion Paper SP II 2019-301, WZB Berlin Social Science Center.

Benabou, R. and Tirole, J. (2006). 'Belief in a just world and redistributive politics', *The Quarterly Journal of Economics*, vol. 121(2), pp. 699–746.

Bohren, J.A. (2016). 'Informational herding with model misspecification', *Journal of Economic Theory*, vol. 163, pp. 222–47.

Bohren, J.A., Haggag, K., Imas, A. and Pope, D.G. (2019a). 'Inaccurate statistical discrimination: An identification problem', Working Paper 25935, National Bureau of Economic Research.

Bohren, J.A., Imas, A. and Rosenberg, M. (2019b). 'The dynamics of discrimination: Theory and evidence', *American Economic Review*, vol. 109(10), pp. 3395–436.

Chauvin, K. (2018). 'A misattribution theory of discrimination', Working paper, https://www.kylechauvin.com/research.

Coffman, K.B., Collis, M. and Kulkarni, L. (2019). 'Stereotypes and belief updating', Working Paper 19–068, Harvard Business School.

Collins, D. (2018). ' "Predictive policing": Big-city departments face lawsuits', *AP News*, 5 July.

Enke, B. (2020). 'What you see is all there is', *Quarterly Journal of Economics*, vol. 135(3), pp. 1363–98.

Epp, C.R., Maynard-Moody, S. and Haider-Markel, D.P. (2014). *Pulled Over: How Police Stops Define Race and Citizenship*, Chicago, IL: University of Chicago Press.

Esponda, I. (2008). 'Behavioral equilibrium in economies with adverse selection', *American Economic Review*, vol. 98(4), pp. 1269–91.

Esponda, I. and Pouzo, D. (2016). 'Berk–Nash equilibrium: A framework for modeling agents with misspecified models', *Econometrica*, vol. 84(3), pp. 1093–130.

Esponda, I. and Vespa, E. (2018). 'Endogenous sample selection: A laboratory study', *Quantitative Economics*, vol. 9(1), pp. 183–216.

Eyster, E. and Rabin, M. (2005). 'Cursed equilibrium', *Econometrica*, vol. 73(5), pp. 1623–72.

Feigenberg, B. and Miller, C. (2022). 'Would eliminating racial disparities in motor vehicle searches have efficiency costs?', *The Quarterly Journal of Economics*, vol. 137(1), pp. 49–113.

Gelman, A., Fagan, J. and Kiss, A. (2007). 'An analysis of the New York City police department's "stop-and-frisk" policy in the context of claims of racial bias', *Journal of the American Statistical Association*, vol. 102(479), pp. 813–23.

Ghandnoosh, N. (2015). 'Black lives matter: Eliminating racial inequity in the criminal justice system', Report, The Sentencing Project.

Glaser, J. (2015). *Suspect Race: Causes and Consequences of Racial Profiling*, New York: Oxford University Press.

Goel, S., Rao, J.M. and Shroff, R. (2016). 'Precinct or prejudice? Understanding racial disparities in New York City's stop-and-frisk policy', *The Annals of Applied Statistics*, vol. 10(1), pp. 365–94.

Harcourt, B.E. (2007). *Against Prediction: Profiling, Policing, and Punishing in an Actuarial Age*, Chicago, IL: University of Chicago Press.

Heckman, J.J. and Durlauf, S.N. (2020). 'An empirical analysis of racial differences in police use of force: A comment', *Journal of Political Economy*, vol. 128(10), pp. 3998–4002.

Heidhues, P., Kőszegi, B. and Strack, P. (2018). 'Unrealistic expectations and misguided learning', *Econometrica*, vol. 86(4), pp. 1159–214.

Heidhues, P., Kőszegi, B. and Strack, P. (2020). 'Overconfidence and discriminiation', Preprint, https://arxiv.org/abs/1909.08497.

Hübert, R. and Little, A.T. (2022). 'Social segregation, inter-group contact and discriminatory policing', Preprint, https://osf.io/9bnwy/.

Hull, P. (2021). 'What marginal outcome tests can tell us about racially biased decision-making', Working Paper 28503, National Bureau of Economic Research.

Jehiel, P. (2018). 'Investment strategy and selection bias: An equilibrium perspective on overoptimism', *American Economic Review*, vol. 108(6), pp. 1582–97.

Knowles, J., Persico, N. and Todd, P. (2001). 'Racial bias in motor vehicle searches: Theory and evidence', *Journal of Political Economy*, vol. 109(1), pp. 203–29.

Knox, D., Lowe, W. and Mummolo, J. (2020). 'Administrative records mask racially biased policing', *American Political Science Review*, vol. 114(3), pp. 619–37.

Knox, D. and Mummolo, J. (2020). 'Making inferences about racial disparities in police violence', *PNAS*, vol. 117(3), pp. 1261–2.

Koehler, J.J. and Mercer, M. (2009). 'Selection neglect in mutual fund advertisements', *Management Science*, vol. 55(7), pp. 1107–21.

Lepage, L.P. (2020). 'Endogenous learning, persistent employer biases, and discrimination', Preprint, https://ssrn.com/abstract=3640663.

Levy, G. and Razin, R. (2017). 'The coevolution of segregation, polarized beliefs, and discrimination: The case of private versus state education', *American Economic Journal: Microeconomics*, vol. 9(4), pp. 141–70.

Levy, G., Razin, R. and Young, A. (2022). 'Misspecifed politics and the recurrence of populism', *American Economic Review*, vol. 112(3), pp. 928–62.

Lum, K. and Isaac, W. (2016). 'To predict and serve?', *Significance*, vol. 13, pp. 14–9.

Mengel, F. and Campos Mercade, P. (2021). 'Non Bayesian statistical discrimination', Preprint, https://ssrn.com/abstract=3843579.

Paluck, E.L., Porat, R., Clark, C.S. and Green, D.P. (2021). 'Prejudice reduction: Progress and challenges', *Annual Review of Psychology*, vol. 72, pp. 533–60.

Rambachan, A. and Roth, J. (2019). 'Bias in, bias out? Evaluating the folk wisdom', Preprint, https://arxiv.org/abs/1909.08518v1.

Stashko, A. (2020). 'Do police maximize arrests or minimize crime? Evidence from racial profiling in U.S. cities', Preprint, https://ssrn.com/abstract=3132046.