Unpacking Name-Based Race Discrimination*

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Abstract

We investigate the extent and underlying mechanisms of how race beliefs associated with applicants' names affect hiring decisions. Using nationally representative data, we find widespread beliefs that people with names perceived to be Black possess lower levels of education, productivity and noncognitive skills. Notably, this race penalty persists when considering only variation in race perception for the *same* name and when omitting distinctly Black names. Conducting an incentivized hiring experiment with real worker data, we find that participants are 30 percentage points (pp) more likely to hire workers perceived to be white compared to Black. Controlling for productivity and noncognitive skills beliefs reduces this racial gap to 21 pp and 20 pp, respectively. Results indicate that race serves as a decision heuristic as employers make faster decisions and display more certainty when perceived race differences between candidates are large. Moreover, the race gap in hiring increases by 25% when employers are forced to make quick decisions. Estimates from a structural drift-diffusion model quantify the effect of beliefs and show that employers differ both in their usage of racial heuristics and inclination to override these heuristics when given sufficient decision time.

Keywords: Race Discrimination, Hiring Discrimination, Name Associations

JEL Codes: J50, J70

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1 Introduction

Names are often one of the first things we learn about people with whom we interact. A vast body of literature highlights the impact of first impressions, in part because they shape the way we process further information (Nisbett and Wilson, 1977; Nisbett and Ross, 1980). Names may thus influence perceptions and decisions, especially when other information is limited. One important example comes from the hiring process. Bertrand and Mullainathan (2004) find that resumes with distinctively Black names, such as Lakisha, receive 50% fewer callbacks from employers compared to resumes with distinctly white names like Emily. The authors postulate that this disparity may be due to employers' use of "quick heuristics" in screening applications. This explanation is supported by Bartoš et al. (2016)'s finding that employers spend less time reviewing resumes of minority job candidates.[1]

In this study we elicit people's beliefs regarding demographic characteristics, noncognitive skills, and productivity levels associated with different worker names. Beliefs are measured probabilistically, which provides precise variation in race associations both within and across respondents for given names. This novel data allows us to estimate the role of race perceptions on hiring decisions more accurately, without relying on distinctly Black names or making assumptions about how people perceive names. We can also estimate how much of hiring discrimination is accounted for by other beliefs than race, including unobserved beliefs about names that are shared across employers. By randomizing the hiring decision time, we further gain insights into race-based heuristics employers may use.

The research design features two stages, similar to those of Barron et al. (2020) and Bohren et al. (2023). In the first stage, we recruit Black and white workers and collect data on their first names and productivity, measured as the share of financial receipts that they correctly transcribe (Abel, 2022). In the second stage, we recruit a nationally representative sample of 1,500 individuals from the U.S., over half of whom have real-life experience making hiring decisions, to serve as employers in our experiment. We first elicit their beliefs about demographic characteristics (race, age, education), noncognitive skills (e.g. responsibility and motivation), and productivity levels for a set of names from our worker sample.[2] For the second task, employers make hiring decisions for ten worker pairs with names drawn from our worker sample. They receive a bonus each time they select the more productive worker.

We present four main results, following a registered pre-analysis plan. Firstly, the data

[1] An extensive literature has explored the effect of names across domains ranging from politics (Barth et al., 2019), education (Kreisman and Smith, 2023), and other life outcomes (Fryer Jr and Levitt, 2004).

[2] We focus on the Black - white gap in hiring and limit our analysis to first names as last names are less indicative of race for these groups (Gaddis, 2017). In fact, Darolia et al. (2016) conduct an audit study with race-neutral first names, signaling race through last names. They find no difference in employer callbacks. This may be different for other race groups. For example, Oreopoulos (2011) shows that immigrants receive fewer employer callbacks if they have Asian compared to English last names.

show substantial variation in beliefs about characteristics across worker names and that these associations are strongly correlated with perceptions of race. Names commonly associated with being Black are associated with lower levels of education and noncognitive skills. The magnitude of the racial disparity is very large. For instance, perceiving a name to be 100% Black compared to 100% white is associated with a 16 pp (47%) decrease in the likelihood of holding a master's degree and a 29 pp (42%) and 26 pp (46%) decrease in the likelihood of being perceived as responsible and trustworthy, respectively - traits that play an increasingly important role in labor markets but are hard to observe from a resume (Deming, 2017).

Our findings reveal that these biased perceptions lead to disparities in worker assessments, resulting in a 25% gap in productivity beliefs based on perceiving someone as Black vs. white. However, this race penalty is *not* primarily driven by differences between distinctly Black names (e.g. Shanice) and distinctly white names (e.g. Heather). Controlling for name fixed effects, which accounts for commonly shared associations of names, only reduces the productivity race penalty by 10 pp or 40%. It remains large at 15%, highlighting the importance of variance in race perceptions *between* employers for the *same* name. This within-name variation in beliefs is important as it may help explain heterogeneity in discrimination observed in recent studies (e.g. Kline et al. (2021)).

The second key finding is that participants' racialized perceptions are highly predictive of their hiring choices. On average, employers are 29.6 pp less likely to hire a worker they perceive as Black compared to white. Controlling for productivity and noncognitive skill beliefs reduces this gap to 21.3 pp and 20.3 pp, respectively. Accounting for age, education, productivity and noncognitive skill beliefs simultaneously reduces the race gap to 13.1 pp. These results are robust to excluding distinctly Black names from our sample. Results are also unchanged when we exclude respondents who suspect that the research is about discrimination, which assuages social desirability concerns.

We find that discrimination varies substantially based on certain employer characteristics. The overall 29.6 pp race gap narrows for female (by 7.5 pp), younger (6.3 pp), Black (12.1 pp), and liberal (11.7 pp) employers as well as those who support race-based affirmative action (13.7 pp). Despite these reductions, the race gap remains substantial and statistically significant (at the 0.1% level) across each of these groups. By contrast, no significant differences in the race gap are observed based on employers' educational attainment, the level of racial diversity in their zip code, or whether they had previous experience with hiring.

Third, we investigate mechanisms underlying discrimination in hiring decisions. Across various tests, we find evidence suggesting that employers use race as a heuristic in their decision-making process. Differences in race perceptions between candidates increase employers' confidence in their hiring decision and reduce the decision time, even after controlling for differences in perceived productivity.[3] However, in cases where a candidate is perceived

[3]The finding that race differences increase hiring certainty provides evidence against the hypothesis that people prefer white candidates due to a lack of certainty about the qualities of Black candidates (Heckman

as both more productive and more likely to be Black, the decision-making time increases, indicating that decision heuristics based on race and productivity beliefs are in conflict.[4]

To further investigate the role of heuristic-based decision-making, we randomize one-third of employers to make hiring decisions within a two-second time frame, reflecting the fact that recruiters often spend very little time reviewing resumes at early screening stages (Cole et al., 2007). We find that time pressure exacerbates hiring discrimination by around 25%, with the most adverse effects observed for Black candidates perceived to be highly productive. Importantly, there is substantial heterogeneity in who is affected by rushed decisions: discrimination increases by almost 70% among white employers who support race-based affirmative action (AA) but has no effect on the hiring decisions of Black employers or white employers who oppose AA.

Fourth, to parse and quantify the role of heuristic biases and analytical belief-based evaluations, we use data on hiring decisions, response times as well as race and productivity beliefs, to estimate the parameters of a structural drift-diffusion model (DDM). The DDM, which is widely used in neuro-psychology, posits that decision-makers sequentially sample information about choice options from memory and make a decision once an evidence threshold has been reached.[5] This process causes decision values to drift gradually in the direction of preferred candidates. Motivated by reduced form evidence, we model this drift to be affected by employers' race and productivity beliefs.

Our structural estimates reveal that both productivity and race beliefs affect the decision drift, and that their relative importance in the decision process varies over time. In quick decisions, there is a significant drift favouring workers with white names, suggesting the use of (race-based) heuristics in hiring decisions, especially when people are under time pressure. Interestingly, despite observing similar levels of discrimination in long hiring decisions between Black employers and white employers who support AA, the underlying mechanisms behind this outcome are very different. Black employers exhibit a relatively weak heuristic response to Black names, whereas white employers who support AA initially display a strong negative heuristic response, which is subsequently overridden in longer decisions. White employers who oppose AA also exhibit a strong heuristic response, but this judgement aligns more closely with that of their slower, analytical cognitive process. Counterfactual analyses based on our structural estimates indicate that, on average, a Black worker would need to be 20.3 pp (1.2 sd) more productive to have an even chance of being hired over a white worker in slow decisions. This figure increases to 39 pp (2.4 sd) for very quick decisions.[6]

and Siegelman, 1993). We also find that the race gap does not differ along employers' level of risk aversion.

[4]This aligns with the concept of implicit association tests (IAT), which measure the unconscious associations of, for example, race (Black vs. white) and evaluations (good vs. bad) by comparing the speed of sorting decisions when concepts and evaluations are aligned versus misaligned (Greenwald et al., 2003).

[5]The DDM relates to a recent set of models. E.g. in Bordalo et al. (2020), memories about past consumption experiences and prices both serve as anchors for evaluating choices. Other models, explore the role of memory in forming beliefs (e.g. Mullainathan (2002); Bordalo et al. (2019); Enke et al. (2020)).

[6]These results align with previous research that highlight the need for members of discriminated groups

Our study relates to an extensive body of literature that uses audit studies to detect discrimination in dimensions such as race, gender, or nationality (for reviews see Baert (2018); Bertrand and Duflo (2017); Neumark (2018)). In these studies the characteristic of interest (e.g. race) is typically signaled through individuals' first names. However, a well-known challenge in interpreting audit study results is that employers may associate candidates with distinctly Black names also with other characteristics important for the hiring decision such as lower educational attainment (Fryer Jr and Levitt, 2004). While other studies have collected name associations (e.g. Baert et al. (2022); Crabtree et al. (2023); Gaddis (2019)), our study is to our knowledge the first to incentivize truthful belief elicitation for demographic characteristics and to validate that reported noncognitive skill associations are predictive of incentivized decisions (in a trust game).

Another key innovation is the collection of data on people's *distribution* of beliefs about names.[7] Simulations based on our data show that if we had followed existing studies and collected binary race associations, we would have missed about *half* of the race penalty in hiring and beliefs. This suggests that a significant share of discrimination occurs between candidates for whom employers agree on the most likely race category but differ in their level of certainty. For example, our data indicate that Colin is perceived as 77% likely to be white, whereas Robert is seen as 60% likely to be white. Yet, for both these names, around 90% of employers believe that the single most likely race category is white. Binary race perception data would treat these two names as equally white and thus fail to attribute employer preferences for Colin to race beliefs, leading to an underestimation of discrimination. A second key benefit of using probabilistic data is the ability to more precisely estimate the variance in race beliefs induced by studies that randomize names. This, in turn, allows calculating local average treatment estimates (LATE) from intent-to-treat estimates reported in audit studies, such as differences in callback rates. The LATE is important as it provides a more accurate measure of the impact of perceiving a candidate as Black.

Our study also contributes to the growing body of literature examining the role of employers' beliefs about workers. Traditional models distinguish between taste-based discrimination (Becker, 1957) and statistical discrimination (Arrow, 1973; Phelps, 1972). Recent research has added more nuance to this categorization by demonstrating that beliefs can often be inaccurate due to biases, stereotypes, or lack of information (e.g. Barron et al. (2020); Bohren et al. (2023); Bordalo et al. (2016, 2019); Coffman et al. (2021); Chakraborty and Serra (2022)). Bohren et al. (2023) develop a model of "inaccurate statistical discrimination" and show that the accuracy of beliefs has crucial implications for identifying underlying mechanisms and for designing policies to reduce discrimination.

Comparing employers' productivity beliefs to actual productivity data of 2,400 workers

to outperform others in order to overcome discrimination (Bohren et al., 2019).

[7] Reporting the (between-subject) variance of the binary race belief measure (such as Crabtree et al. (2023)) does not capture the within-person distribution of beliefs. Abel and Burger (2023) describe in more detail how researchers can access and use our data.

performing the same task, shows that employers' perceived race gap of 25% greatly exceeds the actual productivity difference of 9%. Our paper quantifies the effect of such biased beliefs on hiring decisions and employs a structural model to investigate *how* these beliefs are incorporated into the decision-making process. We are, to our knowledge, the first to apply the DDM to study hiring decisions. Methodologically, we are also the first to extend the DDM to allow decisions to be determined by elicited beliefs rather than relying on stated preferences and to allow the drift to be affected by perceptions of both race and productivity. In addition, randomizing the decision time helps identify the extent to which discrimination operates through heuristic and analytical cognitive processes. These findings relate to a growing literature showing how (biased) beliefs affect how much attention people pay to information, which may inhibit learning (Schwartzstein, 2014; Esponda et al., 2020; Gagnon-Bartsch et al., 2021).

Last, our paper helps explore the reasons behind the large heterogeneity in discrimination documented across jobs and industries in recent studies. For example, Kline and Walters (2021) conclude that "while most jobs barely discriminate, a few discriminate heavily." These findings are inconsistent with traditional models of statistical discrimination, but could be explained by heterogeneity in taste-based discrimination (Charles and Guryan, 2008). Our findings suggest that variation in (race) beliefs across hiring managers is one reason for this type of heterogeneity. This may help explain why variance in discrimination is more common for firms without centralized HR systems in which individual hiring managers have more decision power (Kline et al., 2021). Our results are also in line with studies identifying variation in the decision-making *process* including the time dedicated to screening of applicants as an important source of heterogeneity in discrimination (Bohnet, 2016). Our findings also highlight limitations of interventions to reduce discrimination, e.g. by increasing attention.

The paper proceeds as follows: Section 2 describes the research design and Section 3 introduces the empirical strategy. Section 4 discusses results on name associations and Section 5 investigates the role of these associations on hiring decisions. Section 6 explores underlying mechanisms and reports results from our structural estimation. Section 7 concludes.

2 Study Design

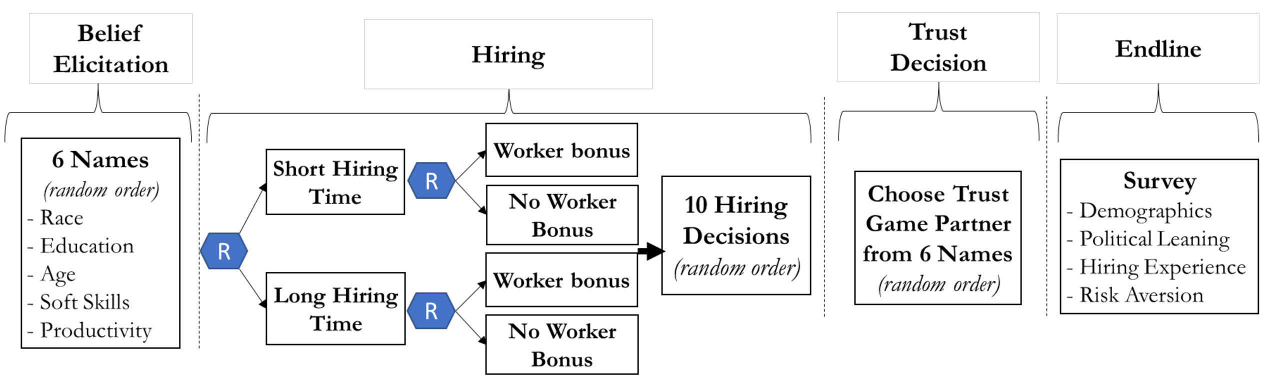
2.1 Worker Recruitment and Name Selection

A key feature of our study design is that it leverages real-life worker productivity data obtained from a previous field experiment. Specifically, we collect data on how people performed in transcribing financial receipts (see Abel (2022) for a detailed description of the study.) For the current study, we obtain permission from 150 of the initial sample of workers to use their first name in our research. We also collect data on incentivized choices in a trust game, as described in more detail below. We over-sample Black workers to obtain a racially balanced sample and categorize worker names as predominately Black, predominately white, or of ambiguous race based on pilot surveys that elicit race perceptions of names.[8] From each of these three categories, we sample five female and five male names. These 30 names are used as our worker sample in the hiring experiment.

2.2 Employer Recruitment and Sample Characteristics

The research design for our hiring experiment, conducted in the second stage, is summarized in Figure 1. We recruit a new sample of 1,500 people based in the U.S. to act as employers in our experiment. These participants are recruited through Prolific, which allows us to recruit a sample that is nationally representative in terms of key demographic characteristics such as age, race, and gender. This represents a significant advantage over other studies that recruit subjects online, which tend to be disproportionately young and white. The characteristics of our sample can be found in Column 3 of Table A1.

Figure 1: Experimental Design



The median (mean) income of participants is approximately USD 45,000 (USD 55,700), which is close to the national median of USD 41,500. Despite being representative on key demographic characteristics, our sample is more educated than the national average with 47% holding a college degree. 56% of our sample has previously been involved in hiring, which is important since it allows us to test whether hiring behavior in our experiment differs for those with actual hiring experience. Our data is also notable for its broad geographical representation, with participants from all 50 states and 1,373 zip code-level locations. By

[8]One challenge is that, to our knowledge, there is no nationally representative data on the race distribution of first names. For our initial categorization in pilot surveys, we use a variety of sources that use data from the New York (Gaddis, 2019) and California (Fryer Jr and Levitt, 2004) birth registrar for the initial categorization and then verify that it aligns with people's perceptions through several pilot surveys.

linking the zip code level data to census data, we are able to learn characteristics of the participants' geographic locations, including levels of racial diversity.

2.3 Belief Elicitation

We inform employers that the study aims to learn about the associations people have with names (see Appendix Figure B4 for details). We first present employers with six names (in random order). The names consist of one female and one male from each of the three categories: distinctly Black, distinctly white, and ambiguous race associations. For each name we collect belief associations from approximately 300 respondents.

We elicit beliefs about race/ethnicity, age, and education levels by asking participants the following question for each name "*Out of 10 people named ... how many people are...?*", followed by the categories of race/ethnicity, age, and education described in more detail below.[9] This method has several key advantages over previous research that asked about a single race category. Most importantly, it provides more nuanced data of the distribution of race beliefs and captures people's level of certainty over name associations.[10] Another advantage is that we incentivize participants to provide accurate answers by informing them that their responses will be compared to official national statistics, and that they will receive a bonus of USD 2.00 if they correctly order the characteristics of five name comparisons.[11]

In addition to eliciting beliefs about race, age, and education, we also collect data on noncognitive skill associations. Specifically, we ask participants to select from a list of seven traits (responsible, trustworthy, cooperative, assertive, self-motivated, perfectionistic, decisive) that they believe are characteristic of someone with a particular name.[12] We chose noncognitive skills that are widely regarded as important in the workplace (Heller and Kessler, 2022). While there is no objective data on how noncognitive skills vary by name (preventing us from incentivizing truthful responses), we can still compare people's responses to incentivized choices described in more detail below.

Last, to elicit beliefs about the productivity of workers, we present participants with six names in random order and ask them to estimate the productivity of workers with each

[9] We mix concepts of race (e.g. Black) and ethnicity (e.g. Hispanic) as preliminary data collections showed that participants are confused by questions that elicit data separately (as e.g. done by the U.S. census).

[10] Conceptually, a larger variance of beliefs may either mean that a person knows that the distribution is more disbursed or that the respondent is more uncertain about the name distribution. Both can be sources of uncertainty. In pilot data collection, we confirmed that reported certainty about associations are negatively correlated with a person's variance in race beliefs.

[11] To further explain this scheme, we present people with a concrete example of worker names and beliefs about age that determine the bonus payout. We do not specify which characteristics we use to determine the payout. In practice, we have administrative data on race and age.

[12] We ask: "*What characteristics do you think does a person with the name NAME have? (Please select all that apply)*". The seven traits are presented in random order.

name. We provide context by explaining that we have collected performance data in a financial receipt transcribing task (see Appendix B.3 for details). We further follow Bohren et al. (2023) and inform participants that a "*typical worker correctly transcribed 65% of receipts*" and incentivize accurate responses by offering a bonus of USD 0.50 for each correct productivity guess they make.

2.4 Hiring Decision and Randomization

After eliciting beliefs, we conduct the hiring experiment in which employers make sequential binary hiring choice for ten pairs of worker names. The ten pairs, presented in random order, are selected from the six names for which beliefs were elicited, and include combinations of workers with both the same and different race categories. Similar to Barron et al. (2020), each time they select the more productive worker, the employer receives a bonus of 10 cents. We also record the time taken to make each hiring decision. The average (median) decision time is 2.1 (1.8) seconds. This means that making correct choices could result in an additional payout of up to USD 1.00 over less than half a minute. Employers do not learn about how many correct choices they made until the end of the experiment.

The hiring experiment features a cross-randomization design that introduces exogenous variation in decision time and worker bonus (Figure 1). For the time variation, one-third of employers is informed that they must make a hiring decision within two seconds in order to be eligible for a bonus in a given hiring round. For the worker bonus variation, one-third of employers are informed before making their choices that the workers have the opportunity to earn an additional payout each time they are selected.[13] This "worker bonus" treatment mimics the benefit workers receive from being selected in real-world hiring decisions. Importantly, the worker bonus does not affect the monetary incentives that employers face and thus only affect hiring choices if people differentially care about the payout of white vs. Black workers, which could be one reason for why employers hire white workers.

After completing the hiring task, we offer participants the opportunity to earn an additional bonus through a trust game.[14] Specifically, we explain that we collected data on how much money each worker in our sample returned in the role of the recipient in the trust game. Participants can then choose a partner from a list of six names (presented in random order) and are paid a bonus according to how much the selected worker decision. Finally, we administer a short survey that collects data on employers' socio-demographic characteristics including age, education, income, location, and race as well as their political leaning, experience in hiring, level of risk aversion, and performance in a cognitive reflection test.

[13]The message reads: *"Each time that you hire a worker, they enter a lottery to win $200 that is paid as part of a wage bonus. It does not affect your payout."*

[14]Specifically, we first explain the trust game and then inform participants: '*'We asked each of the following workers how much they return if they received 20 cents from Person 1 (which gets doubled to 40 cents). You can pick one person. You will receive a bonus equal to the amount that this person decided to return."*

3 Empirical Strategy

3.1 Beliefs of Worker Characteristics and Productivity

Suppose an employer believes the productivity of a worker, y, is determined as

$$y = \alpha + \boldsymbol{r\theta} + \boldsymbol{x\delta} + u$$

where $\boldsymbol{x}$ is a vector of observable worker attributes, $\boldsymbol{\delta}$ is a vector containing the perceived productivity effects of these attributes, $\boldsymbol{r}$ is binary vector containing a single 1 corresponding to the worker's race, $\boldsymbol{\theta}$ reflects perceived race productivity effects, and u is a scalar summarizing the perceived effect of unobservable worker attributes on productivity.

In our experiment, employers are provided with a name, n, and are then asked to state their beliefs regarding the race, observable attributes and productivity of the worker. We denote these as $\hat{\boldsymbol{r}}_n \equiv E(\boldsymbol{r}|n)$, $\hat{\boldsymbol{x}}_n \equiv E(\boldsymbol{x}|n)$ and $\hat{y}_n \equiv E(y|n)$. Since race beliefs are elicited as probabilities, this directly measures $\hat{\boldsymbol{r}}_n = (\hat{r}_{Wn}, \hat{r}_{Bn}, \hat{r}_{Hn}, \hat{r}_{An}, \hat{r}_{On})$ where each element represents the employer's reported probability that a worker with name n is of race white, Black, Hispanic, Asian, or other, respectively.

If the employer believes, consciously or subconsciously, that worker attributes are correlated to race, then this would induce a correlation between race associations for a worker with name n, $\hat{\boldsymbol{r}}_n$ and beliefs about worker attribute k for a worker with name n, $\hat{x}_{kn}$:

$$\hat{x}_{kn} = \eta_k + \hat{\boldsymbol{r}}_n \boldsymbol{\pi}_k + E(e|n) \tag{1}$$

This relationship can be estimated by regressing employer beliefs regarding worker attributes on employer beliefs regarding race across all names, as we do in section 4 below.

If employers form productivity beliefs according to Bayes' rule, productivity predictions for a worker with name n are:

$$\hat{y}_n = \alpha + \hat{\boldsymbol{r}}_n \boldsymbol{\theta} + \hat{\boldsymbol{x}}_n \boldsymbol{\delta} + E(u|n) \tag{2}$$

The relationship between the employer's race beliefs and productivity predictions can be assessed by regressing predicted productivity on race beliefs:

$$\hat{y}_{ni} = \alpha + \beta_B \hat{r}_{Bni} + \beta_H \hat{r}_{Hni} + \beta_A \hat{r}_{Ani} + \beta_O \hat{r}_{Oni} + \hat{\boldsymbol{x}}_{ni} \boldsymbol{\delta} + \lambda_n + u_{ni} \tag{3}$$

where subscript i refers to the beliefs held by employer i. We choose the perceived probability of being white, $\hat{r}_{Wn}$, as the reference category in our empirical analysis, so the race coefficients for race q now represent $\beta_q = \theta_q - \theta_W$, i.e., the perceived productivity effect of belonging to race q compared to white. We cluster standard errors at the employer level to account for correlation in outcomes between choices for the same employer.

When not controlling for employer beliefs regarding worker attributes, the estimated race coefficients reflect both the direct perceived race effect on productivity, as well as the indirect affect that operate through perceived correlations between race and other worker attributes that are believed to determine productivity (Bohren et al., 2022). We can move closer to estimating this perceived race productivity effect by controlling for beliefs regarding commonly observable human capital measures (education and age) and noncognitive skills, $\hat{\boldsymbol{x}}_{ni}$. Our experimental design also allows us to control for name fixed effects, λ_n, which can capture any variation between names and unobservable productivity determinants, like socio-economic status, that is shared between employers. In contrast to other studies in this literature, we directly measure employer beliefs regarding worker attributes that are difficult to observe from resumes. This means we can more comprehensively control for confounding effects that may inflate the race association coefficients.

3.2 Hiring Decisions

When making a hiring decision between two workers with names n_1 and n_2, the employer may compare their predicted productivities and select worker n_2 if $E(y|n_2) > E(y|n_1)$, and candidate n_1 otherwise. Following equation 3.1, the expected difference in productivities can be expressed as:

$$E(y|n_2) - E(y|n_1) = (E(\boldsymbol{r}|n_2) - E(\boldsymbol{r}|n_1))\boldsymbol{\theta} - (E(\boldsymbol{x}|n_2) - E(\boldsymbol{x}|n_1)\boldsymbol{\delta} + E(u|n_2) - E(u|n_1) \quad (4)$$

Assuming that $E(y|n_2) - E(y|n_1)$ is normally distributed allows the estimation of $\boldsymbol{\beta}/\sigma$ and $\boldsymbol{\delta}/\sigma$ with a probit estimator. A linear approximation of this process can be expressed in terms of observable sample data:

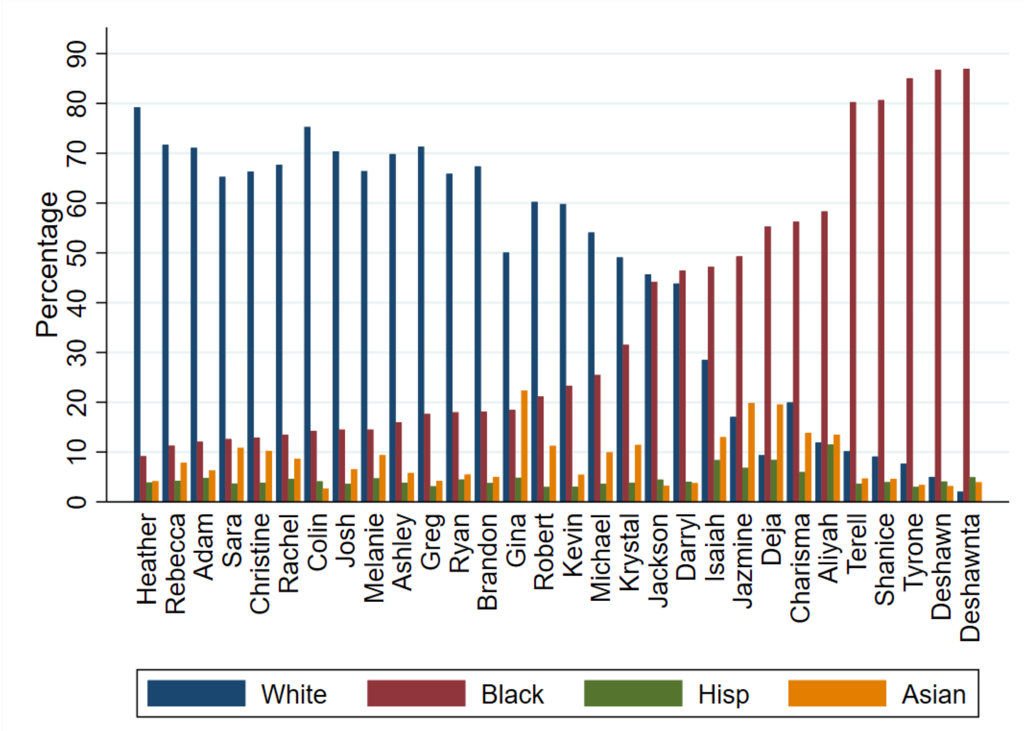
$$h_{ji} = \beta_B \Delta\hat{r}_{Bji} + \beta_H \Delta\hat{r}_{Hji} + \beta_A \Delta\hat{r}_{Aji} + \beta_O \Delta\hat{r}_{Oji} + \Delta\hat{\boldsymbol{x}}_{ji}\boldsymbol{\delta} + v_{ij} \quad (5)$$

where j denotes a specific name pair (n_1, n_2), $\Delta\hat{r}_{qji} \equiv \hat{r}_{qn_2i} - \hat{r}_{qn_1i}$ is the difference in the perceived probabilities that worker n_1 and n_2 are of race q, and $\Delta\hat{\boldsymbol{x}}_{ji} \equiv \hat{\boldsymbol{x}}_{n_2i} - \hat{\boldsymbol{x}}_{n_1i}$ is the perceived difference in worker attributes. The estimated coefficient $\beta_q = \theta_q - \theta_W$ (now implicitly scaled by σ) measures the effect of being perceived to belong to race q rather than being white. As before, we cluster standard errors at the employer level.

4 Name Associations

This section reports descriptive results of the race, age, education, noncognitive skill and productivity beliefs participants hold for the names of workers in our sample.

Figure 2: Race Associations



Notes: The figure shows race associations for different names sorted by race perception (from white to Black). The bars present the average associations across 300 respondents.

4.1 Race

Figure 2 shows the distribution of race associations for the 30 worker names in our sample. The names are ordered based on the perceived likelihood of being Black. Although many names in the sample are clearly categorized as either predominantly Black or white, some names, such as Jackson and Darryl, are perceived to be Black and white in roughly equal frequency. In addition to differences in the aggregate perceptions of names, there is also considerable variation in beliefs for a given name across employers. For example, while Charisma and Alijah share similar aggregate race associations, Figure A3 shows that there is a higher variance in beliefs for Charisma. (It is worth noting that due to our focus on the Black-white race gap in the selection of names, there is limited variation in the perceived likelihood of being Hispanic or Asian.)

Eliciting data on the distribution of race associations has several key implications. Conceptually, it provides a more nuanced understanding of individuals' levels of uncertainty about their beliefs. Appendix Figure A4 shows that had we asked for a single race categorization, we would miss much of the nuance in people's beliefs and discriminatory behavior (as discussed below).[15] From a methodological perspective, the distribution of beliefs about race is crucial for interpreting the results of studies that use names to signal race. For example, differences in call-back rates from sending fictitious resumes present intent to treat estimates. To back out the arguably more meaningful treatment-on-the-treated (LATE) estimate, it is necessary to know the (first stage) variation in race perception that is induced by names.

4.2 Education

Figure A1 shows the distribution of beliefs about the highest level of educational attainment across names. While there are some outliers, there is a clear correlation between beliefs about race and education. Table 1 shows results from specification 1. Names perceived as Black (compared to white) are associated with having 0.73 years (0.73 s.d.) fewer years of education (Col. 1). Next, we compare beliefs about specific categories of educational attainments. Strikingly, perceiving a name as Black lowers the chance that the person is believed to have a master's degree by 16 pp (47%) (Col. 2). By contrast, we do not see a difference for having completed (exactly) a four year degree (Col. 3) and an increase of 9 pp for having completed a two year degree (Col. 4). People also associate Black names with a 10 pp (62%) lower likelihood of holding a high school diploma and 3.8 pp (30%) higher chance of having less than a high school degree (Col. 6). Panel B shows the corresponding results controlling for name fixed effects. Only exploiting within name variation in race beliefs reduces the race gap in the number of years of education by 0.12 (Col. 1). Coefficients for specific education categories also converge towards zero but remain highly significant.

4.3 Age

We elicit age associations by asking participants how many people with a given name fall in each of the following age bins: 18-29, 30-44, 45-59, 60+. Using the midpoint for each bin (and 70 for the 60+ category), we compute the average age for each name. Perceiving a name as Black is associated with being 6.5 years younger (Table A2). One explanation is that distinctly Black names were more commonly used in the 1970s and 1980s (Fryer Jr and Levitt, 2004). Controlling for name fixed effects, the age difference drops by almost 80% to 1.4 years suggesting that much of the age race gap is associated with name-specific associations.[16]

[15] To assist researchers who want to choose names for studies on race and gender discrimination, we are compiling a companion paper with associations for a comprehensive set of names and guidance on how to systematically select names (Abel and Burger, 2023).

[16] To assess how accurate people's beliefs are, we use census data to estimate the actual average age in the U.S. population. Specifically, we look at the frequency of birth at the midpoint of the age bins used in our belief elicitation method, which we use to compute a weighted average as a proxy for the actual age. Figure A2 plots the perceived vs. actual age data for our names, with points on the 45 degree line presenting

Table 1: Race Gap in Education

	Edu (Yr)	Master	Col (4yr)	Col (2yr)	Some Col	High S	Less HS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A:							
Name % Black	-0.733***	-0.159***	-0.003	0.086***	0.138***	-0.099***	0.038***
	(0.038)	(0.006)	(0.005)	(0.004)	(0.007)	(0.005)	(0.004)
R square	.058	.099	.0046	.082	.069	.07	.016
Name Fixed Effect	N	N	N	N	N	N	N
Panel B: Fixed Effects							
Name % Black	-0.612***	-0.124***	0.001	0.053***	0.084***	-0.043***	0.029***
	(0.075)	(0.012)	(0.009)	(0.007)	(0.014)	(0.009)	(0.008)
R square	.068	.12	.012	.097	.084	.098	.022
Name Fixed Effect	Y	Y	Y	Y	Y	Y	Y
Observations	9096	9096	9096	9096	9096	9096	9096
Mean (white)	14.7	.338	.175	.016	.184	.16	.126
SD	.999	.168	.118	.0959	.186	.126	.115

Notes: The dependent variable is a binary measure of whether name is associated with specific education levels. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. Name FE refer to first name fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

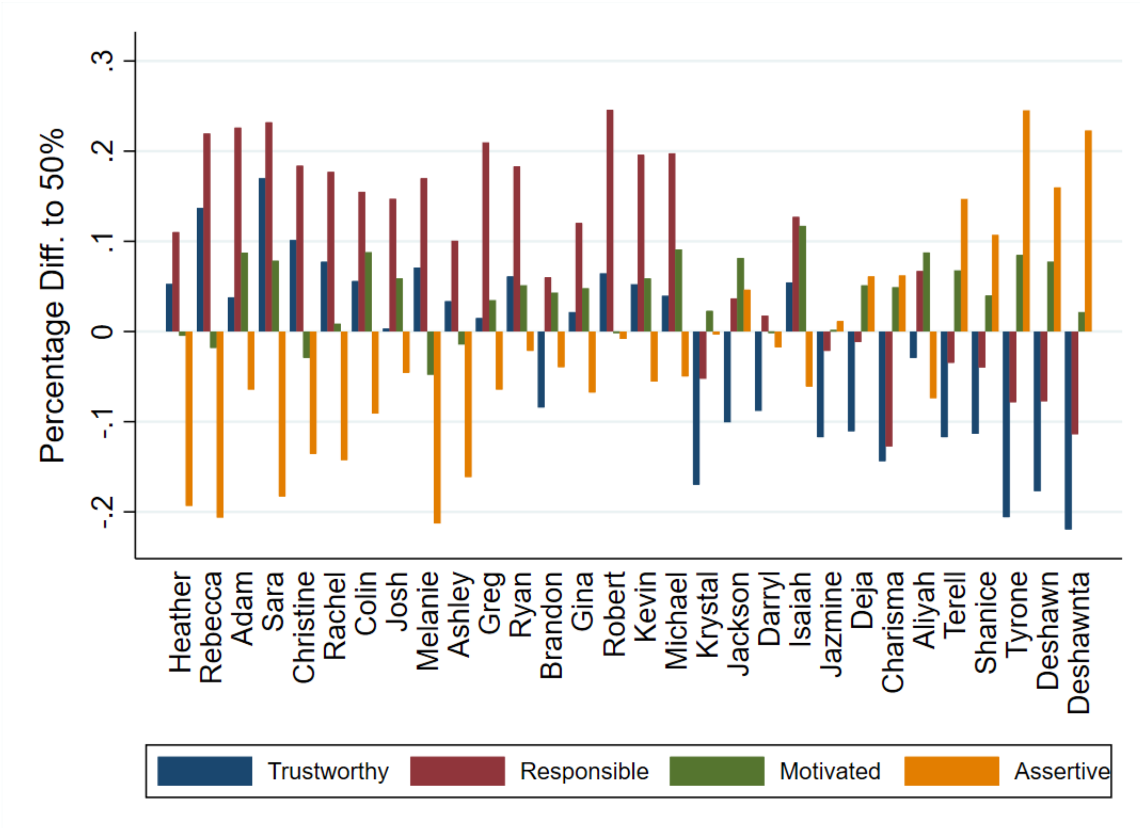
4.4 Noncognitive Skills

Figure 3 shows the belief distribution for four noncognitive skills across names ordered by the perceived share of being Black. Visual inspection shows that perceiving a name as Black is negatively correlated with being trustworthy and responsible, positively correlated with being assertive and uncorrelated with being motivated. (Appendix Figure B1 illustrates similar patterns for the other noncognitive skills.) Table 2 reports the corresponding coefficients from specification 1 for each noncognitive skill. Perceiving a name as Black (compared to white) reduces associations with responsibility by 29.4 pp (42%), trustworthiness by 26.5 pp (46%), cooperativeness by 24.8 pp (40%), and perfectionism by 19.6 pp (65%). By contrast, it increases associations with assertiveness by 34.1 pp (101%) and decisiveness by 12.6 pp (35%), while motivation perceptions are not correlated with race associations. Including name fixed effects reduces most coefficients by around 30-50% but they remain large and significant (Table 2, Panel B).

Noncognitive skill perception data also show clear differences at the intersection of gender and race. For example, gendered associations regarding women being less assertive, more trustworthy, and more cooperative only extend to female names perceived to be white (Table A3). While not the focus of this paper, this points to additional distinct challenges faced by Black women.

accurate perceptions. It shows that people tend to overestimate the age of people with names of younger people (e.g. Isaiah) and underestimate the age of names of older people (e.g. Robert). However, there is a strong positive relationship between perceived and actual age with a correlation coefficient of 0.81.

Figure 3: Noncognitive Skill Associations



Notes: The figure shows noncognitive skill associations for different names sorted by race perception (from white to Black). The bars present the average associations (relative to 50%) across 300 respondents. Responses were collected as binary measures and respondents could select an unlimited number of noncognitive skills.

As previously explained, to test whether these associations affect (economic) behavior, respondents can choose who they want to partner with in a trust game and receive the amount that person returns as a bonus. Figure A5 plots the relative frequency with which names are perceived as trustworthy and how often workers with these names are picked as a partner in the trust game. While there is some divergence (esp. for white men), associations and incentivized choices are highly correlated. Stating that a name is trustworthy increases the probability that this person will choose a worker with that name in the trust game by almost 80%. Overall, these results suggest that the noncognitive skill associations we collect are predictors of incentivized choices.

Table 2: Race Gap in Soft Skill Associations

	Assert.	Motiv.	Respons.	Trustw.	Cooper.	Decis.	Perfec.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A:							
Name % Black	0.341***	0.015	-0.294***	-0.265***	-0.248***	0.126***	-0.196***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.014)
R square	.046	.0021	.038	.03	.027	.0076	.032
Name Fixed Effect	N	N	N	N	N	N	N
Panel B: Fixed Effects							
Name % Black	0.225***	-0.061*	-0.141***	-0.135***	-0.136***	0.098***	-0.095***
	(0.031)	(0.031)	(0.031)	(0.032)	(0.031)	(0.030)	(0.027)
R square	.063	.0097	.058	.047	.035	.021	.06
Name Fixed Effect	Y	Y	Y	Y	Y	Y	Y
Observations	9096	9096	9096	9096	9096	9096	9096
Mean (white)	.337	.514	.696	.579	.616	.355	.301
SD	.499	.498	.493	.5	.499	.494	.435

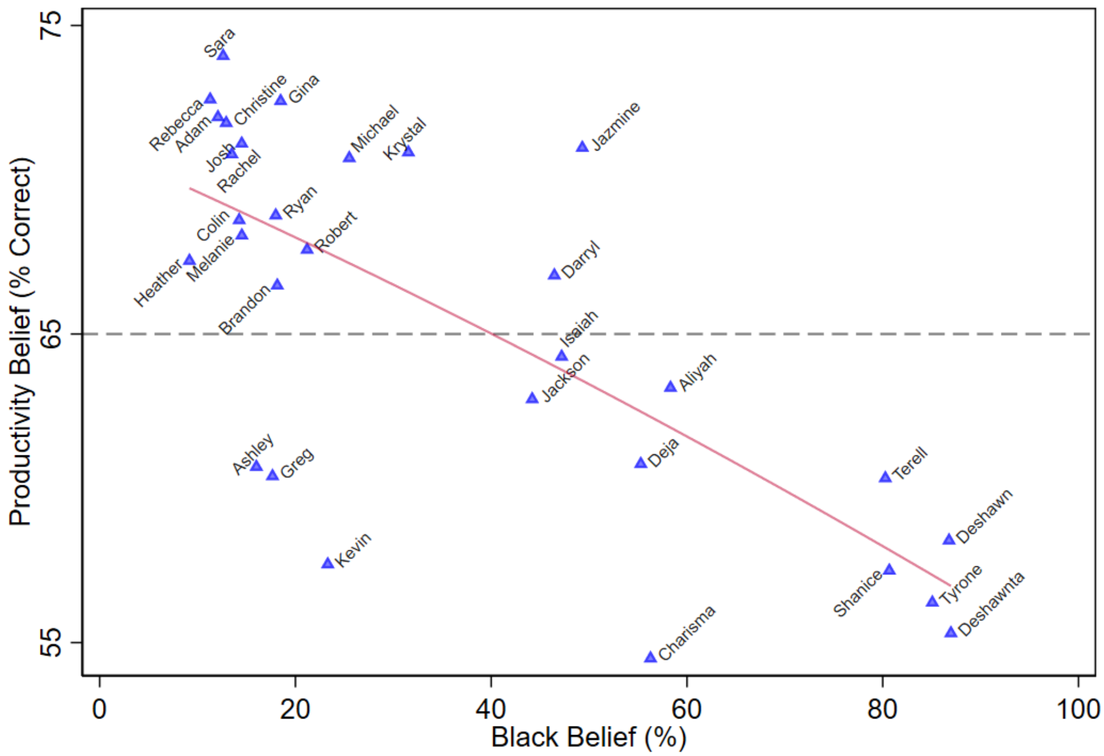
Notes: The dependent variable is a binary measure of whether name is associated with specific soft skill. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. Name FE refer to first name fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5 Perceived Productivity

We first show the relationship between productivity beliefs and race beliefs graphically. Figure 4 plots the average perception of being Black and productivity for each worker name, averaged across 300 employers. While there are some positive (e.g. Jazmine) and negative (e.g. Kevin) outliers, we find a strong negative and relatively linear relationship. Table 3 shows results from specification 3 using individual perceptions of productivity, measured in log of correctly transcribed receipts as the dependent variable. Without control variables a Black name is associated with about 25% lower productivity compared to a white name (Col. 1). While our pre-analysis plan does not include tests of discrimination towards other race groups given the limited variation in perception for names included in our sample, it is noteworthy that the race gap is half the magnitude (12.9%) for Hispanic names and that there is no gap for Asian names (Col. 1).

When we control for the number of years of education, the Black-white race gap slightly decreases to about 23%, reflecting that education is a positive determinant of productivity that is negatively correlated with perceptions of being Black (Col. 2). Every year of education is associated with a 3.1% increase in productivity, meaning that the raw penalty of a Black name is equivalent to about 8 years of education. Controlling for age beliefs only has a very small effect reducing the race productivity gap to 24.1% as age is only weakly correlated with productivity (Col. 3). Controlling for noncognitive skill perceptions reduces

Figure 4: Productivity Beliefs by Worker Name



Notes: The figure shows how productivity beliefs (in % correctly transcribed receipts) are correlated with the perceptions of being Black. The solid line presents a quadratic fit and the grey dotted line presents the average productivity belief.

the race gap by almost a fifth to 21% (Col. 4). This reflects that most of the traits positively associated with productivity, such as trustworthiness and responsibility, are also more likely to be associated with white names. By contrast, while Black names are more likely to be perceived as assertive, this trait is not correlated with productivity perceptions.

For our most flexible specification, we estimate regressions with name fixed effects, which effectively only uses between-subject variation in beliefs for the *same* name to estimate the race gap. This specification reduces the race gap from 25% to 15% (Col. 6) or to 12% when we control for other beliefs (Col. 7). The importance of variation in perceptions for the same name points to an important potential source of heterogeneity in discriminatory behavior observed in audit studies (e.g. Kline et al. (2021)).

To assess the accuracy of employer beliefs, we use data on the actual productivity of 2,400 workers in this task (collected by Abel (2022)). Table A4 compares the productivity race gap as perceived by employers (Panel A) versus the actual data (Panel B). While the perceived race gap is between 22 and 25%, the actual gap is below 9%, implying that employers overes-

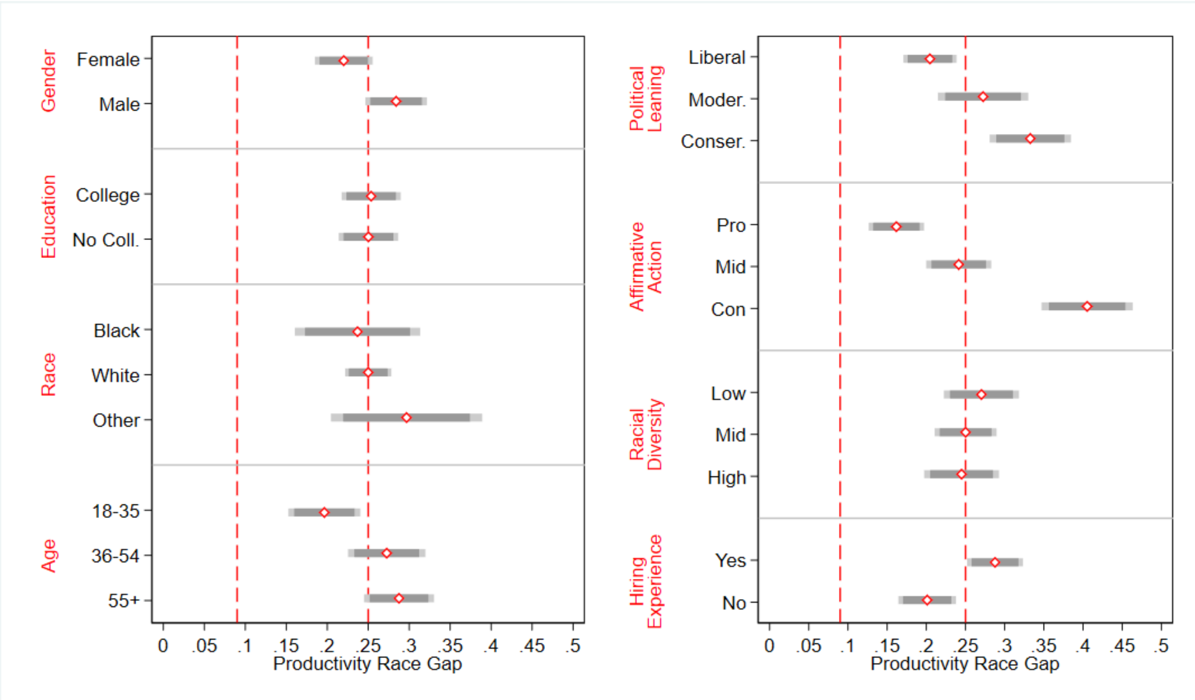
Table 3: Productivity Beliefs

	Dependent Variable: Productivity (Log)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
% Black	-0.252***	-0.229***	-0.241***	-0.213***	-0.191***	-0.152***	-0.119***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.022)	(0.022)
% Hispanic	-0.129***	-0.104**	-0.133***	-0.129***	-0.113***	-0.098**	-0.093**
	(0.043)	(0.043)	(0.043)	(0.042)	(0.042)	(0.044)	(0.044)
% Asian	0.022	0.042	0.027	0.017	0.035	-0.038	-0.040
	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)	(0.028)	(0.028)
Education (yrs)		0.031***			0.025***		0.024***
		(0.005)			(0.005)		(0.004)
Age (yrs)			0.002***		0.001*		0.000
			(0.001)		(0.001)		(0.001)
Assertive				-0.006	-0.006		-0.002
				(0.008)	(0.008)		(0.008)
Self-motivated				0.034***	0.033***		0.035***
				(0.007)	(0.007)		(0.007)
Responsible				0.059***	0.054***		0.054***
				(0.008)	(0.008)		(0.007)
Trustworthy				0.051***	0.047***		0.046***
				(0.008)	(0.008)		(0.008)
Cooperative				0.026***	0.026***		0.027***
				(0.007)	(0.007)		(0.007)
Decisive				0.028***	0.027***		0.031***
				(0.008)	(0.008)		(0.008)
Perfectionistic				0.021***	0.021***		0.015*
				(0.008)	(0.008)		(0.008)
Observations	9091	9091	9091	9091	9091	9091	9091
R square	0.06	0.07	0.06	0.09	0.10	0.12	0.16
Name Fixed Effects	N	N	N	N	N	Y	Y

Notes: The dependent variable in a binary variable for choosing worker 1. Independent variables are coded to show the difference in perception of worker 1 minus that of worker two. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. Name FE refer to first name fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

timate the productivity advantage of white workers by a factor of almost three. Importantly, this finding is inconsistent with the canonical model of statistical discrimination in which employers use accurate information about group averages to the predict the productivity of candidates, but may be explained by models of stereotypes such as Bordalo et al. (2016).

Figure 5: Heterogeneity in Productivity Beliefs



Notes: The figure shows how the race gap in productivity beliefs vary across employer characteristics. The dashed lines present the actual race gap (9%) and average perceived race gap (25%).

Figure 5 shows how productivity beliefs vary across employer characteristics. While every subgroup overestimates the race gap, there is substantial heterogeneity along certain characteristics in how much groups do so. Most strikingly, those supporting race-based affirmative action (AA) think the productivity race gap is 16% while those opposed to AA believe it is more than 40%. Participants involved in real-world hiring also overestimate the race-gap more. By contrast, it does not vary along other characteristics including employers' race and level of education. The next Section will first test the extent to which these employer beliefs affect hiring decisions. Section 6 will then explore mechanisms of how beliefs factor into the decision-making process.

5 Hiring Decisions

5.1 Hiring Race Gap

Figure 6 shows the relationship between race perceptions and hiring probability for each of the worker pairs included in our experiment.[17] The x-axis shows the difference in the likelihood of being Black between the two candidates, averaged across roughly 300 employers. We include worker pairs of similar race, distinctly different race, and intermediate race differences, resulting in three clusters of pairs along the x-axis. The y-axis presents the average hiring probability for the person listed first in the pair. Notably, almost all pairs are above the 50% hiring probability line, indicating the strong negative relationship between perceiving a name as Black and hiring that candidate. While we are fitting a quadratic function, the relationship is almost exactly linear, suggesting that there is not a threshold at which the hiring penalty of being perceived as Black is changing. Pairs above (below) the fitted line present cases where the first worker is hired more (less) than predicted by race perceptions. Over-performing names include Sara, Josh and Isaiah, while under-performing names include Brandon, Krystal, and Charisma. These patterns point to other beliefs, e.g. regarding education, that may systematically vary across names.

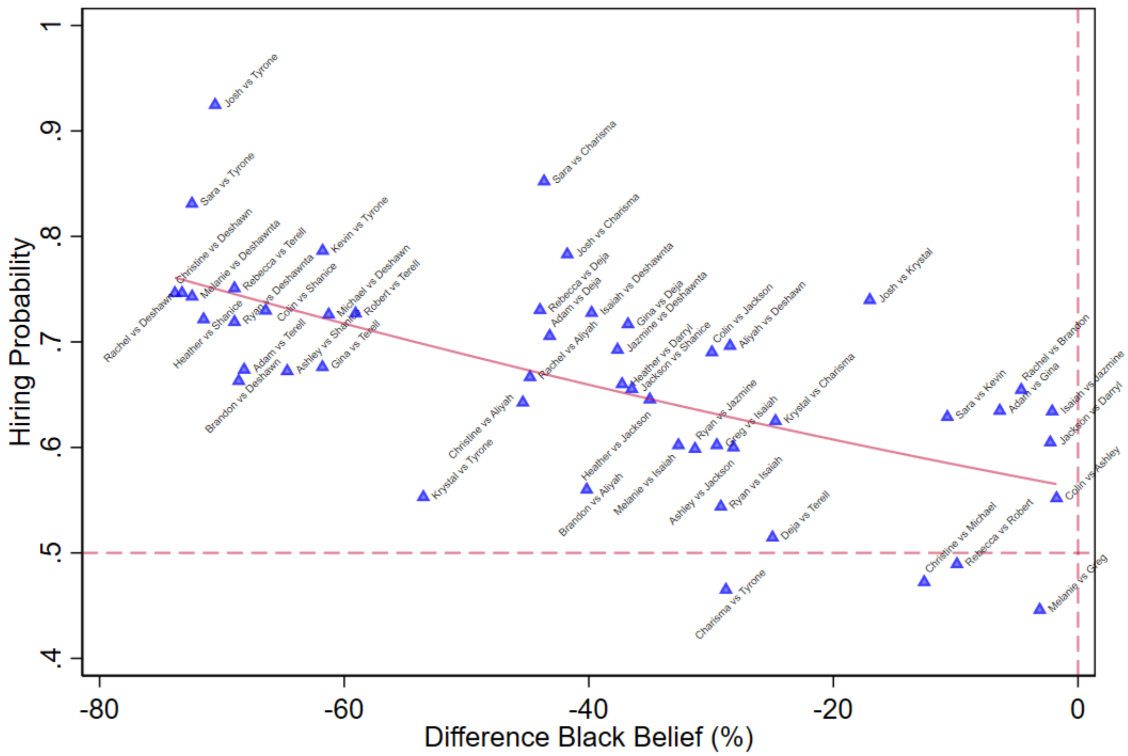
To gain precision and account for other employer beliefs, Table 4 presents results from specification 5, using the full set of more than 14,000 hiring decisions. Without controlling for other beliefs, we find that a worker perceived to be Black is 29.6 pp less likely to be hired than someone with a name perceived to be white (Col. 1). Col. 2 controls for employers' productivity perceptions of the two candidates. A one percentage point advantage in perceived productivity increases the likelihood of being hired by 0.73 pp. Controlling for productivity perceptions reduces the race gap in hiring by roughly 30% to 21.3 pp (Col. 2). As productivity perceptions may not affect hiring decisions linearly, we next include a binary variable indicating whether a worker is perceived to be more productive. This increases the likelihood of being selected by 27 pp but only narrows the race gap to 23.7 pp (Col. 3).

Next we control for perceived differences in years of education (Col. 4) and age (Col. 5). A one year increase in (perceived) education is associated with a 6.3 pp increase in the likelihood of being hired. This implies that being perceived as Black has a similar impact on one's chances of being hired as having almost five fewer years of education. Accounting for differences in education perceptions narrows the hiring race gap by 5 pp (18%). Age has a smaller but still positive effect on hiring and reduces the racial gap in hiring by 2.1 pp (7%).

Perceptions of most noncognitive skills are highly correlated with hiring decisions and explain as much of the variation in hiring as productivity perceptions (Col. 6). For example, perceived a worker as more responsible than their competitor, is associated with a 12.8 pp

[17] While the two names were presented in random order, for expositional purposes we present pairs listing the name perceived more likely perceived as white first.

Figure 6: Hiring Decision by Worker Pair



Notes: The figure shows the hiring probability for the first worker listed for each of the 50 worker pairs included in our study. The x-axis shows the difference in race perceptions between the first and second name listed in the pair. The line presents a quadratic fit.

increases in the chances of being hired. By contrast, the trait most commonly linked to Black names, assertiveness, is not associated with hiring decisions. Overall, accounting for differences in noncognitive skills reduces the race gap by approximately 32% to 20.3 pp, highlighting the importance of employer beliefs about these traits. Notably, perceptions of noncognitive skills remain significant predictors of hiring even after accounting for education, age and productivity beliefs. This is important since many of these latter characteristics are observable to employers on a candidate's resume. This most flexible specification reduces the race gap by about 45% to 13.3 pp (Col. 7).[18]

Lastly, we can estimate the previous specifications with worker pair fixed effects. Akin to our name fixed effects analysis, this specification estimate coefficients only from variation in race beliefs between people for the same candidate pair. Table A5 shows that while this reduces the race coefficient by about 45%, the race gap remains large at 15.8 pp. Results

[18] Although not the focus of this paper, Appendix Table B6 presets results on the effects of Hispanic and Asian names. The race gap in hiring are 11.6 pp for the Hispanic names and 19.2 pp for Asian names. Notably, these coefficients change less when we control for productivity or noncognitive skill perceptions.

Table 4: Race Gap in Hiring

	Dependent Variable: Hire Worker						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black (Dif)	-0.296***	-0.213***	-0.237***	-0.246***	-0.275***	-0.203***	-0.131***
	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)
Productivity (Dif)		0.733***					0.548***
		(0.026)					(0.026)
Wkr. 1 more product.			0.270***				
			(0.010)				
Educ (Dif)				0.063***			0.032***
				(0.005)			(0.004)
Age (Dif)					0.004***		0.002***
					(0.001)		(0.001)
Assertive (Dif)						0.011	0.000
						(0.008)	(0.008)
Motivated (Dif)						0.091***	0.066***
						(0.007)	(0.007)
Responsible (Dif)						0.128***	0.094***
						(0.008)	(0.008)
Trustworthy (Dif)						0.109***	0.075***
						(0.008)	(0.008)
Cooperative (Dif)						0.074***	0.054***
						(0.008)	(0.008)
Decisive (Dif)						0.075***	0.055***
						(0.007)	(0.007)
Perfection. (Dif)						0.077***	0.056***
						(0.009)	(0.008)
Observations	14222	14218	14222	14222	14222	14222	14218
Mean	.626	.626	.626	.626	.626	.626	.626
SD	.484	.484	.484	.484	.484	.484	.484
R square	0.06	0.14	0.13	0.08	0.06	0.14	0.20

Notes: The dependent variable in a binary variable for choosing worker 1. Independent variables are coded to show the difference in perception of worker 1 minus that of worker two. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. Name FE refer to first name fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(not reported) further show that the size of the race gap is robust to including employer fixed effects.

5.2 Subgroups

Figure 7 presents the findings of various subgroup analyses, as specified in our pre-analysis plan (corresponding regression results are in Table B4). We find that women exhibit less discriminatory behavior as the race gap is 26 pp compared to 34 pp for men. In contrast, the race gap is not affected by whether a person has a college degree or not. The hiring race gap among Black employers is 19 pp compared to 33 pp for white employers and 27 pp for other race groups (Col. 4). The fact that we observe a substantial race gap among Black employers provides evidence against racial animus as the main driver of our results. We also find a negative relationship between participants' age and their level of discrimination. The race gap is 50% higher for people over 55 compared to 18 to 35.

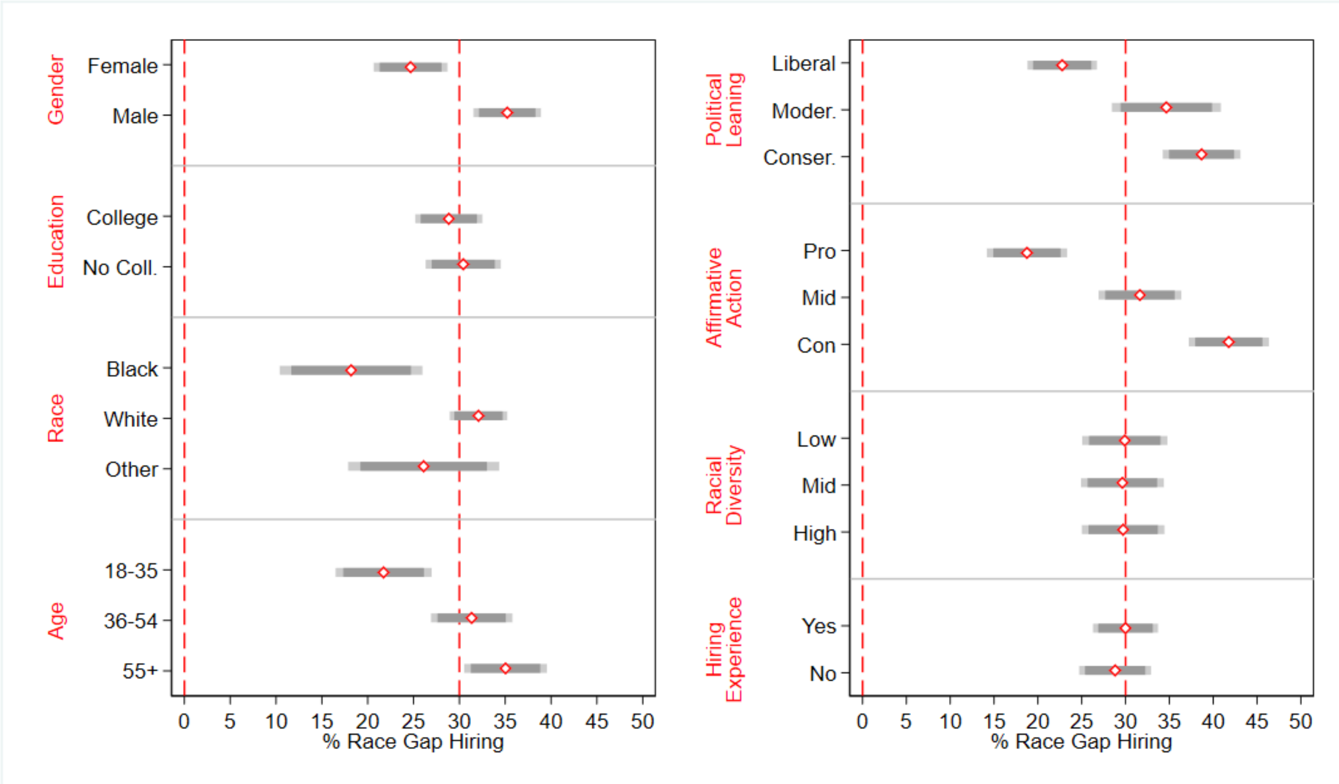
With regard to people's political leaning, we find that the the race gap is 70% larger for conservative compared to liberal employers (39 pp versus 23 pp). Likewise, we observe a strong negative relationship between support for race-based AA and hiring discrimination: Among those opposed to it, the gap is 42 pp compared to 19 pp for those in favor. Next, we look at the role of participants' location. Figure A6 shows how the race gap varies across states. We do not observe a clear geographical pattern of race discrimination. We can also compute the racial diversity of participants' zip-code level area using census data. Dividing this measure into terciles, we find no variation in discriminatory behavior along this dimension, although results (not reported) show that white respondents display a slightly higher race gap if they live in the most diverse areas (35 pp vs. 31.3 pp). Last, hiring discrimination does not differ based on whether participants have (real-world) experience in hiring. This partly assuages some concerns about the external validity of our results.

Figure A7 replicates the same subgroup analyses but controls for differences in productivity, education, age, and noncognitive skill perceptions between workers. While the race gap closes by around 50%, the overall pattern across subgroups persists. Notably, the race gap remains statistically significant for all subgroups at the 0.1% level. It is important to note, however, that these coefficients only provide a correlation between groups, such as measuring the behavior of people with or without a college degree, rather than a causal relationship between obtaining education and exhibiting discriminatory behavior.

5.3 Robustness

In research related to discrimination, participants may be hesitant to reveal their true attitudes and behaviors, which would compromise the internal validity of results. To address

Figure 7: Race Gap in Hiring Across Subgroups



Notes: The Figure is showing how the race gap (Black vs. white) varies across subgroups of employers. Coefficients are from our main specification without control variables estimated separately for subgroups. The bars present 90% and 95% intervals. *Affirmative action* is measuring level of support from 0-100 scale coded as Con (0-33), Mid (34-66) and Pro (67-100). *Racial diversity* refers to zip code level racial fractionalization, divided into terciles. *Hiring experience* refers to whether the respondent has real-life experience in hiring.

this concern, we do not reveal the exact research question at the outset of the study, elicit a range of associations beyond just race, and also included hiring choices for worker pairs without racially distinct names. Despite these efforts, about 33% of respondents suspected at the end of the experiment that the research was related to race.[19] This share increases to 49% when we include other forms of biases and discrimination (e.g. gender). Table B5 replicates our main results separately for those who suspected the research was related to race and those who did not. While we acknowledge endogeneity and misreporting concerns, it is reassuring that our results remain robust, both for the overall race gap and the effect of controlling for beliefs. Specifically, the race gap is only about 1.9 pp (6.5%) smaller for those suspecting the research is related to race (Col. 1-4). Using our broad measure, this difference decreases to less than 1 pp (Col. 5-8).

[19]We ask respondents after the experiment but before asking questions related to race (e.g. affirmative): "In a few words, what do you think is the main question that this research is trying to answer?" We categorize people depending on whether their answer includes words like race, bias, discrimination, Black.

A related concern is that people do not suspect the research question in the beginning, but may alter their behavior once they become aware of the study's focus on race. To investigate this possibility, we analyze how discrimination changed over time by examining the (randomized) order of the hiring pairs. Our results, as shown in Figure B2, indicate that the race gap does not vary systematically across the ten hiring decisions. One possible explanation for these findings is that incentivizing choices may have addressed surveyor demand effects. However, it remains possible that people hide discriminatory behavior. Our results should thus be regarded as a lower bound of the prevalence of discrimination.

One potential sets of concerns about the external validity of our results is related to the choice of names. Would we obtain different results if we had chosen a different set of names and, specifically, if we had excluded distinctly Black names? We address these important questions in two steps. First, we run simulations using 5000 different subsets of the data, each time estimating the race gap for a random sample of 50% of worker pairs (i.e. 25 pairs instead of 50). The results are shown in Figure B3, with dashed lines indicating the bottom and top 5% of estimates. We find that the 5th percentile of estimated coefficients is around 24%, and only 1 percent are below a race gap 21.6% (top left panel).[20]

Second, we reestimate our hiring results and exclude any worker pairs with at least one distinctly Black name. These are defined as having an average perception of being Black above 70% and include Shanice, Tyrone, Deshwanta, Deshawn, and Terell. Table B3 shows that estimates of the race gap remain almost identical (31 pp vs. 30 pp). This reflects the fact that the relationship between perceived race differences and hiring probabilities is linear (as shown in Figure 6) implying that results are robust to excluding pairs with large race differences.

6 Mechanisms

6.1 Motivation: What Explains Decisions that Contradict Beliefs?

The results from Section 5 demonstrate that although productivity beliefs play an important role in hiring decisions, other beliefs about worker attributes, such as race, education and noncognitive skills, also strongly impact employer choices. In fact, in roughly 30% of hiring decisions employers select the worker that they previously predicted to be *less* productive. This may seem surprising given that the hiring task explicitly instructed and incentivized employers to choose the most productive candidate. However, it is in line with a large

[20]Reducing the sample to 25% of worker pair names, the results are very similar, with 5% of race gap coefficients below 20% (top right panel). As previously discussed, including worker pair fixed effects reduces the race gap in our full sample to 16.3%. This result is also robust: only 5% of simulated race gap coefficients fall below 13% and 12% for random subsets of 50% and 25% of worker pairs, respectively (bottom panels).

literature (e.g., Fehr and Rangel (2011)) showing that humans are prone to making errors when faced with simple binary decisions, particularly when placed under time pressure.

One potential explanation for this phenomenon is linked to the process of forming beliefs by retrieving memories about people with the same name. Employers may initially retrieve salient attributes such as race, which are perceived to be correlated with productivity.[21] As this process continues, less salient but more relevant information will be retrieved and beliefs may drift away from this initial race-anchored impression and towards their true productivity belief (which may still be correlated with race beliefs). This process relates to dual-process models of cognition, which posit that one set of processes (labeled System 1 by Stanovich and West (2000)) is fast, reflexive and unavailable for conscious introspection, while the other (System 2) is slow, analytical and able to process information sequentially (Epstein, 1994; Sloman, 1996; Kahneman and Frederick, 2002). Applied to our study, racial discrimination can either be instinctive and subconscious, or deliberate and self-aware.

This cognitive process is both noisy and effortful, and employers may terminate it when the cost of searching for additional evidence exceeds the potential benefits of improving belief accuracy. Due to the inherent noise in this process, employers may make different predictions about people with the same name at different times, leading to inconsistencies between their productivity beliefs and hiring choices, particularly when placed under time pressure.

To explore this prediction, we investigate how the probability of being hired varies based on employers' race and productivity beliefs, as well as the randomly assigned decision time. While we formalize these ideas in Section 6.2, Figure 8 presents a visual representation of our findings. Based on previously elicited employer beliefs, we divide candidate pairs into three race difference groups and four productivity difference groups. As expected, when two workers are predicted to be roughly equally productive and equally likely to be Black, the probability of being hired is close to 50%. This is true for both long (left panel) and short (right panel) decision times.[22]

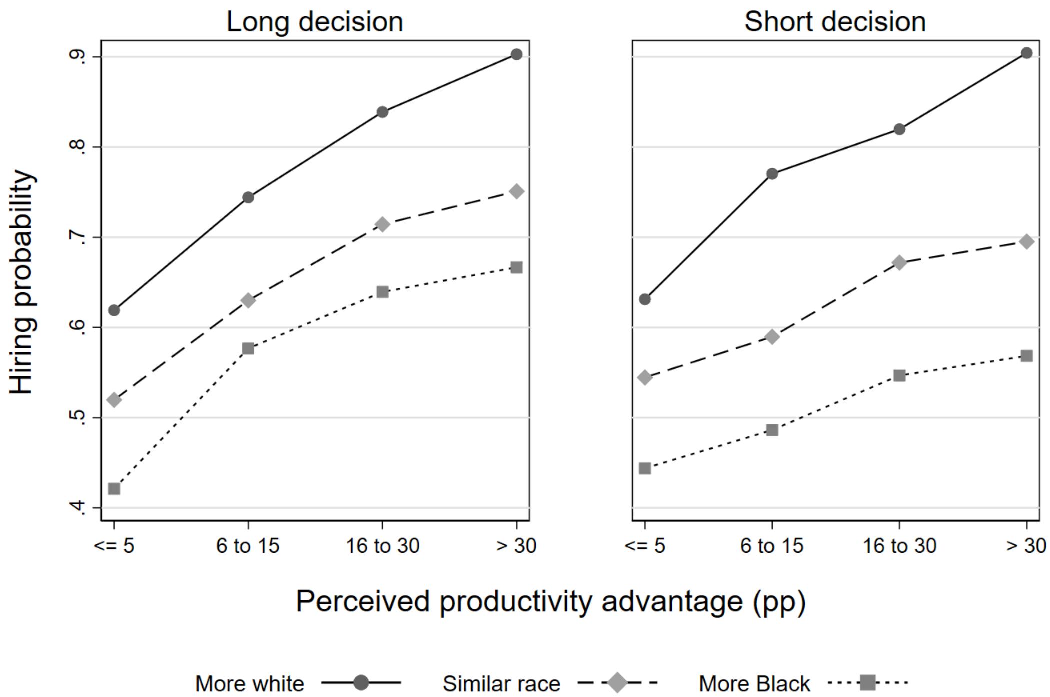
Examining long decisions with workers of a similar race (the middle line in the panel on the left), we observe that the hiring probability gradually increases as a candidate's productivity advantage grows, up to 75% for an advantage exceeding 30 pp. Workers who are perceived as more white receive an additional advantage in the hiring process, which increases from 10 pp to 15 pp as the perceived the productivity advantage grows. Conversely, workers with more Black-sounding names face a hiring penalty of 5 to 10 pp.

For decisions under time pressure, the benefits of (perceived) productivity advantages remain largely unchanged for more white-sounding names (Figure 8, right panel). By contrast,

[21] Race is one of the most common dimensions for social categorization (Hewstone et al., 1991), so should be among the first attributes retrieved from memory.

[22] In order to simplify the comparison we re-index the workers in the pair from which the employer selects so that the first worker is always the one with the higher predicted productivity. We confirm that this does not affect results, which is unsurprising given that names for a given pair were presented in random order.

Figure 8: Hiring Probabilities, by Productivity / Race Perceptions and Decision Time



Notes: "More Black" includes workers perceived to be more than 20pp more likely to be Black; "More white" includes all worker who are perceived to be more than 20pp less likely to be Black; and "Similar race" includes workers whose difference in perceived likelihood of being Black is 20pp or less in absolute value.

there is a notable decrease in the productivity-slope for workers with more Black-sounding names, leading to an almost 50% increase in the hiring race gap for Black workers with large productivity advantages. In other words, Black workers who are perceived to be highly productive are the most adversely affected by rushed hiring decisions.

These findings are in line with the framework presented below, which posits that employers may initially anchor their productivity beliefs to easily retrievable race associations. When they are forced to terminate their search for worker attributes prematurely due to time pressure, productivity beliefs have less influence on hiring decisions, leading to a larger race gap for highly productive workers. In such scenarios, the "error" rate, defined as the inconsistency between hiring choices and stated productivity beliefs, increases from 10 pp for white workers to 43 pp for Black workers.

6.2 Framework

Employers make a simple two-choice hiring decision in our experiment. While economists have focused mainly on observed choice outcomes, cognitive and mathematical psychologists have made significant progress in understanding the joint distribution of choices and response times by modelling the neurological mechanisms that underpin such decisions. Neurophysiological data have provided support for a class of models that posit that individuals make these decisions by sequentially sampling noisy information, allowing them to accumulate evidence favoring one choice over the other (Sewell and Smith, 2016).

The most successful of these models is arguably the drift-diffusion model (DDM), which offers a highly parsimonious representation of the cognitive process underlying binary decision-making (Ratcliff, 1978; Ratcliff and McKoon, 2008). According to the DDM, decision-makers accumulate evidences regarding the relative merit of choosing option a over b through sequential sampling of relevant information stored in memory, such as past consumption decisions and associated pleasure levels, to predict the hedonic impact of each option denoted as $v(a)$ and $v(b)$ (Fehr and Rangel, 2011). These cognitive computations are subject to noise caused by the stochastic nature of neuron firing rates. The relative decision value at time t can then be expressed as

$$z_t = z_{t-1} + \theta(v(a) - v(b)) + e_t \tag{6}$$

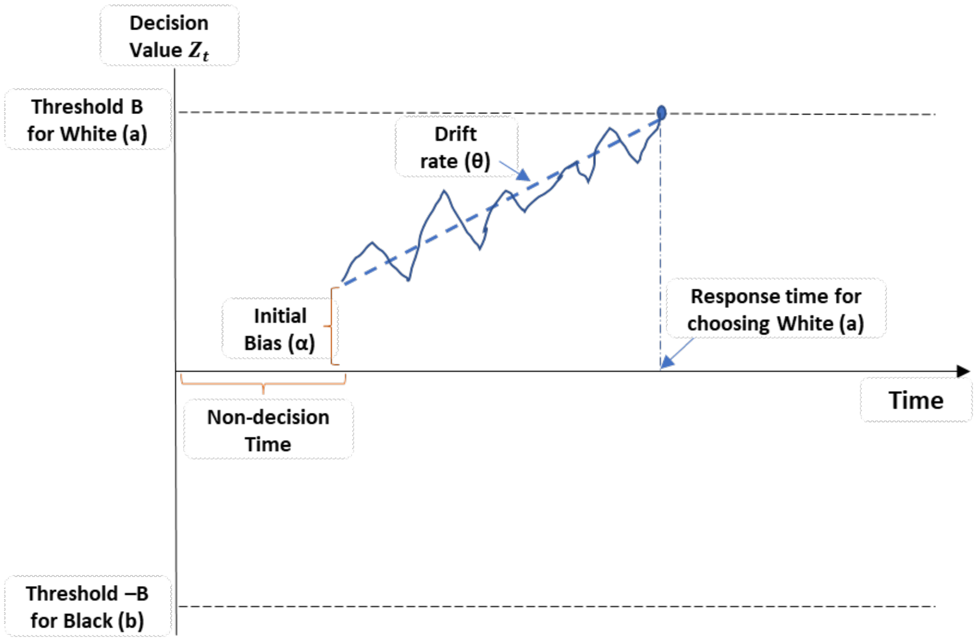
where θ is a constant drift rate, and e_t represents the noise in the mental computations, which is assumed to be identically and independently distributed according to a standard Gaussian distribution[23]. When the decision value z_t surpasses a positive threshold B, option a is selected, while crossing a negative threshold $-B$ leads to the choice of option b. This process entails a sequential likelihood ratio test, which has been demonstrated to be the optimal statistical solution to the decision problem (Bogacz et al., 2006; Gold et al., 2007). The model also distinguishes between non-decision time, which is required for stimulus encoding and motor response generation (Ratcliff and McKoon, 2008), and the decision time, which involves the accumulation of evidence.

The drift rate θ determines the speed at which evidence is accumulated and can be interpreted as the quality of the information available for evaluating the choices. When θ has higher values, decisions are reached more rapidly and consistently. The decision thresholds, B and $-B$, represent the required level of confidence for making a decision. Due to the inherent noise in the evidence accumulation process, different realizations of the same process with identical drift rates may not terminate at the same time or at the same threshold. However, the decision-maker can influence the quality and speed of the decision by adjusting the value of B. Lower values of B correspond to quicker decisions that are more prone to errors, whereas higher values of B lead to slower but more accurate decisions. This illustrates the speed-accuracy trade-off inherent in this model. Experimental manipulations have

[23] The relative decision value is unitless, so the model can be normalised by setting the error variance, drift rate or decision boundary to 1 (Krajbich et al., 2014). We assume the error variance is 1.

consistently confirmed these model predictions (Ratcliff and McKoon, 2008), but it has not been tested in the context of hiring decisions.[24]

Figure 9: Drift Diffusion Model



Notes: Conceptual presentation of the DDM.

Figure 9 illustrates the application of the DDM to our experiment. Employers are presented with candidate names from which they infer that candidate a is white, while candidate b is Black. According to the DDM, employers initiate a cognitive process where they sequentially sample information from their memory, emotions, beliefs and expectations related to these names. This information is utilized to compute decision values for each candidate, which are then combined to generate a relative decision value z_t following equation 6. We elicit these types of beliefs from the employers prior to the hiring task in a incentive-compatible way and without imposing any time constraints.[25]

Based on the descriptive results indicating that both race and productivity beliefs affect the decision and decision time, we specify the drift process as follows: $\theta(v(a) - v(b)) = \theta_1(r_a - r_b) + \theta_2(y_a - y_b)$. θ_1 and θ_2 measure the relative importance of race and productivity during the process of gathering evidence for the hiring decision. Krajbich (2022) proposes an

[24]When subjects are instructed to either make decisions as quickly or as accurately as possible, this produces variation in error rates and response times that are consistent with shifts in the B parameter. Similarly, increasing the difficulty of perception tasks (which causes a slower rate of cognitive information gathering) increases error rates and response times.

[25]This approach is related to DDM experiments on consumption decisions in which the willingness to pay for various products are elicited first. Thereafter, these values are used to determine the drift constant of a subsequent binary purchasing decision (Krajbich et al., 2010).

extension to this model that incorporates heuristic and subconscious racial biases by allowing race to influence the starting value of the evidence gathering process.[26] We specify this as $\alpha = \alpha_1(r_a - r_b)$. This leads to the following estimable equation for the hiring decision:

$$z_t = \alpha_1(r_a - r_b) + (\theta_1(r_a - r_b) + \theta_2(y_a - y_b))t + E_t \tag{7}$$

where $E_t = \sum_{\tau=1}^{t} e_t$

The next section will present reduced form analyses that test the model's predictions regarding the impact of race and productivity beliefs on the hiring choice and decision time. We then estimate a structural model to jointly estimate key parameters of this model including decision thresholds, initial bias, as well as productivity and race drift.

6.3 Reduced Form Analysis

To examine the predictions of the DDM, we begin by analyzing how employers' beliefs impact their decision-making time. According to our model, response times will be shorter when one worker is perceived to be more productive or more likely to be white, and especially when both of these perceptions align. Conversely, if the more productive worker is perceived to have a lower probability of being white, the race and productivity drift will have *opposing* influences on the decision value, resulting in slower decision-making.

Table 5 provides evidence in support of these predictions. A greater (absolute) difference in race beliefs is associated with faster decisions (Col. 1). Choosing between one candidate perceived as Black and one perceived as white shortens decision-making time by 0.19 seconds, equivalent to 0.18 sd, compared to choosing between workers of the same race. While controlling for the (absolute) difference in perceived productivity between candidates reduces this estimate to 0.15 seconds, it remains statistically significant at the one percent level (Col. 2). Additionally, larger differences in perceived productivity also shorten decisions times (Col. 2). These correlations are driven by decisions with unlimited time, which are less affected by noise (Col. 3-4). Overall, these findings confirm our model assumption that both race and productivity beliefs are important determinants of the drift.

[26]Biased starting values capture an immediate bias in favor of white workers that will be particularly influential in short decisions, but that dissipate over longer decisions. This may allow us to distinguish between racial biases that emanate from heuristics (System 1) and more analytical cognitive evaluations (System 2). However, since the estimated starting values are extrapolations of the linear drift function to decision times of zero, which is unobserved in the data, the validity of this interpretation hinges crucially on the assumption of constant drift rates. If System 1 and System 2 processes are more accurately depicted as a gradual shift in what employers attend to, then this process may induce non-constant drift rates which deviate from the DDM assumptions, and which would invalidate the interpretation of starting value estimates as the effect of heuristic biases on employment decisions. One way to test the validity of this assumption is to estimate the DDM separately for hiring decisions made under the randomized short and long decision treatments, and to test whether the drift rates are equal. These tests are performed in Section 6.4 below.

Table 5: Decision Making Time

	Dependent Variable: Decision Time (sec.)					
	(1)	(2)	(3)	(4)	(5)	(6)
Black (Dif), Absolute	-0.193***	-0.153***	-0.023	-0.226***	-0.022	-0.193***
	(0.034)	(0.035)	(0.023)	(0.043)	(0.025)	(0.046)
Productivity (Dif), Absolute		-0.531***	-0.030	-0.742***	-0.028	-0.617***
		(0.091)	(0.058)	(0.107)	(0.063)	(0.128)
Prod (Dif) x Black (Dif)					0.005	0.288**
					(0.067)	(0.129)
Observations	14256	14252	4174	10078	4174	10078
Mean	1.85	1.85	1.22	2.11	1.85	1.85
SD	1.05	1.05	.425	1.12	1.05	1.05
R square	0.00	0.01	0.00	0.02	0.00	0.02
Time	Pooled	Pooled	Short	Long	Short	Long

Notes: The dependent variable in the time people take to make a hiring decision (winsorized at the 5% level). "Prod (Dif)" measures to the difference in productivity between worker 1 and 2 scaled to be between 0 and 1. "Black (Dif)" measures the difference in the share associated as Black between worker 1 and 2 scaled to be between 0 and 1. Specifications in Columns 1-4 use the absolute values of these differences. The interaction term uses the perceived productivity and race of worker 1 minus worker 2. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Next, we investigate the interaction of beliefs. While perceptions of productivity and being Black are negatively correlated, there are many instances where a candidate is perceived as more productive and more likely to be Black. To explore these scenarios, we estimate specifications with an interaction term of differences in perception of being Black and productivity between candidates, without converting belief differences into absolute values. A positive interaction term thus indicates that a candidate is perceived as more productive *and* more likely to be Black. As predicted by the DDM, the coefficient on this interaction term is positive when decision-makers have unlimited time (Col. 6).

The DDM also offers predictions regarding the outcomes of hiring decisions and the effect of time pressure. In particular, it suggests that rushed decisions can exacerbate the race gap in hiring, as employers may place greater emphasis on race during the initial stages of the decision-making process. Confirming this prediction, Column 1 of Table 6 shows that, in the overall sample, the race gap widens by 6.7 pp, or 24.2%, when employers are required to make fast decisions.

Kahneman and Frederick (2002) conceptualize System 2 as a analytical, slow-thinking process that acts as a supervisor that can "endorse, correct, or override" the quick, heuristic judgments of System 1. In the context of our experiment, we hypothesize that System 2 will only override these System 1 judgments under two conditions: First, if System 1 exhibits bias against Black workers, and second, if these biases are not aligned with the analytical

Table 6: Effect of Time Pressure on Discrimination

	Dependent Variable: Hiring							
	Pooled		Black		White Pro AA		White Con AA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black (Dif)	-0.277***	-0.188***	-0.184***	-0.092**	-0.198***	-0.116***	-0.410***	-0.333***
	(0.017)	(0.016)	(0.049)	(0.047)	(0.027)	(0.025)	(0.025)	(0.025)
Short x Black (Dif)	-0.067**	-0.090***	0.011	-0.029	-0.135***	-0.158***	-0.014	-0.023
	(0.028)	(0.027)	(0.075)	(0.069)	(0.047)	(0.044)	(0.042)	(0.044)
Productivity (Dif)		0.780***		0.760***		0.945***		0.555***
		(0.030)		(0.086)		(0.054)		(0.047)
Short x Prod (Dif)		-0.171***		-0.242		-0.236**		-0.025
		(0.056)		(0.152)		(0.095)		(0.088)
Observations	14222	14218	1820	1819	6034	6031	4468	4468
Mean	.626	.626	.592	.592	.591	.591	.682	.682
SD	.484	.484	.492	.492	.492	.492	.466	.466
R square	0.06	0.15	0.02	0.10	0.04	0.14	0.13	0.19
Race	Pooled	Pooled	Black	Black	White	White	White	White
Affirm Action	Pooled	Pooled	Pooled	Pooled	Pro	Pro	Con	Con
P-v.(vs.W-Pro): Black			0.80	0.65			0.000	0.000
P-v.: Short x Black			0.096	0.116			0.055	0.029

Notes: The dependent variable in a binary variable for choosing worker 1. Independent variables are coded to show the difference in perception of worker 1 minus that of worker 2. "Short" is an indicator variable for the randomly assigned fast decision time. Col. 5-6 and 7-8 divide the sample according to whether respondent are in support of race-based Affirmative Action, measured by whether they rate their support above 50 on a 0-100 scale. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

evaluation of System 2. To test this hypothesis, we compare the impact of time pressure[27] on the race gap across three distinct groups: Black employers, white employers in support of race-based Affirmative Action (AA) and white employers more opposed to AA.[28] We focus on support for AA for two reasons. Firstly, it is the single most important predictor of the race gap in hiring (Figure 7) and was specified in our PAP. Secondly, while opposition to race-based AA can stem from various factors, studies indicate that racial resentment is one

[27]To test whether time pressure increases reliance on System 1, we divide our sample based on participants' performance in the cognitive reflection test (CRT) (using Frederick's (2005) three-question survey), which measures people's inclination towards analytical versus heuristic decision-making (Frederick, 2005). In line with predictions from dual process models, we find that the increase in discrimination in short decisions is driven by employers scoring above the median CRT who tend to rely more on analytical decision-making in the absence of time pressure (Table B7, Col. 7). Table B7, Col. 5 shows a similar pattern for productivity beliefs. While perceiving a candidate to be 10 pp more productive increases the chances of hiring that person by 7.8 pp when employers have unlimited time, this effect drops to 6 pp when employers are under time pressure (Table 6, Col. 2). This decrease is also driven by employers who score high on the CRT. These findings are in line with other studies showing that those with higher levels of cognitive reflection are less prone to heuristic biases (Toplak et al., 2011; Hoppe and Kusterer, 2011; Abel et al., 2021).

[28]We split the sample by whether they rate their support for race-based Affirmative Action above 50 on a 0-100 scale. Figure A8 shows the effect of time for each decile.

of the key predictors of such opposition (Feldman and Huddy, 2005; Mangum and Block Jr, 2022). Support for AA can thus act as a proxy for whether people deem it desirable to override the biases of System 1.[29]

Table 7: Role of Beliefs by Time and Subgroup

	Dependent Variable: Hiring					
	Long Decisions			Short Decisions		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Con AA, White						
Black (Dif)	-0.405***	-0.330***	-0.208***	-0.438***	-0.365***	-0.283***
	(0.0252)	(0.0250)	(0.0249)	(0.0368)	(0.0385)	(0.0406)
Productivity (Dif)		0.555***	0.396***		0.524***	0.383***
		(0.0470)	(0.0450)		(0.0746)	(0.0736)
Observations	3148	3148	3148	1320	1320	1320
R square	.131	.194	.255	.141	.189	.216
Panel B: Pro AA, White						
Black (Dif)	-0.196***	-0.113***	-0.0415	-0.325***	-0.269***	-0.180***
	(0.0279)	(0.0256)	(0.0259)	(0.0411)	(0.0405)	(0.0382)
Productivity (Dif)		0.952***	0.738***		0.697***	0.525***
		(0.0550)	(0.0563)		(0.0799)	(0.0806)
Observations	4207	4204	4204	1719	1719	1719
R square	.0259	.144	.198	.0678	.129	.177
Panel C: Black Employers						
Black (Dif)	-0.198***	-0.106**	-0.089*	-0.152**	-0.101*	-0.075
	(0.049)	(0.047)	(0.047)	(0.061)	(0.057)	(0.056)
Productivity (Dif)		0.754***	0.606***		0.532***	0.387***
		(0.086)	(0.083)		(0.128)	(0.134)
Observations	1285	1285	1285	535	534	534
R square	.0249	.112	.151	.0292	.0728	.136
Other Beliefs	No	No	Yes	No	No	Yes

Notes: The dependent variable in a binary variable for choosing worker 1. Independent variables are coded to show the difference in perception of worker 1 minus that of worker two. The data is split by decision time and across subgroups (panel A-C). Other beliefs include age, education, and soft skills. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Our findings indicate that rushed decision-making does not impact the race gap in hiring among Black employers. This suggests that this group does not exhibit a strong negative heuristic response towards candidates with Black names (Table 6, Col. 3-4).[30] Time pressure

[29] Results reported in this section are similar when we split white employers by their political leaning with time pressure affecting liberal but not conservative employers (Table B7, Col. 1-4).

[30] This is consistent with other studies showing that Black people hold less of an implicit race bias (Nosek et al., 2002).

also does not have a discernible effect on the race gap among white employers opposed to AA, who exhibit high levels of discrimination across decision times (Col. 7). Conversely, for white employers who support AA, rushed decisions increase the race gap by 70% from 20 pp to 33 pp (Col. 5). Controlling for productivity beliefs further increases this difference (Col. 6, 8). In sum, white employers who support AA make decisions that align more closely with those of Black employers when given sufficient time. However, when put under time pressure, their decisions align more with those of white employers who do not support AA. These findings suggest that both System 1 and System 2 processes play distinct roles in influencing the race gap in hiring and that their relative importance varies across employers.

To further explore this heterogeneity, we present the hiring results across different subgroups of employers and decision time in Table 7. Panel A shows that among white employers opposed to AA, both race and productivity beliefs have similar effects on decisions in short and long time frames. The race penalty of around 40% decreases by 7 pp (17%) when controlling for productivity beliefs (Col. 2, 5) and an additional 8 to 12 pp when we control for other beliefs (Col. 3, 6). White employers supporting AA exhibit a similar pattern for short decisions: the large race gap of 32.5% closes by similar magnitudes when controlling for productivity and other beliefs (Panel B, Col. 4-6). However, when these employers have unlimited time to make decisions, their pattern diverges: the race gap becomes 40% smaller compared to short decisions (Col. 1), and the race penalty decreases by nearly 50% when controlling for productivity beliefs (Col. 2) and becomes indistinguishable from zero when controlling for other beliefs (Col. 3). Notably, the magnitude of productivity coefficients is approximately 80% larger for this group compared to employers opposing AA, suggesting that productivity beliefs play a more important role when sufficient time is available. In Panel C, we find that the hiring pattern for Black employers closely resembles that of white employers supporting AA when making decisions without time pressure (Col. 1-3). However, changes in coefficients are smaller when Black employers face time constraints (Col. 4-6).

6.4 Structural Estimation of Drift-Diffusion Model

Given the reduced-form analysis' support for the prediction of the the DDM, we proceed to estimate the parameters of the structural model using our experimental data. We start by estimating a single DDM model on the observed response times and hiring decisions pooling data across both short and long decision frames. This model assumes that only the decision thresholds are affected by the time constraint, whereas the drift rates and biased starting values are constant. (Details of the estimation strategy can be found in Appendix A.1.)

Estimates for the pooled employer sample reveal a large and significant effect of race beliefs on the decision drift, indicating a strong bias against hiring workers with Black-sounding names that accumulate with decision time (Table 8, Panel A, Column 1). As expected, productivity beliefs also affect the decisions through a strong positive drift. In line with

Table 8: Drift-diffusion Model: Structural Estimates

	Pooled (1)	White ConAA (2)	White ProAA (3)	Black (4)
Panel A: Pooled Decision Time				
Black drift (θ_1)	-0.356^{***}	-0.599^{***}	-0.219^{***}	-0.239^{***}
	(0.015)	(0.025)	(0.023)	(0.044)
Productivity drift (θ_2)	1.498^{***}	1.254^{***}	1.681^{***}	1.400^{***}
	(0.031)	(0.050)	(0.052)	(0.096)
Threshold: intercept	1.424^{***}	1.444^{***}	1.435^{***}	1.429^{***}
	(0.006)	(0.012)	(0.010)	(0.016)
Threshold: short time	-0.418^{***}	-0.414^{***}	-0.435^{***}	-0.472^{***}
	(0.012)	(0.021)	(0.018)	(0.030)
Black starting point (α_1)	0.012	0.041	-0.010	0.059
	(0.015)	(0.027)	(0.024)	(0.045)
Non-decision time	0.425^{***}	0.422^{***}	0.431^{***}	0.449^{***}
	(0.002)	(0.004)	(0.003)	(0.006)
Observations	13,819	4,354	5,756	1,745
Log Likelihood	$-25,223$	$-7,588$	$-1,0726$	$-3,306$
Panel B: Long Decision				
Black drift (θ_1)	-0.273^{***}	-0.507^{***}	-0.140^{***}	-0.202^{***}
	(0.017)	(0.028)	(0.026)	(0.049)
Productivity drift (θ_2)	1.456^{***}	1.193^{***}	1.654^{***}	1.385^{***}
	(0.033)	(0.054)	(0.056)	(0.105)
Threshold	1.453^{***}	1.475^{***}	1.460^{***}	1.459^{***}
	(0.007)	(0.014)	(0.011)	(0.018)
Black starting point (α_1)	-0.046^{**}	-0.044	-0.056^{*}	0.049
	(0.020)	(0.037)	(0.032)	(0.062)
Non-decision time	0.390^{***}	0.389^{***}	0.400^{***}	0.411^{***}
	(0.004)	(0.007)	(0.005)	(0.012)
Observations	9,923	3,092	4,147	1,254
Log Likelihood	$-20,431$	$-6,088$	$-8,702$	$-2,694$
Panel C: Short Decision				
Black drift (θ_1)	-0.874^{***}	-1.077^{***}	-0.775^{***}	-0.591^{***}
	(0.041)	(0.075)	(0.064)	(0.125)
Productivity drift (θ_2)	1.685^{***}	1.548^{***}	1.741^{***}	1.508^{***}
	(0.097)	(0.164)	(0.161)	(0.241)
Threshold	0.981^{***}	1.005^{***}	0.978^{***}	0.932^{***}
	(0.012)	(0.022)	(0.020)	(0.031)
Black starting point (α_1)	0.203^{***}	0.251^{***}	0.169^{***}	0.171^{**}
	(0.026)	(0.047)	(0.041)	(0.072)
Non-decision time	0.460^{***}	0.460^{***}	0.461^{***}	0.477^{***}
	(0.002)	(0.006)	(0.003)	(0.007)
Observations	3,896	1,262	1,609	491
Log Likelihood	$-4,595$	$-1,431$	$-1,951$	-598

Notes: Robust standard errors clustered at individual level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

DDM predictions, the information threshold of 1.42 for decisions not subjected to time constraints is reduced by 0.42 (30%) when employers are under time pressure.[31] We also estimate that employers require about 0.43 seconds on non-decision time for our task.

Estimating the DDM separately by employer subgroups reveals substantial heterogeneity in how beliefs influence decision drift rates. For Black employers and white employers supporting AA, productivity drift parameters are six to seven times larger than the Black drift parameters (Panel A, Col. 3-4), indicating that decisions are mainly determined by their productivity beliefs. By contrast, the productivity drift is only twice the size of the Black drift for White employers opposed to AA, suggesting that they are more influenced by race beliefs. We also find that race beliefs do not have a significant impact on the starting values in the pooled sample or for any of the subgroups.

We next relax the assumption of constant drift rates across experimental treatments by estimating the DDM separately for short and long decisions. Results reported in Panel B and C of Table 8 show that productivity drift parameters remain relatively constant across decisions times and employer groups. By contrast, the race drift parameter is more than three times larger in the short compared to long decision time in the pooled sample (Col. 1). This confirms the hypothesis that employers focus more on race early in the hiring decision and then gradually shift their attention to other worker attributes that are less salient but more relevant for hiring decisions. We again find large heterogeneity in this pattern across employers. Going from short to long decisions, the ratio of productivity to race drift changes from 2.2 to 12 for white employers supporting AA and from 2.5 to 6.8 for Black employers. By contrast, this ratio of only increases from 1.4 to 2.3 for White employers opposing AA. These estimates help explain the large variation of the effect of time pressure across employers (Table 6).[32] Figure A9 visualizes the changing role of the race drift across decision time and employers by plotting how expected relative decision values evolve.

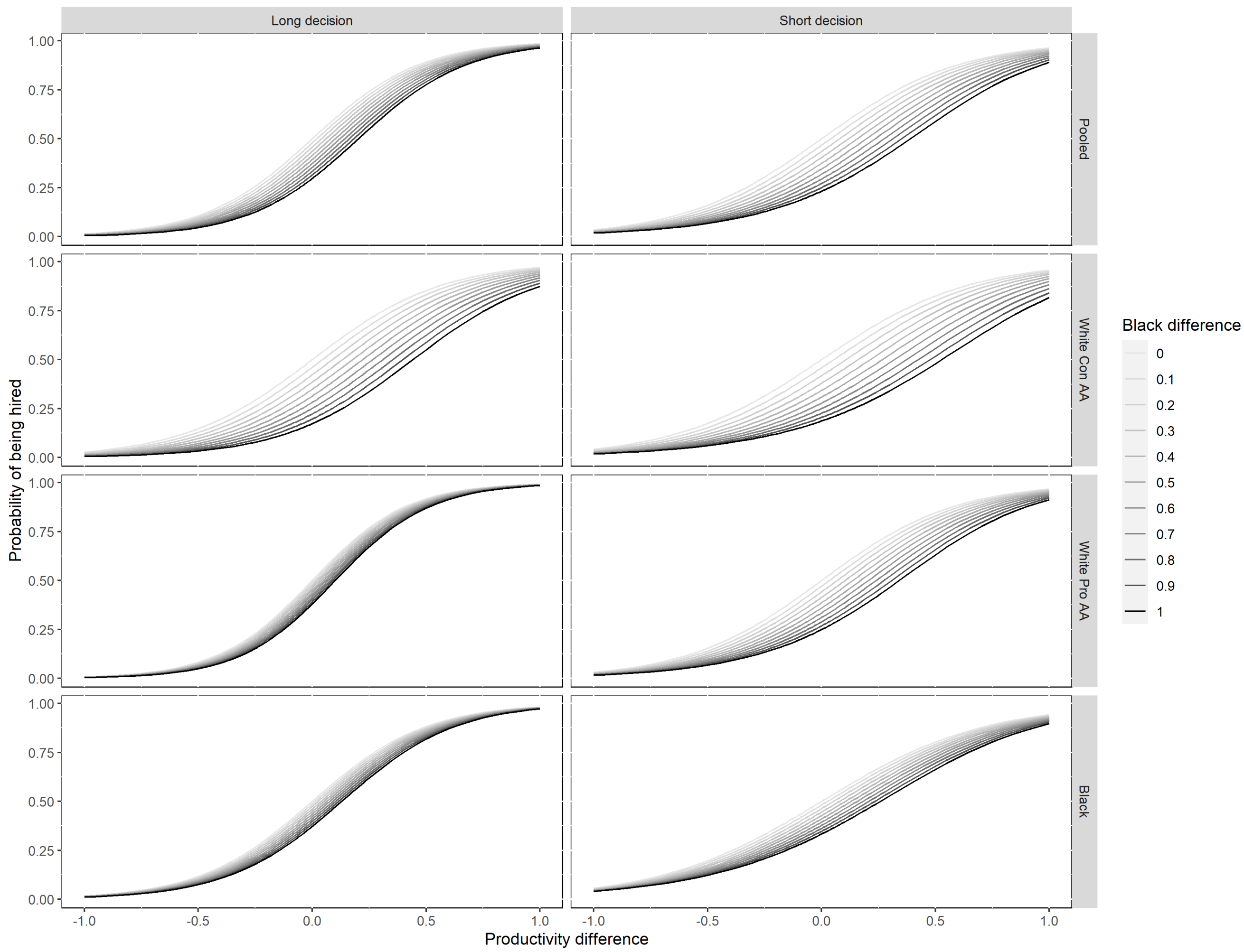
We can use these structural estimates for counterfactual analyses and calculate hiring probabilities for candidate pairs with different combinations of race and productivity differences. Figure 10 plots the hiring probabilities calculated separately across decision times and employer subgroups. Differences in productivity beliefs are plotted on the x-axis, hiring probabilities on the y-axis, and differences in beliefs that the worker is Black (normalized to be non-negative) are presented by different lines. In the pooled sample (top panel), lines have a steeper slope for long than short decisions, reflecting that productivity beliefs have a larger effect on hiring probabilities in decisions without time pressure. The bottom three panels visualize heterogeneity in responses to time pressure across employers. For Black employers and those favoring AA, the productivity profile becomes much steeper for long

[31] A threshold of 1.42 should be interpreted as 1.42 standard deviations of the accumulated noise of mental computations after a second of decision time.

[32] We also find that the starting point is significantly biased against Black workers for some employer subgroups in the long decision frame and that this bias appears to favour Black workers in the short decision frame for all employer subgroups. The fact that our estimates do not support the assumption of constant drift rates across experimental treatments combined with a lack of observations near the intercept means that we should guard against interpreting the starting point estimates as heuristic biases.

decisions, capturing that these employers are more likely to override their heuristic bias and hire more productive (Black) workers when given time.

Figure 10: Simulated Hiring probabilities



The vertical difference between the highest and lowest lines in the graphs indicates the hiring penalty experienced by Black workers at varying levels of productivity differences. Notably, this penalty is larger for short than long decisions and peaks for Black workers with moderate to large productivity advantages (with a maximum around a 25 pp advantage for both decision times).[33] These estimates also provide insights into the necessary (perceived) productivity advantage required by a Black candidate to have an equal chance of being hired, as indicated by the horizontal difference between races at the 50% hiring probability threshold. In the pooled sample, this premium amounts to 20.3 pp for long and 39.0 pp for short decisions. For white employers who oppose AA these figures increase to 52.8 for long

[33]For very large productivity differences the hiring penalty for Black workers decreases, as productivity beliefs outweigh racial biases.

and 44.2 pp for short decisions. For white employers favoring AA the productivity premium is sizable at 34.1 pp for fast decisions but decreases to 10.1 pp for long decisions. Black employers require a more moderate productivity premium of 25.8 pp for short decisions, which decreases to 13.0 pp for fast decisions.

The results in this subsection confirm that the DDM provides a useful framework for understanding the observed relationship between response times and hiring decisions, and helps explain seemingly contradictory responses to productivity beliefs and hiring decisions. Although variations in hiring decisions across short and long experimental treatments can not be completely accounted for in a single DDM with constant drift rates, the structural estimates from separately estimated models indicate that race beliefs have a strong effect on short hiring decisions, but becomes much less important when hiring decisions are longer. We also document important heterogeneity across employer subgroups in how attention to race and productivity beliefs shifts between short and long decisions. The results suggest that while all employer subgroups exhibit some degree of racial discrimination in their hiring decisions, the cognitive processes driving these decisions may vary significantly.

6.5 Alternative Mechanisms

6.5.1 Uncertainty and Risk Aversion

An alternative explanation for the race gap in hiring is that firms may be more hesitant to hire Black applicants due to *uncertainty* regarding their productivity levels (Lazear, 1998).[34] That is, in addition to differences in expected productivity, differences in the variance of productivity beliefs may also influence decision-making (Aigner and Cain, 1977).[35] To test this hypothesis, we ask employers to rate their certainty about picking the more productive worker in each choice after they completed the ten hiring decisions.[36] In line with the DDM's prediction that people facing time pressure reduce the information threshold, we find that employers in the short time frame report being 3.2 pp (0.2 sd) less certain about their choices.

If employers are indeed less certain about productivity of Black workers, race differences between candidates would also reduce certainty. However, our findings suggest the opposite. Perceiving one candidate as Black and one as white increases levels of certainty by 5.3 pp (0.3 sd) (Table A6, Col. 1). Even after controlling for productivity and other beliefs, we observe a similar pattern where perceived race differences increase levels of certainty by 0.2

[34] Race differences in the variance of productivity beliefs can create spurious evidence from audit studies (Heckman and Siegelman, 1993; Neumark, 2012).

[35] One theory proposed in the literature for why firms may be more uncertain about Black candidates is that the majority of hiring managers are white, and people tend to be more effective at evaluating applicants from their own race group (Cornell and Welch, 1996).

[36] We ask: "*You hired NAME over NAME. What do you think is the probability that you picked the more productive person?*"

to 0.3 s.d. (Col. 2-7). This suggests that race differences *reduce* uncertainty in the hiring decision, which is consistent with findings from the DDM that employers use race beliefs to reach an information threshold.

We conduct subgroup analysis levels of risk aversion to further test whether uncertainty is a driver of the race gap in hiring. Risk-averse employers may be more hesitant to hire candidates with unfamiliar names, which could disproportionately harm Black candidates. Contrary to this hypothesis, we find that the race gap in hiring does not widen among more risk-averse managers (Table B4, Col. 8). This result provides further evidence against uncertainty as a driver of the race gap in hiring.[37]

6.5.2 Concerns about Worker Payouts

Last, we explore the variation in whether workers obtain a chance of winning a large bonus for being hired. This offers a clean test of how much employers care about worker welfare in our setting as it does not affect their own payouts. The directional effect on the race gap is unclear ex-ante. If employers prioritize the well-being of white workers over Black workers, it may increase the race gap. On the other hand, if employers care about equity or are averse to inequality, it may reduce the race gap.

We find that the bonus does not change the race gap in hiring (Table A7, Col. 1). One explanation is that the bonus has heterogeneous effects that offset each other. Some employers may prioritize the welfare of white workers, while others may be concerned about reducing inequality and thus favor Black candidates. To investigate heterogeneity of the bonus effect, we analyze the effect on different subgroups of employers. Interestingly, we find that the effect of the bonus does not vary depending on employers' support for race-based affirmative action, political views, or race (Col. 2-7). We interpret this as evidence that concerns about worker welfare, including explanations related to taste-based discrimination, are less relevant in our setting. This may be unsurprising since workers and employers do not interact in our study context. However, preference-based discrimination may still factor into belief formation and help explain why employers hold incorrect beliefs about the productivity of Black workers.

[37] To measure risk aversion, we use the following survey question that has been shown by Falk et al. (2018) to be predictive of incentivized behavior: "*How do you see yourself: Are you a person who is generally willing to take risks, or do you try to avoid taking risks? (1-10 scale)*".

7 Conclusion

We explore the influence of names on hiring decisions, drawing on data from both actual workers and an incentivized hiring experiment in a nationally representative sample. Our analysis reveals racial disparities in beliefs based on workers' names and that these beliefs contribute to a race gap in hiring. These results shed light on one of the fundamental challenges in studying the effect of names, namely, that names are not randomly assigned. People hold many other associations that may be correlated with race and it is unclear to what extent these racial disparities reflect discrimination. We find that other beliefs explain some of the variation in the hiring gap, but that much remains unexplained, especially in rushed decisions. In addition, most of the race penalty remains when we look only at the variation in beliefs for the same name and when we drop the most distinctly Black names. These results address the criticism that discrimination detected through audit studies mainly reflect associations other than race or are driven by the choice of certain names. However, our findings also highlights the importance of measuring (probabilistic) race beliefs to correctly interpret differences in employer behavior measured by audit studies.

An important question is how much name-based discrimination documented by our and previous studies matter for situations outside of experimental settings, especially as other studies using large administrative data sets find that Black names are not correlated with educational (Kreisman and Smith, 2023) and other life outcomes (Fryer Jr and Levitt, 2004) after controlling for other factors, leading Fryer Jr and Levitt (2004) to conclude that "carrying a Black name is primarily the consequence rather than a cause of poverty". One explanation for this disparity in findings is that once people have more information, e.g. through frequent interactions in the classroom, they are less likely to judge others by their name (Kreisman and Smith, 2023).

Yet, there are many situations where name-based discrimination can prevent people from collecting additional information about a person as they may decide not to interview a candidate, accept as a renter, or offer credit (Bartoš et al., 2016). Esponda et al. (2020) show how biased beliefs reduces people's attentiveness to new information and prevents correcting beliefs. Learning requires that people are "willing and able to adjust their behavior" in response to information (Esponda et al., 2020). This can refer to new information and feedback or it may refer to thinking harder about a decision. Our findings show that perceiving someone as Black substantially shortens the time people dedicate to considering other qualities of that candidate. Biased beliefs thus prevents learning from ones *own memory*.

Being "willing and able" to learn also requires that one considers other characteristics than race that may be less salient and harder to retrieve when spending more time on a decision. We find substantial heterogeneity in what beliefs people use in their decision. For rushed decisions, race beliefs are a key determinant of their decisions across all (white) employers. When given unlimited time, some employers put more weight on their productivity beliefs while others are guided by the same beliefs as in rushed decisions. In our data, we identify support for AA as a predictor of who is considering other beliefs than race. Support for AA is also the single biggest predictor in who is holding biased race beliefs, which is consistent with Esponda et al. (2020)'s conclusion that inattention can prevent people from correcting beliefs.

One widely proposed strategy to reduce discrimination is to force people to slow down decision-making and thus reduce the role of heuristic biases associated with System 1 (Krajbich, 2022). Our results suggest that for some employers, this strategy is highly effective in reducing discrimination. However, our results highlight two reasons that limit the effectiveness of these policies: employers may be unwilling to consider other factors than race in their decisions and they may hold biased beliefs about these other characteristics. In our sample, these two tendencies are correlated, which makes it particularly challenging to reduce discriminatory behavior for these employers. Echoing recent papers documenting substantial variation in discriminatory behavior across employers (Kline and Walters, 2021), policies need to address the underlying source of this heterogeneity to be effective.

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A Appendix

A.1 Estimation

In the DDM a decision is reached when the relative decision value, z_t, crosses either of two thresholds, B or $-B$. In the most common version of this model, this process evolves with constant drift v, and is subject to random perturbations, e_t: $z_t = z_{t-1} + v + e_t$. This process is sometimes called a Wiener diffusion process, due to the common normality assumption of the error terms, $e_t \sim Normal(0, \sigma^2)$. We also can allow this process to have a non-zero starting point, α. The total response time to cross a decision threshold, t, consists of both decision time t_D and non-decision time, t_N. This process produces pairs of observable decision outcomes and response times that are random variables, whose distributions depend on four model parameters (v, B, α, t_N). It is often more convenient to reparameterize this model so that $c = 2B$ and $w = \frac{\alpha+B}{2B}$ and to work with the parameter vector (v, c, w, t_N).

The probability density of the response time for decisions that cross the lower threshold can be expressed as (Feller, 1968):

$$f(t|v,c,w) = \frac{\pi}{c}\exp\left(-vcw - \frac{v^2 t}{2}\right) \times \sum_{n=1}^{\infty} k \exp\left(-\frac{k^2\pi^2 t}{2c^2}\right)\sin(k\pi w) \tag{8}$$

This is a defective probability, in as far as it integrates to the conditional probability of crossing the lower threshold, rather than one. The probability density for the upper boundary can be obtained by setting v equal to $-v$ and w equal to $1-w$. Calculating these density values is complicated by the presence of an infinite sum which needs to be approximated, as discussed in (Ratcliff and Tuerlinckx, 2002). However, recent contributions (Blurton et al., 2017; Navarro and Fuss, 2009; Gondan et al., 2014) have improved the efficiency and speed with which these calculations can be performed. We use the *fddm* package in R (Foster, 2023) to calculate the density values and the partial derivatives of the individual densities with respect to the model parameters.

Our implementation of this model allows both race and productivity beliefs to determine the drift $v = \theta_1(r_a - r_b) + \theta_2(y_a - y_b)$. In addition, the starting value is allowed to depend on the difference in race beliefs across workers: $\alpha = \alpha_1(r_a - r_b)$. This requires adding another parameter to the model, so that the parameter vector is effectively $(\theta_1, \theta_2, B, \alpha_1, t_N)$. This does not add any complexity to the estimation process beyond the application of the chain rule to calculate the relevant partial derivatives.

We start the estimation process by dropping all decisions with missing choices, or productivity or race predictions. This is represents about 9.8% of the total sample. As is typical with such models, we also omit a small share of observations with implausibly quick or slow response times. Specifically, we drop 394 decisions with response times shorter than 0.5 seconds or longer than 20 seconds. These decisions comprise 2.3% of the sample, which is consistent with the the "2% to 3% of responses" (Ratcliff and McKoon, 2008, p. 885) that is common for such models.

The maximum likelihood estimates are obtained by using a sequence of numerical optimization routines to identify the parameter values that maximize the likelihood value. This happens in three steps. First, we use the Bayesian global optimization routine implemented in R through the *mlrMBO* package (Bischl et al., n.d.). The optimization is "warm-started" by pre-evaluating the model over a 200 initial parameter values drawn using a space-filling Latin Hypercube design. These estimates are then used in a sequential optimization procedure across 100 additional iterations with Kriging models as surrogate learners and the expected improvement infill criterion. The terminal point of this global optimizer serves as the starting point for our second numerical optimization step, which uses the Nelder-Mead method (Nelder and Mead, 1965) on both the calculated likelihood and gradient values. This method was found to be more efficient and robust in approaching the same terminal point across different starting values than other methods we experimented with. Finally, we use the Berndt-Hall-Hall-Hausman algorithm (Berndt et al., 1974) with starting values determined by the previous estimation step. Both the individual log-likelihood vector as well as the gradient matrix are used, which allow us to cluster standard errors by employer using. These methods are implemented in the *maxLik* package (Henningsen and Toomet, 2011).

A.2 Tables

Table A1: Randomization Balance Table (Time)

Variable	(1) Long Time N	(1) Long Time Mean/SE	(2) Short Time N	(2) Short Time Mean/SE	(3) Total N	(3) Total Mean/SE	T-test P-value (1)-(2)
Female	1001	0.505	492	0.520	1493	0.510	0.590
		(0.016)		(0.023)		(0.013)	
Age	1011	45.077	499	45.339	1510	45.164	0.764
		(0.504)		(0.709)		(0.411)	
White	1017	0.735	502	0.743	1519	0.738	0.753
		(0.014)		(0.020)		(0.011)	
Black	1017	0.127	502	0.133	1519	0.129	0.719
		(0.010)		(0.015)		(0.009)	
Asian	1017	0.061	502	0.068	1519	0.063	0.616
		(0.008)		(0.011)		(0.006)	
High School	1017	0.141	502	0.127	1519	0.136	0.477
		(0.011)		(0.015)		(0.009)	
Some College	1017	0.198	502	0.219	1519	0.205	0.336
		(0.012)		(0.018)		(0.010)	
College Degree	1017	0.483	502	0.456	1519	0.474	0.328
		(0.016)		(0.022)		(0.013)	
Professional Degree	1017	0.168	502	0.193	1519	0.176	0.236
		(0.012)		(0.018)		(0.010)	
Liberal	1014	0.532	498	0.588	1512	0.550	0.036**
		(0.016)		(0.022)		(0.013)	
Conservative	1017	0.274	502	0.235	1519	0.261	0.096*
		(0.014)		(0.019)		(0.011)	
Affirmative Action Support	1006	55.91	498	58.03	1504	56.61	0.231
		(1.02)		(1.44)		(0.835)	
Income	991	56,337	486	54,537	1477	55,744	0.375
		(1157)		(1666)		(950)	
Hiring Experience	1002	0.556	499	0.561	1501	0.558	0.848
		(0.016)		(0.022)		(0.013)	
Trump Vote (State)	997	47.360	489	47.184	1486	47.302	0.730
		(0.286)		(0.422)		(0.237)	
Unemployment (Zip)	997	5.364	489	5.649	1486	5.458	0.151
		(0.084)		(0.180)		(0.082)	
College (Zip)	997	21.222	489	21.364	1486	21.269	0.788
		(0.299)		(0.435)		(0.246)	
F-test of joint significance (p-value)							0.652

Table A2: Race Gap in Age Associations

	Age (Yr)	
	(1)	(2)
Name % Black	-6.525***	-1.389***
	(0.267)	(0.470)
Observations	9096	9096
Mean (white)	37.1	37.1
SD	7.66	7.66
R square	0.08	0.26
Name Fixed Effect	N	Y

Notes: The dependent variable is the associated age, calculated from the mid points of the age bins. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. Name FE refer to first name fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Race and Gender Interaction in Soft Skill Association

	Assert.	Motiv.	Respons.	Trustw.	Cooper.	Decis.	Perfec.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Name % Black	0.287***	-0.006	-0.286***	-0.226***	-0.205***	0.081***	-0.170***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.016)
Name Female	-0.087***	-0.043***	-0.039***	0.031**	0.052***	-0.090***	0.150***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)
Female x % Black	0.075**	-0.000	-0.019	-0.072**	-0.081***	0.042	-0.094***
	(0.029)	(0.030)	(0.028)	(0.028)	(0.030)	(0.031)	(0.024)
Observations	9096	9096	9096	9096	9096	9096	9096
Mean	.471	.54	.586	.478	.524	.421	.254
SD	.499	.498	.493	.5	.499	.494	.435
R square	0.05	0.00	0.04	0.03	0.03	0.01	0.05
Name FE	N	N	N	N	N	N	N
Pv: Fem Black=0	0.56	0.04	0.00	0.04	0.16	0.03	0.00

Notes: The dependent variable is a binary measure of whether name is associated with specific soft skill. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. Name FE refer to first name fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Comparison Productivity Beliefs vs. Actual Productivity

	Dependent Variable: Productivity (log)			
	(1)	(2)	(3)	(4)
Panel A: Beliefs				
Name % Black	-0.252***	-0.229***	-0.241***	-0.219***
	(0.013)	(0.013)	(0.013)	(0.013)
Education (yrs)		0.031***		0.031***
		(0.005)		(0.005)
Age (yrs)			0.002***	0.002***
			(0.001)	(0.001)
Observations	9091	9091	9091	9091
R square	0.06	0.07	0.06	0.07
Panel B: Actual Data				
1 = Black	-0.086***	-0.086***	-0.087***	-0.087***
	(0.021)	(0.021)	(0.021)	(0.021)
Education (yrs)		-0.003		-0.002
		(0.004)		(0.004)
Age (yrs)			-0.000	-0.000
			(0.001)	(0.001)
Observations	2426	2426	2426	2426
R square	0.01	0.01	0.01	0.01

Notes: The dependent variable in the perceived number of correctly transcribed receipts (out of 100). All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. Name FE refer to first name fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Race Gap in Hiring with Pair Fixed Effects

	Dependent Variable: Hire Worker						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black (Dif)	-0.158***	-0.086***	-0.114***	-0.118***	-0.153***	-0.097***	-0.036**
	(0.021)	(0.019)	(0.018)	(0.020)	(0.021)	(0.019)	(0.018)
Productivity (Dif)		0.736***					0.563***
		(0.026)					(0.026)
Wkr. 1 more product.			0.264***				
			(0.010)				
Educ (Dif)				0.057***			0.029***
				(0.004)			(0.004)
Age (Dif)					0.003***		0.001
					(0.001)		(0.001)
Assertive (Dif)						0.012	0.002
						(0.008)	(0.007)
Motivated (Dif)						0.088***	0.064***
						(0.007)	(0.007)
Responsible (Dif)						0.119***	0.087***
						(0.008)	(0.008)
Trustworthy (Dif)						0.100***	0.068***
						(0.008)	(0.008)
Cooperative (Dif)						0.072***	0.051***
						(0.008)	(0.008)
Decisive (Dif)						0.072***	0.051***
						(0.008)	(0.007)
Perfection. (Dif)						0.073***	0.052***
						(0.009)	(0.008)
Observations	14222	14218	14222	14222	14222	14222	14218
Mean	.626	.626	.626	.626	.626	.626	.626
SD	.484	.484	.484	.484	.484	.484	.484
R square	0.09	0.17	0.16	0.11	0.10	0.17	0.22
Pair FE	Y	Y	Y	Y	Y	Y	Y

Notes: The dependent variable in a binary variable for choosing worker 1. Independent variables are coded to show the difference in perception of worker 1 minus that of worker two. Worker pair fixed effects are estimated by including dummies for each possible worker pair employers choose from. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. Name FE refer to first name fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Certainty in Right Hiring Decision

	Confidence: Hired more productive worker (in pp)					
	(1)	(2)	(3)	(4)	(5)	(6)
Black (Dif)	5.347***	3.449***	4.345***	5.410***	4.743***	2.586***
	(0.633)	(0.605)	(0.624)	(0.634)	(0.634)	(0.603)
Productivity (Dif)		0.241***				0.215***
		(0.018)				(0.018)
Educ (Dif)			2.508***			1.813***
			(0.309)			(0.294)
Age (Dif)				-0.031		-0.037
				(0.036)		(0.034)
Assertive (Dif)					0.194	0.022
					(0.376)	(0.362)
Motivated (Dif)					1.132***	0.755**
					(0.362)	(0.350)
Responsible (Dif)					1.935***	1.317***
					(0.391)	(0.378)
Trustworthy (Dif)					1.781***	1.395***
					(0.378)	(0.361)
Cooperative (Dif)					0.868**	0.648*
					(0.377)	(0.364)
Decisive (Dif)					0.031	-0.030
					(0.373)	(0.357)
Perfection. (Dif)					1.512***	1.084***
					(0.438)	(0.420)
Observations	14480	14476	14480	14480	14480	14476
Mean	63.5	63.5	63.5	63.5	63.5	63.5
SD	17.8	17.8	17.8	17.8	17.8	17.8
R square	0.01	0.05	0.02	0.01	0.02	0.06
Name FE	N	N	N	N	N	N

Notes: The dependent variable measures the certainty (in percentage points) participants report for having made the correct hiring decision. Independent variables are coded to show the difference in perception of worker 1 minus that of worker two. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. Name FE refer to first name fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

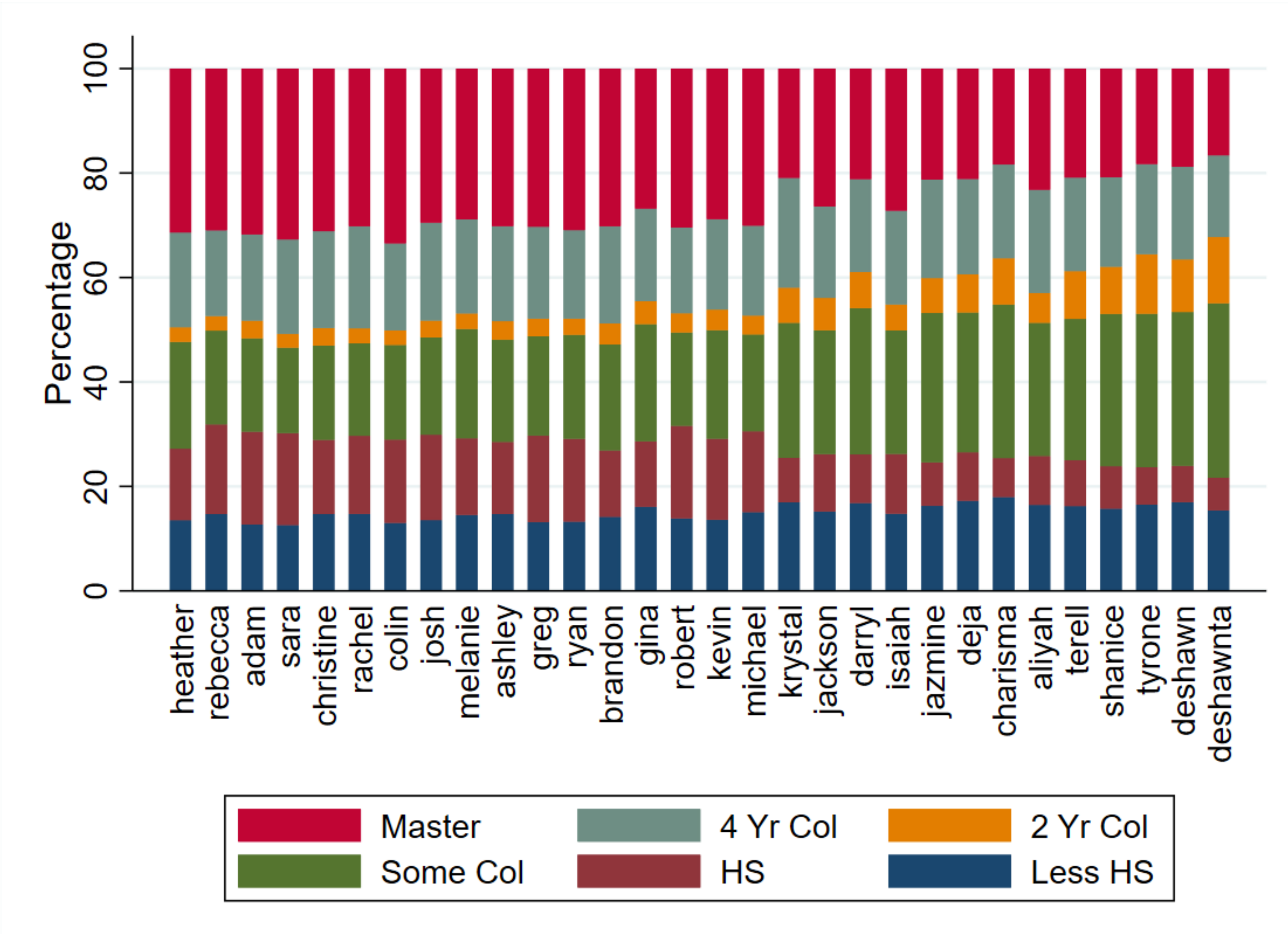
Table A7: Worker Bonus

	Dependent Variable: Hire Worker						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black (Dif)	-0.297***	-0.381***	-0.224***	-0.231***	-0.368***	-0.204***	-0.317***
	(0.017)	(0.024)	(0.024)	(0.024)	(0.024)	(0.049)	(0.020)
Bonus	-0.002	-0.002	-0.004	-0.007	0.003	0.017	-0.012
	(0.013)	(0.020)	(0.017)	(0.018)	(0.018)	(0.035)	(0.015)
Black x Bonus	0.002	-0.010	0.015	0.008	-0.008	0.054	-0.009
	(0.029)	(0.039)	(0.042)	(0.043)	(0.038)	(0.080)	(0.033)
Observations	14222	5791	8303	7761	6424	1820	10502
Mean	.626	.676	.592	.595	.664	.592	.63
SD	.484	.468	.492	.491	.473	.492	.483
R square	0.06	0.11	0.03	0.04	0.10	0.03	0.07
Subgroup	Bonus	AA Con	AA Pro	Liberal	Not Lib	Black	White

Notes: The dependent variable in a binary variable for choosing worker 1. Independent variables are coded to show the difference in perception of worker 1 minus that of worker two. Bonus is a binary variable measuring whether participants were randomly assigned to the treatment in which workers received a chance of earning money for being hired. Column 2-7 estimate regressions for subgroups of employers listed in the bottom row. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

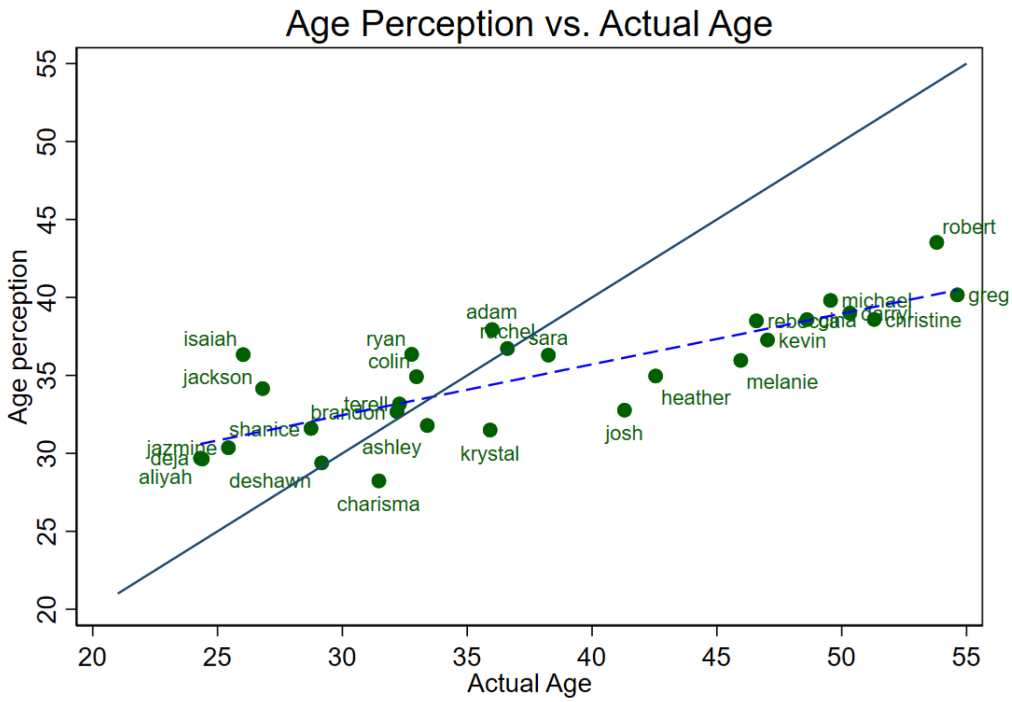
A.3 Figures

Figure A1: Education Associations



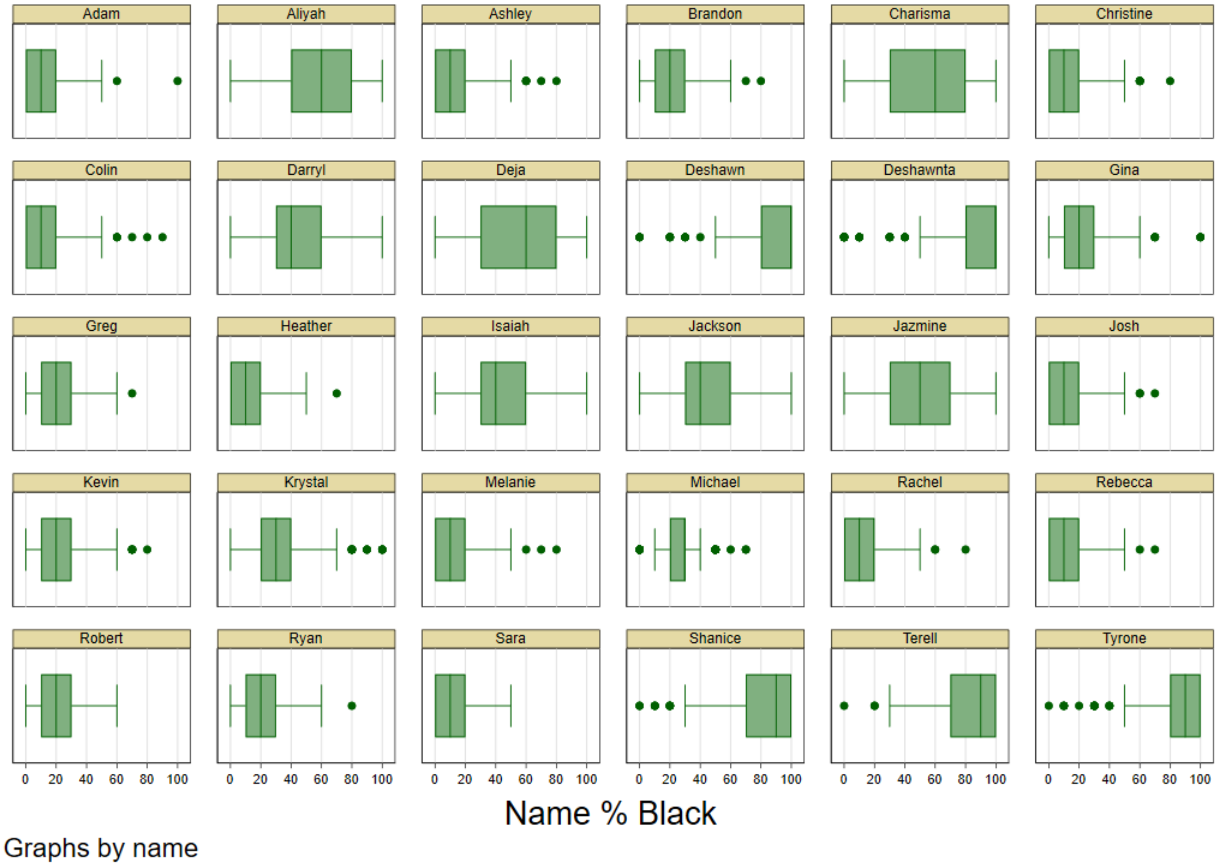
Notes: The figure shows associations of the highest educational attainment for names sorted by race perception (from white to Black). across 300 respondents.

Figure A2: Age Associations vs. Actual



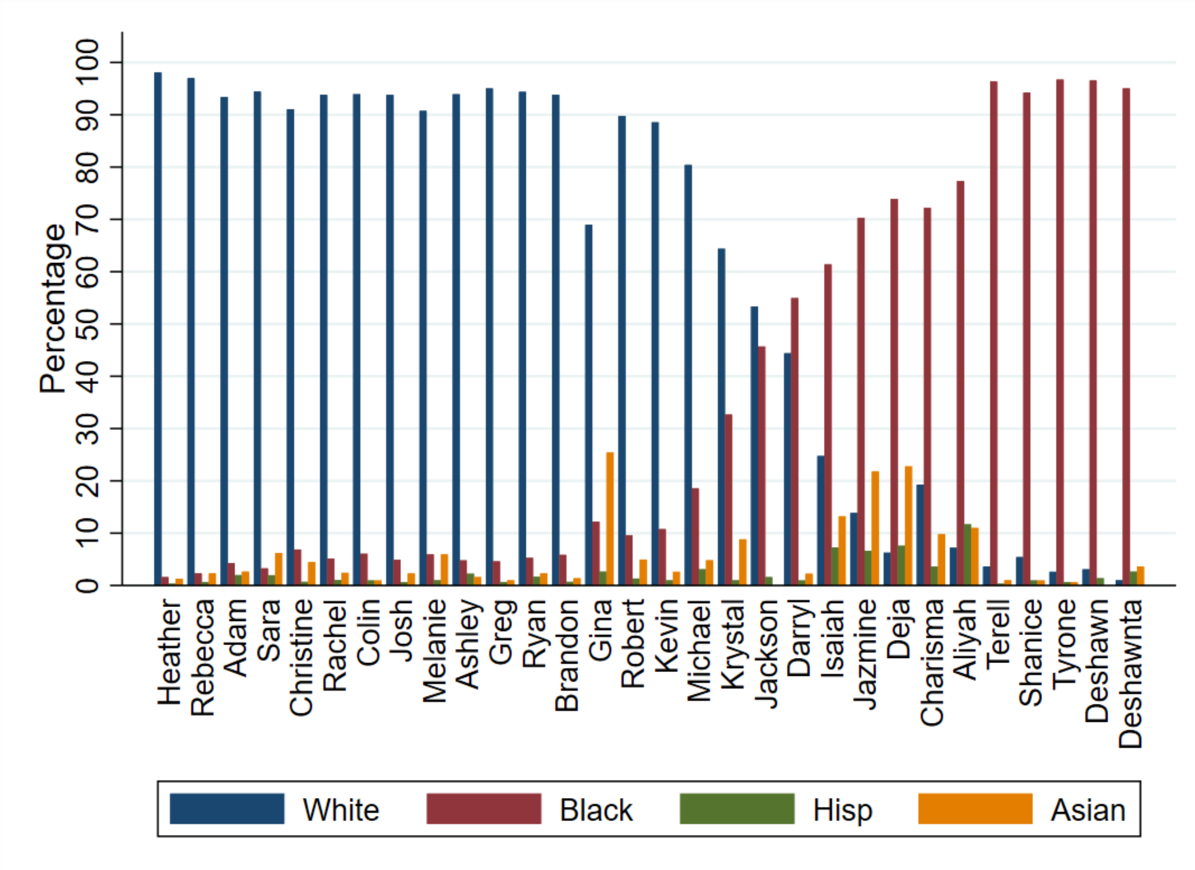
Notes: The figure shows the relationship between age associations and the actual age of people with a given name. Both figures are calculated by taking the weighted average of the midpoints of the age bins. The blue dotted line shows the best linear fit.

Figure A3: Race Belief Distribution for Worker Names



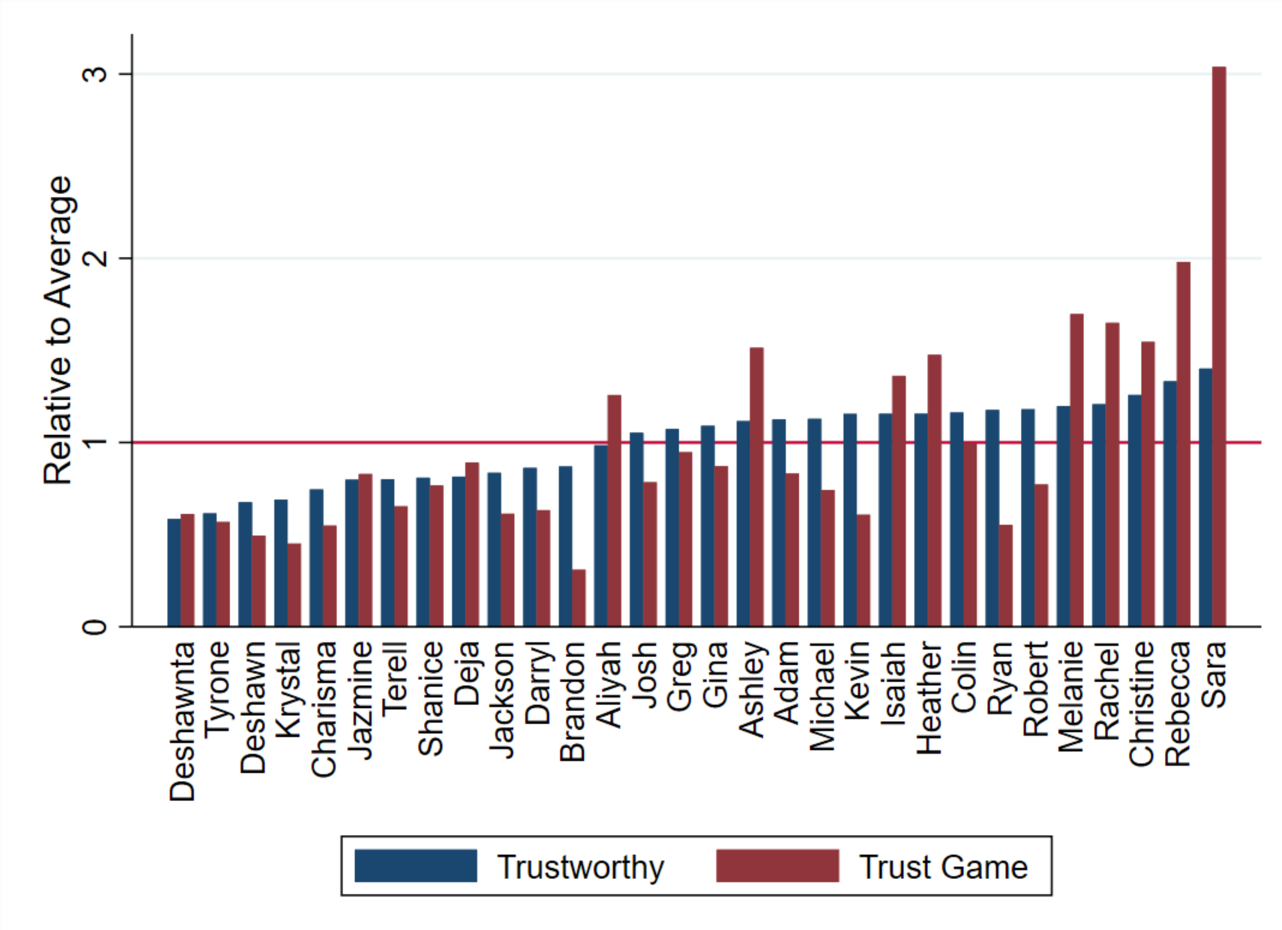
Notes: The boxplot is showing distributions of the average perceptions of being Black across participants. The green area captures the second and third quartile, the vertical line presents the median. Dots present outliers.

Figure A4: Race Belief Distribution Using Binary Elicitation



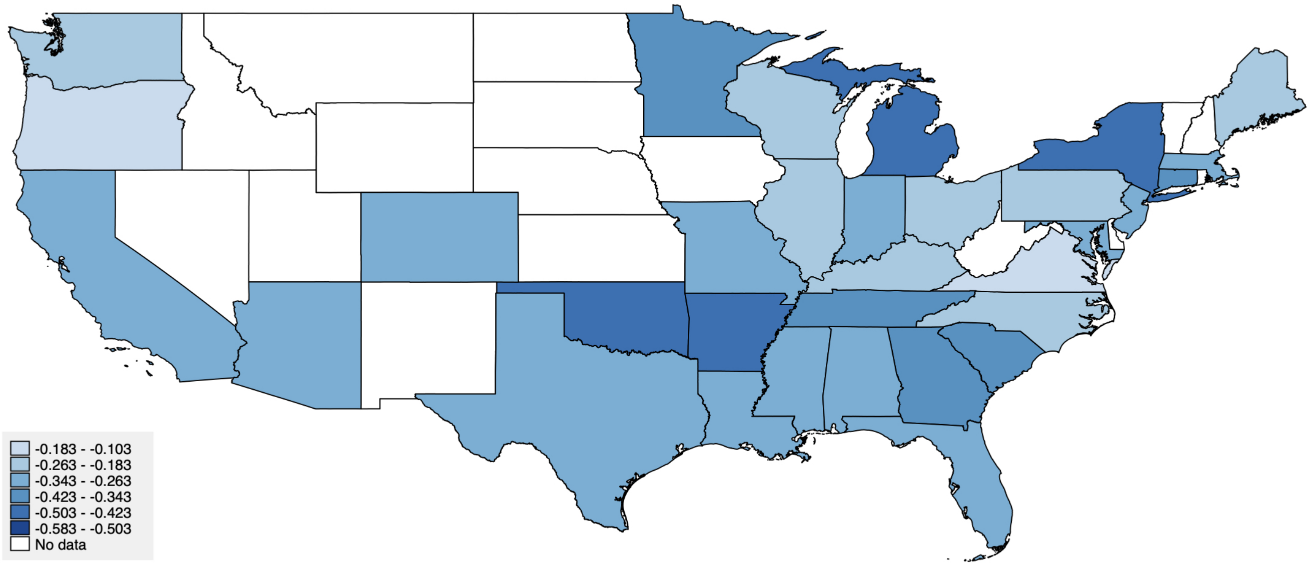
Notes: The figure shows race associations for different names sorted by race perception (from white to Black). We convert the distribution of beliefs into a binary measure, which captures the modal race belief of a given respondent. The bars present the average associations across 300 respondents.

Figure A5: Trust Associations and Behavior



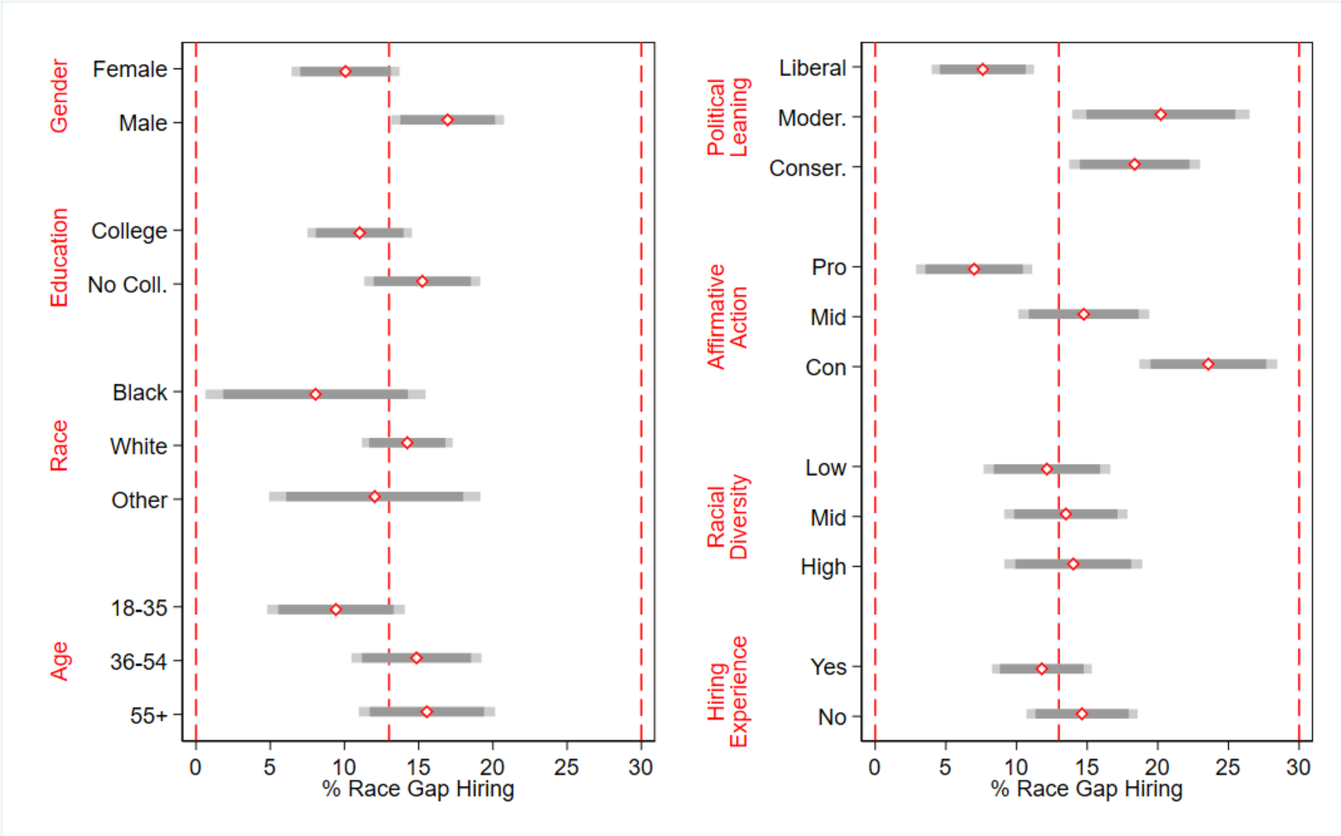
Notes: The blue bars show how frequently names are associated with being trustworthy. The red bars show how often a name was selected as a partner in the trust game. Both measures we divide by their respective average. Names are sorted by perceptions of trustworthiness.

Figure A6: Geographic Variation in Race Gap



Notes: The map shows how the race gap varies geographically. We estimate our main specification separately for each state. We limit the analysis to states for which we observe at least 100 hiring decisions.

Figure A7: Race Gap in Hiring Across Subgroups (with controls)



Note: The Figure is showing how the race gap (Black vs. white) varies across subgroups of employers. Coefficients are from our main specification with control variables (productivity, education, age and noncognitive skill beliefs) estimated separately for subgroups. The bars present 90% and 95% intervals. *Affirmative action* is measuring level of support from 0-100 scale coded as Con (0-33), Mid (34-66) and Pro (67-100). *Racial diversity* refers to zip code level racial fractionalization, divided into terciles. *Hiring experience* refers to whether the respondent has real-life experience in hiring.

Figure A8: Race Gap and AA Support by Time Frame

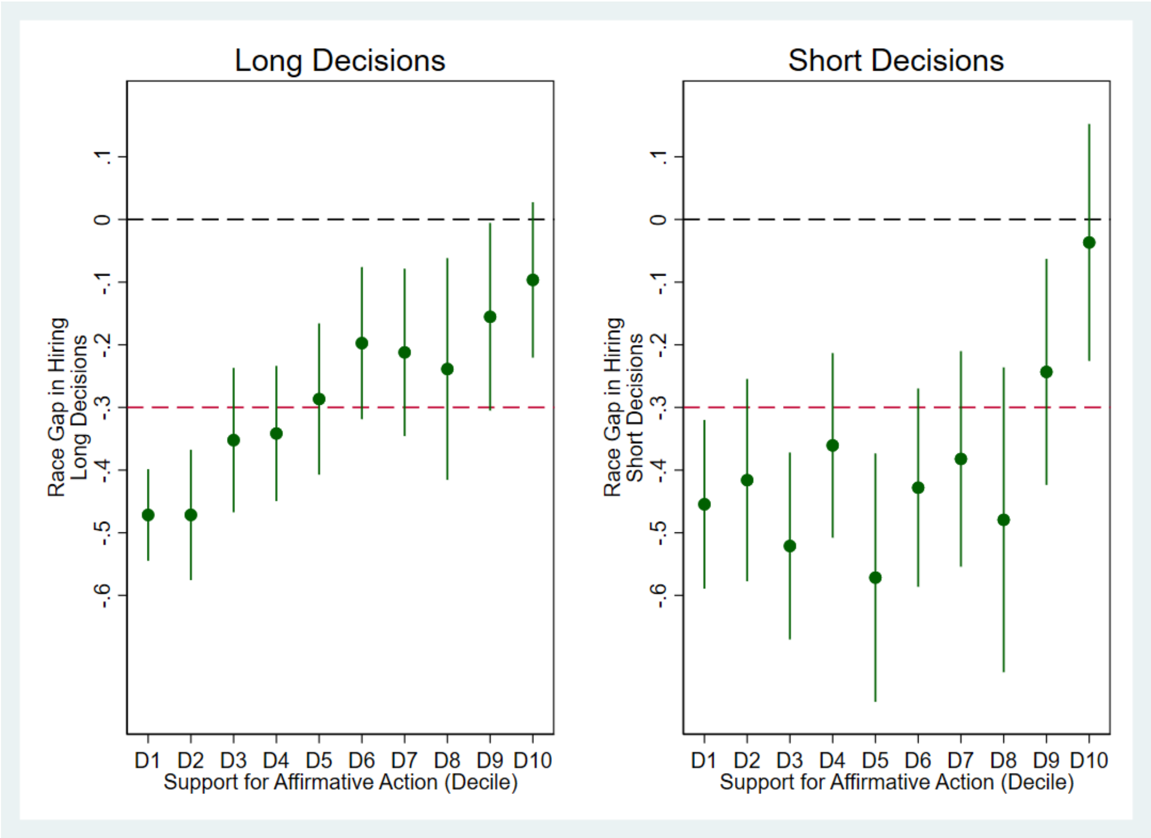
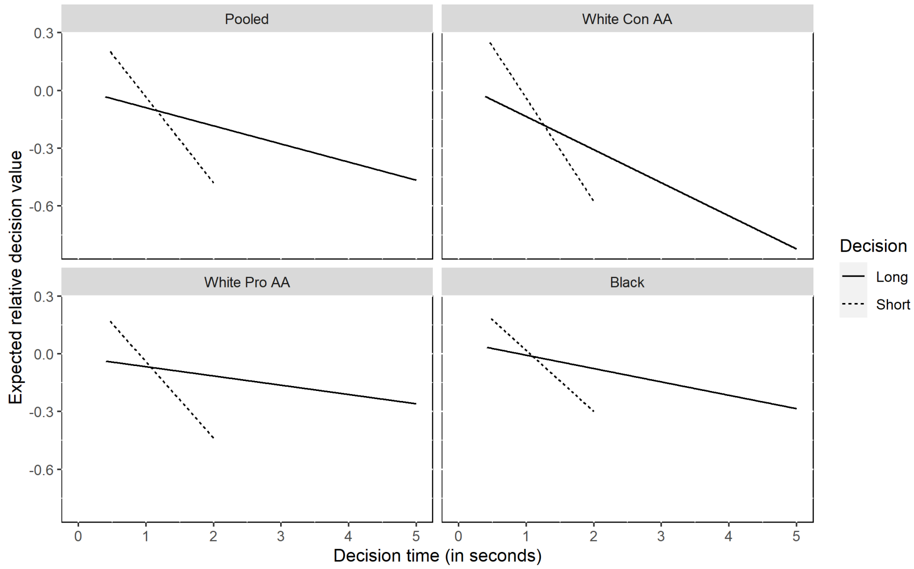


Figure A9: Expected relative decision value



B Online Appendix

B.1 Tables

Table B1: Randomization Balance Table (Bonus)

	(1) No Bonus		(2) Bonus		(3) Total		T-test P-value
Variable	N	Mean/SE	N	Mean/SE	N	Mean/SE	(1)-(2)
Female	1002	0.515	491	0.501	1493	0.510	0.613
		(0.016)		(0.023)		(0.013)	
Age	1013	45.255	497	44.978	1510	45.164	0.754
		(0.497)		(0.731)		(0.411)	
White	1020	0.743	499	0.727	1519	0.738	0.517
		(0.014)		(0.020)		(0.011)	
Black	1020	0.123	499	0.142	1519	0.129	0.292
		(0.010)		(0.016)		(0.009)	
Asian	1020	0.068	499	0.054	1519	0.063	0.291
		(0.008)		(0.010)		(0.006)	
High School	1020	0.130	499	0.148	1519	0.136	0.349
		(0.011)		(0.016)		(0.009)	
Some College	1020	0.202	499	0.210	1519	0.205	0.703
		(0.013)		(0.018)		(0.010)	
College Degree	1020	0.476	499	0.469	1519	0.474	0.783
		(0.016)		(0.022)		(0.013)	
Professional Degree	1020	0.181	499	0.166	1519	0.176	0.465
		(0.012)		(0.017)		(0.010)	
Liberal	1015	0.553	497	0.545	1512	0.550	0.785
		(0.016)		(0.022)		(0.013)	
Conservative	1020	0.262	499	0.261	1519	0.261	0.959
		(0.014)		(0.020)		(0.011)	
Affirmative Action Support	1011	56.72	493	56.39	1504	56.612	0.851
		(1.019)		(1.458)		(0.835)	
Income	987	55,552	490	56,133	1477	55,745	0.772
		(1174)		(1620)		(951)	
Hiring Experience	1006	0.544	495	0.586	1501	0.558	0.121
		(0.016)		(0.022)		(0.013)	
Trump Vote (State)	997	47.147	489	47.619	1486	47.302	0.349
		(0.289)		(0.413)		(0.237)	
Unemployment (Zip)	997	5.503	489	5.366	1486	5.458	0.407
		(0.105)		(0.127)		(0.082)	
College (Zip)	997	21.387	489	21.027	1486	21.269	0.478
		(0.310)		(0.403)		(0.246)	
F-test of joint significance (p-value)							0.477

Table B2: Productivity Beliefs: Binary Race

	Dependent Variable: Productivity (Log)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Race Black (Binary)	-0.135***	-0.120***	-0.126***	-0.106***	-0.091***	-0.029**	-0.019*
	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.011)	(0.011)
Race Hispanic (Binary)	-0.037	-0.030	-0.039	-0.038	-0.034	-0.007	-0.008
	(0.028)	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)	(0.027)
Race Asian (Binary)	0.031**	0.036***	0.034**	0.025*	0.031**	0.016	0.009
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Education (yrs)		0.036***			0.028***		0.026***
		(0.005)			(0.005)		(0.004)
Age (yrs)			0.002***		0.001**		0.000
			(0.001)		(0.001)		(0.001)
Name assertive				-0.014*	-0.013		-0.004
				(0.008)	(0.008)		(0.008)
Name selfmotivated				0.036***	0.035***		0.037***
				(0.008)	(0.008)		(0.008)
Name responsible				0.062***	0.056***		0.053***
				(0.008)	(0.008)		(0.007)
Name trustworthy				0.059***	0.053***		0.051***
				(0.008)	(0.008)		(0.008)
Name cooperative				0.028***	0.028***		0.027***
				(0.008)	(0.008)		(0.007)
Name decisive				0.026***	0.025***		0.030***
				(0.008)	(0.008)		(0.008)
Name perfectionistic				0.033***	0.032***		0.019**
				(0.008)	(0.008)		(0.008)
Observations	8817	8817	8817	8817	8817	8817	8817
Mean	4.14	4.14	4.14	4.14	4.14	4.14	4.14
SD	.328	.328	.328	.328	.328	.328	.328
R square	0.04	0.05	0.04	0.08	0.09	0.12	0.16
Name FE	N	N	N	N	N	Y	Y

Notes: The dependent variable in a binary variable for choosing worker 1. Independent variables are coded to show the difference in perception of worker 1 minus that of worker two. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. Name FE refer to first name fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B3: Race Gap in Hiring: Robustness - Exclude Distinctly Black Names

	Dependent Variable: Hire Worker						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black (Dif)	-0.311***	-0.245***	-0.265***	-0.261***	-0.283***	-0.220***	-0.149***
	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.018)	(0.019)
Hispanic (Dif)	-0.133**	-0.130**	-0.128**	-0.092	-0.118**	-0.123**	-0.095**
	(0.058)	(0.051)	(0.051)	(0.058)	(0.058)	(0.052)	(0.048)
Asian (Dif)	-0.218***	-0.186***	-0.196***	-0.173***	-0.191***	-0.192***	-0.138***
	(0.035)	(0.033)	(0.033)	(0.035)	(0.035)	(0.033)	(0.031)
Productivity (Dif)		0.644***					0.464***
		(0.032)					(0.032)
Wkr. 1 more product.			0.218***				
			(0.013)				
Educ (Dif)				0.061***			0.033***
				(0.006)			(0.005)
Age (Dif)					0.004***		0.002***
					(0.001)		(0.001)
Assertive (Dif)						0.018*	0.009
						(0.010)	(0.010)
Motivated (Dif)						0.089***	0.071***
						(0.009)	(0.009)
Responsible (Dif)						0.142***	0.113***
						(0.010)	(0.010)
Trustworthy (Dif)						0.104***	0.075***
						(0.011)	(0.010)
Cooperative (Dif)						0.072***	0.060***
						(0.010)	(0.010)
Decisive (Dif)						0.077***	0.062***
						(0.010)	(0.009)
Perfection. (Dif)						0.107***	0.092***
						(0.011)	(0.010)
Observations	7729	7726	7729	7729	7729	7729	7726
Mean	.576	.576	.576	.576	.576	.576	.576
SD	.494	.494	.494	.494	.494	.494	.494
R square	0.06	0.12	0.10	0.07	0.06	0.14	0.18
Name FE	N	N	N	N	N	N	N

Notes: The dependent variable in a binary variable for choosing worker 1. Independent variables are coded to show the difference in perception of worker 1 minus that of worker two. This sample exclude any worker pairs that include either of the following distinctly Black names: Deshawn, Deshawnta, Shanice, Terell, and Tyrone. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B4: Subgroups: Race Gap in Hiring

	Dependent Variable: Hire Worker								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Black (Dif)	-0.337***	-0.306***	-0.263***	-0.310***	-0.370***	-0.357***	-0.290***	-0.293***	-0.412***
	(0.018)	(0.020)	(0.020)	(0.015)	(0.018)	(0.018)	(0.020)	(0.018)	(0.031)
Female x Black (Dif)	0.075***								0.060**
	(0.025)								(0.026)
College x Black (Dif)		0.018							0.010
		(0.026)							(0.027)
Old x Black (Dif)			-0.063**						-0.055**
			(0.025)						(0.027)
Black x Black (Dif)				0.121***					0.080**
				(0.038)					(0.040)
Support A.A. x Black (Dif)					0.137***				0.090***
					(0.025)				(0.029)
Liberal x Black (Dif)						0.117***			0.066**
						(0.025)			(0.028)
Hire Exper. x Black (Dif)							-0.008		0.022
							(0.026)		(0.028)
Risk Averse x Black (Dif)								-0.009	0.005
								(0.026)	(0.026)
Observations	13993	14222	14222	14222	14222	14185	14065	14202	13805
Mean	.626	.626	.626	.626	.626	.626	.626	.626	.626
SD	.484	.484	.484	.484	.484	.484	.484	.484	.484
R square	0.06	0.06	0.06	0.06	0.07	0.07	0.06	0.06	0.07
Subgroup	Gender	College	Age	Black	A.A.	Liberal	Exper.	Risk Av.	Joint
P-value: Subgroup=0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
Share Subgroup	0.51	0.55	0.50	0.13	0.60	0.55	0.56	0.45	

Notes: The dependent variable in a dummy for choosing worker 1. Black (Dif) measures the perceived difference in Race between worker 1 and 2. Main terms for subgroups are included in regressions but not reported. College is a dummy for whether people completed at least a four year college. Old is a dummy for whether people are older than the median age of 45 years. Support A.A. is a dummy for whether people express above the median support for race-based affirmative action. Hire Experience is a dummy for whether people have previously been involved in hiring decisisons. Risk averse is a dummy for whether people are above the median level of risk aversion. POC (other) is a dummy if respondents report being non-White and non-Black. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. Name FE refer to first name fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B5: Robustness - Suspect Research Question

	Dependent Variable: Hire Worker							
	Research: Race				Research: Race or Other Bias			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black (Dif)	-0.296***	-0.135***	-0.315***	-0.135***	-0.303***	-0.140***	-0.301***	-0.129***
	(0.017)	(0.016)	(0.025)	(0.024)	(0.020)	(0.019)	(0.020)	(0.020)
Productivity (Dif)		0.550***		0.539***		0.528***		0.568***
		(0.032)		(0.044)		(0.036)		(0.038)
Educ (Dif)		0.027***		0.042***		0.025***		0.039***
		(0.005)		(0.007)		(0.005)		(0.006)
Age (Dif)		0.002***		0.001		0.002***		0.001
		(0.001)		(0.001)		(0.001)		(0.001)
Assertive (Dif)		0.010		-0.021		0.006		-0.006
		(0.009)		(0.014)		(0.011)		(0.011)
Motivated (Dif)		0.069***		0.059***		0.069***		0.062***
		(0.009)		(0.012)		(0.010)		(0.010)
Responsible (Dif)		0.093***		0.097***		0.095***		0.093***
		(0.009)		(0.014)		(0.010)		(0.012)
Trustworthy (Dif)		0.072***		0.079***		0.077***		0.071***
		(0.009)		(0.014)		(0.011)		(0.011)
Cooperative (Dif)		0.061***		0.044***		0.068***		0.044***
		(0.010)		(0.014)		(0.011)		(0.012)
Decisive (Dif)		0.056***		0.058***		0.055***		0.056***
		(0.009)		(0.013)		(0.010)		(0.010)
Perfection. (Dif)		0.062***		0.047***		0.060***		0.055***
		(0.010)		(0.015)		(0.012)		(0.012)
Observations	9353	9353	4484	4480	7132	7132	6705	6701
Mean	.626	.626	.626	.626	.626	.626	.626	.626
SD	.484	.484	.484	.484	.484	.484	.484	.484
R square	0.06	0.20	0.07	0.20	0.06	0.20	0.06	0.20
Suspect Research Q	No	No	Yes	Yes	No	No	Yes	Yes

Notes: The dependent variable in a binary variable for choosing worker 1. Independent variables are coded to show the difference in perception of worker 1 minus that of worker two. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B6: Race Gap in Hiring (All Race Groups)

	Dependent Variable: Hire Worker						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black (Dif)	-0.296***	-0.213***	-0.237***	-0.246***	-0.275***	-0.203***	-0.131***
	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)
Hispanic (Dif)	-0.095**	-0.094**	-0.095**	-0.051	-0.089*	-0.078*	-0.058
	(0.048)	(0.041)	(0.041)	(0.049)	(0.048)	(0.043)	(0.039)
Asian (Dif)	-0.192***	-0.169***	-0.178***	-0.148***	-0.173***	-0.167***	-0.129***
	(0.030)	(0.027)	(0.028)	(0.029)	(0.030)	(0.028)	(0.027)
Productivity (Dif)		0.733***					0.548***
		(0.026)					(0.026)
Wkr. 1 more product.			0.270***				
			(0.010)				
Educ (Dif)				0.063***			0.032***
				(0.005)			(0.004)
Age (Dif)					0.004***		0.002***
					(0.001)		(0.001)
Assertive (Dif)						0.011	0.000
						(0.008)	(0.008)
Motivated (Dif)						0.091***	0.066***
						(0.007)	(0.007)
Responsible (Dif)						0.128***	0.094***
						(0.008)	(0.008)
Trustworthy (Dif)						0.109***	0.075***
						(0.008)	(0.008)
Cooperative (Dif)						0.074***	0.054***
						(0.008)	(0.008)
Decisive (Dif)						0.075***	0.055***
						(0.007)	(0.007)
Perfection. (Dif)						0.077***	0.056***
						(0.009)	(0.008)
Observations	14222	14218	14222	14222	14222	14222	14218
Mean	.626	.626	.626	.626	.626	.626	.626
SD	.484	.484	.484	.484	.484	.484	.484
R square	0.06	0.14	0.13	0.08	0.06	0.14	0.20
Name FE	N	N	N	N	N	N	N

Notes: The dependent variable in a binary variable for choosing worker 1. Independent variables are coded to show the difference in perception of worker 1 minus that of worker two. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. Name FE refer to first name fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

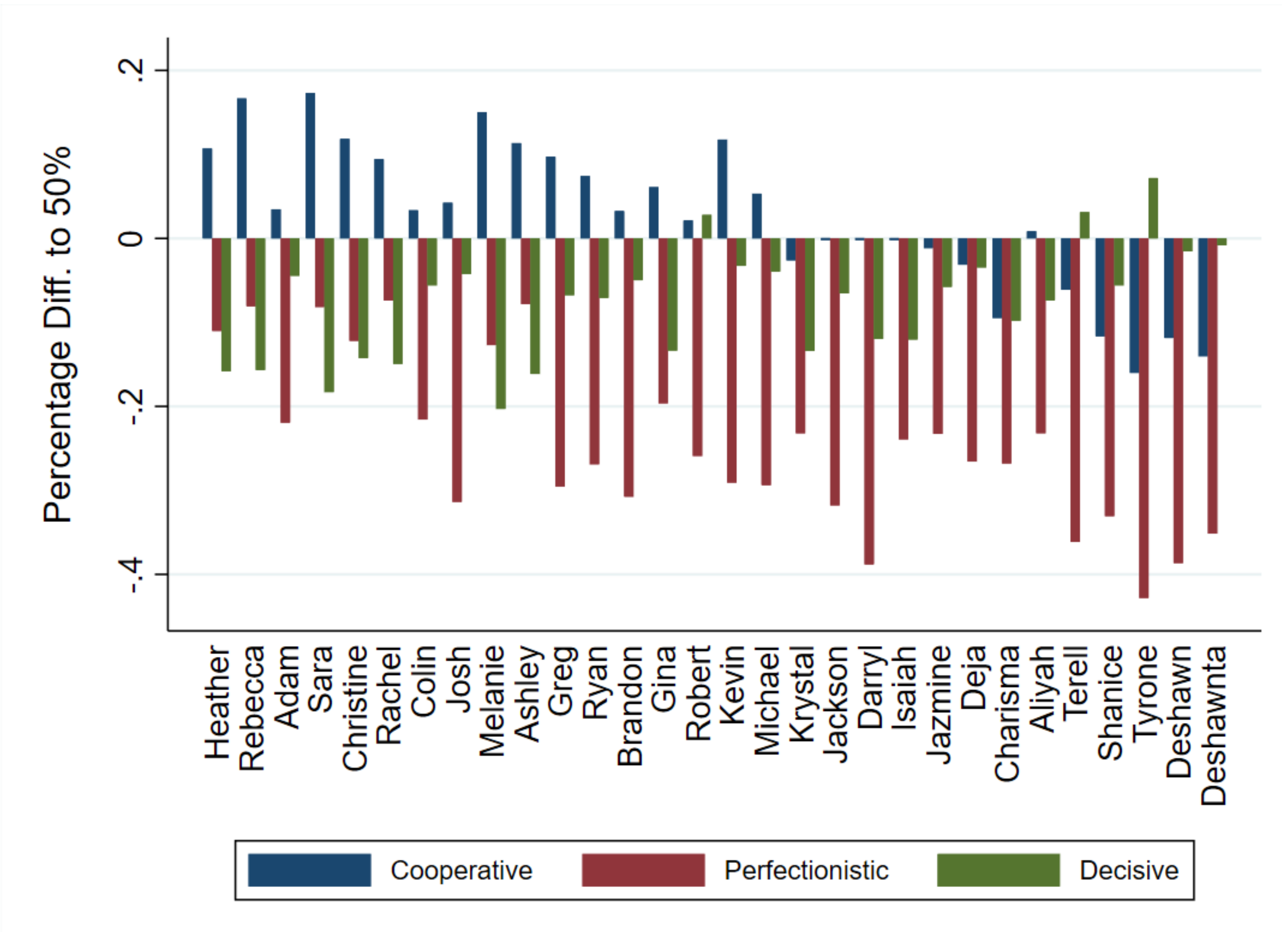
Table B7: Effect of Time Pressure on Discrimination

	Liberal		Conservative		Low CRT		High CRT	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black (Dif)	-0.205***	-0.111***	-0.382***	-0.307***	-0.252***	-0.164***	-0.299***	-0.208***
	(0.024)	(0.022)	(0.027)	(0.027)	(0.025)	(0.024)	(0.022)	(0.021)
Short x Black (Dif)	-0.075*	-0.113***	-0.017	-0.013	-0.003	-0.038	-0.123***	-0.141***
	(0.039)	(0.037)	(0.048)	(0.048)	(0.042)	(0.040)	(0.037)	(0.037)
Productivity (Dif)		0.909***		0.588***		0.690***		0.882***
		(0.041)		(0.050)		(0.041)		(0.046)
Short x Prod (Dif)		-0.246***		-0.019		-0.052		-0.316***
		(0.085)		(0.086)		(0.078)		(0.082)
Observations	7761	7757	3763	3763	6570	6569	7652	7649
Mean	.595	.595	.676	.676	.622	.622	.63	.63
SD	.491	.491	.468	.468	.485	.485	.483	.483
R square	0.04	0.14	0.11	0.17	0.04	0.12	0.08	0.17
Group	Liberal	Liberal	Conserv	Conserv	Low CRT	Low CRT	High CRT	High CRT

Notes: The dependent variable in a binary variable for choosing worker 1. Independent variables are coded to show the difference in perception of worker 1 minus that of worker two. is an indicator variable for the randomly assigned fast decision time. Col. 1-4 and 5-8 divide the sample according to whether respondents' political leaning and whether they scored above the median in the cognitive reflection test, respectively. All estimations are OLS. Robust standard errors clustered at individual level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

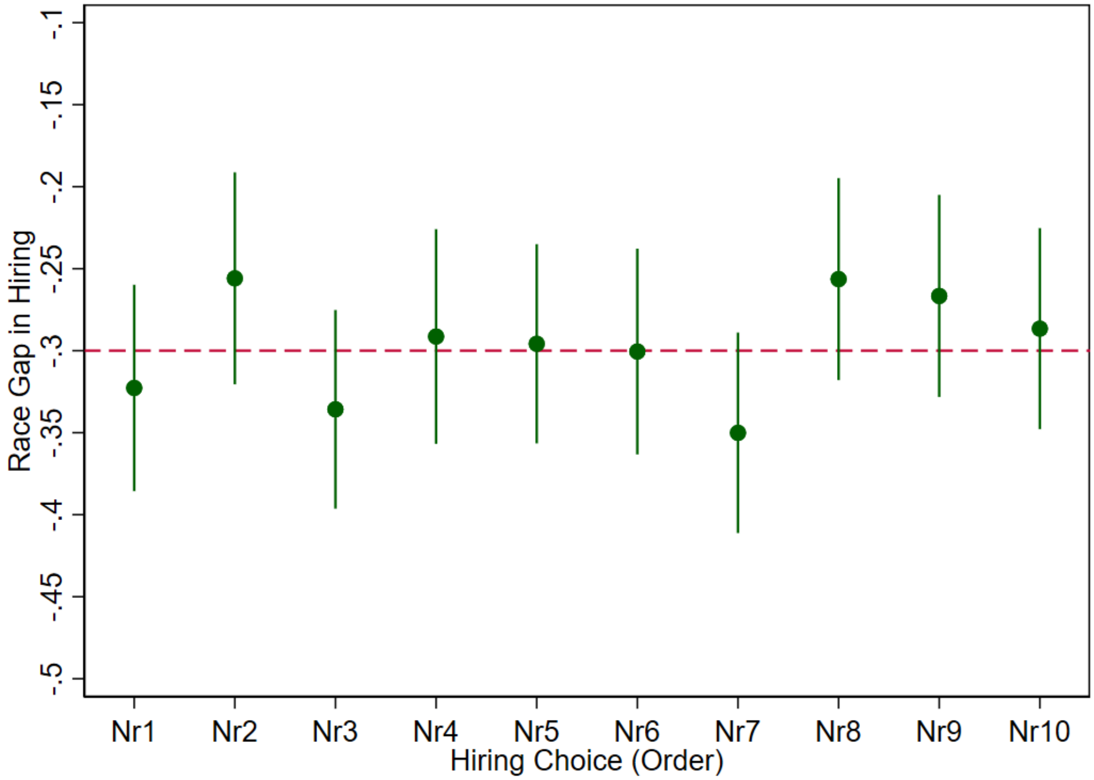
B.2 Figures

Figure B1: Noncognitive Skill Associations



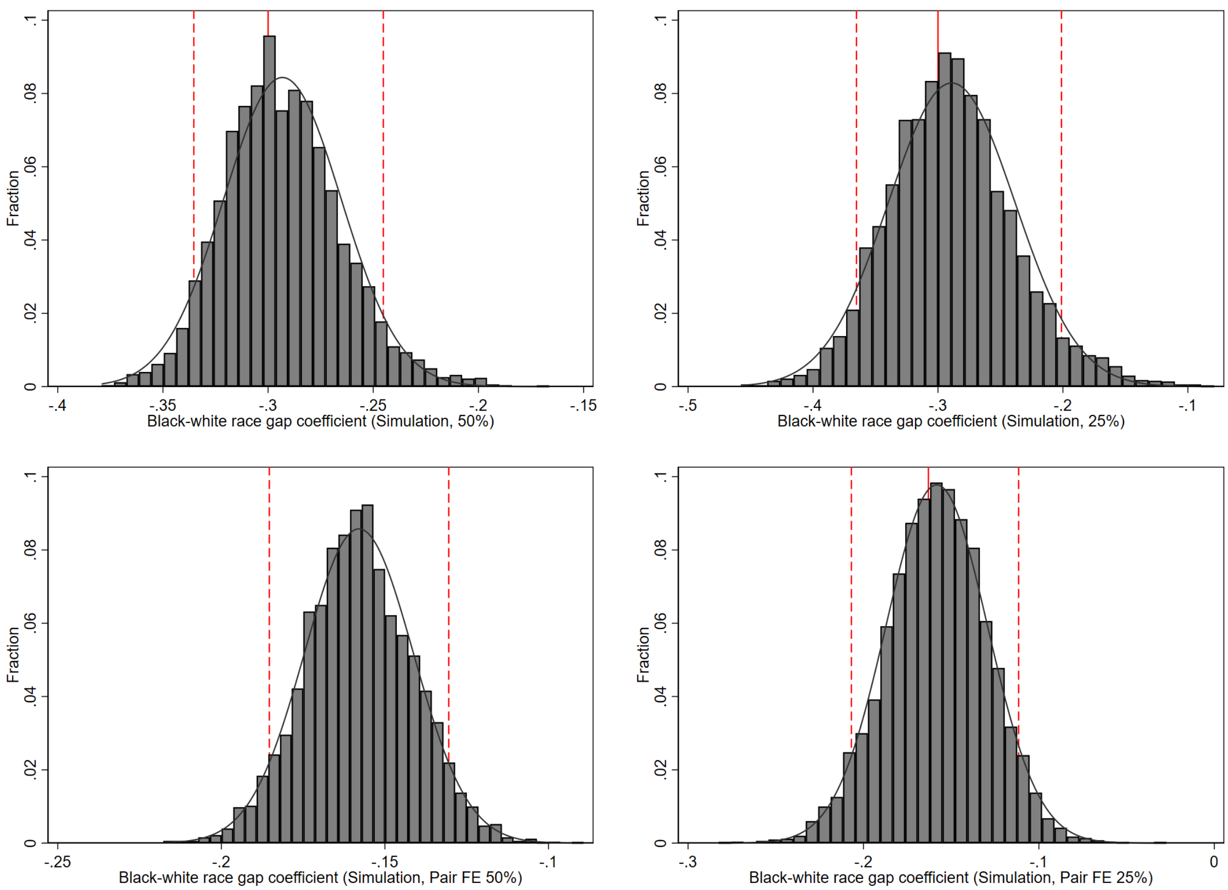
Notes: The figure shows the box plot for perceptions of being Black for each name. The shaded (green) area shows the 25th to 75 percentil area.

Figure B2: Hiring Choice Order Effects



Notes: The figure shows how the race gap varies across the ten randomly assigned rounds of hiring decisions. We estimate our main specification separately for each round. The red line presents the average race gap.

Figure B3: Robustness: Simulation of subsets of worker pairs



B.3 Research Design

Consent

Thank you for your participation in this survey! Your participation is greatly appreciated.

Purpose

This survey asks for your associations of names with personal characteristics. You will receive at least **$1.60**. In addition, you may receive a **bonus**. The survey should take about **10** minutes.

Confidentiality

This task is designed to be confidential, meaning that one cannot link the answers with you. Your participation in the following survey is entirely voluntary, and you may refuse to complete any part. By completing and submitting the following survey, you affirm that you are at least 18 years old and that you give your consent for Martin Abel, Bowdoin College Assistant Professor of Economics (m.abel@bowdoin.edu), to use your answers in his research.

○ I agree

○ I don't agree (will exit survey)

Figure B4: Consent Form