

Public perceptions of discrimination at large firms

Patrick Kline, Evan K. Rose, and Christopher R. Walters*

July 27, 2026

Abstract

We field and analyze an online survey eliciting beliefs about discrimination and other aspects of recruiting conduct by 164 large firms. One-third of respondents report having put off applying for a job due to fear of discrimination. For each firm, we construct measures of perceived discrimination, hiring discretion, and selectivity. Average beliefs about treatment of applicants with race- and sex-distinctive names correlate strongly with beliefs about broader notions of discrimination. Firms thought to prefer White job applicants are also viewed as favoring older workers, while perceptions of race and gender discrimination are unrelated. Despite substantial inter-respondent disagreement, average beliefs about recruiting biases are nearly perfectly correlated across demographic groups. We compare these average beliefs to experimental estimates of discrimination derived from a large resume correspondence study. Perceived gender discrimination strongly correlates with experimental estimates of gender contact gaps, while beliefs about racial discrimination are weakly related to experimental estimates of racial contact gaps. Respondents tend to believe that selective firms discriminate more often and that managers have less hiring discretion at such firms. In contrast, the correspondence study evidence suggests that discretion is a positive predictor of racial discrimination and that much discrimination occurs at less selective firms.

Keywords: Discrimination, Beliefs, Survey Analysis, Ranking Methods

JEL Codes: J71, C11, C13

*Kline: UC Berkeley and NBER, pkline@econ.berkeley.edu; Rose: University of Chicago and NBER, ekrose@uchicago.edu; Walters: UC Berkeley and NBER, crwalters@econ.berkeley.edu. This project was approved by the Berkeley Committee for the Protection of Human Subjects. CPHS Protocol Number: 2021-09-14653. We thank Jordan Cammarota, Anh-Huy Nguyen, and Nico Rotundo for outstanding research assistance.

1 Introduction

Employment discrimination by large employers has recently been the subject of detailed empirical study (Miller, 2017; Hoffman, Kahn and Li, 2018; Kline, Rose and Walters, 2022; Mocanu, 2022; Kline, Rose and Walters, 2024). This line of work finds that race and sex discrimination varies substantially among firms, with smaller biases among federal contractors, more discrimination in customer-facing sectors, and more discrimination in organizations that grant managers greater discretion in hiring. While recent survey evidence clarifies the role that race plays in shaping attitudes towards public policy (Alesina, Ferroni and Stantcheva, 2021; Haaland and Roth, 2023), less is known about what the public believes regarding discrimination by specific employers.

Are the employer biases documented in recent empirical work an open secret? Firms have strong legal and economic incentives to conceal any biases in their hiring processes. Yet workers invest considerable effort in learning about prospective employers, and large firms develop reputations—through social networks and, increasingly, online platforms—regarding their recruiting practices. Becker (1957) argued that the deleterious effects of discrimination on employment would be mitigated if employer biases were concentrated in a small share of firms, since minority-group workers could still find employment among other unprejudiced employers. However, if job seekers are unaware of which employers are biased, they may find it difficult to avoid discrimination, which can give rise to excess unemployment and lower wages (Black, 1995; Bowlus and Eckstein, 2002).

This paper examines public perceptions of hiring practices at 164 large U.S. employers using a survey of over 6,000 respondents. The survey oversamples job seekers and racial minorities to assess whether groups more likely to experience discrimination hold systematically different beliefs. The survey asks respondents to rate a randomly selected set of five large firms regarding their treatment of job applicants based on race and sex. One arm of the survey also asks about treatment based on age. The firms studied here all belong to the Fortune 500 and are a superset of those analyzed in a large resume

correspondence experiment by Kline, Rose and Walters (2022).

To understand views on multiple forms of discrimination, respondents are randomly assigned to one of two survey arms, each with a distinct set of questions. The *names arm* asks how likely firms are to favor entry-level job applicants with different sorts of distinctive names. These questions can be viewed as eliciting beliefs about the likely effects of a correspondence experiment conveying race or gender through names, although the term “correspondence experiment” is never used in the survey. A second *conduct arm* directly elicits the likelihood that each firm will “discriminate against” a particular group, which captures views on discrimination beyond differential treatment of distinctive names.

Survey responses establish that the public perceives labor market discrimination to be pervasive. Roughly a third of respondents state that they have put off applying for a job out of fear of discrimination. This share rises to nearly 45% for Black respondents but exceeds 20% even for White respondents. These responses suggest discrimination looms large in the minds of job applicants of all racial groups.

We use two different approaches to aggregating perceptions of firm-level discrimination across respondents. The first approach simply averages beliefs about each firm coded on a 1 to 5 Likert (1932) scale, resulting in a cardinal measure of discrimination perceptions. The second approach converts cardinal responses into rank-ordered comparisons and aggregates them using a variant of the classic Borda (1784) score. This ordinal approach eliminates differences across respondents in the location and scale of responses, and has desirable properties for aggregating rankings in settings where the Independence of Irrelevant Alternatives (IIA) assumption is violated (Korba, Cléménçon and Sibony, 2017; Shah and Wainwright, 2018). The cost of the Borda approach is that only beliefs about relative conduct of firms are preserved.

While these aggregates measure the “wisdom of crowds,” respondents will inevitably vary in their individual beliefs. To measure these deviations, we develop indices of interrespondent disagreement in the cardinal rating and pairwise rank ordering of firms that these aggregates quantify. Our analysis finds that cardinal Likert ratings of firm discrimi-

nation tend to be diffuse, reflecting substantial inter-respondent disagreement. Moreover, respondents frequently offer the same rating to multiple firms. However, among those respondents who do offer distinct ratings, their firm rankings agree more often than chance, suggesting somewhat greater consensus about firms’ relative conduct than about rating levels.

After accounting for sampling error, we find that both the Likert and Borda measures of average beliefs about firm discrimination are widely dispersed. Average beliefs about gender bias are the most variable: some firms are widely viewed as preferring men, while others are thought to prefer women. Average beliefs about age-related bias are least dispersed of the discrimination questions, though most firms are viewed as preferring younger workers. Consistent with experimental evidence (Kline and Walters, 2021; Kline, Rose and Walters, 2022), respondents tend to believe that discrimination against White applicants is rare.

Next, we document three facts about the correlation structure of average beliefs across several dimensions of firm conduct. First, average beliefs about the treatment of applicants with racially distinctive names correlate strongly with average beliefs about broader notions of racial discrimination. In other words, respondents tend to rank the racial preferences of firms similarly regardless of how questions about racial bias are posed. Second, firms that are thought to prefer White job applicants tend to also be seen as favoring older workers. However, average beliefs about firm preferences over race are uncorrelated with average beliefs about firms’ gender preferences. Third, average beliefs about which firms have strong racial, gender, or age preferences are nearly perfectly correlated across respondents of different demographic groups. Although Black respondents have somewhat stronger beliefs about the overall prevalence of racial discrimination, their beliefs about relative tendencies of firms to discriminate differ little from the beliefs of White respondents.

We then examine the extent to which these average beliefs about firms predict the experimental contact gaps in the large-scale correspondence experiment of Kline, Rose and

Walters (2022). Average beliefs about racial discrimination are weak and generally statistically insignificant predictors of experimental race contact gaps, though marginally significant relationships emerge in specifications with industry fixed effects. Controlling for the perceived selectivity of firms strengthens the relationship between race discrimination beliefs and contact gaps, reflecting that respondents tend to believe that more selective firms discriminate more heavily while the experimental evidence suggests otherwise. In contrast, perceived gender discrimination significantly predicts firm-specific gender contact gaps, both within and between industries and with or without controlling for selectivity beliefs.

These findings on perceptions of discrimination suggest three key conclusions. First, while views vary widely across individual respondents, gender discrimination in entry-level hiring appears to be an open secret: average beliefs about gender discrimination are widely dispersed and these views correlate strongly with experimental gender gaps. A plausible explanation for this state of affairs is that certain forms of gender discrimination, though illegal, are viewed as socially acceptable, e.g., preferences for female employees at women’s apparel stores. Awareness of such patterns may aid job seekers by allowing them to target employers who will not penalize them based on gender, as in Becker’s original theory.

Second, average beliefs about racial discrimination are less widely dispersed and only weakly related to experimental evidence. One interpretation of this finding is that beliefs about racial discrimination are often mistaken. Consistent with widespread uncertainty of this kind, respondents decline to rank firms’ relative racial conduct in most pairwise comparisons, and disagree with one another in over a third of strict comparisons. In addition to generating potentially sizable psychic costs, mistaken beliefs can generate misallocation, a possibility bolstered by our finding that a large share of respondents report having put off applying to jobs out of fear of discrimination. Misallocation of this nature is an important feature of search models of discrimination with heterogeneous employer conduct (e.g., Black, 1995; Bowlus and Eckstein, 2002). In such models,

uncertainty and mistaken beliefs about *which* employers discriminate can generate excess unemployment and equilibrium wage penalties, as job seekers devote time and effort applying to discriminatory firms before finding an unbiased employer.

Third, the positive correlation between perceptions of firm selectivity and racial bias suggests the public believes discrimination takes place behind closed doors at elite institutions. Here, public beliefs depart sharply from the related academic evidence, which finds more discrimination at less profitable employers offering less attractive jobs as well as more bias among employers with higher levels of managerial hiring discretion. Whether this departure reflects mistaken beliefs among the public or incompleteness in academic attempts to measure discriminatory conduct is an interesting question for future research.

The rest of the paper is organized as follows. The next section describes the survey design and provides some descriptive statistics on the respondents. Section 3 provides a first look at the survey data. Section 4 describes the two methods of aggregating beliefs. Section 5 uses these methods to summarize average beliefs about firms and develops measures of the disagreement underlying them. Section 6 studies the covariance structure of average beliefs about firm discrimination. Section 7 reports which firms are thought to have the strongest preferences for different worker characteristics. Section 8 compares firm beliefs to experimental evidence. Section 9 concludes.

2 Data

Our data come from a Qualtrics survey conducted between June and October of 2023. The survey asks each respondent a battery of questions about their perceptions of recruiting practices at five firms randomly selected from a list of 164 Fortune 500 companies.

2.1 Survey sample

The survey was designed to oversample Black respondents and current job seekers. Qualtrics sampled respondents via two methods: probability sampling and convenience sampling. The recruited *probability sample* is a nationally representative panel of survey respondents who agree to fill out whatever survey they are assigned by Qualtrics. The remaining respondents are a *convenience sample* that specifically opted in to take our survey.

Both samples were screened to meet certain demographic guidelines. In both samples, we sought a 50/50 mix of Black and White respondents. Since Qualtrics' panel of probability sample respondents is nationally representative, we quickly exhausted their recruited pool of Black respondents. This required us to rely heavily on convenience sampling to meet our target sample sizes of 6,000 respondents. In the convenience sample, we additionally sought for 1/6th of the respondents to have a bachelor's degree or higher credential and roughly 50% to be actively looking for work, although we did not meet this latter target.

Table 1 shows some descriptive statistics on the survey analysis sample. This sample has already been screened for certain quality checks. First, Qualtrics removed some respondents as part of their usual screening procedures designed to weed out non-human respondents. Non-human respondents were primarily a concern for the convenience sample, as the probability sample was comprised of experienced survey takers for whom Qualtrics had a longer run record of responses. Next, we dropped respondents who failed an attention check that required them to recall the names of the companies they were asked about in the survey. We also remove respondents who straightline answers to all the questions about firms described in the next section, and all of a respondent's answers to any question where they selected "Don't know / prefer not to answer" for three or more firms.

The sample described in Table 1 includes all individuals who survive these quality checks. The total sample size is 6,515 respondents, 4,139 of whom were recruited via convenience

Table 1: Descriptive statistics

	All		Probability		Convenience	
	Count	Share	Count	Share	Count	Share
Gender						
Female	4406	0.676	1317	0.554	3089	0.746
Male	2109	0.324	1059	0.446	1050	0.254
Race						
Black	3217	0.494	1068	0.449	2149	0.519
White	2714	0.417	1069	0.45	1645	0.397
Other or Mixed Race	584	0.09	239	0.101	345	0.083
Hispanic						
Hispanic	694	0.107	275	0.116	419	0.101
Not Hispanic	5821	0.893	2101	0.884	3720	0.899
Age						
[18,25)	832	0.128	177	0.074	655	0.158
[25,40)	2023	0.311	734	0.309	1289	0.311
[40,65)	2558	0.393	959	0.404	1599	0.386
65+	1102	0.169	506	0.213	596	0.144
Marital Status						
Married	2224	0.341	1008	0.424	1216	0.294
Never Married	2850	0.437	870	0.366	1980	0.478
Other	1441	0.221	498	0.21	943	0.228
Education						
No High School Diploma	273	0.042	62	0.026	211	0.051
High School Diploma	1620	0.249	415	0.175	1205	0.291
Some College / Associate Degree	2725	0.418	1008	0.424	1717	0.415
Bachelor's / Graduate Degree	1897	0.291	891	0.375	1006	0.243
Employment						
Working As Paid Employee	3233	0.496	1369	0.576	1864	0.45
Working Self-employed	578	0.089	168	0.071	410	0.099
Not Working: Looking For Work	795	0.122	143	0.06	652	0.158
Not Working: Retired	993	0.152	425	0.179	568	0.137
Not Working: Other	916	0.141	271	0.114	645	0.156
Income						
Less Than \$5,000	431	0.066	67	0.028	364	0.088
\$5,000 To \$29,999	1784	0.274	467	0.197	1317	0.318
\$30,000 To \$59,999	2048	0.314	672	0.283	1376	0.332
\$60,000 To \$99,999	1297	0.199	588	0.247	709	0.171
\$100,000 Or More	955	0.147	582	0.245	373	0.09
N. Of Respondents	6515		2376		4139	

Notes: This table presents summary statistics for respondents in the full sample, the probability sample (drawn from Qualtrics' recruited panel of potential respondents), and the convenience sample (who voluntarily opt in to the survey). All respondents were asked about their characteristics at the beginning of the survey.

sampling. While race and sex are roughly balanced in the recruited sample, the convenience sample skews heavily female. Overall, roughly two thirds of respondents are women. Nearly half of the overall sample self-identifies as Black and roughly 44% of the sample reports an age younger than 40. Most respondents who self-identified as neither Black nor White report membership in multiple racial groups.

While the modal respondent had some college, about 29% had a bachelor's degree or higher. Roughly half of respondents report working as paid employees, with many listing their status as either looking for work or retired. Thirty-five percent of respondents report annual income above \$60,000. For comparison, in the 2025 CPS-ASEC, the share was 34% (U.S. Census Bureau, 2025).

2.2 Survey design

The survey consists of four main blocks: an introductory block on beliefs about company selectivity and desirability, two blocks on beliefs about discrimination, and a final concluding block. All respondents are shown the first and final block, while each respondent is shown either the second block or the third block with equal probability.

Block zero: Respondent characteristics [all respondents]. Before beginning the survey, all respondents provide information on their demographic characteristics, employment status, and income.

Block one: Survey introduction [all respondents]. The survey begins with a vignette about hiring at entry-level jobs. All respondents are asked the following question.

In this survey, we're interested in understanding people's perceptions of entry-level jobs. Some examples of entry-level jobs include cashier, sales associate, delivery driver, and customer service representative. Have you held an entry-level job in the last 2 years? [*Yes/No/Prefer not to answer*]

In addition to soliciting information about the respondent's background, this question is

meant to squarely frame the idea of an entry-level job in the respondent’s mind.

We then ask a series of questions on a five point Likert (1932) scale about a randomly selected set of five firms. This set is constructed by first drawing one of three well-known “anchor” firms—KFC, Home Depot, or Coca-Cola—with equal probability. The remaining four firms are chosen without replacement from a list of 161 firms that nests the set of 108 firms studied in Kline, Rose and Walters (2022). For firms that may be better recognized by their popular brands, we listed them alongside the firm name (e.g., Pep Boys for Icahn Enterprises, or Loft stores, Lane Bryant, Ann Taylor for Ascena Retail Group).

A first set of questions probes the respondent’s beliefs about the selectivity and desirability of entry-level jobs at these five firms:

In this section of the survey, we’d like to understand your beliefs about the hiring practices of five U.S. companies. We will ask you a series of questions about the likelihood that individuals are contacted for a job interview, hired for a job, and accept a job at these companies.

Respondents are then shown the following question, which asks them to rate the likelihood of a high-school graduate applying to an entry-level job at each company successfully passing an interview, which is our measure of perceived *selectivity*.

Consider a **high-school graduate** with 1-2 years of relevant experience who has applied to an entry-level job.

Please indicate the likelihood that an applicant would be able to successfully **pass an interview** with each of the following companies.

Responses are elicited for each of the five companies on a 5-point scale ranging from “very unlikely” to “very likely.” Respondents also have the option to select “Don’t know / prefer not to answer” for each firm.

We then ask the likelihood that this high-school graduate would accept the job if offered

it, which is our measure of perceived *desirability*.

Please indicate the likelihood that this applicant would **accept an entry-level job** at each of these companies, if offered one.

The survey subsequently branches into two arms, which are randomly assigned with equal probability. The *names arm* asks a series of questions about the likely treatment of distinctive names at the 5 firms. The *conduct arm* asks about the treatment of race, sex, and age at these firms. In order to avoid priming, each respondent is exposed to only one arm.

Block 2: Names arm [50% of sample]. The names arm measures the relative likelihood that each firm would contact and hire applicants to an entry-level job with different racially and gender-distinctive names. It begins by providing the following context:

Now suppose two equally qualified applicants apply to these same five companies. As before, the applicants are both **high-school graduates with 1-2 years of relevant experience**, but the **applications use different names**. Each name is either distinctively white or black and either distinctively male or female.

Here are some examples of such names:

Distinctively **black** names: Lawanda and Reginald

Distinctively **white** names: Allison and Edgar

Distinctively **female** names: Charlotte and Ebony

Distinctively **male** names: Matthew and Tremayne

Respondents are asked about both race and gender in random order. The first question in the names arm measures the relative likelihood that each firm would *contact* an applicant to an entry-level job. For race, the question reads:

For each company, please indicate how much more likely you believe the company is to **contact a job applicant** with a distinctively [black/white] name than an applicant with a distinctively [white/black] name.

Responses are elicited on a 5-point scale ranging from “much less likely” to “much more likely,” along with a “Don’t know / prefer not to answer” option. Since the question is predicated on the notion that the applicants are equally qualified, it arguably elicits what respondents believe would result from a correspondence experiment.

The second question measures the relative likelihood each firm would *hire* an applicant. For race, it reads:

For each company, please indicate how much more likely you believe the company is to **hire a job applicant** with a distinctively [black/white] name than an applicant with a distinctively [white/black] name.

Responses are elicited using the same structure as the first question. See Appendix C for an example of how both questions were presented to respondents on the survey platform.

The questions for gender are analogous. To examine whether the order in which the groups are presented is important, respondents are asked about the relative chances of a Black vs. White applicant or White vs. Black applicant (and likewise a male vs. female or female vs. male) with equal probability. We refer to the choice of group order as the question’s framing.

Finally, for both race and gender, respondents are asked to rate their confidence in their responses to the pair of questions, with answers ranging from “not at all confident” to “extremely confident.”

Block 3: Conduct arm [50% of sample]. Instead of the names arm, half of respondents were randomized into the conduct arm. In this block, we ask about discrimination more broadly. For each type of discrimination (i.e., race, sex, or age), we randomly varied the question’s framing by picking the potential target of discrimination (e.g., Black or White workers) with equal probability. The question is structured for race as follows:

Please indicate how likely you think it is that each company below would

discriminate against [black/white] job seekers.

Responses are elicited on a 5-point scale ranging from “very unlikely” to “very likely,” as in previous questions, alongside an opt-out option. Respondents also rate their confidence in the same way as in the names arm. See Appendix C for an example of how this questions was presented to respondents on the survey platform.

Respondents are also asked a variant of this question focused on gender and age discrimination, where the group discriminated against either is younger or older (below/above the age of 40), or male or female, chosen with equal probability in each case. The order of the questions is random.

Block 4: Conclusion [all respondents]. To conclude the survey, we ask all respondents two final questions tied to the labor economics literature on discrimination. The first question elicits beliefs about the level of discretion that hiring managers possess. The second is about whether discrimination has influenced the respondent’s job search. The first question takes the usual Likert form:

At most companies, hiring decisions are made by individual managers. However, companies differ in the amount of oversight placed on these hiring decisions. For each company, please indicate how likely you think it is that managers can **hire their preferred candidate without input** from colleagues or superiors.

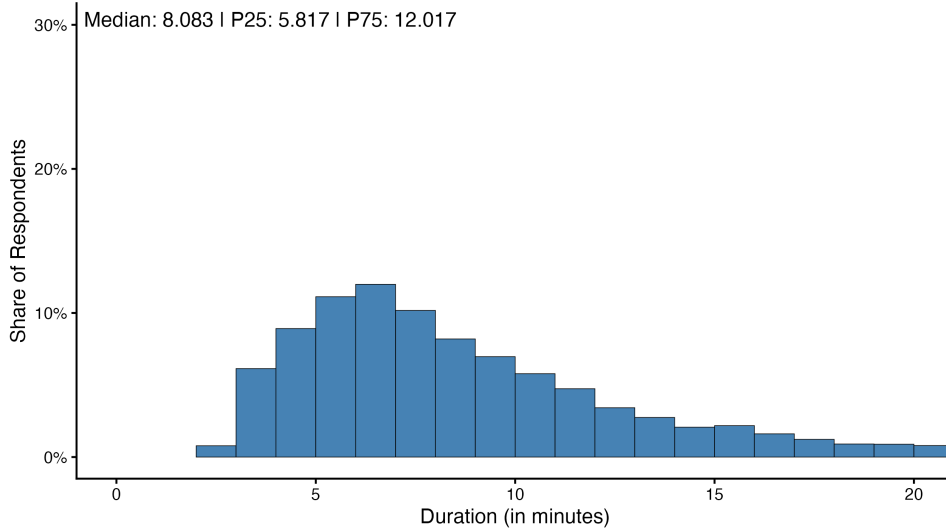
Finally, we asked respondents a simple yes/no question: “Have you ever put off applying for a job out of fear of discrimination?”. This question is meant to probe whether the respondent’s beliefs about discrimination have influenced their own search behavior.

3 A first look at the survey data

Respondents in our estimation sample demonstrated substantive engagement with the survey. Figure 1 reports the distribution of time spent on the survey. The median respondent spent 8.1 minutes completing the questions, the 25th percentile was 5.8 minutes,

and the 75th percentile was 12.0 minutes.

Figure 1: Distribution of survey completion times



Notes: This figure shows the distribution of time spent completing the survey for respondents in the final analysis dataset. The analysis dataset applies several quality controls, including dropping respondents who fail an attention check and respondents who straightline all responses to key questions. See section 2.1 for further details on the sample.

Respondents also report familiarity with entry-level jobs and express a reasonable degree of confidence in their answers. Roughly 40% of respondents report having worked an entry-level job in the past two years. Table 2 reports the distribution of self-assessed confidence in answers to questions about the likely discriminatory behavior of five randomly selected firms. For each question, less than a third of respondents reported being “Not at all confident” or only “Slightly confident” in their answer. The share reporting “Not at all confident” was lowest (2.6%) for the Discrimination Female (Conduct) question and highest (4.8%) for the Discrimination Black (Contact) question pair, suggesting respondents had stronger beliefs about relative patterns of firm gender discrimination than racial discrimination.

In addition to eliciting confidence about their answers, we asked respondents who indicated that at least one of the companies was likely to discriminate against Black job seekers in either arm of the survey where they obtained the information supporting this belief. Figure 2 reports the information sources these respondents listed. The most com-

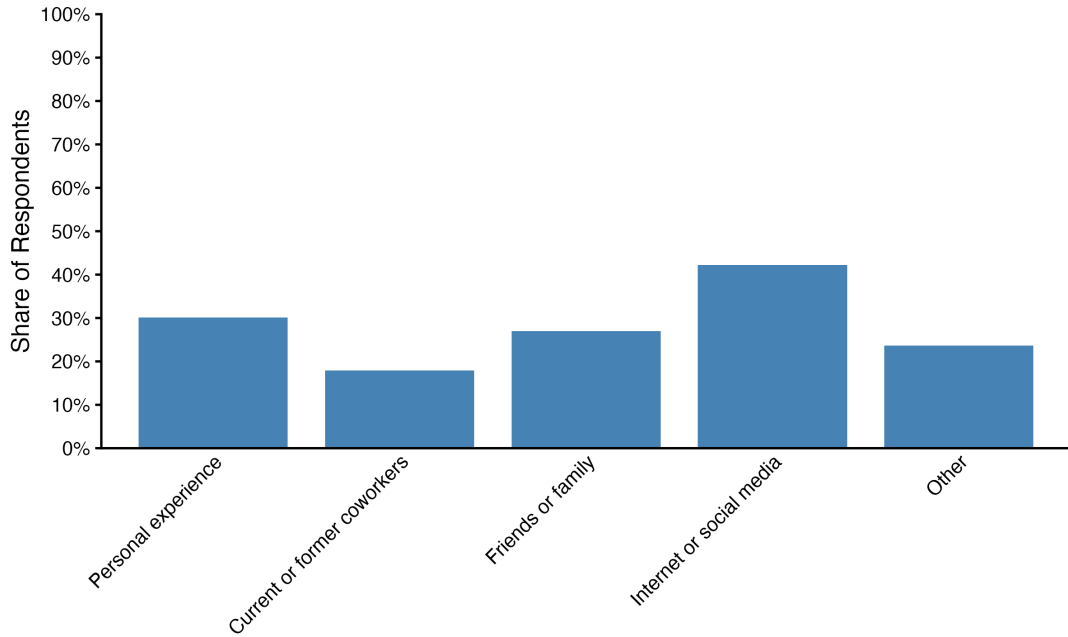
Table 2: Summary of respondent confidence assessments

Measure	Not at all confident	Slightly confident	Somewhat confident	Very confident	Extremely confident	Missing
Discrimination Older (Conduct)	3.5	16.2	34.9	31.1	14.0	0.2
Discrimination Female (Conduct)	2.6	15.1	31.1	33.1	17.8	0.2
Discrimination Black (Conduct)	3.6	17.9	30.6	31.4	16.1	0.3
Discrimination Female (Contact)	4.3	22.0	35.5	26.5	11.5	0.3
Discrimination Black (Contact)	4.8	21.3	35.0	25.8	13.1	0.1

Notes: This table reports the distribution of respondents’ confidence assessments for the primary questions in the names and conduct arms. As discussed in Section 2.2, confidence was assessed on a five point scale after each question in the conduct arm and after each pair of questions (for contact and for hiring likelihoods) in the names arm. Question text: How confident are you in your responses to the [question/two questions] above?

monly reported sources of information were internet or social media, followed by personal experience, and family and friends.

Figure 2: Information source underlying racial discrimination perceptions

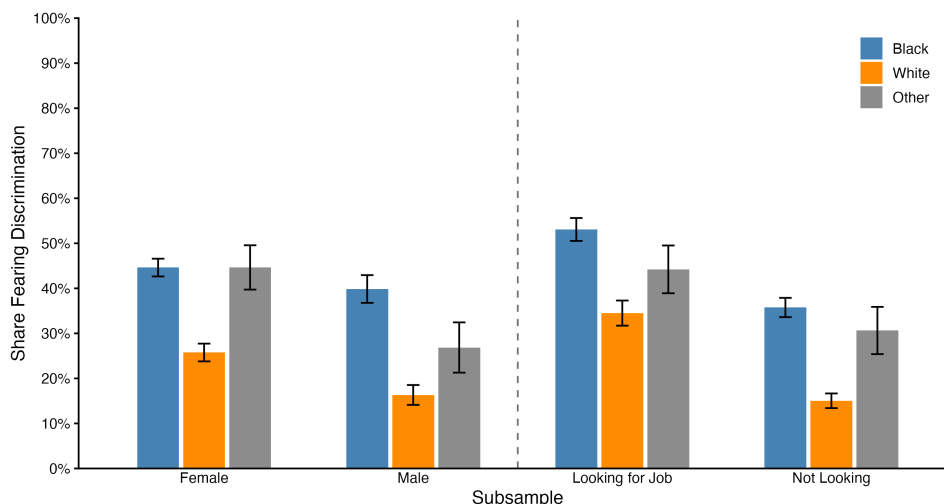


Notes: This figure shows the distribution of reported sources of information about firm-level discrimination. This question was only asked of respondents who indicated a company was very or somewhat likely to discriminate against Black job seekers in the conduct arm or indicated a company was much more or somewhat more likely to contact / hire a job seeker with a distinctively White name (or much less / somewhat less likely to contact / hire a job seeker with a distinctively Black name) in the names arm. Question text: Your responses indicated that you think [company] is likely to discriminate against Black applicants. What sources of information did you use to arrive at this conclusion?

A striking finding of the survey is that roughly one third of respondents report having put off applying for a job out of fear of discrimination. Figure 3 breaks down answers to this question by race and sex. Women are slightly more likely than men to report having been

deterred from applying by discrimination. While a sizeable share of White respondents state that discrimination has affected their job search behavior, Black respondents are substantially more likely than White respondents to be deterred by discrimination.

Figure 3: Application deterred by fear of discrimination



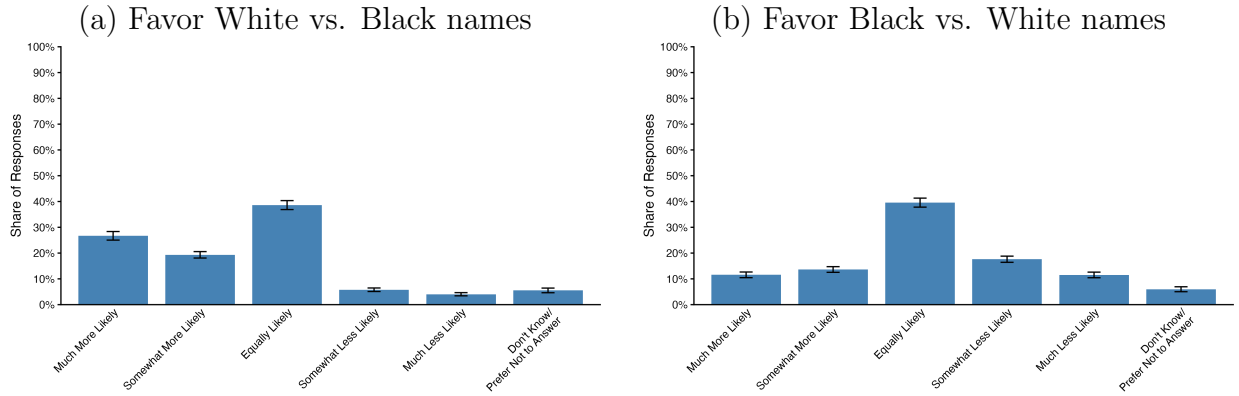
Notes: This figure reports the share of respondents who have ever been deterred from applying to a job due to fears of discrimination. Panel A breaks down respondents by race and sex, while Panel B breaks down responses by race and job search status. Question text: Have you ever put off applying for a job out of fear of discrimination?

Another clear pattern, illustrated in the second panel, is that fear of discrimination is elevated among current job seekers of all races. More than half of Black respondents currently seeking a job state that fear of discrimination has deterred them from applying to a job. Roughly one third of White job seekers report the same.

Having established that perceived discrimination influences reported labor market search behavior, we now turn to examining beliefs about what sorts of discrimination are most prevalent. Figure 4 summarizes responses to the two variants of the question about racial discrimination from the survey's names arm, with the version listing White names first in panel A and the version listing Black names first in panel B.

When distinctively White names are contrasted with distinctively Black names, a large share (27%) of respondents state that White names are much more likely to be contacted. However, when Black names are contrasted with White names, only about 12% say that Black names are much less likely to be contacted. Hence, there appears to be a

Figure 4: Distribution of perceived contact discrimination



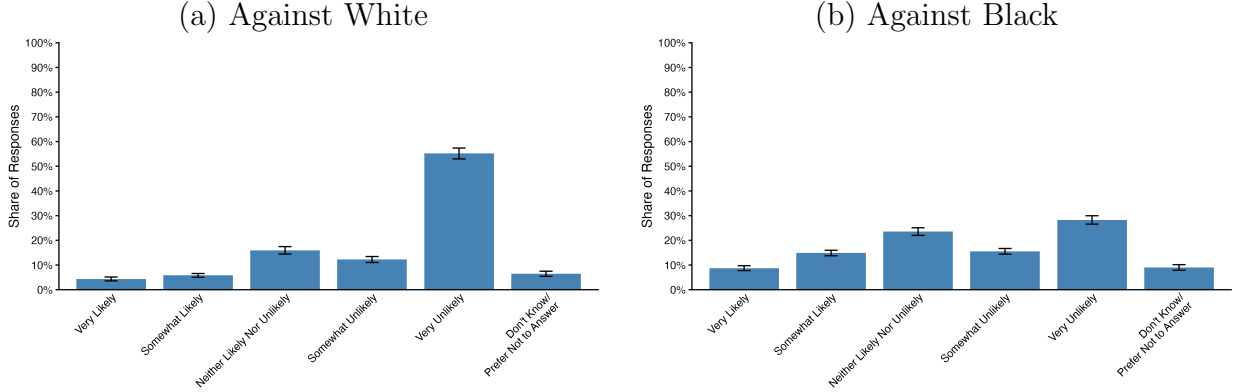
Notes: This figure reports the distribution of companies’ perceived relative likelihood of contacting job seekers with different racially distinctive names. Only respondents in the names arm were asked this question. Panel A shows answers for the random subset of respondents asked about favoring White vs. Black names, while panel B shows answers for those shown the opposite structure. Question text: Please indicate how much more likely you believe the company is to contact a job applicant with a distinctively [White / Black] name than an applicant with a distinctively [Black / White] name.

non-negligible asymmetry in how respondents interpret the Likert scale across these two question framings.

Even larger asymmetries arise among variants of the conduct discrimination question summarized in Figure 5. Respondents are skeptical of the idea that White job seekers are discriminated against, with over half of respondents stating that such forms of discrimination are “very unlikely.” This view accords with evidence from the large correspondence experiment analyzed by Kline, Rose and Walters (2022), who fail to reject the null hypothesis that no firms strictly prefer distinctively White to distinctively Black names. Because most respondents hold this view, there turns out to be little usable variation in this phrasing of the question. In contrast, conduct variants of the sex discrimination and age discrimination questions have lower shares of respondents claiming that discrimination is very unlikely and more who think discrimination is very likely, as shown in Appendix Figures A1 and A2.

In our primary results, we combine framing variations of each question to extract as much information as possible. This is accomplished by reversing the Likert scale across question variants to make directions comparable, then pooling data for all variants. We show below that firm-level beliefs are strongly correlated across question variants within-

Figure 5: Distribution of perceived racial discrimination likelihood



Notes: This figure reports the distribution of companies’ perceived likelihood of discriminating against White job seekers (panel A) and against Black job seekers (panel B). Only respondents in the conduct arm were shown this question, with the against White vs. against Black framing chosen at random. Question text: Please indicate how likely you think it is that each company below would discriminate against [White / Black] job seekers.

arm with one exception: Beliefs about firm discrimination “against White” job seekers show no significant variation. We therefore use only the “against Black” framing to measure beliefs about firm-level racial discrimination in the conduct arm. It will turn out that beliefs are strongly correlated *across* the names and conduct arms as well, so we also build pooled measures for each type of discrimination that combine the responses in both arms.

Since the Likert scores are based on subjects’ interpretations of terms like “much more likely” and “somewhat more likely,” it is plausible that not all respondents grade on the same scale. The asymmetries in responses to question framings documented above suggest further differences in scales across responses. Comparing the naive approach of simply averaging Likert scores for each firm to the rank-ordered approaches developed below allows us to examine sensitivity to respondent scale heterogeneity and potential framing effects.

4 Aggregation methods

We consider two approaches to aggregating responses to the questions in the names and conduct arms of the survey, as well as questions about firm selectivity and discretion. The

first approach—Likert averaging—simply uses average responses on the 1-5 Likert scale for each firm. This approach exploits all the cardinal information embedded in numerical codings of Likert responses, but also relies on this common grading scale accurately capturing beliefs across respondents. The second approach—Borda ranking—relaxes this assumption by using only within-respondent ordinal comparisons as captured by Borda scores. While this method is more flexible, the cost is that only relative comparisons across firms are recovered, resulting in the loss of cardinal information about the intensity of perceptions.

4.1 Likert averaging

The Likert averaging approach first codes responses on a 1-5 scale (e.g., “Very likely” $\rightarrow$ 5, “Very unlikely” $\rightarrow$ 1). When combining two framings of the same question, we reverse the scale so that larger numbers always indicate more discrimination against the same group. We then take firm-level averages of responses for each question, or, equivalently, regress responses on a set of firm dummies using ordinary least squares (OLS). “Don’t know / prefer not to answer” responses are excluded from the means. We refer to the sample average response for firm j , which we denote by $\hat{L}_j$, as the *Likert score*, and use L_j to denote the population average Likert score for firm j .

Although the Likert scores are easy to construct, using them to understand beliefs can be challenging. Respondents may interpret the Likert options differently: a high-scoring firm for one respondent may be low-scoring for another even if their beliefs about conduct are identical. Even for the same respondent, the difference in beliefs about conduct between “very unlikely” and “somewhat unlikely” may not be the same as between “somewhat likely” and “very likely,” although this method assigns both comparisons the same unit difference in scores.

These differences in grading scales across respondents and response categories generate two problems. One is that grading scale variation induces noise that inflates the standard errors on each firm’s $\hat{L}_j$. A separate difficulty is that the units in which L_j is measured

rely on the Likert cardinalization, which can be difficult to interpret when grading scales differ. The Borda scores help to address both of these difficulties.

4.2 Borda ranking

Borda (1784) scores were introduced as a positional voting system based on rank-ordered ballots that delivered global rankings. In our context, Borda scores are useful because they leverage *intra*-personal comparisons of firm Likert ratings in a way that differences out respondent-specific rating thresholds.

To formally define Borda scores, let i index respondents and $C_i \subset \{1, \dots, J\}$ denote respondent i 's choice set, which is randomly assigned with $|C_i| = 5$. Write $j \succ_i k$ if respondent i ranks firm j strictly above firm k , meaning they assigned j a strictly greater Likert rating than k , and $j \sim_i k$ if i is indifferent between them, meaning they assigned them the same Likert response. Define the *points* that firm j receives in the comparison with firm k for respondent i as

$$w_{ijk} = \mathbf{1}\{j \succ_i k\} + \frac{1}{2}\mathbf{1}\{j \sim_i k\}.$$

Note that ties yield half a point, while a strict win over another item yields a whole point.

Recall that each choice set C_i is comprised of a single anchor firm, drawn at random from the set $\mathcal{A}$, and four non-anchors drawn without replacement from the set $\mathcal{N}$. The Borda score is designed to measure the expected win rate of firm j against a randomly selected opponent. For this to be a meaningful ranking metric, opponent strength should be equalized across all firms. However, our survey design prevents anchors from facing other anchors as opponents. To ensure anchors and non-anchors face opponents of equal expected strength, we work with a version of the Borda score that measures each firm's win rate against a randomly selected opponent in $\mathcal{N}$.

Some respondents decline to rate every firm in their choice set. Let $\mathcal{E}_i \subseteq C_i$ denote the

set of firms that respondent i rates. Let $e_{ij} = |(\mathcal{E}_i \cap \mathcal{N}) \setminus \{j\}|$ count the eligible non-anchor opponents that respondent i can compare with firm j . Absent item non-response, $e_{ij} = |C_i| - 1 - \mathbf{1}\{j \in \mathcal{N}\}$. Define the *Borda score* for firm j as

$$\hat{B}_j = \underbrace{\frac{\mathbf{1}\{j \in \mathcal{N}\}}{2|\mathcal{N}|}}_{\text{phantom self-tie}} + \underbrace{\frac{|\mathcal{N}| - \mathbf{1}\{j \in \mathcal{N}\}}{|\mathcal{N}|}}_{\text{rescaling}} \times \frac{\sum_{i: j \in \mathcal{E}_i} \sum_{k \in (\mathcal{E}_i \cap \mathcal{N}) \setminus \{j\}} w_{ijk}}{\underbrace{\sum_{i: j \in \mathcal{E}_i} e_{ij}}_{\text{win rate}}}.$$

Thus, for each respondent i rating all five firms, the number of pairwise comparisons in which j could have been ranked above some non-anchor firm evaluates to 4 for anchors but only 3 for non-anchors. Respondents with item non-response contribute fewer comparisons.¹

The “win rate” term gives the share of times that respondents who could have ranked firm j higher than some other non-anchor firm did so. The first term grants each non-anchor a phantom self-tie, while the second factor rescales the win rate. This ensures that, at the population level, anchors and non-anchors are both evaluated as averages over exactly $|\mathcal{N}|$ comparisons.

Borda scores can be viewed as relaxations of alternative methods commonly used to analyze rank-ordered lists and survey responses such as the rank-ordered logit model (Beggs, Cardell and Hausman, 1981; Hausman and Ruud, 1987; Allison and Christakis, 1994; Abdulkadiroğlu et al., 2020; Caldwell, Haegele and Heining, 2025). Logit methods rely on IIA, an assumption often found to be violated in actual choice data (Davidson and Marschak, 1959; Ballinger and Wilcox, 1997). In a context such as our survey, where choice sets have been randomly assigned, IIA is the assumption that the probability of ordering j higher than k is independent of which other firms, besides j and k , are included in the respondent’s choice set.

¹Our main analysis drops respondents rating fewer than three firms. Consequently, every retained respondent has $e_{ij} \geq 1$ for each rated firm, which ensures the win rate is well defined. Roughly 10% of retained respondents rate only three or four of their five firms for a given question (10.3% for the pooled race measure and 10.1% for the pooled gender measure).

Borda scores remain interpretable under a weaker condition known as strong stochastic transitivity (SST), which can be thought of as a probabilistic version of transitivity. In our setting, under SST if firm j is viewed as more discriminatory than firm k by the average respondent, and firm k is likewise viewed as more discriminatory than l , then j will be viewed as more discriminatory than l on average as well. Appendix Section D defines SST formally and shows that the population analogues of Borda scores recover the correct ordering of firms by average beliefs when it holds along with other regularity conditions.

4.3 Estimation

Both the estimated Likert scores $\hat{L}_j$ and the Borda scores $\hat{B}_j$ are unbiased for their population counterparts L_j and B_j , conditional on the realized pattern of item response and under the assumption that non-response is unrelated to beliefs. They are also consistent and asymptotically normal under standard regularity conditions as the number of respondents grows large. We estimate their associated asymptotic standard errors $\mathbb{V}[\hat{L}_j]^{1/2}$ and $\mathbb{V}[\hat{B}_j]^{1/2}$ analytically. Since the sampling variability in these standard error estimates is asymptotically negligible, we treat $\mathbb{V}[\hat{L}_j]$ and $\mathbb{V}[\hat{B}_j]$ as known throughout our analysis.

5 Average beliefs and disagreement

Having defined the Likert and Borda scores for firms, this section reports averages of these scores across the firms in our survey. We also describe some measures of average disagreement between respondents that summarize aspects of the data that average belief measures mask.

5.1 Measuring averages and disagreement

Denote the average Likert score across firms in our sample by $\bar{L} = J^{-1} \sum_{j=1}^J \hat{L}_j$ and the corresponding average Borda score by $\bar{B} = J^{-1} \sum_{j=1}^J \hat{B}_j$. These estimates measure the

average respondent's beliefs about the average firm in our study, which we will denote by $\mu_L = J^{-1} \sum_{j=1}^J L_j$ and $\mu_B = J^{-1} \sum_{j=1}^J B_j$, respectively.

It is also interesting to measure the extent to which respondents disagree about particular firms. Before discussing estimators, we first introduce some population metrics of disagreement.

5.1.1 Disagreement estimands

Let L_{Rj} and $L_{R'j}$ denote the Likert ratings of two distinct randomly sampled respondents who both rate firm j . The average mean absolute difference (AMAD) of the Likert responses is

$$AMAD_L := \frac{1}{J} \sum_{j=1}^J \mathbb{E} |L_{Rj} - L_{R'j}|.$$

This quantity measures the average absolute difference, in Likert points, between two randomly selected respondents evaluating the same firm, averaged equally across firms.

A corresponding AMAD measure of disagreement for the Borda ratings can be defined in terms of firm pairs. Let w_{Rjk} and $w_{R'jk}$ measure the Borda points assigned to firm j against firm k by two distinct randomly sampled respondents who both rate these firms. The Borda AMAD is

$$AMAD_B := \frac{1}{J} \sum_{j=1}^J \frac{1}{|\mathcal{N}| - \mathbf{1}\{j \in \mathcal{N}\}} \sum_{k \in \mathcal{N} \setminus \{j\}} \mathbb{E} |w_{Rjk} - w_{R'jk}|.$$

This quantity measures the average absolute difference in pairwise Borda comparisons between two randomly selected respondents evaluating the same pair of firms, where the second firm in each comparison is restricted to the set of non-anchor firms.

Note that $|w_{ijk} - w_{i'jk}| \in \{0, 1/2, 1\}$, with the value $1/2$ resulting when one respondent indicates firms j and k are tied and the other indicates a strict ordering. Define the tie

share and the strict disagreement share as follows

$$TS := \frac{1}{J} \sum_{j=1}^J \frac{1}{|\mathcal{N}| - \mathbf{1}\{j \in \mathcal{N}\}} \sum_{k \in \mathcal{N} \setminus \{j\}} \mathbb{E}[1\{L_{Rj} = L_{Rk}\}],$$

$$DS := \frac{1}{J} \sum_{j=1}^J \frac{1}{|\mathcal{N}| - \mathbf{1}\{j \in \mathcal{N}\}} \sum_{k \in \mathcal{N} \setminus \{j\}} \mathbb{E}[|w_{Rjk} - w_{R'jk}| \mid w_{Rjk} \neq 1/2, w_{R'jk} \neq 1/2].$$

While the tie share is an average feature of individual respondents' comparisons, the disagreement share is a feature of respondent pairs. A high tie share indicates the absence of strong beliefs over the ordering of firms. A DS near $1/2$ indicates a lack of consensus among those respondent pairs who possess strong beliefs.

The following approximation decomposes the Borda AMAD into the tie share and disagreement share:

$$AMAD_B \approx DS(1 - TS)^2 + TS(1 - TS).$$

To understand this expression, consider a pair of randomly sampled respondents evaluating the same pair of firms, and suppose each respondent ties the firms independently with common probability TS . Both respondents rank the firms strictly with probability $(1 - TS)^2$, in which case their comparison contributes a full point of disagreement with probability DS ; exactly one respondent ties with probability $2TS(1 - TS)$, in which case the comparison contributes half a point. Summing these contributions yields the expression above. The approximation is exact when the probability of a tie is constant across firm pairs. In our data, the discrepancies yield small overestimates of $AMAD_B$. As the decomposition makes clear, in the absence of ties $AMAD_B$ would coincide with the strict disagreement share DS , and when TS is large there are fewer opportunities for strict disagreement over firm ranks, which mechanically depresses $AMAD_B$.

The Likert and Borda AMADs are measured on different scales. A useful benchmark that facilitates their comparison is to contrast each measure with its expectation under uniform random ratings (URR): i.e., when each respondent independently chooses from each of the five Likert options with equal probability. $AMAD_L$ equals 1.6 under URR,

while $AMAD_B$ is 0.48, the tie share is 0.2, and the disagreement share is 0.5. $AMAD$ values near these benchmarks indicate respondents' beliefs are diffuse, while lower values suggest a more concentrated distribution of Likert item ratings. Tie shares well above 0.2 indicate widespread indifference, while DS below 0.5 indicates directional agreement among strict rankers.

Although we will tentatively interpret the $AMAD$ s and DS as capturing disagreement, they could also reflect various sorts of measurement error. For example, gross errors in clicking on the questions, a hasty reading of the question, or a generally erratic answer that would be unlikely to be replicated if the respondent were to answer the same question again, will tend to inflate each of the $AMAD$ measures. Similarly, such errors would push the disagreement share toward its benchmark of $1/2$, implying our estimates of DS understate consensus among strict rankers. On the other hand, independent measurement errors in ratings would tend to decrease tie shares, which we will find are far above the URR benchmark.

5.1.2 Disagreement estimators

To estimate these quantities we average across the relevant pairs of respondents. Let L_{ij} denote the rating of firm j by sample respondent i and define $\mathcal{R}_j = \{i : j \in \mathcal{E}_i\}$ as the set of respondents rating firm j . The scalar $n_j = |\mathcal{R}_j|$ gives the number of such respondents. An unbiased estimator of $AMAD_L$ is

$$\widehat{AMAD}_L := \frac{1}{J} \sum_{j=1}^J \binom{n_j}{2}^{-1} \sum_{i \in \mathcal{R}_j} \sum_{i' \in \mathcal{R}_j: i' < i} |L_{ij} - L_{i'j}|.$$

Let $\mathcal{R}_{jk} \subseteq \mathcal{R}_j$ denote the set of respondents rating both firms j and k , and $n_{jk} = |\mathcal{R}_{jk}|$ the number of such respondents. A consistent estimator of $AMAD_B$ is

$$\widehat{AMAD}_B := \frac{1}{J} \sum_{j=1}^J \frac{\sum_{k \in \mathcal{N} \setminus \{j\}} \sum_{i \in \mathcal{R}_{jk}} \sum_{i' \in \mathcal{R}_{jk}: i' < i} |w_{ijk} - w_{i'jk}|}{\sum_{k \in \mathcal{N} \setminus \{j\}} \binom{n_{jk}}{2}}.$$

Corresponding estimators of the tie share and strict disagreement share are

$$\widehat{TS} := \frac{1}{J} \sum_{j=1}^J \frac{\sum_{k \in \mathcal{N} \setminus \{j\}} \sum_{i \in \mathcal{R}_{jk}} \mathbf{1}\{L_{ij} = L_{ik}\}}{\sum_{k \in \mathcal{N} \setminus \{j\}} n_{jk}},$$

$$\widehat{DS} := \frac{1}{J} \sum_{j=1}^J \frac{\sum_{k \in \mathcal{N} \setminus \{j\}} \sum_{i \in \mathcal{S}_{jk}} \sum_{i' \in \mathcal{S}_{jk}: i' < i} |w_{ijk} - w_{i'jk}|}{\sum_{k \in \mathcal{N} \setminus \{j\}} \binom{s_{jk}}{2}}$$

where $\mathcal{S}_{jk} = \{i \in \mathcal{R}_{jk} : w_{ijk} \neq 1/2\}$ is the set of respondents that offer a strict ordering of firms j and k and $s_{jk} = |\mathcal{S}_{jk}|$ the number of such respondents. Firms with no eligible pairs are omitted from the average.

For questions fielded under multiple framings, respondent pairs entering the disagreement measures are restricted to the same framing. Pooled measures combining the conduct and names arms likewise restrict pairs to the same arm. This prevents differences in mean responses across framings and arms from contaminating the disagreement measures.

Since $\widehat{AMAD}_L$, $\widehat{AMAD}_B$, and $\widehat{DS}$ are all second order U-statistics, we compute their respondent-clustered standard errors analytically from their Hájek projection (Van der Vaart, 2000). $\widehat{TS}$ is a sample average to which traditional standard error formulas apply.

5.2 Results

Table 3 reports equally weighted average beliefs across the 164 firms in the survey as measured by Likert and Borda scores for key outcomes. For the race discrimination questions, there are 7,743 total responses in the conduct arm (where as noted in Section 3 we use only the “against Black” framing), roughly 15,200 each in the two questions from the names arm, and 22,922 total responses for the pooled measure that combines the names and conduct arms. Each of the three anchor firms receives roughly 1,500 responses for the pooled race measure, while the remaining 161 firms receive about 110 responses each.

The number of unique respondents for each race discrimination question scales similarly. As noted above, the number of responses is not five times the number of respondents for each question because “Don’t know / prefer not to answer” answers are excluded from both Likert and Borda calculations. For the pooled race measures, for example, there are 4.9 responses per respondent on average, implying respondents opted out of about 2.6% of potential responses.²

These sample sizes yield precise estimates of average beliefs about firm-specific racial discrimination, as reflected in the small standard errors of both the average Likert and Borda scores. Average Likert scores in the Conduct arm are 2.66, indicating that on average firms are viewed as between neither likely nor unlikely and somewhat unlikely to discriminate against Black job seekers. Average scores in the names arm are 3.4-3.5, indicating a belief that firms slightly prefer White names on average. Average Borda scores are near 0.5 by construction—the Borda means would be exactly 0.5 but for item non-response and the anchor firm correction noted in Section 4.2.

Sample sizes for the gender discrimination questions behave similarly, except in the conduct arm where we combine the “against male” and “against female” framings. As a result, the pooled gender discrimination outcome includes 30,477 responses and 6,251 distinct respondents. Each of the three anchor firms receives roughly 2,000 responses for the pooled gender measure, while the remaining 161 firms receive about 145 responses each. Likert responses suggest respondents believe the average firm prefers male job seekers. Age discrimination is only probed in the conduct arm, where responses indicate beliefs that firms favor younger workers on average.

The firm characteristics questions on desirability, selectivity, and manager discretion were asked of all respondents and thus have similar sample sizes to the pooled gender discrimination measure. As a result, average beliefs regarding these characteristics are measured with greater precision.

Turning to respondent disagreement, the Discrimination Black (Conduct) question has a

²Firm-specific shares of “Don’t know / prefer not to answer” responses are reported in Table A8.

Table 3: Sample sizes, means, and disagreement by question

Outcome	Sample		Likert		Borda			
	Responses	Respondents	Avg Score	AMAD	Avg Score	AMAD	Tie Share	Disagree Share
Race								
Discrimination Black (Conduct)	7,743	1,594	2.661 (0.027)	1.463 (0.015)	0.503 (0.001)	0.306 (0.008)	0.573 (0.009)	0.360 (0.024)
Discrimination Black (Contact)	15,179	3,112	3.407 (0.016)	1.180 (0.012)	0.498 (0.001)	0.325 (0.007)	0.559 (0.006)	0.408 (0.019)
Discrimination Black (Hire)	15,167	3,102	3.451 (0.016)	1.169 (0.012)	0.498 (0.001)	0.298 (0.006)	0.597 (0.006)	0.421 (0.021)
Discrimination Black (Pooled)	22,922	4,706	3.154 (0.015)	1.275 (0.010)	0.499 (0.001)	0.319 (0.005)	0.564 (0.005)	0.397 (0.016)
Gender								
Discrimination Female (Conduct)	15,245	3,136	3.170 (0.022)	1.314 (0.013)	0.502 (0.001)	0.302 (0.006)	0.578 (0.006)	0.359 (0.019)
Discrimination Female (Contact)	15,232	3,115	3.181 (0.015)	1.152 (0.011)	0.503 (0.001)	0.339 (0.006)	0.481 (0.006)	0.372 (0.017)
Discrimination Female (Hire)	15,193	3,112	3.201 (0.015)	1.147 (0.011)	0.502 (0.001)	0.321 (0.006)	0.508 (0.006)	0.347 (0.017)
Discrimination Female (Pooled)	30,477	6,251	3.176 (0.013)	1.234 (0.009)	0.502 (0.001)	0.321 (0.005)	0.529 (0.004)	0.364 (0.013)
Age								
Discrimination Older (Conduct)	14,594	3,004	3.253 (0.019)	1.430 (0.011)	0.498 (0.001)	0.342 (0.007)	0.505 (0.006)	0.390 (0.018)
Firm characteristics								
Firm Desirability	30,966	6,360	3.879 (0.011)	1.238 (0.009)	0.499 (0.000)	0.355 (0.003)	0.524 (0.004)	0.485 (0.007)
Firm Selectivity	30,806	6,391	2.485 (0.010)	1.238 (0.007)	0.501 (0.001)	0.342 (0.003)	0.379 (0.004)	0.304 (0.006)
Manager Discretion	30,298	6,210	3.221 (0.013)	1.440 (0.007)	0.500 (0.001)	0.345 (0.003)	0.491 (0.004)	0.398 (0.007)

Notes: Each entry in the “Avg Score” column gives the equally weighted average score across all 164 firms. “AMAD” gives the average mean absolute difference measures defined in Section 5.1. “Tie Share” and “Disagree Share” give the objects $\widehat{TS}$ and $\widehat{DS}$, which are also defined in Section 5.1. The Disagree Share averages over firms with at least one pair of strict rankers, which excludes three firms for the Discrimination Black (Conduct) measure. Numbers in parentheses are analytical standard error estimates clustered by respondent. The total number of responses is less than five times the number of respondents because “Don’t know / prefer not to answer” responses are dropped from the analysis. Responses are signed such that higher values indicate more perceived discrimination against the group in the outcome title, or more desirability/selectivity/discretion for the firm characteristics questions. “Conduct” refers to responses in the conduct arm, “Contact” and “Hire” refer to the two questions in the names arm, and “Pooled” combines the conduct arm with the contact question in the names arm.

Likert AMAD of roughly 1.46, indicating that two randomly selected respondents evaluating the same firm differ by about 1.46 Likert points on average. This is only slightly below the uniform random ratings benchmark of 1.6, indicating that respondents offered highly diffuse answers to this question. The corresponding Borda AMAD of 0.31 is more substantially below its URR benchmark of 0.48. Much of this gap is driven by ties: 57% of pairwise comparisons result in ties, far above the URR benchmark of 0.2. However,

respondents who strictly rank firm pairs disagree only 36% of the time, far below the 50% benchmark. Thus, there seems to be greater agreement about firm ranks than levels, at least among those respondents with strong beliefs. The contact and hiring versions of the race questions have lower Likert AMADs and higher disagreement shares than the conduct version of the question but similar Borda AMADs and tie shares.

The conduct version of the Discrimination Female question has a lower Likert AMAD than the Discrimination Black (Conduct) question but a comparable Borda AMAD, tie share, and disagreement share. The Likert AMADs and disagreement shares for the remaining gender questions are generally smaller than those found for their race counterparts, however their Borda AMADs are higher, which is partially attributable to lower tie shares. The age discrimination question exhibits a higher Borda AMAD than the other conduct questions. Respondents are notably more willing to strictly rank firms on age discrimination, though those who do so disagree at similar rates.

The Firm Desirability and Selectivity questions exhibit identical Likert AMADs of 1.24. However, their Borda AMADs of 0.34-0.36 are among the highest of all questions. Notably, Firm Desirability has a disagreement share very near $1/2$, suggesting respondents issue largely idiosyncratic ratings of which firms are desirable. This finding may indicate that respondents had difficulty parsing the intended revealed preference nature of this question. In contrast, Firm Selectivity has the lowest disagreement share of all questions, indicating relatively broad consensus among respondents with strong beliefs.

In sum, respondents exhibit substantial disagreement in firm beliefs when measured in Likert points, in some cases approaching the level that uniform random ratings would generate. The Borda comparisons suggest less diffuse beliefs about firm rankings. For most questions, half or more of pairwise comparisons result in ties, indicating that respondents frequently decline to rank firms. However, among those who do rank, disagreement shares sit well below $1/2$ for most discrimination questions, indicating partial consensus about firm ordering.

6 The covariance structure of average beliefs

This section studies the covariance structure of average beliefs about firms. We begin by studying dispersion across firms in their Likert and Borda scores, which measures the extent to which some firms are believed to be more biased than others. Then we study the correlation between the average beliefs measured by different questions. Finally, we estimate the correlation between the average firm beliefs of different subpopulations of respondents.

6.1 Estimating Signal Variances

To summarize dispersion in average beliefs across firms, we will be interested in the signal variances

$$\sigma_L^2 = \frac{1}{J} \sum_{j=1}^J (L_j - \mu_L)^2, \quad \sigma_B^2 = \frac{1}{J} \sum_{j=1}^J (B_j - \mu_B)^2.$$

These objects capture the variance in average beliefs that would result if we surveyed an infinite population of respondents. The finite sample analogs of these variances will be biased up due to sampling uncertainty in the scores driven by the disagreement documented in the AMAD measures of the previous section.

Unbiased estimators of the variances can be obtained by subtracting the sampling variances $V_{Lj} = \mathbb{V}[\hat{L}_j - \bar{L}]$ and $V_{Bj} = \mathbb{V}[\hat{B}_j - \bar{B}]$ as follows

$$\hat{\sigma}_L^2 = \frac{1}{J} \sum_{j=1}^J \left((\hat{L}_j - \bar{L})^2 - V_{Lj} \right), \quad \hat{\sigma}_B^2 = \frac{1}{J} \sum_{j=1}^J \left((\hat{B}_j - \bar{B})^2 - V_{Bj} \right).$$

While $\hat{\sigma}_L^2$ and $\hat{\sigma}_B^2$ are unbiased, sampling error can lead to negative estimates in finite samples. To avoid such logical inconsistencies, we refine our variance estimates with a correction proposed by Katz (1961) that ensures the estimates are positive. This correction nudges noisy and small variance estimates up but collapses to the uncorrected estimate when the variance is precisely estimated. Katz (1961) shows that these shape-constrained estimators are minimax and admissible under squared error loss. We use

$\hat{\sigma}_L^2$ and $\hat{\sigma}_B^2$ to refer to the corrected variance estimators for Likert and Borda scores, respectively. Appendix F details their construction.

6.2 Dispersion results

Table 4 reports estimates of the dispersion in Likert and Borda scores. The column “Std Dev” reports the naive sample standard deviation of scores, while “Signal Std Dev” reports the square roots $\hat{\sigma}_L$ and $\hat{\sigma}_B$ of the minimax variance estimates that account for sampling error. The square of the ratio of the signal to the naive standard deviations gives the reliability of the scores. A reliability of one would indicate that the firm scores possess no sampling uncertainty, while a reliability of zero would indicate that the signal variance is zero. The column “T-stat no signal” reports t -statistics from tests of the null hypothesis that the true signal variance is zero.

Table 4: Variance of firm-level beliefs

Outcome	Likert				Borda			
	Std Dev	Signal Std Dev	Reliability	T-stat no signal	Std Dev	Signal Std Dev	Reliability	T-stat no signal
Race								
Discrimination Black (Conduct)	0.319	0.240	0.566	6.133	0.078	0.066	0.729	8.704
Discrimination Black (Contact)	0.250	0.214	0.736	9.016	0.070	0.064	0.828	12.014
Discrimination Black (Hire)	0.241	0.204	0.718	8.778	0.067	0.061	0.824	11.579
Discrimination Black (Pooled)	0.262	0.235	0.806	11.557	0.070	0.066	0.885	15.453
Gender								
Discrimination Female (Conduct)	0.396	0.362	0.833	13.422	0.086	0.081	0.894	15.345
Discrimination Female (Contact)	0.398	0.377	0.898	15.459	0.099	0.094	0.905	16.799
Discrimination Female (Hire)	0.416	0.396	0.907	16.579	0.101	0.096	0.913	17.565
Discrimination Female (Pooled)	0.381	0.367	0.927	20.247	0.090	0.087	0.946	22.571
Age								
Discrimination Older (Conduct)	0.248	0.195	0.621	6.920	0.056	0.046	0.673	7.771
Firm characteristics								
Firm Desirability	0.142	0.106	0.563	5.914	0.038	0.032	0.679	8.101
Firm Selectivity	0.595	0.588	0.975	35.540	0.141	0.139	0.975	37.756
Manager Discretion	0.377	0.362	0.923	18.813	0.087	0.084	0.937	20.264

Notes: This table reports estimates of the dispersion of Likert and Borda scores for several survey questions. “Conduct” refers to responses in the conduct arm, “Contact” and “Hire” refer to the two questions in the names arm, and “Pooled” combines the conduct arm with the contact question in the names arm. Columns labeled “Std Dev” report the square root of the sample variance of estimates. “Signal Std Dev” reports the square roots $\hat{\sigma}_L$ and $\hat{\sigma}_B$ of the Katz (1961)-corrected minimax variance estimates that account for sampling error. “Reliability” is the squared ratio of “Signal Std Dev” to “Std Dev”. “T-stat no signal” reports $\hat{\sigma}_L^2/\widehat{V}[\hat{\sigma}_L^2]^{0.5}$ and $\hat{\sigma}_B^2/\widehat{V}[\hat{\sigma}_B^2]^{0.5}$, which allows a t -test of the null hypothesis that the signal standard deviation is zero.

With Likert scores, accounting for sampling error yields modest reductions in the esti-

mated standard deviations. The Discrimination Black (Conduct) scores are the noisiest, with a reliability of only 57%, which is largely attributable to the fact that the sample size for this question is roughly one half of that used for the contact questions. However, the remaining Discrimination Black scores all have reliabilities exceeding 70%. The reliabilities of the Discrimination Female scores are generally higher, all exceeding 80%. The Discrimination Older (Conduct) scores have a reliability of only 62%.

For each question, a t-test easily rejects the null hypothesis that the true signal standard deviation is zero. The estimated signal standard deviations of Likert scores for the racial discrimination questions range from 0.20 to 0.24, or roughly a fifth to a quarter of a Likert point. The standard deviations associated with questions about sex discrimination are higher, ranging from 0.36 to 0.40. The age discrimination question has a smaller standard deviation of 0.20.

Interestingly, the question on firm desirability has the smallest signal standard deviation of all measures. In contrast, the questions about firm selectivity and manager discretion exhibit extremely large signal standard deviations, indicating widely dispersed average beliefs about these firm characteristics. Remarkably, the firm selectivity measure has a reliability of 98%, indicating trivially small standard errors on the Likert scores derived from this question.

The Borda measures show similar patterns but the score reliabilities are generally higher, particularly for the race questions. As with Likert scores, we can decisively reject the null of zero signal variance in all cases. Signal variances are higher for sex discrimination than race discrimination questions, and smallest for age discrimination. The firm desirability measure exhibits the weakest signal, while firm selectivity exhibits the strongest.

As noted in Section 3, these results pool responses to the different framings of questions in the names and conduct arm. Figure A3 shows that firm-level beliefs are tightly correlated when estimated in each framing separately with the exception of the conduct arm for race discrimination. Table A1 reports signal variances for each question and framing separately. Consistent with the limited dispersion in responses documented in Section 3,

the signal variance is lowest for beliefs about discrimination against White workers in the conduct arm, with the t-test of no signal failing to reject.

Average beliefs may reflect respondents’ impressions of industry-level patterns as opposed to the conduct of specific firms. Table A2 explores the role of industry in generating the dispersion documented in Table 4 by computing the same statistics for industry-demeaned Likert and Borda scores (to capture dispersion within-industry) and industry-average scores (to capture between-industry variation). Industries are defined as two-digit SIC codes and merged as the modal industry code for each firm’s establishments in the InfoGroup Historical Datafiles (InfoGroup, 2019), the same mapping used in Kline, Rose and Walters (2024).³ For most questions, the within- and between-industry components are comparable, although the signal standard deviation tends to be larger between-industry. For beliefs about discrimination against Black workers elicited in the conduct arm, for example, industry average beliefs capture 53% of the total variance in average firm beliefs. Between industry-variation is also important for beliefs about manager discretion and selectivity. We explore industry-level beliefs about conduct further below.

6.3 Correlation across questions

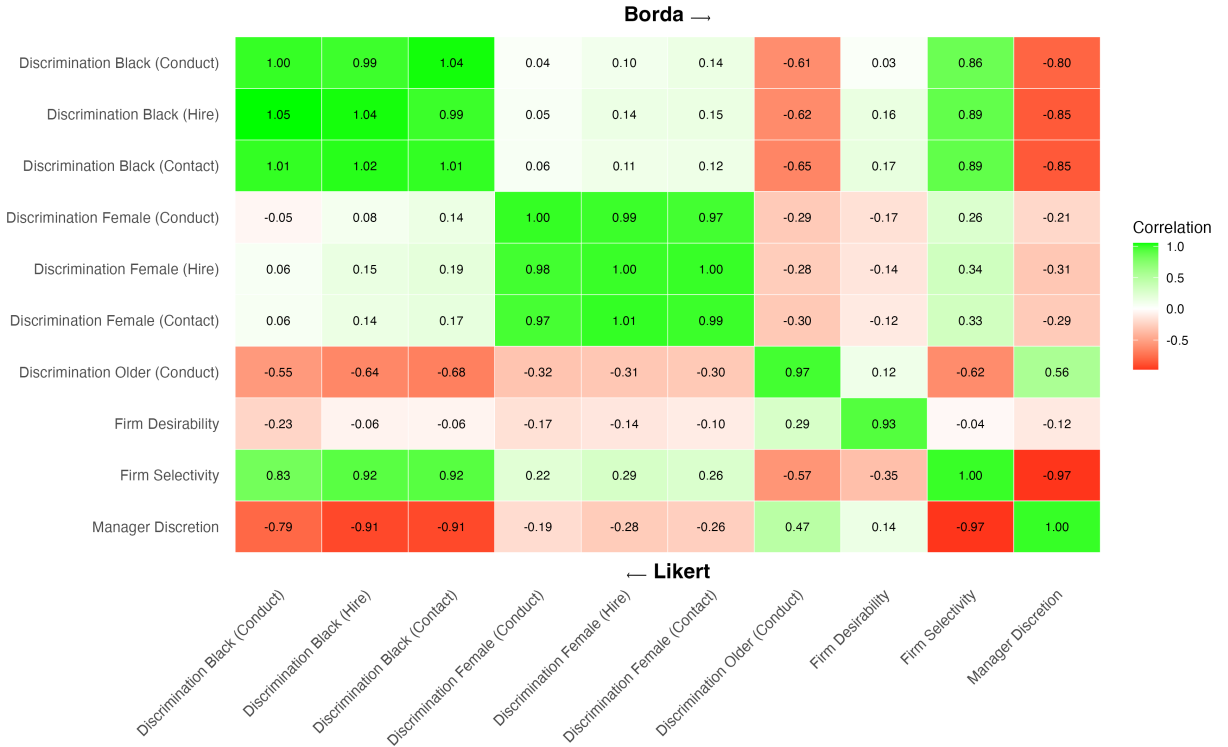
Figure 6 reports signal correlations of firm beliefs across questions. The lower triangle of the Figure reports the estimated signal correlation of the Likert scores. The upper triangle shows the correlation structure of the firm Borda scores. The diagonals show the correlation between the Likert and Borda measures of beliefs for each question. As described in the Appendix, these correlation estimates remove the influence of sampling error by using an estimate of the covariance matrix of the noise between the two questions.

Despite the different scales on which the Likert and Borda estimators measure beliefs, the correlation matrix turns out to be very nearly symmetric. This symmetry suggests the

³Industry assignments are reported in Table A8.

information content of Likert scores, which encode both interpersonal and intrapersonal comparisons, agrees closely with that of Borda scores, which exclusively aggregate intrapersonal comparisons. Indeed, the estimated signal correlations between Likert and Borda scores reported on the diagonal of Figure 6 are approximately one in nearly all cases. The only exception is Firm Desirability, which exhibits an estimated signal correlation of 0.93 between the Likert and Borda scores.

Figure 6: Correlation of firm-level beliefs across questions



Notes: This figure reports the pairwise signal correlation in firm-level parameters across survey questions. Parameters are signed such that more positive values indicate discrimination against the group in the question label. Entries below the diagonal report the signal correlation in Likert scores. Entries above the diagonal give the signal correlation in Borda scores. Entries on the diagonal give the signal correlation between Likert and Borda scores for the same question. In all cases the denominators of these correlations are formed using the Katz (1961)-corrected minimax variance estimators described in Section 6.1. For question pairs that are never asked of the same respondent (e.g., questions in the names and conduct arms) the sample covariance is used in the numerator. For covariances between pairs of questions asked of the same individual, we subtract an analytical estimate of the sampling covariance from the numerator. Finite-sample noise in the resulting correlation estimates can cause them to exceed one in absolute value.

Beliefs about racial discrimination are essentially perfectly correlated across questions. Evidently, respondent beliefs about the overall discriminatory conduct of firms align closely with their beliefs about the treatment of job applicants with racially distinctive names—that is, what would be measured in a typical audit study—at both the contact

and hiring stage. The same pattern is found among the sex discrimination questions, which exhibit nearly perfect correlation as well.

Interestingly, the race and sex questions are only weakly correlated with each other. In contrast, companies believed to discriminate against Black candidates are perceived as being substantially less likely to discriminate against older candidates. Companies believed to discriminate against women are thought to be less likely to discriminate against older workers.

Firm desirability is not strongly correlated with measures of discrimination. However, firms believed to exhibit the most selective hiring are believed to discriminate heavily against Black and younger job seekers. Such firms are also believed to prefer men to women, although the relationship is weaker. While selectivity logically introduces an opportunity for bias, the direction of the biases—favoring, for example, older over younger workers—was not obvious ex-ante. These correlations suggest a belief that elite institutions are biased against less powerful groups that are more broadly disadvantaged in American society.

Finally, firms believed to exhibit greater manager discretion are thought to exhibit less discrimination against Black job seekers, women, and young workers. The strongest correlate of perceived discretion is selectivity: the most selective firms are thought to exhibit the least discretion, perhaps because hiring processes are believed to be more standardized.

The strong negative relationship between perceptions of manager discretion and racial discrimination is surprising in light of recent research indicating that discretion is an important conduit through which bias arises (Hoffman, Kahn and Li, 2018; Kline, Rose and Walters, 2022; Mocanu, 2022). One possibility is that these discretion-discrimination correlations are driven by the strong negative correlation between discretion and selectivity. Unfortunately, the partial correlation between beliefs about discrimination and perceived discretion conditional on selectivity is fundamentally underidentified due to the near perfect collinearity between discretion and selectivity.

6.4 Correlation across subpopulations

Thus far, we have analyzed the properties of average beliefs under the tacit assumption that there is a shared wisdom of the crowd. However, it is possible that views differ systematically among respondents with different observed characteristics. For instance, one might suspect that Black respondents have more information about racial discrimination than White respondents, in which case the correlation in average beliefs about racial discrimination across racial groups might be weak.

To investigate such hypotheses, we compute Likert and Borda scores separately for subpopulations defined by demographic groups and answers to the questions about looking for work and fear of discrimination. Table 5 reports estimates of the signal correlation in beliefs across these groups. We also report tests of the null hypothesis that the beliefs of the two groups have signal correlation equal to one along with tests of the more stringent null hypothesis that the groups share identical average beliefs. Panel A contains results for Likert scores, while panel B studies Borda scores.⁴

The first three columns of the table study beliefs about race discrimination. While we can confidently reject that Likert scores are equal across Black and White respondents, their signal correlation is estimated to be very close to one. A formal test of perfect correlation fails to reject. This finding suggests that Black and White respondents differ only in the mean or dispersion of their average beliefs as quantified by the Likert scores. Indeed, Table A3 shows that Black respondents have both higher scores on average, indicating they believe the average firm is more likely to discriminate, and higher signal variance, indicating greater dispersion in their average beliefs. The correlation across Black and White respondents in Borda scores is similarly high, indicating strong agreement about relative conduct across firms as well. The tests for equality of Borda scores reject, however, providing further evidence of differences in the level of agreement across groups.

Beliefs about racial discrimination are strongly correlated between all the other subgroups

⁴Appendix Table A4 presents the raw correlations in estimated scores across groups without correction for estimation error.

Table 5: Cross-sample signal correlations

	Discrimination Black (Pooled)			Discrimination Female (Pooled)		
	Corr	CMD p-value	Wald p-value	Corr	CMD p-value	Wald p-value
		$H_0 : \rho = 1$	$H_0 : \theta_1 = \theta_2$		$H_0 : \rho = 1$	$H_0 : \theta_1 = \theta_2$
Panel A: Likert						
Black vs White	0.996	0.470	0.002	1.001	0.476	0.396
Female vs Male	1.015	0.430	0.166	0.981	0.334	0.002
Looking for a Job vs Not	0.934	0.060	0.042	0.993	0.412	0.402
Feared Discrimination vs Not	1.003	0.602	0.002	0.988	0.170	0.044
Age ≥ 40 vs < 40	0.952	0.336	0.118	0.983	0.048	0.052
At Least Some College vs HS Diploma or less	0.897	0.250	0.152	0.953	0.088	0.012
Convenience vs Probability	0.932	0.206	0.152	0.981	0.180	0.138
Confident vs Not (Gender)	0.916	0.134	0.004	1.015	0.828	0.554
Confident vs Not (Race)	0.944	0.212	0.008	0.964	0.066	0.068
Panel B: Borda						
Black vs White	0.954	0.314	0.002	1.000	0.488	0.454
Female vs Male	0.970	0.284	0.268	0.969	0.188	0.028
Looking for a Job vs Not	1.000	0.474	0.392	0.984	0.230	0.184
Feared Discrimination vs Not	0.989	0.412	0.402	0.991	0.490	0.396
Age ≥ 40 vs < 40	0.936	0.056	0.012	1.000	0.218	0.156
At Least Some College vs HS Diploma or less	1.018	0.728	0.400	0.992	0.540	0.008
Convenience vs Probability	1.022	0.534	0.524	0.990	0.302	0.272
Confident vs Not (Gender)	1.001	0.532	0.406	0.979	0.098	0.098
Confident vs Not (Race)	0.988	0.350	0.292	0.970	0.044	0.032
N	164			164		

Notes: This table reports the correlation in beliefs across sample groups. Columns labeled “Corr” give the estimated signal correlation in firm-level parameters across the two groups. Columns labeled “CMD p-value” test for a perfect linear relationship between the scores in the two groups via Classical Minimum Distance (CMD) estimation. Columns labeled “Wald p-value” evaluate the null hypothesis that the two vectors of firm-level parameters are equal via a Wald test. Both tests rely on bootstrap p-values; see Appendix G for details. Panel A uses Likert scores, while panel B uses Borda scores. Because the signal correlation is estimated as the ratio of the sample covariance to the product of estimated signal standard deviations, finite-sample noise can cause point estimates to exceed one.

considered as well. We cannot reject the null of perfect correlation of Likert and Borda scores at the 10% level for any pair of groups with two exceptions. For Likert scores the difference between those looking for a job vs. not has a p value 0.06. For Borda scores, the estimated signal correlation in beliefs between those under vs. over age 40 is 0.936 ($p = 0.056$). In many cases, such as for men and women or those with some college vs. a high school degree or lower, we cannot reject perfect equality of the scores. Reassuringly, we also cannot reject that beliefs are equal in the convenience and probability samples, which suggests the information encoded in the Likert and Borda scores is not especially sensitive to the method used to sample respondents.

The last three columns of Table 5 repeat this exercise for sex discrimination. Here, signal correlations are indistinguishable from one at the 5% level across all groups for

both Likert and Borda scores except for the under vs. over 40 age split for Likert and the confident vs. not (Race) split for Borda. However, the Wald tests provide strong evidence that Likert scores are not identical across sexes, educational attainment, fear of discrimination, and age. For Borda, the tests indicate that scores differ across sex, education groups, and race confidence levels. This finding again signals that the location and scale of beliefs can differ across groups without meaningfully affecting firm rankings in scores.

7 Which firms are thought to discriminate?

We now turn to listing some of the firms that are thought to have the strongest preferences over race and sex. With $J = 164$ firms, the standard errors for any particular firm's Likert score or Borda score will generally be non-trivial. We therefore use shrinkage estimators when reporting collections of firm-level estimates. We follow the recommendation in Walters (2024) and use an estimator that allows the distribution of latent parameters to depend on the precision of their estimates. See Appendix Section E for details.

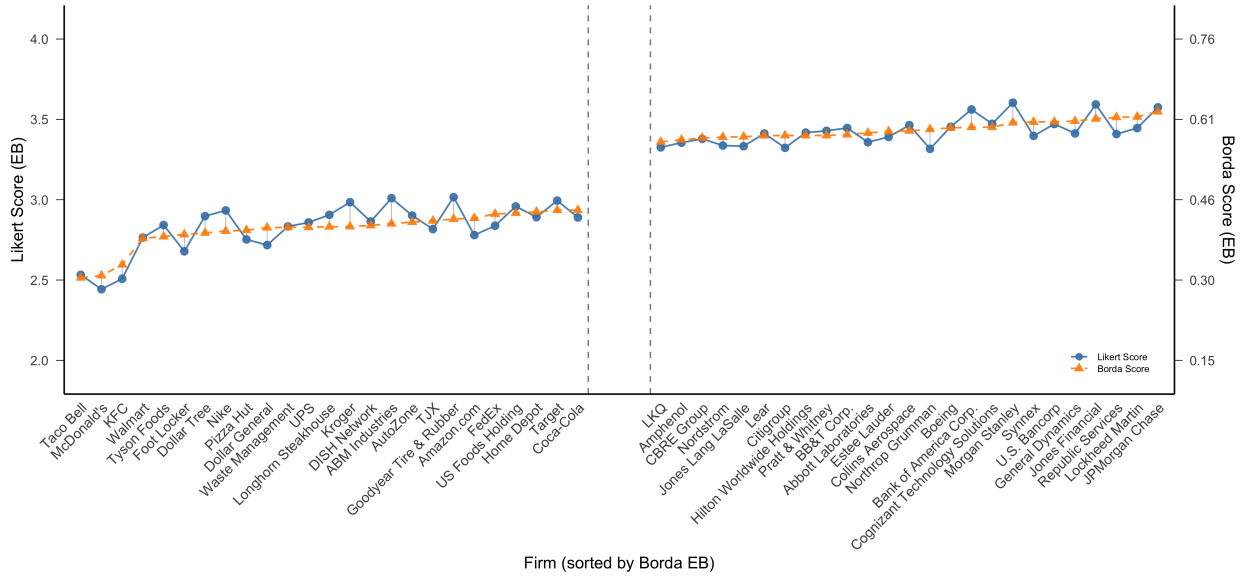
In what follows, we report beliefs about firms whose shrunk Borda scores B_j^* are among the top 25 or bottom 25 of those estimated. We then move on to assessing industry average scores.

7.1 Top / bottom 25 firms

Figure 7 reports shrunk Likert and Borda scores for racial discrimination using the outcome pooling the names and conduct arms. The non-monotonicities in the L_j^* series reflect differences in the rankings of the shrunk Likert and Borda scores. While such rank disagreements are common, their magnitude is generally quite small, typically consisting of a swap in adjacent ranks. Estimates for each firm in the sample are reported in Table A8.

The firms thought least likely to discriminate against Black job seekers are Taco Bell,

Figure 7: Top/bottom 25 firms by perceived discrimination against Black job seekers

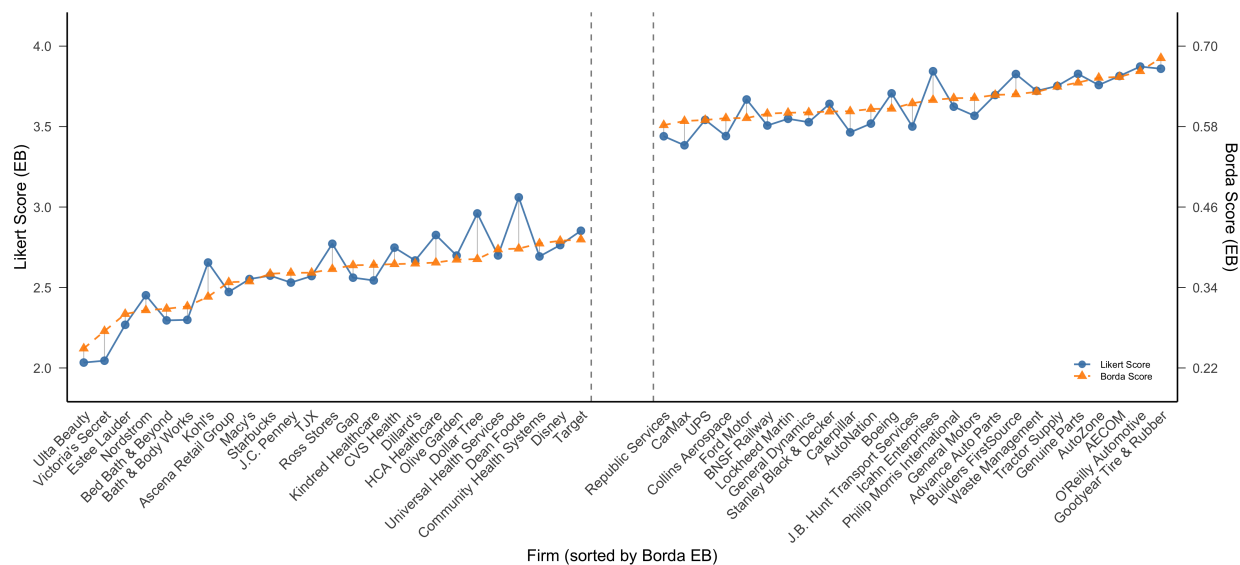


Notes: This figure reports the top and bottom 25 firms ranked by their perceived likelihood of discriminating against Black job seekers according to their shrunk (EB) Borda scores, or B_j^* . The outcome pools responses to both versions of the race question in the conduct arm and both framings of the contact question in the names arm, as in “Discrimination Black (Pooled)” in Table 4. For comparison, the figure also reports shrunk Likert scores, or L_j^* . Firms on the right-hand side of the figure are perceived as more likely to discriminate against Black job seekers. Estimates for each firm in the sample are reported in Table A8.

McDonald’s, and KFC. In contrast, respondents believe JPMorgan Chase, Lockheed Martin, and Republic Services are the most likely to discriminate against Black job seekers. The difference in Likert scores between the top and bottom two firms is about 1. The difference in Borda scores across the top and bottom firms is roughly 0.32, indicating the top firm is 32 percentage points more likely than the bottom firm to be rated by the typical respondent as more discriminatory than a randomly selected non-anchor.

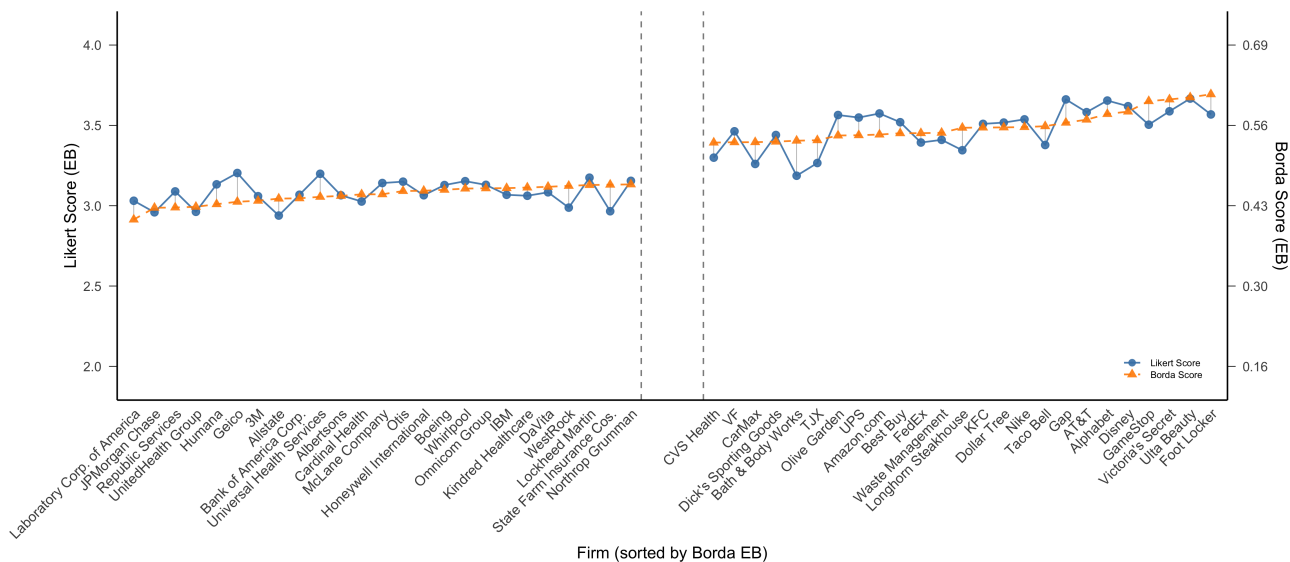
Figure 8 reports corresponding Likert and Borda scores for gender discrimination. Respondents believe that Ulta Beauty, Victoria’s Secret, and Estée Lauder strongly favor women while Goodyear Tire & Rubber, O’Reilly Automotive, and AECOM strongly favor men. Here, the magnitude of the difference in average Likert scores between the top and bottom firm pairs is about 1.8 points. The difference in Borda scores is about 0.44, implying the firms that favor men most are 44 percentage points more likely to be rated by the typical respondent as favoring men more than a randomly selected non-anchor firm.

Figure 8: Top/bottom 25 firms by perceived discrimination against female job seekers



Notes: This figure reports the top and bottom 25 firms ranked by their perceived likelihood of discriminating against female job seekers according to their shrunken (EB) Borda scores, or B_j^* . For comparison, the figure also reports shrunken Likert scores, or L_j^* . The outcome pools responses to both versions of the gender question in the conduct arm and both framings of the contact question in the names arm, as in “Discrimination Female (Pooled)” in Table 4. Firms on the right-hand side of the figure are perceived as more likely to discriminate against female job seekers, while firms on the left-hand side are perceived as more likely to discriminate against male job seekers. Estimates for each firm in the sample are reported in Table A8.

Figure 9: Top/bottom 25 firms by perceived discrimination against older job seekers



Notes: This figure reports the top and bottom 25 firms ranked by their perceived likelihood of discriminating against older job seekers according to their shrunken (EB) Borda scores, or B_j^* . For comparison, the figure also reports shrunken Likert scores, or L_j^* . The outcome pools both versions of the age question in the conduct arm. Firms on the right-hand side of the figure are perceived as more likely to discriminate against older job seekers. Estimates for each firm in the sample are reported in Table A8.

Finally, Figure 9 reports perceptions of firms’ age preferences. Consistent with lower overall agreement across respondents about age discrimination, the dispersion in beliefs is more muted here, as evidenced by the small jump in scores between the bottom and top 25 firms.

The two firms believed to favor young workers most are Foot Locker and Ulta Beauty, while the two that favor older workers most are Laboratory Corp. of America and JP-Morgan Chase. The gap in Likert and Borda scores between the top and bottom firms is comparatively small—roughly 0.54 and 0.21, respectively.

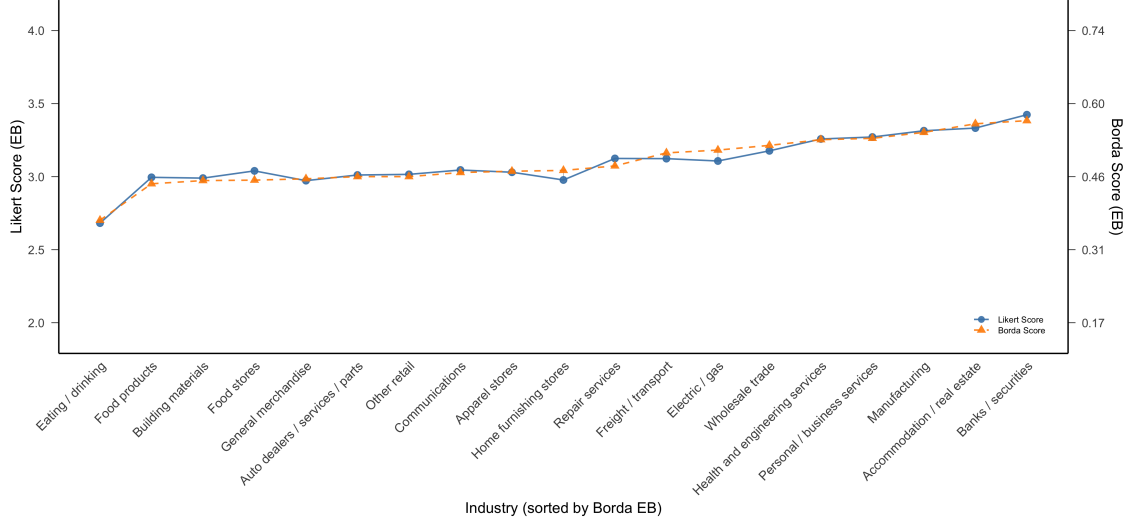
7.2 Industry-level beliefs

As noted in Section 6.2, a large share of the variation in Likert and Borda scores across firms can be captured by variation in industry-average beliefs. Figure 10 examines the structure of beliefs across industries by plotting EB estimates of average Likert and Borda scores for firms in major industry categories. Panel A studies beliefs about discrimination against Black workers using the same data underlying Figure 7. Panel B studies discrimination against Female workers using the data from Figure 8. Finally, panel C studies age discrimination using the data from Figure 9.

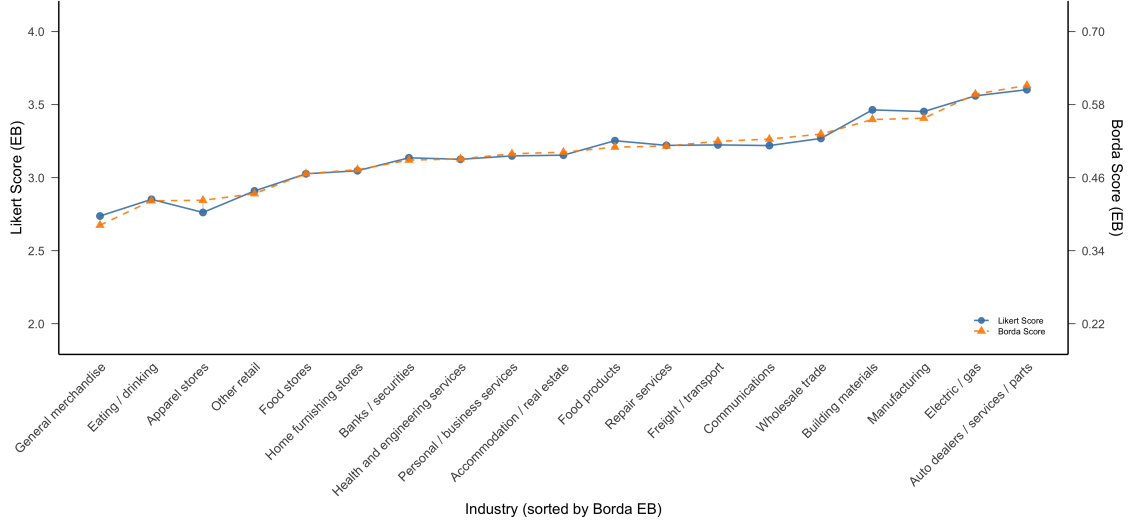
Industry-average beliefs about discrimination against Black workers exhibit non-trivial dispersion, but less than was found across firms. The sector where firms are believed least likely to discriminate against Black workers is the eating / drinking sector, which has an average Likert score about three quarters of point below the banks / securities sector, where workers believe firms are most likely to discriminate against Black workers. The difference in Borda scores across the top / bottom industries is also non-trivial. Compared to a random firm, a firm in the eating / drinking sector is roughly 20 percentage points less likely to be ranked as more discriminatory than a firm in the banks / securities sector. Ranking industries by Borda scores and Likert scores also roughly agree, although there are some cases of non-monotonicity. Notably, the auto sector, which exhibited the largest contact gaps in Kline, Rose and Walters (2024) receives a middling score here under both

Figure 10: Distribution of industry-average beliefs

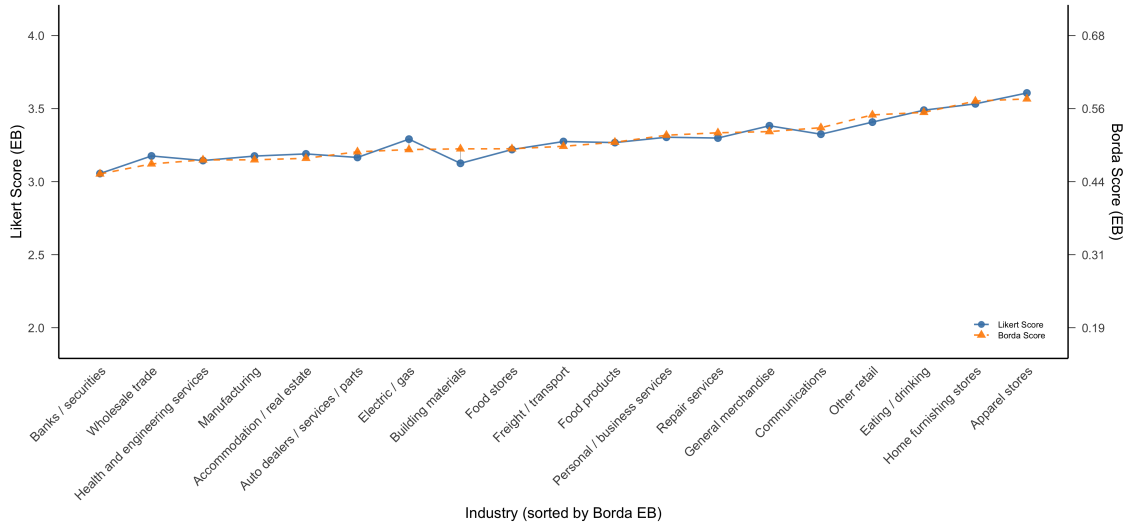
a) Against Black job seekers



b) Against female job seekers



c) Against older job seekers



Notes: This figure reports industry-average beliefs ranked by their shrunk (EB) Borda scores, or B_j^* , and shrunk Likert scores, or L_j^* , for race, gender, and age. The outcome is the same as in Figure 7, 8, and 9, but averaged by industry. Industries are defined as two-digit SIC codes and merged as the modal code for each firm's establishments in the InfoGroup Historical Datafiles (InfoGroup, 2019), the same mapping used in Kline, Rose and Walters (2024). See Table A8 for assignments.

the Borda and Likert rankings.

Beliefs about gender discrimination at the industry level show more dispersion than beliefs about race discrimination. The sectors where firms are judged least likely to discriminate against women are general merchandise, eating / drinking, and apparel stores. The eating/drinking establishments ranking is broadly consistent with the matched-pair audit evidence of Neumark, Bank and Van Nort (1996), who find that women are preferred at lower-price restaurants of the sort that are considered in our survey. The auto sector, electric / gas utilities, and manufacturing are thought to be the most favorable to men. The gap in average Likert scores between the top and bottom industries is about 0.9 points, while the gap in EB Borda scores is roughly 24 percentage points. As they did for race, Borda and Likert scores closely agree on the industry ranking.

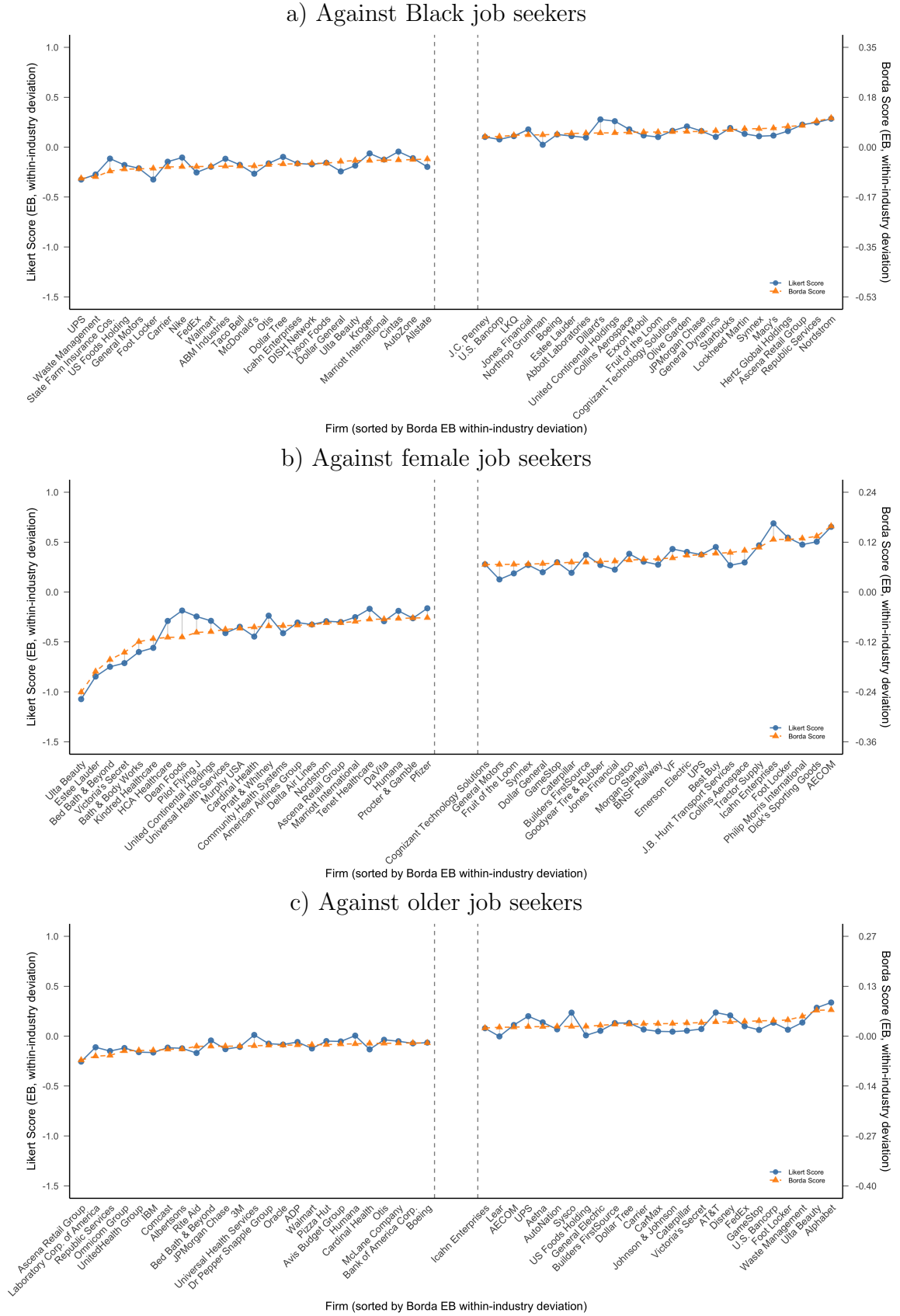
Average beliefs about age discrimination across industries show less dispersion than for race and gender but exhibit intuitive patterns. Sectors such as apparel, home furnishings, and eating and drinking are thought to favor younger workers, while banks and securities, wholesale trade, and health and engineering services are thought to favor older workers.

7.3 Within-industry deviations

Section 6.2 also established that a meaningful share of the variation in Likert and Borda scores across firms persists within industry. Figure 11 reports the top/bottom 25 firms ranked by the deviation of beliefs from their industry's average. As in Figure 10, panel A studies race discrimination, panel B studies sex discrimination, while panel C studies age discrimination using the same data as Figure 9.

Compared to their industry peers, Nordstrom, Republic Services, and Ascena Retail Group (i.e., Ann Taylor / Loft) are thought to be most likely to discriminate against Black workers, while UPS, Waste Management, and State Farm are thought to be least likely. AECOM, Dick's Sporting Goods, and Philip Morris are viewed as most likely to favor men, while the three firms thought most likely to favor women relative to their

Figure 11: Top/bottom 25 firms by within-industry deviations in beliefs



industry are Ulta Beauty, Estée Lauder, and Bed Bath & Beyond. Finally, Alphabet (Google), Ulta Beauty, and Waste Management show relative within-industry preference for younger workers, while Ascena, Laboratory Corp, and Republic Services show the opposite.

8 Comparing beliefs to an experiment

In this section, we examine whether the average beliefs of respondents align with experimental evidence on the conduct of particular firms. For this purpose, we use the large scale correspondence experiment described in Kline, Rose and Walters (2022), which sent up to 1,000 resumes to each of 108 Fortune 500 companies.

We will focus our attention on the 97 of those 108 companies studied in Kline, Rose and Walters (2024), which had enough employer responses to compute reliable measures of proportional contact gaps between applications with different signaled characteristics. For example, the proportional race contact gap measures the difference in log contact rates between applications with distinctively White and distinctively Black names. Kline, Rose and Walters (2024) document that roughly half of the variation in these proportional gaps is between industry.

Denoting the estimated gaps by $\hat{\theta}_j$, we consider linear models of the form

$$\hat{\theta}_j = \beta_0 + \beta_1 S_j + \beta_2 X_j + \varepsilon_j$$

where S_j denotes either the Likert score L_j or the Borda score B_j , and X_j are controls such as industry dummies or other measures of beliefs for firm j . The parameter β_1 can be interpreted as a semi-elasticity giving the percent change in contact gap expected from a unit increase in the relevant score. When industry fixed effects are included, β_1 measures alignment between beliefs and contact gaps within industry.

To estimate β_1 , we replace the unknown Likert and Borda scores with their empirical proxies $\hat{L}_j$ and $\hat{B}_j$ and fit errors in variables (EIV) regressions (Fuller, 1987) using the

variance estimators described in Section 6.1 to estimate the reliability of each proxy $\hat{S}_j$. One can think of these EIV regressions as jackknife IV estimators where a set of firm dummies are the instruments used to address the measurement error in $\hat{S}_j$ (Devereux, 2007). As Chen, Gu and Kwon (2025) emphasize, EIV regression estimates are robust to arbitrary correlation between the standard errors and the underlying signals.

The expert forecasting literature (DellaVigna and Pope, 2018; DellaVigna, Pope and Vivaldi, 2019) often finds that some individuals have a greater ability to forecast experimental outcomes than others. We explore heterogeneity by estimating β_1 in distinct subpopulations of respondents. Our use of the Katz (1961) estimator of variance $\hat{\sigma}_\xi^2$ ensures the bivariate EIV tests are always computable, even in subpopulations with low signal strength.

8.1 Forecasting racial contact gaps

Panel A of Table 6 shows results for Black-White proportional contact gaps. For reference, the mean gap in the experiment is 9.5 log points (i.e., 0.095), indicating that distinctive White names were contacted about 10% more often than distinctively Black names.

Columns (1) and (5) reveal that beliefs about racial discrimination are insignificantly related to firm-level racial contact gaps. Controlling for industry fixed effects substantially increases the estimated EIV coefficient. Columns (2) and (6) reveal a positive relationship for both the Likert and Borda based measures of beliefs, significant at the 5 and 10% level, respectively. By the Frisch-Waugh-Lovell theorem, the difference between the coefficients with industry fixed effects and those omitting them as controls is attributable to the between-industry relationship between beliefs and contact gaps. Evidently, average industry-level beliefs about racial discrimination are negatively correlated with racial contact gaps in the experiment.

As noted in Section 6.3, beliefs about firm discrimination are strongly related to perceived selectivity. Columns (3) and (7) examine whether the weak predictive power of beliefs for racial contact gaps is due to a belief that selective firms are more discriminatory. These

Table 6: Experimental measures of discrimination vs. average beliefs

	Likert				Borda			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Race								
Discrimination Beliefs	-0.007 (0.065)	0.196 (0.095)	0.351 (0.152)	0.751 (0.299)	-0.082 (0.226)	0.546 (0.327)	0.833 (0.433)	2.054 (0.705)
Selectivity Beliefs			-0.181 (0.065)	-0.375 (0.145)			-0.535 (0.215)	-1.220 (0.419)
Panel B: Gender								
Discrimination Beliefs	0.148 (0.057)	0.126 (0.060)	0.159 (0.056)	0.132 (0.064)	0.563 (0.229)	0.598 (0.253)	0.629 (0.225)	0.623 (0.268)
Selectivity Beliefs			-0.043 (0.046)	0.034 (0.069)			-0.174 (0.200)	0.203 (0.321)
Industry FE		X		X		X		X

Notes: This table reports Errors-in-Variables (EIV) regressions of experimental log contact gaps for race (panel A) and gender (panel B) on Likert and Borda scores. All columns pool responses from the names and conduct arms recoded so that larger values indicate higher perceived contact/conduct gaps. Appendix Table A5 shows results separately for the names and conduct arms. Columns (1) and (5) include no additional controls; columns (2) and (6) add two-digit industry fixed effects; columns (3) and (7) control for selectivity beliefs, which are treated as error ridden with known reliability; columns (4) and (8) include both industry fixed effects and selectivity beliefs. The EIV treats the regressor as measured with error; the measurement-error variance supplied to the estimator equals the sample variance of the observed regressor minus the Katz (1961)-corrected estimate $\hat{\sigma}_S^2$ of its signal variance.

specifications account for measurement error in both the discrimination and selectivity beliefs using a multivariate extension of the Katz (1961) procedure described in Appendix F. Conditioning on perceived selectivity raises the coefficients on discriminatory beliefs, yielding statistical significance at the 5% level for the Likert score and at the 10% level for the Borda score. Finally, columns (4) and (8) condition on both industry and selectivity beliefs. This yields the largest coefficients on discriminatory beliefs, both of which are significant at the 5% level.

It is possible that respondents infer racial discrimination from a firm's workforce composition, in which case our belief measure would reflect beliefs about Black representation rather than independent beliefs about discrimination. Appendix Table A6 shows that firms in 3-digit NAICS industries with a higher share of Black workers are believed to be less likely to discriminate against Black workers.⁵ A 10 percentage point increase in the industry Black share is associated with a 0.15 to 0.25 point decrease in average Likert

⁵This exercise merges industries to firms at the NAICS3 level to provide a more granular measure of composition and because the EEOC data used is reported for NAICS codes. The merge is still based on modal establishments in the InfoGroup Historical Datafiles (InfoGroup, 2019).

scores, for example, depending on how industries are weighted. Nevertheless, Appendix Table A7 shows that controlling for industry race shares has negligible effects on our β_1 estimates, leaving them close to zero and statistically insignificant.

8.2 Forecasting gender contact gaps

Panel B of Table 6 reports the results for gender discrimination. For reference, the overall gender contact gap is -0.6 log points, which is statistically indistinguishable from zero. In contrast to the earlier findings for racial discrimination, columns (1) and (5) show that the estimated value of β_1 for gender discrimination is distinguishable from zero with both the Likert and Borda measures.

Columns (2) and (6) show that the estimated values of β_1 are remarkably insensitive to the inclusion of industry fixed effects. The general insensitivity of the EIV point estimates to industry fixed effects suggests that respondent beliefs predict both industry average gender contact gaps and firm-specific variation in contact gaps within industries. Controlling for selectivity beliefs likewise has little effect on estimates of β_1 . This diminished sensitivity reflects the earlier finding in Figure 6 that beliefs regarding gender discrimination are only weakly related to perceived selectivity.

Appendix Table A6 shows that respondent beliefs about gender discrimination are systematically related to the female share of entry-level employees in each firm’s 3-digit NAICS industry. A 10 percentage point increase in the industry female share, for example, is associated with a 0.13 to 0.15 decrease in the firm’s Likert score, indicating a shift towards stronger perceived preferences for women. Appendix Table A7 shows that once we control for the industry-level female share of either all workers or front-line workers, our estimates of β_1 fall by a half to a third and are no longer statistically significant.

8.3 Heterogeneity across sub-samples

We showed in Table 5 that beliefs are nearly perfectly correlated across sample splits such as race, gender, or age. Given this finding, there is little reason to expect the EIV

results in Table 6 to differ across groups except in the scale of the coefficients. Figure A4 reports regressions of contact gaps on beliefs for the same sub-samples considered earlier. The estimated coefficients differ significantly across groups in very few cases.

8.4 Perceived discretion, selectivity, and contact gaps

Section 6.3 established that perceptions of discrimination against Black and, to a lesser extent, female job seekers are correlated with perceptions of employer selectivity and discretion. We now study the extent to which experimental contact gaps track these beliefs.

Table 7 shows that both perceived selectivity and perceived discretion seem to predict racial contact gaps but in directions opposite to those predicted by respondent beliefs about racial discrimination. Firms thought to be more selective have smaller racial contact gaps, while firms thought to exhibit the most hiring discretion exhibit larger racial contact gaps. Controlling for industry fixed effects weakens the magnitude of the estimated relationships but leaves the sign of the estimated relationships unaltered. Evidently, a substantial amount of racial discrimination takes place at firms believed to be unselective.

Gender contact gaps are insignificantly related to beliefs about selectivity and discretion. Conditioning on industry fixed effects yields similar conclusions, though Likert discretion scores become significant negative predictors of gender contact gaps, implying a preference for women. Borda scores point towards the same preference but are statistically insignificant. Selectivity is generally unrelated to gender preferences regardless of whether industry controls are included.

9 Conclusion

Though firms devote considerable effort to cultivating favorable reputations, our analysis suggests the public believes many large employers engage in biased (and potentially

Table 7: Contact gaps, perceived discretion, and perceived selectivity

	Likert				Borda			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Race								
Selectivity	-0.053 (0.027)	-0.017 (0.041)			-0.207 (0.110)	-0.095 (0.182)		
Discretion			0.114 (0.038)	0.049 (0.135)			0.432 (0.167)	0.160 (0.550)
Panel B: Gender								
Selectivity	-0.017 (0.046)	0.009 (0.067)			-0.021 (0.199)	0.113 (0.313)		
Discretion			-0.043 (0.070)	-0.347 (0.146)			-0.079 (0.315)	-0.791 (0.692)
Industry FE		X		X		X		X

Notes: This table reports Errors-in-Variables (EIV) regressions of contact gaps on Likert and Borda scores for firm-level beliefs about selectivity and hiring discretion. The EIV treats the regressor as measured with error; the measurement-error variance supplied to the estimator equals the sample variance of the observed regressor minus the Katz (1961)-corrected estimate $\hat{\sigma}_S^2$ of its signal variance. Each entry in the table is the coefficient on either selectivity or discretion beliefs from separate regressions of either race or gender contact gaps on beliefs. Panel A studies race contact gaps, while panel B studies gender contact gaps.

illegal) recruiting practices. These beliefs are widely held but diffuse: average beliefs are similar across demographic groups, yet individual respondents frequently decline to rank firms' relative conduct, and those who do disagree with one another over a third of the time.

Average beliefs about gender discrimination align closely with gender contact gaps in a large-scale correspondence experiment. In this sense, gender discrimination appears to be an open secret. Beliefs about racial discrimination are more weakly related to racial contact gaps, approaching statistical significance only within industry or after conditioning on beliefs about firm selectivity. While recent research points to manager discretion as an important mediator of sex and race discrimination, perceived discrimination is inversely related to average beliefs about manager discretion. Instead, respondents tend to believe the most selective firms are the most biased.

A large share of respondents report having put off applying for a job out of fear of discrimination. The substantial inter-respondent disagreement we document raises the

possibility that views about bias are inaccurate in a substantial share of individual cases. Little is known about the psychic and economic costs of mistakenly inferring bias where it does not exist, or of failing to recognize bias where it does exist. Quantifying these costs is an important priority for future research.

References

- Abdulkadiroğlu, Atila, Parag A Pathak, Jonathan Schellenberg, and Christopher R Walters.** 2020. “Do parents value school effectiveness?” *American Economic Review*, 110(5): 1502–1539.
- Alesina, Alberto, Matteo F Ferroni, and Stefanie Stantcheva.** 2021. “Perceptions of racial gaps, their causes, and ways to reduce them.” National Bureau of Economic Research.
- Allison, Paul D, and Nicholas A Christakis.** 1994. “Logit models for sets of ranked items.” *Sociological methodology*, 199–228.
- Ballinger, T Parker, and Nathaniel T Wilcox.** 1997. “Decisions, error and heterogeneity.” *The Economic Journal*, 107(443): 1090–1105.
- Becker, Gary S.** 1957. *The Economics of Discrimination*. University of Chicago Press.
- Beggs, Steven, Scott Cardell, and Jerry Hausman.** 1981. “Assessing the potential demand for electric cars.” *Journal of econometrics*, 17(1): 1–19.
- Black, Dan A.** 1995. “Discrimination in an equilibrium search model.” *Journal of labor Economics*, 13(2): 309–334.
- Borda, JC de.** 1784. “Mémoire sur les élections au scrutin.” *Histoire de l’Academie Royale des Sciences pour 1781 (Paris, 1784)*.
- Bowlus, Audra J, and Zvi Eckstein.** 2002. “Discrimination and skill differences in an equilibrium search model.” *International Economic Review*, 43(4): 1309–1345.
- Caldwell, Sydnee, Ingrid Haegele, and Jörg Heining.** 2025. “Bargaining and inequality in the labor market.” National Bureau of Economic Research.
- Chen, Jiafeng, Jiaying Gu, and Soonwoo Kwon.** 2025. “Empirical Bayes shrinkage (mostly) does not correct the measurement error in regression.” *arXiv preprint arXiv:2503.19095*.

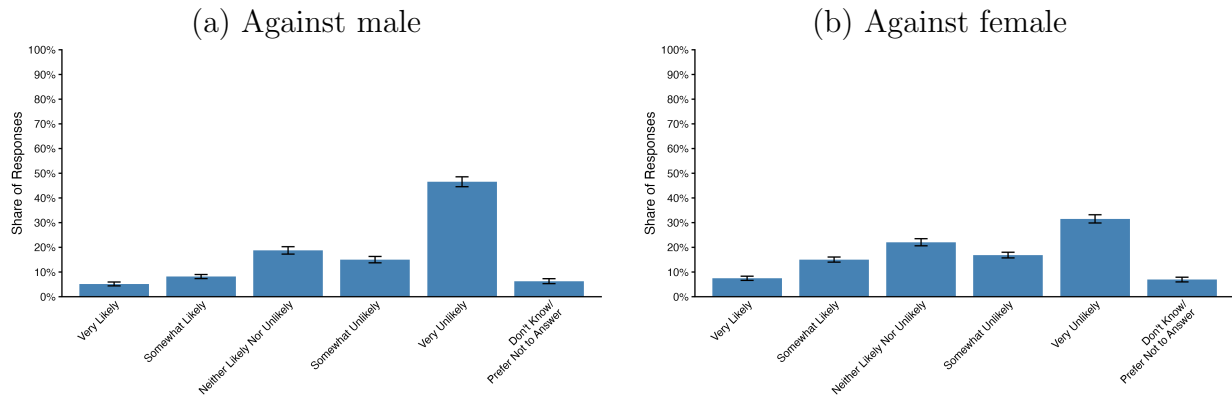
- Davidson, Donald, and Jacob Marschak.** 1959. “Experimental tests of a stochastic decision theory.” *Measurement: Definitions and theories*, 17(2).
- DellaVigna, Stefano, and Devin Pope.** 2018. “Predicting experimental results: who knows what?” *Journal of Political Economy*, 126(6): 2410–2456.
- DellaVigna, Stefano, Devin Pope, and Eva Vivaldi.** 2019. “Predict science to improve science.” *Science*, 366(6464): 428–429.
- Devereux, Paul J.** 2007. “Improved errors-in-variables estimators for grouped data.” *Journal of Business & Economic Statistics*, 25(3): 278–287.
- Fuller, Wayne A.** 1987. “Measurement Error Models.” *Wiley Series in Probability and Statistics*.
- Haaland, Ingar, and Christopher Roth.** 2023. “Beliefs about racial discrimination and support for pro-black policies.” *Review of Economics and Statistics*, 105(1): 40–53.
- Hausman, Jerry A., and Paul A. Ruud.** 1987. “Specifying and testing econometric models for rank-ordered data.” *Journal of Econometrics*, 34(1): 83–104.
- Hoffman, Mitchell, Lisa B Kahn, and Danielle Li.** 2018. “Discretion in hiring.” *The Quarterly Journal of Economics*, 133(2): 765–800.
- InfoGroup.** 2019. “Historical Datafiles.”
- Katz, Morris W.** 1961. “Admissible and minimax estimates of parameters in truncated spaces.” *The Annals of Mathematical Statistics*, 32(1): 136–142.
- Kline, Patrick, Evan K Rose, and Christopher R Walters.** 2022. “Systemic discrimination among large US employers.” *The Quarterly Journal of Economics*, 137(4): 1963–2036.
- Kline, Patrick, Evan K Rose, and Christopher R Walters.** 2024. “A Discrimination Report Card.” *American Economic Review*, 114(8): 2472–2525.

- Kline, Patrick M, and Christopher R Walters.** 2021. “Reasonable doubt: Experimental detection of job-level employment discrimination.” *Econometrica*, 89(2): 765–792.
- Korba, Anna, Stephan Cl  men  on, and Eric Sibony.** 2017. “A learning theory of ranking aggregation.” 1001–1010, PMLR.
- Likert, Rensis.** 1932. “A technique for the measurement of attitudes.” *Archives of Psychology*, 22(140): 5–55.
- Miller, Conrad.** 2017. “The persistent effect of temporary affirmative action.” *American Economic Journal: Applied Economics*, 9(3): 152–90.
- Mocanu, Tatiana.** 2022. “Designing gender equity: Evidence from hiring practices and committees.” Working paper.
- Neumark, David, Roy J Bank, and Kyle D Van Nort.** 1996. “Sex discrimination in restaurant hiring: An audit study.” *The Quarterly journal of economics*, 111(3): 915–941.
- Newey, Whitney K, and Daniel McFadden.** 1994. “Large sample estimation and hypothesis testing.” *Handbook of econometrics*, 4: 2111–2245.
- Portnoy, Stephen.** 1982. “Maximizing the probability of correctly ordering random variables using linear predictors.” *Journal of Multivariate Analysis*, 12(2): 256–269.
- Shah, Nihar B, and Martin J Wainwright.** 2018. “Simple, robust and optimal ranking from pairwise comparisons.” *Journal of machine learning research*, 18(199): 1–38.
- U.S. Census Bureau.** 2025. “PINC-11. Income Distribution to \$250,000 or More for Males and Females: 2024.” *Current Population Survey, 2025 Annual Social and Economic (ASEC) Supplement*, Table PINC-11 (Person income in 2024, CPS 2025 ASEC).
- Van der Vaart, Aad W.** 2000. *Asymptotic Statistics*. Vol. 3, Cambridge university press.

Walters, Christopher. 2024. “Empirical Bayes methods in labor economics.” In *Handbook of Labor Economics*. Vol. 5, 183–260. Elsevier.

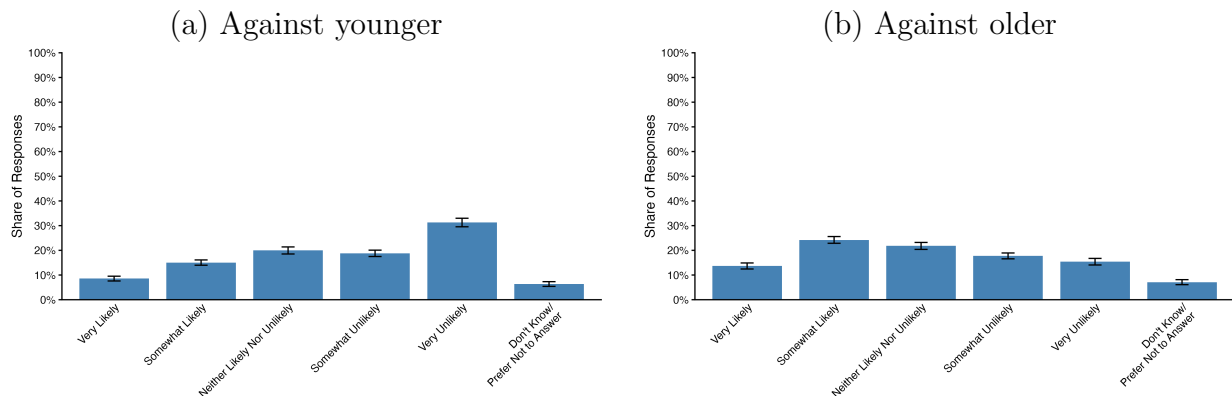
Appendix A: Additional figures

Figure A1: Distribution of perceived gender discrimination likelihood



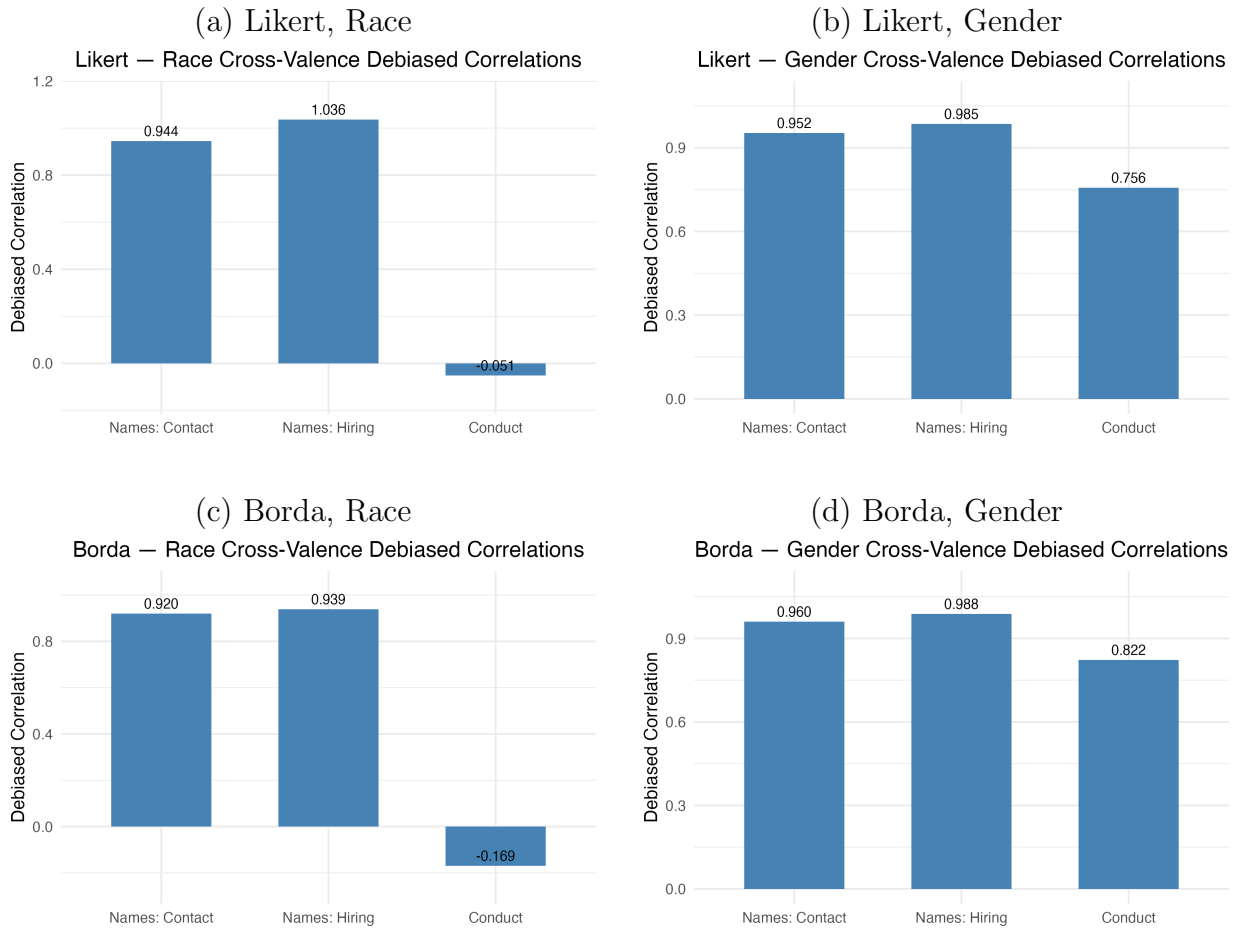
Notes: This figure reports the distribution of companies' perceived likelihood of discriminating against male job seekers (panel A) and against female job seekers (panel B). Only respondents in the conduct arm were shown this question, with the against female vs. against male framing chosen at random. Question text: Please indicate how likely you think it is that each company below would discriminate against [male / female] job seekers.

Figure A2: Distribution of perceived age discrimination likelihood



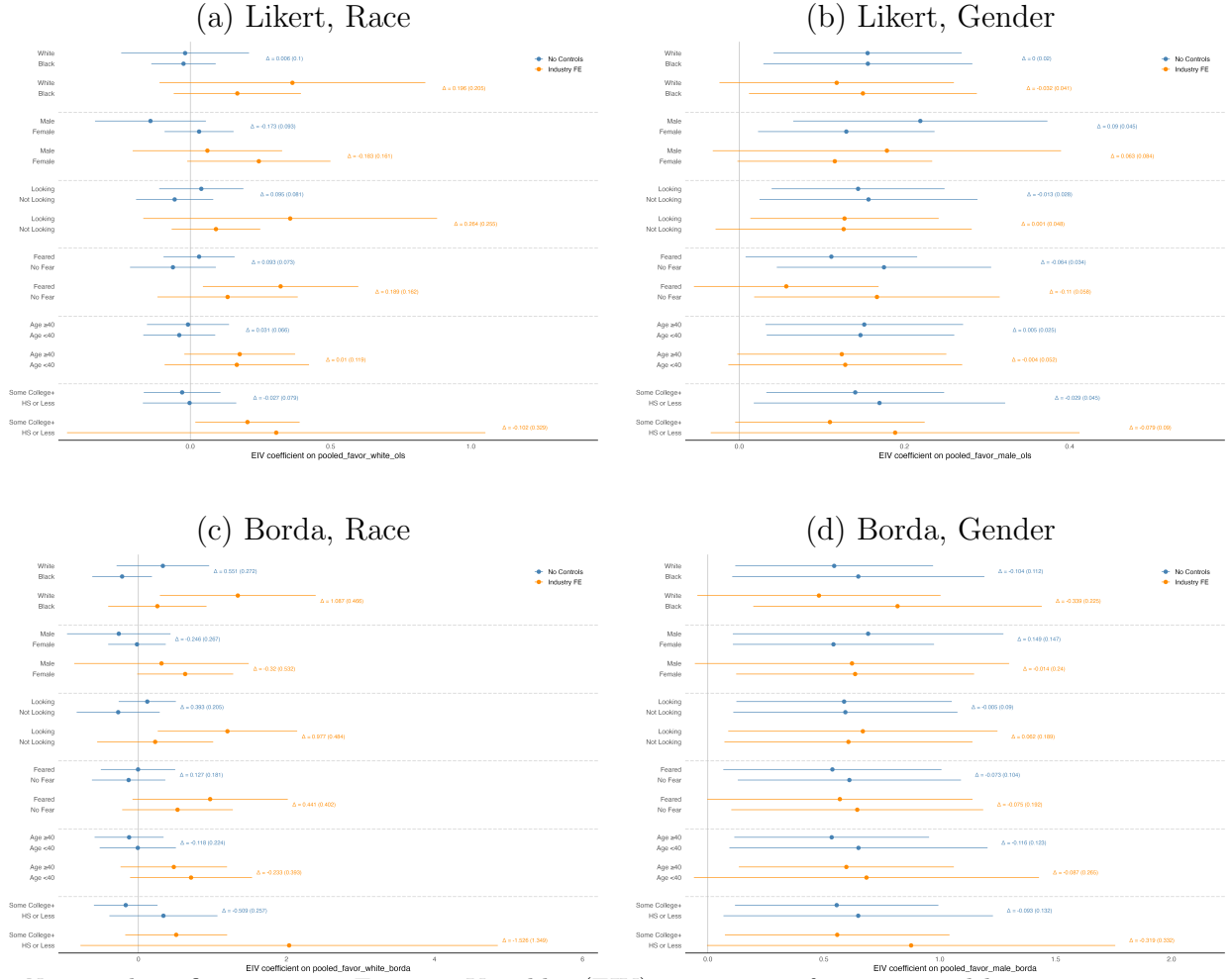
Notes: This figure reports the distribution of companies' perceived likelihood of discriminating against younger job seekers (panel A) and against older job seekers (panel B). Only respondents in the conduct arm were shown this question, with the against younger vs. against older framing chosen at random. Question text: Please indicate how likely you think it is that each company below would discriminate against [younger / older] job seekers.

Figure A3: Correlation in beliefs across question framings



Notes: These figures report debiased correlation in Likert (panels A and B) and Borda (panels C and D) scores across randomized framings of the contact, hiring, and conduct questions. Correlations are computed by estimating firm-level scores for each framing separately and dividing their sample correlation by the square root of the product of debiased variances. Scores are reversed in one framing, so that a correlation of 1 indicates perfect alignment of firm-level beliefs across the two framings.

Figure A4: Experimental measures of discrimination vs. beliefs, by subgroup



Notes: These figures report Errors-in-Variables (EIV) regressions of experimental log contact gaps on corresponding beliefs for various subsamples. The specifications and estimators are identical to columns (1) and (2) of Table 6 for panels A and B and columns (5) and (6) for panels C and D, except the sample is restricted to the group listed on the y-axis. The Δ note on the graph reports the difference in EIV coefficients between the subgroups along with its standard error. Panel A uses Likert scores for race beliefs and contact gaps, while panel C uses Borda scores. Panels B and D do the same for gender beliefs and contact gaps.

Appendix B: Additional tables

Table A1: Signal variances of firm-level beliefs across question framings

Outcome	Likert				Borda			
	Std Dev	Signal Std Dev	Reliability	T-stat no signal	Std Dev	Signal Std Dev	Reliability	T-stat no signal
Race								
Discrimination Black (Contact)	0.250	0.214	0.736	9.016	0.070	0.064	0.828	12.014
Discrimination Black - Black Wording (Contact)	0.335	0.283	0.714	8.782	0.090	0.079	0.777	10.388
Discrimination Black - White Wording (Contact)	0.229	0.150	0.429	4.476	0.065	0.052	0.622	6.657
Discrimination Black (Hire)	0.241	0.204	0.718	8.778	0.067	0.061	0.824	11.579
Discrimination Black - Black Wording (Hire)	0.331	0.278	0.706	8.783	0.085	0.074	0.770	9.997
Discrimination Black - White Wording (Hire)	0.210	0.124	0.352	3.576	0.062	0.049	0.615	6.511
Discrimination Black (Conduct)	0.319	0.240	0.566	6.133	0.078	0.066	0.729	8.704
Discrimination Black - Black Wording (Conduct)	0.319	0.240	0.566	6.133	0.078	0.066	0.729	8.704
Discrimination Black - White Wording (Conduct)	0.181	0.034	0.036	-1.755	0.032	0.010	0.098	0.284
Gender								
Discrimination Female (Contact)	0.398	0.377	0.898	15.459	0.099	0.094	0.905	16.799
Discrimination Female - Male Wording (Contact)	0.390	0.352	0.815	10.681	0.101	0.092	0.820	11.467
Discrimination Female - Female Wording (Contact)	0.448	0.411	0.842	11.940	0.109	0.100	0.841	12.692
Discrimination Female (Hire)	0.416	0.396	0.907	16.579	0.101	0.096	0.913	17.565
Discrimination Female - Male Wording (Hire)	0.414	0.377	0.831	11.139	0.100	0.091	0.828	11.569
Discrimination Female - Female Wording (Hire)	0.455	0.420	0.850	12.487	0.111	0.102	0.853	13.426
Discrimination Female (Conduct)	0.396	0.362	0.833	13.422	0.086	0.081	0.894	15.345
Discrimination Female - Male Wording (Conduct)	0.367	0.308	0.706	8.239	0.081	0.071	0.781	9.052
Discrimination Female - Female Wording (Conduct)	0.473	0.430	0.826	12.143	0.106	0.098	0.856	13.104
Age								
Discrimination Older (Conduct)	0.248	0.195	0.621	6.920	0.056	0.046	0.673	7.771
Discrimination Older - Younger Wording (Conduct)	0.393	0.330	0.706	8.514	0.097	0.087	0.806	11.386
Discrimination Older - Older Wording (Conduct)	0.328	0.252	0.592	6.966	0.079	0.064	0.660	8.073

Notes: This table reports estimates of the dispersion of Likert and Borda scores for each framing of key questions in the names and conduct arms. “Black wording” indicates that Black workers were the disfavored group in the question, and analogously for “White wording,” “Female wording,” etc. Columns labeled “Std Dev” report the square root of the sample variance of estimates. “Signal Std Dev” reports the square root of asymptotically unbiased estimates of the variances of scores, or $\hat{\sigma}_L$ and $\hat{\sigma}_B$, respectively. “Reliability” is the squared ratio of “Signal Std Dev” to “Std Dev”. “T-stat no signal” reports $\hat{\sigma}_L^2 / \widehat{\mathbb{V}}[\hat{\sigma}_L^2]^{0.5}$ and $\hat{\sigma}_B^2 / \widehat{\mathbb{V}}[\hat{\sigma}_B^2]^{0.5}$, which allows a t-test of the null hypothesis that the signal standard deviation is zero.

Table A2: Within- vs. between industry variance of firm-level beliefs

Outcome	Likert				Borda			
	Std Dev	Signal Std Dev	Reliability	T-stat no signal	Std Dev	Signal Std Dev	Reliability	T-stat no signal
Panel A: Within-industry								
Race								
Discrimination Black (Conduct)	0.258	0.165	0.407	3.751	0.059	0.045	0.577	5.608
Discrimination Black (Contact)	0.178	0.130	0.534	5.211	0.050	0.042	0.696	7.834
Discrimination Black (Hire)	0.173	0.124	0.512	4.951	0.049	0.041	0.710	8.020
Discrimination Black (Pooled)	0.187	0.152	0.662	7.302	0.049	0.044	0.793	10.419
Gender								
Discrimination Female (Conduct)	0.321	0.282	0.774	10.629	0.066	0.060	0.840	12.140
Discrimination Female (Contact)	0.303	0.279	0.844	12.042	0.075	0.069	0.852	13.003
Discrimination Female (Hire)	0.312	0.288	0.852	12.416	0.076	0.071	0.864	13.443
Discrimination Female (Pooled)	0.293	0.277	0.891	15.999	0.067	0.064	0.915	17.687
Age								
Discrimination Older (Conduct)	0.196	0.134	0.463	4.524	0.043	0.030	0.497	4.886
Firm characteristics								
Firm Desirability	0.116	0.076	0.422	3.836	0.032	0.025	0.595	6.231
Firm Selectivity	0.328	0.316	0.926	20.128	0.074	0.071	0.918	19.400
Manager Discretion	0.204	0.178	0.766	9.423	0.047	0.042	0.804	10.782
Panel B: Between-industry								
Race								
Discrimination Black (Conduct)	0.187	0.174	0.867	5.185	0.051	0.049	0.932	7.089
Discrimination Black (Contact)	0.176	0.170	0.942	7.950	0.050	0.049	0.962	9.870
Discrimination Black (Hire)	0.168	0.163	0.937	7.625	0.045	0.044	0.958	9.203
Discrimination Black (Pooled)	0.183	0.179	0.957	9.613	0.049	0.049	0.975	12.242
Gender								
Discrimination Female (Conduct)	0.233	0.226	0.946	8.468	0.055	0.054	0.971	11.088
Discrimination Female (Contact)	0.257	0.254	0.973	11.392	0.065	0.064	0.975	12.059
Discrimination Female (Hire)	0.276	0.272	0.977	12.653	0.066	0.065	0.977	12.580
Discrimination Female (Pooled)	0.243	0.241	0.980	13.795	0.059	0.059	0.986	16.381
Age								
Discrimination Older (Conduct)	0.151	0.142	0.887	5.565	0.036	0.035	0.913	6.284
Firm characteristics								
Firm Desirability	0.081	0.075	0.856	4.892	0.021	0.020	0.877	5.346
Firm Selectivity	0.497	0.496	0.996	32.357	0.120	0.120	0.996	33.045
Manager Discretion	0.317	0.315	0.988	17.401	0.073	0.073	0.990	18.505

Notes: This table reports estimates of the dispersion of Likert and Borda scores within- and between-industry. The outcomes are defined as in Table 4. Panel A presents within-industry variation computed by subtracting industry-average Likert or Borda scores from each firm's score, while panel B studies the dispersion in industry averages. The columns are the same as in Table 4.

Table A3: Means and signal variances across sub-samples

Subgroup	Race: Discrimination Black (Pooled)					Gender: Discrimination Female (Pooled)					Age: Discrimination Older (Conduct)				
	N resp.	Likert		Borda		N resp.	Likert		Borda		N resp.	Likert		Borda	
		Mean	Signal Std Dev	Mean	Signal Std Dev		Mean	Signal Std Dev	Mean	Signal Std Dev		Mean	Signal Std Dev	Mean	Signal Std Dev
Race															
Black	2,313	3.365	0.311	0.500	0.083	3,099	3.203	0.360	0.502	0.083	1,530	3.218	0.200	0.498	0.042
White	2,393	2.953	0.165	0.499	0.050	3,152	3.149	0.372	0.502	0.091	1,474	3.288	0.188	0.499	0.049
Gender															
Female	3,184	3.201	0.252	0.499	0.069	4,231	3.238	0.404	0.503	0.093	2,026	3.242	0.198	0.498	0.044
Male	1,522	3.055	0.198	0.500	0.060	2,020	3.051	0.297	0.502	0.077	978	3.276	0.197	0.497	0.049
Job Search															
Looking for a Job	2,025	3.190	0.240	0.499	0.069	2,673	3.170	0.378	0.503	0.092	1,297	3.220	0.226	0.497	0.051
Not Looking for a Job	2,681	3.127	0.239	0.500	0.063	3,578	3.180	0.358	0.502	0.084	1,707	3.275	0.176	0.499	0.048
Feared Discrimination															
Feared Discrimination	1,707	3.379	0.256	0.500	0.069	2,222	3.209	0.397	0.501	0.092	1,044	3.268	0.217	0.497	0.045
Did Not Fear Discrimination	2,999	3.025	0.224	0.499	0.064	4,029	3.156	0.351	0.503	0.085	1,960	3.246	0.193	0.498	0.050
Age															
Age ≥ 40	2,651	3.125	0.251	0.499	0.073	3,519	3.173	0.368	0.501	0.091	1,687	3.373	0.186	0.498	0.047
Age < 40	2,055	3.190	0.222	0.500	0.059	2,732	3.181	0.371	0.504	0.083	1,317	3.088	0.242	0.498	0.051
Education															
At Least Some College	3,332	3.186	0.246	0.499	0.070	4,445	3.206	0.395	0.502	0.095	2,126	3.293	0.210	0.499	0.049
HS Diploma or Less	1,374	3.080	0.223	0.501	0.053	1,806	3.102	0.306	0.504	0.068	878	3.147	0.167	0.498	0.042
Sample Type															
Convenience Sample	3,046	3.139	0.240	0.499	0.064	3,988	3.163	0.352	0.503	0.083	1,870	3.212	0.193	0.498	0.042
Probability Sample	1,660	3.183	0.239	0.501	0.067	2,263	3.195	0.394	0.502	0.093	1,134	3.318	0.192	0.499	0.051
Confidence (Gender)															
Confident (Gender)	2,001	3.145	0.278	0.501	0.071	2,778	3.229	0.380	0.502	0.084	1,528	3.256	0.197	0.497	0.045
Not Confident (Gender)	2,690	3.164	0.212	0.499	0.062	3,457	3.133	0.354	0.502	0.091	1,471	3.247	0.218	0.500	0.052
Confidence (Race)															
Confident (Race)	1,968	3.182	0.293	0.501	0.067	2,860	3.149	0.359	0.501	0.083	1,586	3.240	0.202	0.497	0.043
Not Confident (Race)	2,732	3.138	0.200	0.499	0.066	3,382	3.198	0.381	0.503	0.092	1,410	3.262	0.219	0.500	0.051

Notes: This table reports the total number of respondents, average firm-level beliefs, and the dispersion in beliefs across firms for key sample sub-groups and outcomes. “N resp.” is the number of unique survey respondents for each question-sample combination. “Mean” is the average Likert or Borda score equally weighted across firms, as is reported in Table 3. “Signal Std Dev” reports the square roots $\hat{\sigma}_L$ and $\hat{\sigma}_B$ of the Katz (1961)-corrected minimax variance estimates that account for sampling error, as in Table 4.

Table A4: Raw correlations in beliefs across samples

	Discrimination Black	Discrimination Female
Panel A: Likert (Raw Correlation)		
Black vs White	0.641	0.864
Female vs Male	0.624	0.803
Looking for a Job vs Not	0.635	0.857
Feared Discrimination vs Not	0.675	0.850
Age ≥ 40 vs < 40	0.638	0.849
At Least Some College vs HS Diploma or less	0.563	0.770
Convenience vs Probability	0.627	0.848
Confident vs Not (Gender)	0.626	0.873
Confident vs Not (Race)	0.645	0.830
Panel B: Borda (Raw Correlation)		
Black vs White	0.744	0.896
Female vs Male	0.737	0.848
Looking for a Job vs Not	0.793	0.883
Feared Discrimination vs Not	0.775	0.884
Age ≥ 40 vs < 40	0.729	0.892
At Least Some College vs HS Diploma or less	0.725	0.833
Convenience vs Probability	0.807	0.889
Confident vs Not (Gender)	0.797	0.880
Confident vs Not (Race)	0.789	0.871

Notes: This table reports the raw correlation in estimated beliefs across sample groups without adjustment for over-dispersion due to sampling error. Panel (a) uses Likert scores, while panel (b) uses Borda scores.

Table A5: Experimental measures of discrimination vs. contact and conduct beliefs

	Likert				Borda			
	Contact		Conduct		Contact		Conduct	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Race								
Beliefs	-0.021 (0.075)	0.236 (0.125)	0.045 (0.075)	0.280 (0.155)	0.012 (0.238)	0.843 (0.389)	-0.235 (0.240)	0.173 (0.392)
Panel B: Gender								
Beliefs	0.134 (0.055)	0.131 (0.065)	0.157 (0.060)	0.120 (0.065)	0.547 (0.218)	0.667 (0.276)	0.573 (0.245)	0.510 (0.263)
Industry FE	X		X		X		X	

Notes: This table reports Errors-in-Variables (EIV) regressions of experimental log contact gaps for race (panel A) and gender (panel B) on Likert and Borda scores from the names and conduct arms. Columns (1), (2), (5), and (6) use beliefs elicited from the contact question in names arm, while columns (3), (4), (7), and (8) use beliefs elicited from the conduct arm. Responses are recoded so that larger values indicate higher perceived contact/conduct gaps. Columns (2), (4), (6), and (8) add two-digit industry fixed effects. The EIV treats the regressor as measured with error; the measurement-error variance supplied to the estimator equals the sample variance of the observed regressor minus the Katz (1961)-corrected estimate $\hat{\sigma}_S^2$ of its signal variance.

Table A6: Beliefs vs. workforce composition

	Likert		Borda	
	Firm-level	Equal NAICS3	Firm-level	Equal NAICS3
Panel A: Race				
Black share: all jobs	-0.246 (0.051)	-0.150 (0.066)	-0.062 (0.013)	-0.040 (0.015)
NAICS3 industries	48	48	48	48
Firms	164	164	164	164
Black share: front-line jobs	-0.150 (0.058)	-0.064 (0.057)	-0.038 (0.015)	-0.019 (0.013)
NAICS3 industries	45	45	45	45
Firms	158	158	158	158
Panel B: Gender				
Female share: all jobs	-0.152 (0.018)	-0.131 (0.017)	-0.036 (0.005)	-0.031 (0.004)
NAICS3 industries	48	48	48	48
Firms	164	164	164	164
Female share: front-line jobs	-0.139 (0.020)	-0.125 (0.017)	-0.033 (0.005)	-0.029 (0.004)
NAICS3 industries	48	48	48	48
Firms	164	164	164	164

Notes: This table reports regressions of firm-level beliefs for race discrimination (panel A) and gender discrimination (panel B) on industry race and gender composition drawn from EEOC data merged at the NAICS3 level. Coefficients are normalized to reflect the implied impact of a 10 percentage point increase in shares. Industry-level workforce composition is taken from EEO-1 data from 2023 and merged at the NAICS3 level using the modal code for each firm’s establishments in the InfoGroup Historical Datafiles (InfoGroup, 2019). Front-line jobs are comprised of the EEO-1 job categories for sales workers, administrative support/clerical workers, craft workers, laborers and helpers, and service workers. The beliefs outcomes pool responses from the names and conduct arms recoded so that larger values indicate higher perceived contact/conduct gaps. All regressions are run at the NAICS3 level with robust standard errors. Columns titled “Firm-level” weight by the number of firms in each industry, while columns titled “Equal NAICS3” weight each industry equally. Firms where data for the assigned industry is suppressed due to confidentiality policies are omitted.

Table A7: Experimental measures of discrimination vs. beliefs and workforce composition

	Likert			Borda		
	No share	Front-line share	All-jobs share	No share	Front-line share	All-jobs share
Panel A: Race						
Discrimination beliefs	-0.007 (0.065)	-0.019 (0.078)	-0.021 (0.080)	-0.082 (0.226)	-0.110 (0.280)	-0.130 (0.293)
Black share: front-line jobs		-0.633 (0.405)			-0.632 (0.397)	
Black share: all jobs			-0.264 (0.449)			-0.279 (0.446)
Firms	97	96	97	97	96	97
Panel B: Gender						
Discrimination beliefs	0.148 (0.057)	0.082 (0.075)	0.094 (0.079)	0.563 (0.229)	0.225 (0.294)	0.270 (0.315)
Female share: front-line jobs		-0.263 (0.173)			-0.308 (0.171)	
Female share: all jobs			-0.206 (0.190)			-0.252 (0.190)
Firms	97	97	97	97	97	97

Notes: This table reports Errors-in-Variables (EIV) regressions of experimental log contact gaps for race (panel A) and gender (panel B) on Likert and Borda scores. All columns pool responses from the names and conduct arms recoded so that larger values indicate higher perceived contact/conduct gaps. Columns (1) and (4) include no additional controls; columns (2) and (5) control for composition among front-line jobs; columns (3) and (6) control composition among all jobs. The EIV treats the regressor as measured with error; the measurement-error variance supplied to the estimator equals the sample variance of the observed regressor minus the Katz (1961)-corrected estimate $\hat{\sigma}_S^2$ of its signal variance. Race and gender composition is assigned at the NAICS3 level, with industry-level workforce data taken from EEO-1 data from 2023 and merged at the NAICS3 level using the modal code for each firm's establishments in the InfoGroup Historical Datafiles (InfoGroup, 2019). Firms in industries where composition measures are suppressed are omitted. Standard errors are clustered at the NAICS3-level.

Table A8: Firm-specific estimates

Firm	Industry Group	Respondents with Firm in Choice Set	Race					Gender					Age				
			Discrimination Black (Pooled)					Discrimination Female (Pooled)					Discrimination Older (Conduct)				
			Likert		Borda		DK Share	Likert		Borda		DK Share	Likert		Borda		DK Share
			Raw	EB	Raw	EB		Raw	EB	Raw	EB		Raw	EB	Raw	EB	
JPMorgan Chase	Banks / securities	160	3.687 (0.118)	3.575	0.639 (0.024)	0.622	0.017	3.318 (0.110)	3.306	0.536 (0.021)	0.534	0.013	2.735 (0.167)	2.959	0.388 (0.033)	0.426	0.029
Lockheed Martin	Manufacturing	179	3.519 (0.112)	3.446	0.626 (0.022)	0.612	0.022	3.576 (0.100)	3.548	0.610 (0.021)	0.604	0.017	3.126 (0.157)	3.174	0.447 (0.032)	0.463	0.011
Republic Services	Electric / gas	154	3.480 (0.130)	3.408	0.627 (0.025)	0.612	0.117	3.463 (0.108)	3.440	0.591 (0.022)	0.585	0.107	2.986 (0.148)	3.089	0.395 (0.030)	0.426	0.113
Jones Financial	Banks / securities	152	3.712 (0.118)	3.593	0.625 (0.026)	0.609	0.037	3.397 (0.119)	3.376	0.573 (0.024)	0.568	0.007	3.25 (0.165)	3.241	0.452 (0.037)	0.470	0.000
General Dynamics	Manufacturing	157	3.482 (0.121)	3.413	0.617 (0.022)	0.604	0.000	3.552 (0.097)	3.527	0.610 (0.020)	0.604	0.033	3.232 (0.154)	3.238	0.498 (0.034)	0.498	0.028
U.S. Bancorp	Banks / securities	181	3.553 (0.115)	3.471	0.614 (0.021)	0.603	0.008	2.779 (0.098)	2.805	0.455 (0.021)	0.458	0.006	3.325 (0.146)	3.301	0.523 (0.028)	0.516	0.024
Synnex	Personal / business services	138	3.466 (0.137)	3.397	0.616 (0.023)	0.603	0.033	3.465 (0.117)	3.438	0.575 (0.023)	0.570	0.023	3.147 (0.160)	3.186	0.533 (0.030)	0.522	0.029
Morgan Stanley	Banks / securities	161	3.732 (0.123)	3.604	0.616 (0.025)	0.601	0.034	3.482 (0.106)	3.458	0.576 (0.022)	0.572	0.099	2.983 (0.153)	3.089	0.459 (0.040)	0.475	0.119
Cognizant Technology Solutions	Personal / business services	140	3.575 (0.144)	3.472	0.610 (0.030)	0.593	0.033	3.476 (0.122)	3.447	0.574 (0.023)	0.570	0.053	3 (0.165)	3.103	0.487 (0.037)	0.491	0.015
Bank of America Corp.	Banks / securities	151	3.664 (0.112)	3.562	0.606 (0.026)	0.593	0.009	3.056 (0.108)	3.066	0.476 (0.022)	0.478	0.014	2.92 (0.196)	3.068	0.398 (0.041)	0.441	0.000
Boeing	Manufacturing	149	3.547 (0.142)	3.454	0.605 (0.026)	0.591	0.104	3.756 (0.111)	3.706	0.616 (0.021)	0.610	0.049	3.047 (0.170)	3.128	0.433 (0.034)	0.456	0.045
Northrop Grumman	Manufacturing	139	3.356 (0.131)	3.317	0.603 (0.026)	0.589	0.054	3.427 (0.108)	3.407	0.527 (0.022)	0.525	0.051	3.097 (0.172)	3.155	0.445 (0.035)	0.464	0.046
Collins Aerospace	Health and engineering services	168	3.552 (0.126)	3.464	0.597 (0.024)	0.586	0.033	3.465 (0.109)	3.441	0.601 (0.021)	0.596	0.025	3.014 (0.152)	3.107	0.452 (0.035)	0.468	0.026
Estee Lauder	Personal / business services	173	3.454 (0.122)	3.391	0.598 (0.027)	0.585	0.000	2.206 (0.096)	2.268	0.291 (0.022)	0.304	0.000	3.277 (0.130)	3.281	0.528 (0.030)	0.519	0.000
Abbott Laboratories	Health and engineering services	163	3.410 (0.117)	3.358	0.592 (0.022)	0.582	0.033	3.096 (0.099)	3.101	0.488 (0.020)	0.489	0.025	3.103 (0.158)	3.160	0.452 (0.030)	0.466	0.013
BB&T Corp.	Banks / securities	158	3.523 (0.116)	3.447	0.588 (0.022)	0.579	0.009	3.163 (0.105)	3.164	0.481 (0.020)	0.482	0.006	3.182 (0.144)	3.211	0.467 (0.029)	0.476	0.000
Pratt & Whitney	Manufacturing	160	3.5 (0.117)	3.428	0.587 (0.023)	0.577	0.097	3.184 (0.108)	3.183	0.471 (0.021)	0.473	0.105	3.125 (0.169)	3.171	0.466 (0.033)	0.477	0.135
Hilton Worldwide Holdings	Accommodation / real estate	170	3.487 (0.117)	3.418	0.588 (0.025)	0.577	0.050	3.121 (0.097)	3.124	0.486 (0.020)	0.487	0.025	3.186 (0.153)	3.211	0.461 (0.030)	0.472	0.041
Citigroup	Banks / securities	167	3.366 (0.116)	3.323	0.586 (0.022)	0.577	0.008	3.299 (0.096)	3.291	0.524 (0.019)	0.523	0.019	2.962 (0.144)	3.072	0.467 (0.028)	0.476	0.000
Lear	Manufacturing	163	3.479 (0.115)	3.412	0.586 (0.022)	0.577	0.093	3.301 (0.113)	3.290	0.543 (0.021)	0.541	0.142	3.233 (0.177)	3.223	0.525 (0.034)	0.516	0.130
Jones Lang LaSalle	Accommodation / real estate	151	3.379 (0.129)	3.333	0.585 (0.025)	0.575	0.087	3.228 (0.120)	3.223	0.557 (0.022)	0.553	0.128	3 (0.177)	3.104	0.455 (0.042)	0.474	0.172
Nordstrom	General merchandise	177	3.383 (0.108)	3.337	0.584 (0.024)	0.574	0.000	2.413 (0.087)	2.452	0.301 (0.018)	0.310	0.011	3.369 (0.128)	3.346	0.496 (0.030)	0.497	0.012
CBRE Group	Accommodation / real estate	158	3.439 (0.127)	3.379	0.581 (0.021)	0.572	0.070	3.384 (0.111)	3.367	0.542 (0.022)	0.540	0.074	3.190 (0.175)	3.202	0.474 (0.037)	0.483	0.159
Amphenol	Manufacturing	159	3.406 (0.113)	3.355	0.578 (0.023)	0.569	0.073	3.263 (0.101)	3.257	0.538 (0.019)	0.536	0.074	3.066 (0.165)	3.139	0.453 (0.032)	0.468	0.103
LKQ	Wholesale trade	139	3.368 (0.136)	3.326	0.574 (0.026)	0.565	0.103	3.433 (0.114)	3.411	0.562 (0.023)	0.558	0.104	3.241 (0.161)	3.238	0.465 (0.038)	0.478	0.129
Merck	Manufacturing	174	3.358 (0.103)	3.318	0.569 (0.021)	0.561	0.062	3.302 (0.099)	3.294	0.529 (0.018)	0.528	0.058	3.291 (0.140)	3.284	0.489 (0.032)	0.492	0.081
Pfizer	Manufacturing	182	3.528 (0.110)	3.454	0.569 (0.023)	0.561	0.016	3.272 (0.101)	3.265	0.494 (0.020)	0.494	0.029	3.013 (0.149)	3.106	0.464 (0.032)	0.475	0.050
Hertz Global Holdings	Repair services	140	3.359 (0.113)	3.318	0.569 (0.024)	0.561	0.028	3.260 (0.110)	3.253	0.508 (0.022)	0.507	0.015	3.254 (0.172)	3.237	0.514 (0.036)	0.508	0.017
United Continental Holdings	Freight / transport	175	3.484 (0.098)	3.425	0.567 (0.021)	0.560	0.015	2.905 (0.097)	2.923	0.420 (0.018)	0.424	0.006	3.101 (0.144)	3.160	0.459 (0.034)	0.473	0.025
Ascena Retail Group	Apparel stores	172	3.370 (0.121)	3.326	0.566 (0.025)	0.558	0.025	2.409 (0.109)	2.472	0.340 (0.024)	0.351	0.012	3.169 (0.135)	3.205	0.448 (0.035)	0.466	0.025
Honeywell International	Wholesale trade	163	3.3 (0.128)	3.274	0.563 (0.022)	0.556	0.052	3.152 (0.106)	3.154	0.517 (0.021)	0.517	0.065	2.929 (0.169)	3.065	0.436 (0.029)	0.454	0.054
Wells Fargo	Banks / securities	152	3.429 (0.126)	3.371	0.559 (0.024)	0.552	0.000	3.076 (0.120)	3.087	0.472 (0.021)	0.473	0.000	2.814 (0.186)	3.016	0.456 (0.034)	0.471	0.000
Laboratory Corp. of America	Health and engineering services	173	3.311 (0.113)	3.280	0.559 (0.023)	0.552	0.024	3.072 (0.100)	3.079	0.472 (0.022)	0.474	0.006	2.896 (0.145)	3.031	0.369 (0.029)	0.406	0.013
Omnicom Group	Personal / business services	167	3.355 (0.118)	3.314	0.558 (0.022)	0.552	0.093	3.352 (0.102)	3.339	0.530 (0.018)	0.529	0.099	3.053 (0.145)	3.130	0.442 (0.028)	0.458	0.074
3M	Wholesale trade	148	3.149 (0.121)	3.154	0.558 (0.025)	0.551	0.029	3.133 (0.106)	3.137	0.506 (0.022)	0.506	0.022	2.923 (0.163)	3.059	0.410 (0.031)	0.437	0.000
ADP	Personal / business services	162	3.440 (0.125)	3.380	0.557 (0.024)	0.550	0.121	3.218 (0.109)	3.215	0.487 (0.020)	0.488	0.107	3.197 (0.168)	3.209	0.464 (0.034)	0.476	0.062
IBM	Personal / business services	191	3.434 (0.102)	3.381	0.554 (0.021)	0.548	0.029	3.156 (0.094)	3.157	0.5 (0.019)	0.500	0.032	2.952 (0.148)	3.068	0.441 (0.030)	0.458	0.046
Dell Technologies	Personal / business services	161	3.316 (0.120)	3.284	0.551 (0.022)	0.545	0.015	3.371 (0.103)	3.357	0.532 (0.021)	0.531	0.013	3.562 (0.164)	3.416	0.534 (0.033)	0.522	0.000
Tractor Supply	Wholesale trade	155	3.182 (0.126)	3.184	0.547 (0.025)	0.542	0.018	3.796 (0.100)	3.753	0.650 (0.020)	0.643	0.007	3.132 (0.164)	3.176	0.456 (0.036)	0.471	0.029
WestRock	Manufacturing	171	3.298 (0.130)	3.273	0.545 (0.024)	0.540	0.236	3.361 (0.117)	3.344	0.572 (0.021)	0.568	0.233	2.817 (0.152)	2.988	0.447 (0.029)	0.462	0.241
DaVita	Health and engineering services	160	3.175 (0.110)	3.169	0.543 (0.022)	0.538	0.142	2.794 (0.104)	2.823	0.422 (0.021)	0.426	0.090	2.968 (0.160)	3.083	0.443 (0.031)	0.461	0.113
Community Health Systems	Health and engineering services	132	3.143 (0.135)	3.162	0.543 (0.025)	0.538	0.030	2.643 (0.116)	2.693	0.402 (0.024)	0.409	0.031	3.018 (0.195)	3.112	0.470 (0.037)	0.480	0.000
Cardinal Health	Wholesale trade	153	3.417 (0.116)	3.363	0.542 (0.021)	0.537	0.018	2.769 (0.102)	2.799	0.442 (0.022)	0.446	0.014	2.859 (0.167)	3.026	0.422 (0.033)	0.448	0.015
Builders FirstSource	Manufacturing	180	3.442 (0.108)	3.385	0.542 (0.023)	0.537	0.030	3.873 (0.098)	3.826	0.638 (0.020)	0.631	0.011	3.464 (0.147)	3.386	0.537 (0.031)	0.525	0.028

Firm	Industry Group	Respondents with Firm in Choice Set	Race					Gender					Age				
			Discrimination Black (Pooled)					Discrimination Female (Pooled)					Discrimination Older (Conduct)				
			Likert		Borda		DK Share	Likert		Borda		DK Share	Likert		Borda		DK Share
			Raw	EB	Raw	EB		Raw	EB	Raw	EB		Raw	EB	Raw	EB	
American Airlines Group	Freight / transport	164	3.242 (0.105)	3.222	0.541 (0.024)	0.536	0.000	2.886 (0.098)	2.905	0.436 (0.021)	0.440	0.013	3.362 (0.155)	3.315	0.493 (0.033)	0.494	0.000
Macy's	General merchandise	159	3.149 (0.122)	3.156	0.541 (0.026)	0.536	0.017	2.494 (0.111)	2.553	0.343 (0.022)	0.353	0.006	3.314 (0.165)	3.277	0.547 (0.036)	0.528	0.000
Apple	Personal / business services	172	3.370 (0.124)	3.326	0.540 (0.025)	0.535	0.000	3.229 (0.101)	3.225	0.532 (0.021)	0.530	0.000	3.386 (0.155)	3.329	0.537 (0.030)	0.526	0.000
Emerson Electric	Health and engineering services	155	3.515 (0.115)	3.441	0.540 (0.025)	0.535	0.038	3.582 (0.106)	3.551	0.590 (0.022)	0.584	0.027	2.924 (0.152)	3.053	0.482 (0.031)	0.487	0.029
DowDuPont	Manufacturing	153	3.184 (0.121)	3.182	0.539 (0.028)	0.535	0.058	3.326 (0.106)	3.315	0.565 (0.019)	0.563	0.055	3.143 (0.147)	3.186	0.467 (0.028)	0.476	0.061
BNSF Railway	Freight / transport	158	3.093 (0.124)	3.114	0.539 (0.025)	0.534	0.070	3.535 (0.108)	3.507	0.608 (0.021)	0.602	0.066	3.346 (0.147)	3.313	0.5 (0.032)	0.499	0.037
Geico	Banks / securities	177	3.346 (0.105)	3.308	0.538 (0.020)	0.534	0.016	3.225 (0.098)	3.222	0.481 (0.019)	0.482	0.024	3.171 (0.148)	3.204	0.413 (0.027)	0.436	0.050
International Paper	Manufacturing	140	3.139 (0.118)	3.145	0.537 (0.024)	0.533	0.018	3.440 (0.101)	3.422	0.540 (0.020)	0.538	0.015	3.293 (0.146)	3.281	0.450 (0.033)	0.467	0.094
Humana	Banks / securities	170	3.412 (0.105)	3.362	0.535 (0.019)	0.531	0.022	2.925 (0.099)	2.942	0.422 (0.019)	0.426	0.025	3.056 (0.152)	3.133	0.407 (0.027)	0.432	0.027
Procter & Gamble	Manufacturing	170	3.202 (0.113)	3.192	0.535 (0.021)	0.531	0.000	3.160 (0.100)	3.161	0.494 (0.019)	0.494	0.018	3.108 (0.150)	3.164	0.484 (0.029)	0.488	0.039
Quest Diagnostics	Health and engineering services	153	3.231 (0.119)	3.218	0.534 (0.025)	0.530	0.009	2.909 (0.118)	2.935	0.465 (0.021)	0.467	0.014	3.203 (0.173)	3.210	0.497 (0.027)	0.498	0.015
Johnson & Johnson	Health and engineering services	174	3.279 (0.114)	3.254	0.533 (0.021)	0.530	0.015	3.077 (0.089)	3.082	0.463 (0.020)	0.465	0.018	3.218 (0.139)	3.237	0.533 (0.027)	0.524	0.013
Microsoft	Personal / business services	156	3.216 (0.129)	3.211	0.532 (0.025)	0.529	0.000	3.172 (0.104)	3.173	0.513 (0.020)	0.513	0.013	3.333 (0.167)	3.285	0.550 (0.034)	0.531	0.000
Aetna	Banks / securities	158	3.273 (0.126)	3.252	0.532 (0.023)	0.528	0.020	3 (0.110)	3.015	0.474 (0.022)	0.476	0.034	3.352 (0.151)	3.313	0.498 (0.032)	0.498	0.027
Intel	Personal / business services	185	3.291 (0.099)	3.262	0.530 (0.021)	0.527	0.022	3.339 (0.092)	3.329	0.529 (0.017)	0.528	0.011	3.425 (0.150)	3.359	0.541 (0.027)	0.530	0.024
General Electric	Manufacturing	168	3.333 (0.116)	3.297	0.529 (0.021)	0.526	0.018	3.704 (0.095)	3.670	0.582 (0.019)	0.578	0.006	3.268 (0.137)	3.271	0.523 (0.026)	0.517	0.000
Conduent	Wholesale trade	151	3.202 (0.127)	3.199	0.529 (0.023)	0.526	0.048	3.239 (0.104)	3.235	0.529 (0.020)	0.528	0.027	3.171 (0.148)	3.204	0.475 (0.029)	0.482	0.026
UGI	Electric / gas	181	3.151 (0.113)	3.151	0.528 (0.023)	0.525	0.085	3.522 (0.098)	3.499	0.577 (0.019)	0.573	0.053	3.351 (0.164)	3.298	0.486 (0.028)	0.490	0.086
Universal Health Services	Health and engineering services	163	3.402 (0.119)	3.351	0.528 (0.026)	0.525	0.018	2.665 (0.099)	2.699	0.394 (0.021)	0.400	0.006	3.162 (0.146)	3.199	0.417 (0.032)	0.444	0.013
Aramark	Personal / business services	149	3.183 (0.139)	3.194	0.527 (0.025)	0.524	0.070	3.147 (0.105)	3.150	0.507 (0.022)	0.506	0.072	3.530 (0.155)	3.414	0.513 (0.034)	0.508	0.070
Ryder System	Freight / transport	151	3.255 (0.121)	3.237	0.525 (0.022)	0.522	0.113	3.438 (0.114)	3.415	0.553 (0.022)	0.550	0.117	3.118 (0.170)	3.166	0.454 (0.041)	0.473	0.121
Exxon Mobil	Auto dealers / services / parts	161	3.181 (0.113)	3.176	0.524 (0.023)	0.521	0.033	3.333 (0.107)	3.321	0.580 (0.021)	0.575	0.013	3.323 (0.170)	3.275	0.459 (0.032)	0.471	0.016
Kindred Healthcare	Health and engineering services	168	3.282 (0.104)	3.255	0.524 (0.021)	0.521	0.031	2.497 (0.100)	2.544	0.370 (0.021)	0.377	0.013	2.918 (0.175)	3.062	0.437 (0.035)	0.459	0.000
Cisco Systems	Manufacturing	150	3.361 (0.108)	3.320	0.522 (0.025)	0.520	0.018	3.295 (0.105)	3.286	0.536 (0.020)	0.534	0.041	3.453 (0.159)	3.362	0.471 (0.030)	0.479	0.015
Nationwide	Banks / securities	147	3.030 (0.131)	3.074	0.522 (0.022)	0.519	0.000	3.234 (0.107)	3.230	0.498 (0.020)	0.498	0.000	3.247 (0.147)	3.251	0.466 (0.030)	0.476	0.024
McLane Company	Wholesale trade	149	3.323 (0.119)	3.289	0.521 (0.022)	0.519	0.119	3.3 (0.112)	3.290	0.546 (0.022)	0.544	0.155	3.070 (0.168)	3.141	0.427 (0.030)	0.448	0.149
Stanley Black & Decker	Manufacturing	157	3.345 (0.110)	3.306	0.521 (0.020)	0.519	0.008	3.68 (0.106)	3.641	0.612 (0.021)	0.606	0.020	3.131 (0.168)	3.174	0.481 (0.029)	0.486	0.000
Dillard's	General merchandise	159	3.365 (0.105)	3.323	0.518 (0.025)	0.516	0.025	2.631 (0.099)	2.668	0.372 (0.021)	0.379	0.007	3.069 (0.169)	3.140	0.547 (0.036)	0.528	0.000
UnitedHealth Group	Health and engineering services	167	3.188 (0.111)	3.180	0.517 (0.021)	0.515	0.033	3.013 (0.107)	3.026	0.448 (0.020)	0.451	0.012	2.797 (0.140)	2.962	0.401 (0.028)	0.427	0.013
Allstate	Banks / securities	174	3.140 (0.111)	3.142	0.517 (0.021)	0.515	0.000	2.969 (0.105)	2.985	0.450 (0.018)	0.453	0.012	2.778 (0.133)	2.939	0.418 (0.029)	0.441	0.011
Fruit of the Loom	Food stores	153	3.184 (0.116)	3.179	0.516 (0.024)	0.514	0.017	3.228 (0.103)	3.224	0.539 (0.022)	0.536	0.014	3.343 (0.135)	3.322	0.500 (0.031)	0.499	0.014
Tenet Healthcare	Health and engineering services	171	3.238 (0.112)	3.220	0.514 (0.020)	0.512	0.016	2.937 (0.099)	2.953	0.421 (0.021)	0.425	0.030	3.2 (0.163)	3.214	0.519 (0.034)	0.511	0.071
AECOM	Health and engineering services	158	3.159 (0.119)	3.161	0.511 (0.028)	0.511	0.018	3.866 (0.104)	3.814	0.668 (0.023)	0.657	0.020	3.397 (0.150)	3.342	0.528 (0.036)	0.517	0.014
Oracle	Personal / business services	165	3.25 (0.113)	3.230	0.512 (0.026)	0.511	0.074	3.203 (0.095)	3.201	0.515 (0.019)	0.514	0.057	3.125 (0.156)	3.174	0.469 (0.029)	0.478	0.100
Jabil	Manufacturing	172	3.231 (0.131)	3.223	0.509 (0.028)	0.510	0.278	3.104 (0.099)	3.109	0.494 (0.022)	0.495	0.299	3.259 (0.168)	3.243	0.468 (0.041)	0.480	0.348
Marriott International	Accommodation / real estate	156	3.202 (0.110)	3.191	0.510 (0.026)	0.510	0.008	2.876 (0.099)	2.896	0.428 (0.021)	0.432	0.000	3.216 (0.142)	3.234	0.475 (0.028)	0.481	0.013
Philip Morris International	Health and engineering services	160	3.066 (0.120)	3.090	0.508 (0.025)	0.508	0.016	3.653 (0.094)	3.624	0.632 (0.021)	0.626	0.020	3.043 (0.159)	3.126	0.446 (0.035)	0.465	0.000
Whirlpool	Manufacturing	147	3.229 (0.121)	3.217	0.508 (0.025)	0.508	0.000	3.674 (0.111)	3.632	0.581 (0.022)	0.577	0.007	3.090 (0.160)	3.153	0.436 (0.034)	0.458	0.000
VF	Apparel stores	157	3.035 (0.124)	3.069	0.507 (0.024)	0.507	0.009	3.231 (0.105)	3.227	0.509 (0.020)	0.509	0.020	3.591 (0.148)	3.463	0.557 (0.036)	0.534	0.000
Ford Motor	Manufacturing	152	3.268 (0.114)	3.245	0.506 (0.026)	0.506	0.000	3.710 (0.107)	3.668	0.601 (0.020)	0.596	0.000	3.105 (0.121)	3.159	0.451 (0.032)	0.466	0.000
HCA Healthcare	Health and engineering services	170	3.258 (0.101)	3.235	0.506 (0.022)	0.505	0.008	2.799 (0.102)	2.826	0.374 (0.021)	0.381	0.000	3.284 (0.149)	3.273	0.464 (0.029)	0.474	0.026
J.C. Penney	General merchandise	167	3.123 (0.116)	3.131	0.502 (0.026)	0.502	0.019	2.481 (0.102)	2.531	0.357 (0.021)	0.365	0.006	3.185 (0.147)	3.213	0.485 (0.034)	0.489	0.000
Disney	Other retail	164	3.097 (0.124)	3.118	0.498 (0.026)	0.500	0.026	2.732 (0.101)	2.764	0.408 (0.021)	0.413	0.013	3.875 (0.155)	3.619	0.636 (0.035)	0.585	0.014
AT&T	Communications	176	3.118 (0.110)	3.123	0.499 (0.023)	0.499	0.000	3.172 (0.095)	3.172	0.508 (0.020)	0.508	0.006	3.724 (0.134)	3.582	0.589 (0.023)	0.572	0.000
Sysco	Wholesale trade	172	3.024 (0.115)	3.052	0.497 (0.021)	0.497	0.046	3.396 (0.100)	3.381	0.528 (0.019)	0.527	0.036	3.679 (0.149)	3.517	0.513 (0.030)	0.509	0.037
United Rentals	Personal / business services	153	3.082 (0.122)	3.104	0.495 (0.023)	0.496	0.018	3.390 (0.108)	3.373	0.569 (0.020)	0.566	0.007	3.263 (0.152)	3.258	0.493 (0.027)	0.495	0.013

Firm	Industry Group	Respondents with Firm in Choice Set	Race					Gender					Age				
			Discrimination Black (Pooled)					Discrimination Female (Pooled)					Discrimination Older (Conduct)				
			Likert		Borda		DK Share	Likert		Borda		DK Share	Likert		Borda		DK Share
			Raw	EB	Raw	EB		Raw	EB	Raw	EB		Raw	EB	Raw	EB	
Delta Air Lines	Freight / transport	153	2.916 (0.121)	2.974	0.495 (0.020)	0.495	0.009	2.850 (0.115)	2.881	0.436 (0.022)	0.440	0.007	3.438 (0.145)	3.374	0.517 (0.031)	0.511	0.000
Alphabet	Health and engineering services	143	3.2 (0.145)	3.211	0.492 (0.026)	0.494	0.022	3.182 (0.114)	3.182	0.522 (0.023)	0.521	0.029	3.910 (0.150)	3.654	0.624 (0.033)	0.581	0.043
Charter Communications	Communications	173	3.062 (0.119)	3.086	0.491 (0.023)	0.492	0.008	3.170 (0.100)	3.170	0.501 (0.019)	0.501	0.042	3.268 (0.149)	3.263	0.520 (0.027)	0.515	0.057
Gap	Apparel stores	161	3.224 (0.107)	3.208	0.490 (0.025)	0.492	0.017	2.520 (0.096)	2.561	0.369 (0.021)	0.377	0.013	3.967 (0.158)	3.662	0.600 (0.032)	0.566	0.016
Bed Bath & Beyond	Home furnishing stores	161	3.058 (0.119)	3.083	0.487 (0.025)	0.489	0.008	2.226 (0.103)	2.296	0.300 (0.021)	0.312	0.013	3.494 (0.149)	3.402	0.532 (0.035)	0.519	0.000
XPO Logistics	Freight / transport	158	3.444 (0.102)	3.390	0.486 (0.022)	0.487	0.085	3.447 (0.100)	3.428	0.558 (0.021)	0.555	0.066	3.055 (0.159)	3.133	0.485 (0.037)	0.489	0.083
Victoria's Secret	Apparel stores	163	3.131 (0.130)	3.148	0.482 (0.028)	0.487	0.009	1.949 (0.106)	2.045	0.262 (0.024)	0.279	0.019	3.791 (0.148)	3.588	0.654 (0.031)	0.605	0.000
GameStop	Home furnishing stores	171	2.798 (0.114)	2.871	0.484 (0.024)	0.486	0.008	3.364 (0.103)	3.350	0.546 (0.021)	0.544	0.000	3.679 (0.154)	3.504	0.655 (0.033)	0.602	0.000
O'Reilly Automotive	Auto dealers / services / parts	143	3.03 (0.128)	3.070	0.482 (0.027)	0.486	0.010	3.927 (0.102)	3.873	0.676 (0.022)	0.666	0.007	3.118 (0.164)	3.168	0.465 (0.033)	0.476	0.000
Performance Food Group	Wholesale trade	161	3.045 (0.125)	3.078	0.483 (0.024)	0.486	0.051	3.15 (0.106)	3.152	0.492 (0.020)	0.492	0.085	3.25 (0.143)	3.256	0.460 (0.032)	0.472	0.053
PepsiCo	Food products	152	3.161 (0.109)	3.157	0.481 (0.023)	0.483	0.008	3.390 (0.101)	3.375	0.543 (0.021)	0.541	0.014	3.421 (0.166)	3.334	0.518 (0.034)	0.511	0.000
Sherwin-Williams	Building materials	182	3.205 (0.102)	3.190	0.481 (0.019)	0.482	0.022	3.523 (0.093)	3.502	0.554 (0.017)	0.552	0.022	2.921 (0.152)	3.051	0.475 (0.031)	0.482	0.013
Pilot Flying J	Auto dealers / services / parts	162	3.026 (0.115)	3.054	0.477 (0.025)	0.481	0.042	3.338 (0.100)	3.327	0.511 (0.021)	0.511	0.045	2.985 (0.151)	3.090	0.505 (0.030)	0.503	0.056
CVS Health	Other retail	154	3.210 (0.105)	3.196	0.477 (0.025)	0.481	0.000	2.716 (0.100)	2.748	0.371 (0.021)	0.378	0.000	3.328 (0.150)	3.299	0.552 (0.033)	0.534	0.000
AutoNation	Auto dealers / services / parts	145	3.317 (0.123)	3.286	0.474 (0.026)	0.479	0.019	3.551 (0.113)	3.519	0.617 (0.024)	0.609	0.022	3.3 (0.150)	3.282	0.542 (0.035)	0.526	0.032
Sears Holdings	Repair services	164	3.017 (0.108)	3.040	0.475 (0.024)	0.478	0.025	2.974 (0.105)	2.989	0.459 (0.020)	0.461	0.013	3.471 (0.172)	3.351	0.525 (0.032)	0.517	0.042
Dick's Sporting Goods	Other retail	171	3.08 (0.117)	3.098	0.476 (0.023)	0.478	0.016	3.466 (0.103)	3.445	0.577 (0.020)	0.573	0.006	3.571 (0.154)	3.440	0.555 (0.034)	0.535	0.013
Ulta Beauty	Personal / business services	158	3 (0.110)	3.027	0.474 (0.022)	0.477	0.034	1.960 (0.094)	2.034	0.237 (0.022)	0.253	0.007	3.861 (0.137)	3.667	0.670 (0.034)	0.608	0.027
Cintas	Personal / business services	152	3.196 (0.133)	3.199	0.470 (0.028)	0.477	0.085	3.131 (0.119)	3.136	0.516 (0.022)	0.515	0.122	3.164 (0.166)	3.193	0.508 (0.030)	0.505	0.164
Avis Budget Group	Repair services	146	3.189 (0.116)	3.183	0.473 (0.024)	0.476	0.000	3.305 (0.116)	3.294	0.515 (0.023)	0.514	0.007	3.172 (0.159)	3.200	0.479 (0.029)	0.485	0.000
Mondelez International	Food products	151	3.032 (0.123)	3.067	0.471 (0.026)	0.476	0.069	3.270 (0.103)	3.263	0.537 (0.020)	0.535	0.035	3.159 (0.168)	3.189	0.486 (0.033)	0.490	0.031
Caterpillar	Wholesale trade	148	3.071 (0.133)	3.108	0.466 (0.028)	0.473	0.097	3.496 (0.123)	3.464	0.614 (0.024)	0.606	0.065	3.344 (0.169)	3.289	0.537 (0.033)	0.524	0.086
Comcast	Communications	192	3.125 (0.097)	3.122	0.469 (0.021)	0.471	0.014	3.262 (0.093)	3.257	0.551 (0.019)	0.549	0.005	3.090 (0.148)	3.153	0.459 (0.034)	0.472	0.013
Otis	Manufacturing	162	3.066 (0.116)	3.086	0.460 (0.027)	0.467	0.054	3.550 (0.104)	3.522	0.584 (0.023)	0.579	0.019	3.087 (0.134)	3.150	0.433 (0.031)	0.454	0.042
Albertsons	Food stores	156	3.153 (0.114)	3.153	0.461 (0.026)	0.467	0.008	2.986 (0.108)	3.002	0.447 (0.021)	0.450	0.020	2.919 (0.183)	3.065	0.411 (0.038)	0.445	0.000
Verizon	Communications	176	3.096 (0.103)	3.101	0.464 (0.021)	0.467	0.016	3.030 (0.095)	3.039	0.492 (0.018)	0.492	0.000	3.243 (0.148)	3.248	0.537 (0.036)	0.522	0.000
Genuine Parts	Auto dealers / services / parts	175	3.122 (0.109)	3.125	0.461 (0.025)	0.467	0.000	3.876 (0.100)	3.827	0.658 (0.021)	0.649	0.000	2.944 (0.137)	3.056	0.459 (0.026)	0.469	0.000
State Farm Insurance Cos.	Banks / securities	156	3.231 (0.137)	3.228	0.461 (0.024)	0.465	0.009	2.979 (0.104)	2.994	0.440 (0.020)	0.444	0.007	2.746 (0.168)	2.966	0.447 (0.033)	0.464	0.000
J.B. Hunt Transport Services	Freight / transport	166	2.835 (0.122)	2.913	0.457 (0.025)	0.463	0.034	3.525 (0.102)	3.500	0.624 (0.020)	0.618	0.031	3.293 (0.148)	3.279	0.483 (0.030)	0.488	0.024
Icahn Enterprises	Health and engineering services	176	3.031 (0.100)	3.045	0.456 (0.023)	0.461	0.016	3.886 (0.093)	3.844	0.630 (0.021)	0.623	0.023	3.276 (0.134)	3.278	0.511 (0.028)	0.508	0.073
Carrier	Manufacturing	150	3.092 (0.116)	3.106	0.455 (0.024)	0.461	0.039	3.374 (0.102)	3.360	0.517 (0.022)	0.516	0.028	3.324 (0.146)	3.300	0.544 (0.033)	0.529	0.056
CarMax	Auto dealers / services / parts	159	2.911 (0.119)	2.968	0.454 (0.024)	0.460	0.019	3.404 (0.115)	3.384	0.597 (0.022)	0.592	0.027	3.268 (0.153)	3.260	0.550 (0.030)	0.534	0.014
Bath & Body Works	Other retail	172	2.865 (0.117)	2.930	0.452 (0.025)	0.458	0.000	2.228 (0.104)	2.299	0.302 (0.023)	0.315	0.000	3.15 (0.162)	3.187	0.558 (0.034)	0.537	0.000
Ross Stores	General merchandise	182	2.899 (0.106)	2.941	0.453 (0.023)	0.458	0.007	2.741 (0.101)	2.772	0.363 (0.021)	0.371	0.012	3.597 (0.150)	3.465	0.543 (0.032)	0.528	0.025
Murphy USA	Auto dealers / services / parts	165	2.914 (0.120)	2.972	0.450 (0.024)	0.457	0.162	3.213 (0.112)	3.210	0.522 (0.020)	0.521	0.160	3.306 (0.162)	3.275	0.454 (0.031)	0.468	0.143
Rite Aid	Other retail	155	3.029 (0.119)	3.060	0.447 (0.025)	0.455	0.010	2.973 (0.106)	2.989	0.429 (0.021)	0.433	0.013	3.060 (0.155)	3.136	0.498 (0.033)	0.498	0.000
General Motors	Manufacturing	161	2.954 (0.131)	3.018	0.450 (0.022)	0.455	0.000	3.599 (0.104)	3.567	0.632 (0.019)	0.626	0.000	3.191 (0.139)	3.219	0.489 (0.028)	0.492	0.000
Dr Pepper Snapple Group	Food products	163	3.059 (0.116)	3.081	0.446 (0.025)	0.453	0.025	3.255 (0.105)	3.249	0.552 (0.020)	0.550	0.013	3.101 (0.145)	3.160	0.458 (0.028)	0.470	0.014
Starbucks	Eating / drinking	206	2.921 (0.102)	2.953	0.444 (0.022)	0.450	0.000	2.536 (0.093)	2.574	0.359 (0.017)	0.364	0.020	3.515 (0.141)	3.428	0.545 (0.029)	0.532	0.010
Olive Garden	Eating / drinking	155	2.95 (0.108)	2.985	0.440 (0.026)	0.449	0.000	2.662 (0.101)	2.698	0.378 (0.021)	0.385	0.000	3.708 (0.137)	3.564	0.567 (0.031)	0.545	0.014
Publix Super Markets	Food stores	153	2.856 (0.111)	2.912	0.438 (0.025)	0.447	0.028	2.931 (0.105)	2.949	0.433 (0.021)	0.437	0.014	3.432 (0.157)	3.354	0.511 (0.036)	0.506	0.026
Dean Foods	Food products	156	3.025 (0.114)	3.051	0.437 (0.022)	0.444	0.008	3.053 (0.094)	3.060	0.396 (0.020)	0.402	0.007	3.232 (0.168)	3.229	0.529 (0.031)	0.520	0.000
Advance Auto Parts	Auto dealers / services / parts	129	2.769 (0.116)	2.851	0.432 (0.027)	0.443	0.000	3.754 (0.121)	3.696	0.639 (0.023)	0.630	0.000	3.153 (0.179)	3.181	0.471 (0.034)	0.481	0.017
Best Buy	Home furnishing stores	186	3.044 (0.091)	3.049	0.437 (0.022)	0.443	0.007	3.525 (0.095)	3.503	0.571 (0.019)	0.568	0.016	3.611 (0.126)	3.520	0.565 (0.026)	0.549	0.022
Safeway	Food stores	157	3.039 (0.116)	3.065	0.436 (0.021)	0.441	0.028	3.06 (0.107)	3.069	0.467 (0.020)	0.469	0.007	2.987 (0.156)	3.093	0.511 (0.029)	0.508	0.013
Kohl's	General merchandise	152	2.823 (0.111)	2.887	0.431 (0.025)	0.440	0.009	2.610 (0.108)	2.655	0.319 (0.022)	0.330	0.000	3.615 (0.153)	3.468	0.505 (0.034)	0.503	0.000

Firm	Industry Group	Respondents with Firm in Choice Set	Race					Gender					Age				
			Discrimination Black (Pooled)					Discrimination Female (Pooled)					Discrimination Older (Conduct)				
			Likert		Borda		DK Share	Likert		Borda		DK Share	Likert		Borda		DK Share
			Raw	EB	Raw	EB		Raw	EB	Raw	EB		Raw	EB	Raw	EB	
Costco	General merchandise	170	3.1 (0.098)	3.101	0.432 (0.023)	0.439	0.000	3.163 (0.103)	3.164	0.463 (0.020)	0.465	0.000	3.442 (0.140)	3.382	0.491 (0.031)	0.493	0.013
Walgreens Boots Alliance	Other retail	165	3.081 (0.111)	3.094	0.429 (0.025)	0.439	0.075	3.138 (0.102)	3.141	0.484 (0.019)	0.485	0.050	3.321 (0.138)	3.305	0.526 (0.028)	0.519	0.036
Lowe's	Building materials	162	2.846 (0.106)	2.898	0.429 (0.024)	0.438	0.008	3.420 (0.110)	3.400	0.543 (0.021)	0.541	0.006	3.111 (0.159)	3.165	0.500 (0.032)	0.499	0.012
Coca-Cola	Food products	2210	2.892 (0.031)	2.889	0.436 (0.006)	0.436	0.003	3.362 (0.028)	3.361	0.541 (0.005)	0.541	0.004	3.409 (0.040)	3.412	0.522 (0.008)	0.521	0.003
Target	General merchandise	161	2.942 (0.121)	2.994	0.425 (0.025)	0.436	0.000	2.826 (0.105)	2.853	0.410 (0.021)	0.415	0.000	3.719 (0.157)	3.520	0.554 (0.040)	0.529	0.015
Home Depot	Building materials	2130	2.894 (0.031)	2.891	0.433 (0.006)	0.433	0.006	3.486 (0.029)	3.484	0.580 (0.006)	0.580	0.006	3.197 (0.045)	3.207	0.488 (0.009)	0.489	0.009
US Foods Holding	Wholesale trade	163	2.9 (0.118)	2.959	0.421 (0.024)	0.431	0.035	3.115 (0.104)	3.120	0.485 (0.021)	0.486	0.045	3.220 (0.168)	3.223	0.511 (0.029)	0.508	0.078
FedEx	Freight / transport	155	2.726 (0.126)	2.838	0.419 (0.024)	0.429	0.000	3.219 (0.116)	3.216	0.538 (0.022)	0.535	0.014	3.481 (0.150)	3.393	0.573 (0.032)	0.549	0.000
Amazon.com	Other retail	171	2.705 (0.105)	2.780	0.412 (0.022)	0.421	0.008	3.060 (0.106)	3.069	0.457 (0.019)	0.459	0.000	3.677 (0.123)	3.574	0.561 (0.025)	0.547	0.010
Goodyear Tire & Rubber	Auto dealers / services / parts	129	2.943 (0.135)	3.016	0.403 (0.027)	0.419	0.011	3.921 (0.109)	3.860	0.698 (0.023)	0.685	0.000	3.037 (0.183)	3.122	0.509 (0.038)	0.504	0.018
TJX	General merchandise	165	2.738 (0.111)	2.817	0.408 (0.021)	0.416	0.008	2.529 (0.098)	2.571	0.357 (0.022)	0.366	0.019	3.28 (0.155)	3.266	0.560 (0.035)	0.537	0.000
AutoZone	Auto dealers / services / parts	163	2.842 (0.111)	2.901	0.401 (0.024)	0.414	0.008	3.805 (0.104)	3.758	0.665 (0.021)	0.656	0.019	3.091 (0.143)	3.154	0.451 (0.029)	0.465	0.000
ABM Industries	Repair services	170	2.967 (0.117)	3.010	0.396 (0.025)	0.411	0.000	3.352 (0.100)	3.340	0.573 (0.020)	0.570	0.006	3.260 (0.156)	3.253	0.557 (0.038)	0.532	0.000
DISH Network	Communications	158	2.810 (0.103)	2.864	0.399 (0.020)	0.407	0.017	3.474 (0.106)	3.451	0.575 (0.022)	0.570	0.000	3.324 (0.143)	3.302	0.545 (0.037)	0.526	0.014
Kroger	Food stores	172	2.949 (0.109)	2.985	0.392 (0.024)	0.405	0.008	2.896 (0.103)	2.917	0.445 (0.022)	0.449	0.012	3.317 (0.158)	3.285	0.508 (0.033)	0.505	0.012
Longhorn Steakhouse	Eating / drinking	166	2.843 (0.113)	2.906	0.395 (0.021)	0.405	0.009	2.860 (0.102)	2.882	0.439 (0.021)	0.442	0.000	3.395 (0.146)	3.345	0.586 (0.032)	0.558	0.012
UPS	Personal / business services	173	2.790 (0.110)	2.858	0.388 (0.025)	0.404	0.000	3.569 (0.100)	3.542	0.599 (0.021)	0.593	0.012	3.671 (0.132)	3.549	0.568 (0.032)	0.546	0.023
Waste Management	Electric / gas	160	2.738 (0.119)	2.834	0.385 (0.027)	0.404	0.009	3.770 (0.109)	3.722	0.645 (0.024)	0.635	0.020	3.494 (0.144)	3.410	0.573 (0.031)	0.550	0.012
Dollar General	General merchandise	168	2.583 (0.121)	2.717	0.386 (0.026)	0.403	0.000	2.957 (0.112)	2.977	0.456 (0.023)	0.459	0.000	3.301 (0.163)	3.271	0.492 (0.035)	0.494	0.024
Pizza Hut	Eating / drinking	183	2.686 (0.099)	2.753	0.388 (0.021)	0.398	0.007	3.051 (0.094)	3.058	0.447 (0.018)	0.450	0.006	3.410 (0.154)	3.343	0.512 (0.032)	0.508	0.012
Nike	Apparel stores	175	2.870 (0.117)	2.933	0.381 (0.024)	0.397	0.016	3.012 (0.101)	3.024	0.485 (0.020)	0.486	0.000	3.644 (0.129)	3.537	0.588 (0.031)	0.559	0.011
Dollar Tree	General merchandise	151	2.806 (0.126)	2.898	0.372 (0.027)	0.393	0.030	2.935 (0.120)	2.960	0.378 (0.023)	0.386	0.007	3.744 (0.164)	3.517	0.595 (0.035)	0.559	0.000
Foot Locker	Apparel stores	161	2.524 (0.124)	2.679	0.375 (0.024)	0.390	0.000	3.368 (0.113)	3.352	0.561 (0.024)	0.556	0.013	3.797 (0.156)	3.568	0.670 (0.032)	0.613	0.000
Tyson Foods	Food products	161	2.760 (0.115)	2.842	0.377 (0.020)	0.386	0.028	3.201 (0.106)	3.200	0.500 (0.020)	0.500	0.020	3.260 (0.149)	3.258	0.507 (0.029)	0.505	0.000
Walmart	General merchandise	170	2.682 (0.107)	2.764	0.369 (0.022)	0.383	0.000	2.988 (0.098)	3.001	0.439 (0.019)	0.442	0.000	3.111 (0.167)	3.163	0.471 (0.035)	0.481	0.000
KFC	Eating / drinking	2175	2.505 (0.032)	2.508	0.332 (0.007)	0.333	0.005	2.947 (0.029)	2.948	0.442 (0.005)	0.442	0.006	3.508 (0.046)	3.509	0.561 (0.010)	0.558	0.007
McDonald's	Eating / drinking	170	2.280 (0.109)	2.443	0.287 (0.024)	0.313	0.000	2.927 (0.106)	2.946	0.426 (0.021)	0.430	0.006	3.618 (0.153)	3.470	0.548 (0.036)	0.528	0.000
Taco Bell	Eating / drinking	176	2.421 (0.100)	2.532	0.291 (0.020)	0.308	0.000	2.928 (0.103)	2.946	0.455 (0.020)	0.458	0.006	3.476 (0.157)	3.378	0.599 (0.036)	0.561	0.000

Notes: This table reports industry assignments, estimated Likert and Borda scores, their standardized errors, and EB shrunk estimates for each firm in the sample. “DK Share” indicates the share of responses that were “Don’t know / prefer not to answer.” The columns under the “Race” label report estimates for the Discrimination Black (pooled) measure. The columns under the “Gender” label report estimates for the Discrimination Female (pooled) measure. The columns under the “Age” label report estimates for the Discrimination Older (Conduct) measure. Firms are sorted by the EB Borda score for race.

Appendix C: Survey instrument

Figure A5: Discrimination question in names arm

Now suppose two equally qualified applicants apply to these same five companies.

As before, the applicants are both **high-school graduates with 1-2 years of relevant experience**, but the **applications use different names**. Each name is either distinctively white or black and either distinctively male or female.

Here are some examples of such names:
Distinctively **black** names: Lawanda and Antwan
Distinctively **white** names: Amanda and Brett
Distinctively **female** names: Rebecca and Latonya
Distinctively **male** names: Finn and Lamar

For each company, please indicate how much more likely you believe the company is to **contact a job applicant** with a distinctively **black** name than an applicant with a distinctively white name.

	Much more likely	Somewhat more likely	Equally likely to contact both	Somewhat less likely	Much less likely	Don't know/prefer not to answer
Johnson & Johnson	☐	☐	☐	☐	☐	☐
Morgan Stanley	☐	☐	☐	☐	☐	☐
Murphy USA	☐	☐	☐	☐	☐	☐
Home Depot	☐	☐	☐	☐	☐	☐
Bed Bath & Beyond	☐	☐	☐	☐	☐	☐

For each company, please indicate how much more likely you believe the company is to **hire a job applicant** with a distinctively **black** name than an applicant with a distinctively white name.

	Much more likely	Somewhat more likely	Equally likely to contact both	Somewhat less likely	Much less likely	Don't know/prefer not to answer
Johnson & Johnson	☐	☐	☐	☐	☐	☐
Morgan Stanley	☐	☐	☐	☐	☐	☐
Murphy USA	☐	☐	☐	☐	☐	☐
Home Depot	☐	☐	☐	☐	☐	☐
Bed Bath & Beyond	☐	☐	☐	☐	☐	☐

Notes: This figure shows how the key discrimination question was presented in the names arm of the survey. The “Black vs. White” framing of the race discrimination questions is shown.

Figure A6: Discrimination question in conduct arm

Please indicate how likely you think it is that each company below would **discriminate against black** job-seekers.

	Very likely	Somewhat likely	Neither likely nor unlikely	Somewhat unlikely	Very unlikely	Don't know/ prefer not to answer
Dr Pepper Snapple Group	☐	☐	☐	☐	☐	☐
Allstate	☐	☐	☐	☐	☐	☐
Stanley Black & Decker (DeWalt, Lenox, Porter Cable)	☐	☐	☐	☐	☐	☐
Performance Food Group (Vistar, PFG Customized)	☐	☐	☐	☐	☐	☐
KFC	☐	☐	☐	☐	☐	☐

0%

Survey Completion

100%

→

Notes: This figure displays how the key discrimination question was presented in the conduct arm of the survey. The “against Black” framing of the race discrimination question is shown.

Appendix D: Borda scores and SST

To define the population analogue of the Borda score, we posit a collection of *pairwise win and tie probabilities* $\{p_{jk}, t_{jk}\}$. These primitives, which are defined for all firm pairs, describe how a randomly drawn respondent would order any two firms appearing together in a choice set. Section D.1 provides a random utility model that serves as one possible foundation for such probabilities.

The *expected pairwise score* is

$$w_{jk} := p_{jk} + \frac{1}{2}t_{jk}.$$

Pairs involving at least one non-anchor firm can co-occur in a choice set C_i . For such pairs, the primitives are identified by the survey:

$$p_{jk} = \Pr(j \succ_i k \mid j, k \in C_i), \quad t_{jk} = \Pr(j \sim_i k \mid j, k \in C_i), \quad w_{jk} = \mathbb{E}[w_{ijk}],$$

where the probabilities are taken over a randomly drawn respondent i conditional on both j and k appearing in their choice set. Note that $p_{jk} + p_{kj} + t_{jk} = 1$, which implies $w_{jk} + w_{kj} = 1$.

With this notation, the *population Borda score* of firm j can be written

$$B_j := \mathbb{E} \left[\hat{B}_j \right] = \frac{\mathbf{1}\{j \in \mathcal{N}\}}{2|\mathcal{N}|} + \frac{|\mathcal{N}| - \mathbf{1}\{j \in \mathcal{N}\}}{|\mathcal{N}|} \mathbb{E} \left[\frac{\sum_{k \in (C_i \cap \mathcal{N}) \setminus \{j\}} w_{jk}}{|C_i| - 1 - \mathbf{1}\{j \in \mathcal{N}\}} \mid j \in C_i \right],$$

where the remaining expectation averages over the random composition of the choice set. With item non-response, an analogous identity holds conditional on the realized rated sets $\{\mathcal{E}_i\}$: provided non-response is unrelated to beliefs, the interior expectation is replaced by the comparison-weighted average $\sum_{i: j \in \mathcal{E}_i} \sum_{k \in (\mathcal{E}_i \cap \mathcal{N}) \setminus \{j\}} w_{jk} / \sum_{i: j \in \mathcal{E}_i} e_{ij}$, so that $\hat{B}_j$ remains conditionally unbiased.

Since each non-anchor pair appears in the same choice set with equal probability, random

assignment of non-anchors yields the simplification

$$B_j = \frac{1}{|\mathcal{N}|} \left[\frac{1}{2} \mathbf{1}\{j \in \mathcal{N}\} + \sum_{k \in \mathcal{N} \setminus \{j\}} w_{jk} \right].$$

Intuitively, the population Borda score grants each non-anchor a phantom self-tie but otherwise treats them symmetrically to anchors. Under item non-response the simplification holds with opponents weighted by their relative response propensities; the ranking arguments below require only that these weights be positive and are unaffected.

As noted in the main text, Borda scores remain interpretable under a weaker condition than IIA known as strong stochastic transitivity (SST). To handle ties appropriately, we define SST in terms of the expected pairwise score w_{jk} .

Note that $w_{jk} \geq 0.5$ if and only if j beats k at least as often as k beats j .

Definition 1 (Strong stochastic transitivity). For all distinct firms j, k, ℓ , if

$$w_{jk} \geq 0.5 \quad \text{and} \quad w_{k\ell} \geq 0.5, \quad \text{then} \quad w_{j\ell} \geq \max\{w_{jk}, w_{k\ell}\}.$$

While models predicated on IIA satisfy SST, the converse is not true. Many random utility models (e.g., multinomial probit) satisfy SST while violating IIA. The next subsection (Section D.1) discusses a more general class of random utility models in which IIA fails due to context-dependence but SST continues to hold.

Korba, Cl  men  on and Sibony (2017) and Shah and Wainwright (2018) show that when SST holds, every firm faces every other firm as an opponent, and ties are impossible, the population Borda ordering coincides with the underlying preference ordering. In our design, anchors and non-anchors face different schedules of opponents. The ‘‘common-opponent’’ Borda score defined above corrects for this asymmetry by evaluating all firms against the same reference population ($\mathcal{N}$). This modification recovers the correct *global* ranking of both anchor and non-anchor firms provided preferences satisfy SST, knife-edge indifferences are ruled out, and the non-anchor set is rich enough to distinguish any two

firms that the population distinguishes.

Proposition 1 (Global Consistency of Common-Opponent Borda under SST). Assume:

1. **Strong Stochastic Transitivity (SST):** The pairwise scores $\{w_{jk}\}$ satisfy SST.
2. **No knife-edge indifference:** For all distinct firm pairs j, k , $w_{jk} \neq 0.5$.
3. **Symmetric Design:** The survey consists of two disjoint sets of firms, $\mathcal{A}$ (Anchors) and $\mathcal{N}$ (Non-anchors). Choice sets are formed by drawing one firm uniformly from $\mathcal{A}$ and drawing four uniformly without replacement from $\mathcal{N}$.
4. **Distinguishability:** For any distinct firms j, k with $w_{jk} \neq 0.5$, there exists at least one $\ell \in \mathcal{N} \setminus \{j, k\}$ such that $w_{j\ell} \neq w_{k\ell}$.

Then, for *any* pair of distinct firms $j, k \in \mathcal{A} \cup \mathcal{N}$, the population Borda ranking coincides with the pairwise majority relation:

$$B_j > B_k \iff w_{jk} > 0.5 \quad (\iff p_{jk} > p_{kj}).$$

Proof. See Section D.2. □

D.1 Context-dependent preferences

A simple way to represent non-IIA preferences is to work with a context-dependent rank order logit model in which Likert scores are allowed to depend on the choice set C_i . This yields choice probabilities of the form:

$$\Pr(j \succ_i k \mid C_i) = \frac{\exp(L_{j,C_i})}{\exp(L_{j,C_i}) + \exp(L_{k,C_i})}.$$

To obtain a tractable class of such models, suppose the menu-dependent worths admit additive item-specific biases,

$$L_{j,C} = L_j + b_j(C),$$

where L_j is the intrinsic worth and $b_j(C)$ captures context effects. Define the menu-

specific worth gap

$$\Delta_{jk}(C) = L_{j,C} - L_{k,C}.$$

The following proposition establishes a sufficient condition for this model to retain the transitivity properties of the standard rank-ordered logit model despite the violation of IIA.

Proposition 2 (Sufficient Condition for SST). Let C_{xy} denote any menu containing x and y . The context-dependent rank-ordered logit model satisfies Strong Stochastic Transitivity if, for every triple of firms (j, k, l) and every collection of menus C_{jk}, C_{kl}, C_{jl} , the following implication holds:

$$\Delta_{jk}(C_{jk}) \geq 0 \quad \text{and} \quad \Delta_{kl}(C_{kl}) \geq 0 \quad \implies \quad \Delta_{jl}(C_{jl}) \geq \max\{\Delta_{jk}(C_{jk}), \Delta_{kl}(C_{kl})\}.$$

Proof. The choice probability $\Pr(j \succ_i k \mid C_i)$ is a strictly increasing function of the worth gap $\Delta_{jk}(C_i)$. Consequently, the probabilistic inequalities defining SST map directly to the algebraic inequalities on the utility gaps stated above. $\square$

In the standard rank-ordered logit model, where $b_j(C) = 0$, this condition holds automatically because $\Delta_{jl} = \Delta_{jk} + \Delta_{kl}$, and the sum of two non-negative numbers exceeds their maximum. Thus, in this context-dependent model, SST holds provided the context effects $b_j(C)$ are not sufficiently heterogeneous across menus to disrupt the additivity of the utility gaps.

D.2 Proof of Proposition 1

We analyze the properties of the *population* Borda score B_j under the “Common-Opponent” definition provided above. Recall that $\mathcal{N}$ denotes the set of non-anchor firms and the score is defined as:

$$B_j = \frac{1}{|\mathcal{N}|} \left[\frac{1}{2} \mathbf{1}\{j \in \mathcal{N}\} + \sum_{\ell \in \mathcal{N} \setminus \{j\}} w_{j\ell} \right],$$

where $w_{j\ell} = p_{j\ell} + \frac{1}{2}t_{j\ell}$ is the expected pairwise score. For anchors, the $\frac{1}{2}$ term vanishes and the score reduces to the average pairwise score against all non-anchors. For non-anchors, the additional $\frac{1}{2}$ can be interpreted as a phantom self-match scored as a tie, ensuring that all firms' scores are averages over exactly $|\mathcal{N}|$ terms.

Proof. Define the relation $\succ^*$ by $j \succ^* k$ if and only if $w_{jk} > 1/2$ (equivalently, $p_{jk} > p_{kj}$). We first verify that $\succ^*$ is a strict total order. Completeness and asymmetry follow from Assumption 2 (No Knife Edge Indifference) together with the identity $w_{jk} + w_{kj} = 1$: for any distinct pair, exactly one of $w_{jk} > 1/2$ and $w_{kj} > 1/2$ holds. For transitivity, suppose $j \succ^* k$ and $k \succ^* \ell$. Then $w_{jk} > 1/2$ and $w_{k\ell} > 1/2$, so SST implies $w_{j\ell} \geq \max\{w_{jk}, w_{k\ell}\} > 1/2$. Hence $j \succ^* \ell$. We show that $j \succ^* k$ implies $B_j > B_k$ for any distinct pair, regardless of their class assignment.

Recall that under SST, if $j \succ^* k$, then for any third firm ℓ :

- If $\ell \succ^* j \succ^* k$, then SST gives $w_{\ell k} \geq w_{\ell j}$, i.e., $w_{j\ell} \geq w_{k\ell}$.
- If $j \succ^* k \succ^* \ell$, then SST gives $w_{j\ell} \geq w_{k\ell}$.
- If $j \succ^* \ell \succ^* k$, then $w_{j\ell} > 0.5 > w_{k\ell}$.

Thus, $j \succ^* k$ implies $w_{j\ell} \geq w_{k\ell}$ for all $\ell \neq j, k$.

Since all scores share the common denominator $|\mathcal{N}|$, it suffices to compare numerators.

We consider the three possible class configurations for the pair j, k .

Case 1a: Both are Anchors ($j, k \in \mathcal{A}$). The phantom terms vanish for both firms, so

$$B_j - B_k = \frac{1}{|\mathcal{N}|} \sum_{\ell \in \mathcal{N}} (w_{j\ell} - w_{k\ell}).$$

Since $j \succ^* k$, SST implies $w_{j\ell} \geq w_{k\ell}$ for all $\ell \in \mathcal{N}$. The Distinguishability assumption ensures that the inequality is strict for at least one ℓ . Thus $B_j > B_k$.

Case 1b: Both are Non-Anchors ($j, k \in \mathcal{N}$). The phantom $\frac{1}{2}$ terms cancel in the

difference:

$$B_j - B_k = \frac{1}{|\mathcal{N}|} \left[(w_{jk} - w_{kj}) + \sum_{\ell \in \mathcal{N} \setminus \{j,k\}} (w_{j\ell} - w_{k\ell}) \right].$$

The direct term $w_{jk} - w_{kj} = 2w_{jk} - 1$ is strictly positive because $j \succ^* k$ implies $w_{jk} > 1/2$.

The indirect terms are non-negative by SST. Thus $B_j > B_k$.

Case 2: j is an Anchor, k is a Non-Anchor ($j \in \mathcal{A}, k \in \mathcal{N}$). The phantom term is present only for k :

$$B_j - B_k = \frac{1}{|\mathcal{N}|} \left[\left(w_{jk} - \frac{1}{2} \right) + \sum_{\ell \in \mathcal{N} \setminus \{k\}} (w_{j\ell} - w_{k\ell}) \right].$$

Since $j \succ^* k$, we have $w_{jk} > 1/2$, so the first term is strictly positive. Every term in the sum is non-negative by SST. Thus $B_j > B_k$.

Case 3: j is a Non-Anchor, k is an Anchor ($j \in \mathcal{N}, k \in \mathcal{A}$). The phantom term is present only for j :

$$B_j - B_k = \frac{1}{|\mathcal{N}|} \left[\left(\frac{1}{2} - w_{kj} \right) + \sum_{\ell \in \mathcal{N} \setminus \{j\}} (w_{j\ell} - w_{k\ell}) \right].$$

Since $j \succ^* k$, we have $w_{kj} < 1/2$, so the first term is strictly positive. Every term in the sum is non-negative by SST. Thus $B_j > B_k$.

In all cases, $j \succ^* k \implies B_j > B_k$. It remains to establish the converse. Suppose $B_j > B_k$. By Assumption 2 and the identity $w_{jk} + w_{kj} = 1$, either $j \succ^* k$ or $k \succ^* j$. If $k \succ^* j$, the argument above yields $B_k > B_j$, a contradiction. Hence $j \succ^* k$, that is, $w_{jk} > 1/2$. $\square$

Appendix E: Shrinkage

Following Walters (2024), we implement an Empirical Bayes shrinkage procedure that accounts for precision dependence: the possibility that the distribution of latent firm parameters varies with the precision of their estimates. First, we remove the dependence of the mean on the precision by fitting regressions of the estimates on their log variances. Let the mean-detrended residuals be:

$$\tilde{L}_j := \hat{L}_j - \hat{\gamma}_{L0} - \hat{\gamma}_{L1} \ln V_{Lj}, \quad \tilde{B}_j := \hat{B}_j - \hat{\gamma}_{B0} - \hat{\gamma}_{B1} \ln V_{Bj},$$

where $(\hat{\gamma}_{L0}, \hat{\gamma}_{L1}, \hat{\gamma}_{B0}, \hat{\gamma}_{B1})$ are the fitted regression coefficients.

Next, we allow the variance of the underlying signal to vary with precision. We estimate the following model of the conditional variance of the residuals by nonlinear least squares:

$$\mathbb{E} \left[\tilde{L}_j^2 \mid V_{Lj} \right] = V_{Lj} + \underbrace{\kappa_L (V_{Lj})^{\delta_L}}_{\tau_{L,j}^2}, \quad \mathbb{E} \left[\tilde{B}_j^2 \mid V_{Bj} \right] = V_{Bj} + \underbrace{\kappa_B (V_{Bj})^{\delta_B}}_{\tau_{B,j}^2}.$$

Here, $\tau_{\cdot,j}^2$ represents the conditional variance of the true signal for firm j . We use the fitted parameters $(\hat{\kappa}, \hat{\delta})$ to construct estimated signal variances $\hat{\tau}_{\cdot,j}^2$.

Finally, we construct shrinkage estimators by shrinking the residuals and adding back the estimated mean trends:

$$L_j^* = \hat{\gamma}_{L0} + \hat{\gamma}_{L1} \ln V_{Lj} + \left(\frac{\hat{\tau}_{L,j}^2}{\hat{\tau}_{L,j}^2 + V_{Lj}} \right) \tilde{L}_j,$$

$$B_j^* = \hat{\gamma}_{B0} + \hat{\gamma}_{B1} \ln V_{Bj} + \left(\frac{\hat{\tau}_{B,j}^2}{\hat{\tau}_{B,j}^2 + V_{Bj}} \right) \tilde{B}_j.$$

The shrinkage factors in parentheses represent the reliability ratios of the residuals. Adapting the shrinkage intensity to the specific noise profile of each unit—as achieved here by the variable reliability ratio—not only yields an improved linear predictor but also

potentially improves the accuracy of rankings over the raw point estimates. In particular, if the underlying signals are normally distributed, then the ordering of the shrinkage estimators generally maximizes the probability of correctly ranking the items (Portnoy, 1982).

Appendix F: Katz (1961) shape-constrained variance estimators

The correction depends on the squared standard errors $\mathbb{V}[\hat{\sigma}_L^2]$ and $\mathbb{V}[\hat{\sigma}_B^2]$ of the variance estimators. We first derive asymptotically unbiased estimators $\widehat{\mathbb{V}}[\hat{\sigma}_L^2]$ and $\widehat{\mathbb{V}}[\hat{\sigma}_B^2]$ of these quantities analytically.

Let $\hat{L} = (\hat{L}_1 - \bar{L}, \dots, \hat{L}_J - \bar{L})'$ and $\hat{B} = (\hat{B}_1 - \bar{B}, \dots, \hat{B}_J - \bar{B})'$. Letting $\mathbf{1}$ denote a $J \times 1$ vector of ones, these definitions ensure $\mathbf{1}'\hat{L} = \mathbf{1}'\hat{B} = 0$. Denote the associated variance matrices of these vectors by $\Sigma_L = \mathbb{V}[\hat{L}]$ and $\Sigma_B = \mathbb{V}[\hat{B}]$. We estimate these matrices analytically and will treat them as known.

Under the maintained assumption that the Likert and Borda estimates have reached their asymptotic normal limit, we have

$$\hat{L} \sim N(L, \Sigma_L), \quad \hat{B} \sim N(B, \Sigma_B),$$

where $L = (L_1 - \mu_L, \dots, L_J - \mu_L)'$ and $B = (B_1 - \mu_B, \dots, B_J - \mu_B)'$.

In this notation, we can write the variance component estimators

$$\hat{\sigma}_L^2 = \frac{\hat{L}'\hat{L} - \text{tr}(\Sigma_L)}{J}, \quad \hat{\sigma}_B^2 = \frac{\hat{B}'\hat{B} - \text{tr}(\Sigma_B)}{J}.$$

Recall that if $X \sim N(\mu, \Sigma)$ then $\mathbb{V}[X'X] = 2\text{tr}(\Sigma^2) + 4\mu'\Sigma\mu$. We therefore use the following unbiased estimators of $\mathbb{V}[\hat{\sigma}_L^2]$ and $\mathbb{V}[\hat{\sigma}_B^2]$:

$$\begin{aligned} \widehat{\mathbb{V}}[\hat{\sigma}_L^2] &= \frac{2\text{tr}(\Sigma_L^2) + 4\left(\hat{L}'\Sigma_L\hat{L} - \text{tr}(\Sigma_L^2)\right)}{J^2} = \frac{4\hat{L}'\Sigma_L\hat{L} - 2\text{tr}(\Sigma_L^2)}{J^2} \\ \widehat{\mathbb{V}}[\hat{\sigma}_B^2] &= \frac{2\text{tr}(\Sigma_B^2) + 4\left(\hat{B}'\Sigma_B\hat{B} - \text{tr}(\Sigma_B^2)\right)}{J^2} = \frac{4\hat{B}'\Sigma_B\hat{B} - 2\text{tr}(\Sigma_B^2)}{J^2}. \end{aligned}$$

Define the z -scores $z_L = \hat{\sigma}_L^2 / \widehat{\mathbb{V}}[\hat{\sigma}_L^2]^{1/2}$ and $z_B = \hat{\sigma}_B^2 / \widehat{\mathbb{V}}[\hat{\sigma}_B^2]^{1/2}$, and let $\phi(\cdot)$ and $\Phi(\cdot)$

denote the standard normal pdf and cdf, respectively. The corrected estimators take the form:

$$\dot{\sigma}_L^2 = \hat{\sigma}_L^2 + \widehat{\mathbb{V}}[\hat{\sigma}_L^2]^{1/2} \frac{\phi(z_L)}{\Phi(z_L)}, \quad \dot{\sigma}_B^2 = \hat{\sigma}_B^2 + \widehat{\mathbb{V}}[\hat{\sigma}_B^2]^{1/2} \frac{\phi(z_B)}{\Phi(z_B)}.$$

Note that these formulas correspond to the mean of a normal distribution truncated from below at zero. Consequently, noisy estimates of the variance components are nudged up by the product of their standard error and an inverse Mills ratio evaluated at the z-score of the point estimate. When the standard error is small, the estimator collapses to the uncorrected estimate. Katz (1961) shows that these shape-constrained estimators are minimax and admissible under squared error loss.

Bivariate generalization

Specifications that include two error-ridden scores—for example, the regressions of contact gaps on discrimination beliefs controlling for selectivity beliefs in Table 6—require an estimate of the joint signal covariance matrix of the two scores rather than a single signal variance. In those specifications, we work with a matrix analogue of the Katz (1961) correction.

Let $\hat{X}_j = (\hat{S}_{1j}, \hat{S}_{2j})'$ collect the two estimated scores for firm j , let $\hat{\Sigma}_X$ denote the (weighted) sample covariance matrix of $\{\hat{X}_j\}_{j=1}^J$ across firms, and let $\hat{\Sigma}_{err}$ denote the average sampling covariance matrix of the estimation errors in $\hat{X}_j$. The diagonal entries of $\hat{\Sigma}_{err}$ are the noise variances entering the univariate corrections above, while the off-diagonal entry is an analytical estimate of the sampling covariance between the two scores, which is nonzero when the same respondents contribute to both. The raw signal covariance estimate is

$$\hat{\Omega} = \hat{\Sigma}_X - \hat{\Sigma}_{err}.$$

While $\hat{\Omega}$ is asymptotically unbiased, sampling error can render it indefinite in finite samples. Moreover, because the sampling error in the scores has a non-degenerate covariance matrix, the population signal covariance must lie strictly below the population covariance of the observed scores: both Ω and $\Sigma_X - \Omega$ are positive definite. The parameter space

is therefore the bounded convex set of positive definite matrices lying between zero and Σ_X .

We discipline $\hat{\Omega}$ with a shape constraint that imposes both requirements at once. Maintaining the assumption that the scores have reached their asymptotic normal limit, $\text{vech}(\hat{\Omega}) \sim N(\text{vech}(\Omega), V_\Omega)$, where we estimate V_Ω analytically via the delta method, treating the firm-level estimation errors as independent across firms with common covariance $\hat{\Sigma}_{err}$. The corrected estimator is the mean of this normal distribution truncated to the constraint set:

$$\dot{\Omega} = \mathbb{E} \left[Z \mid Z \text{ and } \hat{\Sigma}_X - Z \text{ positive definite} \right], \quad \text{vech}(Z) \sim N \left(\text{vech}(\hat{\Omega}), \hat{V}_\Omega \right),$$

where $\hat{\Sigma}_X$ is treated as known in the constraint. Because the constraint set is convex, $\dot{\Omega}$ lies in its interior: the corrected signal matrix and the implied noise matrix

$$\dot{\Sigma}_{err} = \hat{\Sigma}_X - \dot{\Omega}$$

are both positive definite by construction, so the measurement-error covariance supplied to the bivariate EIV estimator is always a proper covariance matrix, even in subpopulations with weak signal.

When there is a single score, the constraint set reduces to the interval $(0, \hat{\sigma}_X^2)$ and $\dot{\Omega}$ reduces to the mean of a normal distribution truncated to that interval, a two-sided analogue of the Katz (1961) formula in the preceding section with the inverse Mills ratio replaced by its two-sided counterpart. The one- and two-sided corrections coincide whenever the sampling distribution places negligible mass above $\hat{\sigma}_X^2$, which is the empirically relevant case for the scores we study.

The same logic applies in the matrix case, where the correction leaves precisely estimated interior signal matrices essentially unchanged and binds only when $\hat{\Omega}$ approaches the boundary of the constraint set. Because the truncated mean has no closed form in the matrix case, we compute $\dot{\Omega}$ by Monte Carlo, drawing $\text{vech}(Z)$ from the estimated normal

limit and averaging the draws for which both Z and $\hat{\Sigma}_X - Z$ are positive definite.⁶ Regressors measured without error (e.g., industry composition shares) are excluded from the correction and enter the EIV with zero assigned noise.

⁶We draw in batches until 5,000 accepted draws accumulate, up to a maximum of 50,000 draws, using a fixed seed. Acceptance rates are recorded in our replication output. In the rare event that no draw is accepted, we substitute the nearest positive semidefinite matrix to $\hat{\Omega}$.

Appendix G: CMD and Wald tests

To test perfect correlation between the population scores of two groups we use the classical minimum distance (CMD) estimator to impose that the population scores are linearly related. To test equality between two groups we use a classic Wald test, which is a special case of CMD.

The inputs to the tests are:

- Y_1 : a $J \times 1$ vector of estimated scores in group 1
- Y_2 : a $J \times 1$ vector of estimated scores in group 2
- V_1 : a $J \times J$ variance matrix of the scores in group 1
- V_2 : a $J \times J$ variance matrix of the scores in group 2

For example, Y_1 could be the sample Borda score for White respondents, Y_2 the score for Black respondents, and (V_1, V_2) the corresponding first-step estimates of their variance matrices. In our application, $J = 164$.

A large sample approximation

Because the $2J$ entries of $Y = (Y_1', Y_2')'$ are averages over scores of independent observations, we work with a normal approximation

$$Y \sim N \left(\begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix}, \begin{bmatrix} V_1 & 0 \\ 0 & V_2 \end{bmatrix} \right).$$

Here, the $J \times 1$ vectors θ_1 and θ_2 give the population scores in the two groups.

Null Hypotheses

A first hypothesis that interests us is that there exists $(c_0, c_1) \in \mathbb{R}^2$ such that:

$$H_{linear} : \theta_1 = c_0 1_J + c_1 \theta_2,$$

where 1_J denotes a vector of ones. Note that H_{linear} corresponds to the null that the group 1's vector of population means θ_1 is perfectly correlated with group 2's vector θ_2 .

A second hypothesis that interests us takes the form

$$H_{equal} : \theta_1 = \theta_2.$$

This more stringent null of equal population means is the one that leads to a classic Wald test.

Test statistics

The CMD estimator of H_{linear} solves the generalized nonlinear least squares problem

$$\min_{(c_0, c_1, t') \in \mathbb{R}^{J+2}} \left(Y - \begin{pmatrix} c_0 1_J + c_1 t \\ t \end{pmatrix} \right)' \begin{bmatrix} V_1 & 0 \\ 0 & V_2 \end{bmatrix}^{-1} \left(Y - \begin{pmatrix} c_0 1_J + c_1 t \\ t \end{pmatrix} \right). \quad (1)$$

Denote the minimized value of the minimum distance criterion function by $\hat{Q}$. Standard large sample arguments (e.g., section 9 of Newey and McFadden, 1994) give $\hat{Q} \mid H_{linear} \sim \chi^2(J - 2)$ asymptotically.

To test H_{equal} , we use the Wald statistic

$$\hat{W} = (Y_1 - Y_2)' (V_1 + V_2)^{-1} (Y_1 - Y_2).$$

Standard asymptotic theory gives $\hat{W} \mid H_{equal} \sim \chi^2(J)$ as the number of respondents grows large. Because we have some small cells, these large sample approximations may not be accurate. We therefore opt to bootstrap the test statistics in order to achieve an asymptotic refinement.

Bootstrap procedure

To bootstrap each test we resample the microdata with replacement for each group,

yielding raw inputs

$$(Y_1^{(b)}, Y_2^{(b)}, V_1^{(b)}, V_2^{(b)})$$

for each bootstrap draw $b = 1, \dots, B$. In practice, we use $B = 499$ bootstrap replications.

Both tests impose the relevant null on the bootstrap DGP via centering. To test H_{equal} , we impose the null by subtracting the full-sample estimates (Y_1, Y_2) from each bootstrap input $(Y_1^{(b)}, Y_2^{(b)})$. This yields the bootstrap Wald statistic

$$\hat{W}^{(b)} = \left(Y_1^{(b)} - Y_2^{(b)} - (Y_1 - Y_2) \right)' \left(V_1^{(b)} + V_2^{(b)} \right)^{-1} \left(Y_1^{(b)} - Y_2^{(b)} - (Y_1 - Y_2) \right).$$

To impose H_{linear} , we subtract $(Y_1 - c_0^* 1_J - c_1^* t^*, Y_2 - t^*)$ from $(Y_1^{(b)}, Y_2^{(b)})$, where (c_0^*, c_1^*, t^*) are the full-sample minimizers of (1). Feeding these centered inputs to the CMD procedure yields bootstrap test statistic $\hat{Q}^{(b)}$. We compute bootstrap p -values for H_{equal} and H_{linear} as:

$$\hat{p}_{equal} := \frac{1 + \#\{\hat{W}^{(b)} > \hat{W}\}}{1 + B}, \quad \hat{p}_{linear} := \frac{1 + \#\{\hat{Q}^{(b)} > \hat{Q}\}}{1 + B},$$

where the $\#\{\cdot\}$ operator counts the number of bootstrap draws for which the condition is true.