

Belief polarization about racial discrimination in hiring: Evidence from an information experiment

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Abstract

In this paper, I investigate a novel channel of belief polarization: divergent interpretations of information. I conduct an online experiment with Democrats and Republicans in the US to study beliefs about hiring discrimination against Black workers. I first establish that Democrats believe there is more racial hiring discrimination than Republicans do, and I then evaluate how various pieces of information affect beliefs. I find that Democrats' beliefs about racial hiring discrimination are responsive to information on the Black-White wage gap, while Republicans' beliefs are not. As a result, wage gap information fails to reduce (and even increases) the partisan difference in beliefs about hiring discrimination. Moreover, even after both groups agree about the extent of racial hiring discrimination, participants change their opinions about whether it is a problem in line with politically motivated reasoning. Together, these findings highlight key challenges in using information to reduce polarization.

Key words: polarization, information, beliefs, discrimination

JEL codes: C91, D72, D83, D91, J71, P16

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1 Introduction

Political polarization has been rising over the past forty years in the US, with Democrats and Republicans exhibiting decreasing overlap in their political views (Canen et al., 2021). Given the adverse effects of polarization, such as political gridlock (Binder, 2014; Mian et al., 2014), theoretical and empirical researchers have sought to investigate its sources.

Literature from political science and economics finds that polarization is driven by Democrats’ and Republicans’ exposure to distinct information (DellaVigna and Gentzkow, 2010; Zhuravskaya et al., 2020). A natural policy proposal for reducing polarization is therefore through information dissemination. Indeed, information can be effective at reducing belief polarization when the information is unequivocally relevant (Grigorieff et al., 2018; Mu, 2022; Haaland and Roth, 2021).

Less is known about how belief polarization responds to information that is open to interpretation. Information that voters encounter often requires processing, which may depend on one’s model of the world. Consider, for example, how information on racial wage gaps affects beliefs about racial discrimination. If one believes that wage gap information reflects labor market discrimination, then this information may move one’s beliefs about racial discrimination. If instead, one believes that wage gap information reflects differences in educational attainment, for example, then the information may not move beliefs about racial discrimination. If information is processed differently by Democrats and Republicans, the effect on belief polarization becomes unclear.

These patterns are especially relevant in the context of racial discrimination in the labor market. Democrats and Republicans are polarized on this topic, as Democrats believe there is more labor market discrimination than Republicans do (Alesina et al., 2021). Beliefs about racial discrimination are themselves important in that they drive demand for policies including affirmative action and redistribution, and are relevant for Diversity, Equity, and Inclusion (DEI) training. DEI training uses information to teach people about obstacles minorities face in the labor market, including racial discrimination. Despite their popularity, results on the effectiveness of DEI training are mixed (Chang et al., 2019), potentially because we know little about the types of information that affect beliefs about labor market discrimination.

In this paper, I conduct a pre-registered online information experiment to examine belief polarization about hiring discrimination against Black workers in the US. The experiment consists of a within-subject design with five rounds using a sample of 1100 Democrats and

1100 Republicans. I elicit quantified and incentivized beliefs about racial hiring discrimination using the method from Haaland and Roth (2021). Each round, participants receive potentially useful information and state their updated beliefs about racial hiring discrimination.

The experiment reveals several key patterns and results. At baseline, I first establish that Democrats and Republicans are polarized on this topic. Consistent with the literature, Democrats believe there is more racial hiring discrimination than Republicans do.

I find that Democrats update their beliefs about racial hiring discrimination in response to information on the Black-White wage gap, while Republicans do not. Democrats overestimate the Black-White wage gap at baseline and revise downward their beliefs about hiring discrimination when they learn that the wage gap is smaller than expected. In contrast, Republicans underestimate the wage gap at baseline but do not revise their beliefs about hiring discrimination in response. As a result, the belief gap about hiring discrimination between Democrats and Republicans slightly decreases, but not statistically significantly.

I then provide evidence on the role of educational attainment in explaining the wage gap. That is, I tell participants how much of the wage gap is explained by differences in educational attainment between Black and White workers. Both Democrats and Republicans substantially overestimate the extent to which educational attainment explains the Black-White wage gap, with Republicans overestimating even more than Democrats. Upon finding out that educational attainment explains less of the wage gap than they thought, Democrats revise upwards their beliefs about the extent of racial hiring discrimination. Republicans, on the other hand, do not significantly revise their beliefs about racial discrimination in response. This leads to a marginally significant widening of the belief gap.

A natural question is what drives the observed differences in belief-updating between Democrats and Republicans in response to wage gap information. One explanation could be that Republicans' hiring discrimination beliefs are more difficult to move than Democrats' beliefs in general. This explanation, however, is challenged by one of the five rounds in which Republicans' beliefs move more than Democrats' beliefs. A remaining explanation is that Democrats and Republicans hold different interpretations about the relationship between wage gaps and labor market discrimination. These divergent interpretations could reasonably arise through Democrats and Republicans forming models of the world using distinct sources of news.

At the end of my study, I replicate a finding from Haaland and Roth (2021) that learning the results from an experiment measuring racial discrimination closes the belief gap between Democrats and Republicans. Even though both groups then agree about the extent of

hiring discrimination, I find that participants change their opinions about the information depending on their political affiliation.

Relative to their own baseline responses, Republicans are more likely than Democrats to decrease their belief that the observed discrimination is (1) a successful measure of discrimination, and (2) a problem. The difference between Democrats' and Republicans' updating behaviors is consistent with politically motivated reasoning, and highlights a channel through which convergence in beliefs may not yield convergence in policy demand. Recent literature identifies other cases in which information fails to reduce polarization in policy demand and asserts that this may be driven by Democrats' and Republicans' differing beliefs about the role of government (Haaland and Roth, 2021; Marino et al., 2023). My findings demonstrate that this may occur outside of people's beliefs about the government.

This paper highlights crucial limitations of one of the leading proposals for reducing polarization: information dissemination. Contrary to standard economic models that suggest information decreases belief polarization, I find that information may fail to reduce (and even increase) belief polarization when Democrats and Republicans have divergent interpretations of information. Furthermore, even when groups agree on the facts of a political topic, biased reasoning may enable the persistence of polarization in policy demand. As Democrats and Republicans become more polarized in their worldviews, these findings become increasingly relevant.

The paper proceeds as follows. Section 2 summarizes the literature and highlights my contribution. Section 3 describes my experimental design. Section 4 defines my hypotheses. Section 5 reviews my experimental findings in each round. Section 6 discusses, and section 7 concludes.

2 Literature on labor market discrimination beliefs

Recent literature explores beliefs about labor market discrimination as a mechanism for how information on labor market disparities affects demand for policy. Settele (2022) finds that exposing participants to a larger gender wage gap increases their demand for policies to combat the wage gap, likely through an increase in beliefs about the extent of gender discrimination in the labor market. Alesina et al. (2021) find that White Republicans are more likely to believe inequities are caused by individual actions, while White Democrats attribute inequities to systemic conditions, including discrimination. Together, these findings highlight that while information on labor market inequities may affect beliefs about

discrimination, the relationship may differ for Democrats and Republicans.

In evaluating how people update beliefs about racial discrimination in hiring, we may be concerned that political motivations could lead to biased belief updating (Redlawsk, 2002; Slothuus and De Vreese, 2010). In line with biased updating, Thaler (2019) finds that Democrats believe information more when it suggests there is more racial discrimination in hiring than they thought, relative to information that suggests there is less. Republicans believe information more when it suggests that there is less racial discrimination in hiring than they thought. If motivated reasoning drives belief-updating patterns in my context, then it could dampen the effects of information on belief depolarization.

Haaland and Roth (2021) develop a method of eliciting quantified and incentivized beliefs about racial discrimination in hiring using results from a fake resume study. In fake resume studies, researchers send out fake resumes in response to real job postings. The resumes only differ in whether the applicant’s name sounds White or Black, and the researchers measure how often the fake applicants receive callbacks for interviews. Haaland and Roth (2021) measure participants’ hiring discrimination beliefs as their predictions of callback rates for applicants with Black-sounding names and applicants with White-sounding names in a fake resume study. I adopt their methodology of eliciting beliefs. The authors find that presenting participants with results from a similar experiment on racial discrimination successfully closes the partisan gap in beliefs. In this paper, I add to our collective knowledge about how belief polarization responds to information that may be interpreted differently by Democrats and Republicans. Because labor market discrimination is notoriously difficult to measure, understanding belief-updating in response to ambiguous information is especially important in this context.

3 Experiment

I conduct an online information experiment on the survey platform Prolific, a widely-used survey platform for social science research, using oTree software (Chen et al., 2016). The experiment was preregistered on AsPredicted.org (Project #127316) before data collection began in April 2023. I use a within-subject experimental design consisting of five rounds. Each round, participants receive some information and state their updated beliefs about racial hiring discrimination.

The primary outcome variable across rounds is participants’ beliefs about racial discrimination in hiring. Following Haaland and Roth (2021), I measure beliefs about racial discrimi-

nation in hiring by asking participants to predict the results of Bertrand and Mullainathan (2004)’s fake resume study. In Bertrand and Mullainathan (2004) (hereafter, “BM”), researchers sent out fake resumes in response to real job postings. Resumes were randomized in terms of education, experience, and other qualifications listed, and systematically differed in whether the name on the resume sounded White or Black. The researchers measured how often employers contacted these fake applicants for an interview. They found that applicants with Black-sounding names needed to send out 50% more resumes than applicants with White-sounding names to receive a callback for an interview.

I elicit participants’ predictions of callback rates for applicants with White-sounding names and for applicants with Black-sounding names in BM. This method of eliciting beliefs about racial discrimination in hiring is (1) quantified, which ensures comparability across participants’ responses, and (2) incentivized, which increases the likelihood that participants are accurately reporting their beliefs (Gächter and Renner, 2010).

3.1 Design overview

At the start of the study, I describe the BM experiment to participants. They are told that researchers ran an experiment to measure racial discrimination in the labor market in which they sent out fake resumes in response to real job postings. The fake resumes had identical qualifications, and differed only in whether the name on the resume sounded White or Black. The researchers measured the callback rates for resumes with Black-sounding names and for resumes with White-sounding names to determine the extent to which employers discriminate.

After presenting participants with this information, I ask how much they agree that a difference in callback rates between applicants with Black-sounding names and White-sounding names would reflect that employers base their callback decisions in part on the race of the applicant. I also ask whether they believe that if BM finds a higher White callback rate than Black callback rate, this would be a problem that should be solved. Similarly, I then ask whether a higher Black callback rate would be a problem that should be solved. Then, the first round begins.

Round 1: Participants state their best guesses of the callback rates for applicants with White-sounding names and applicants with Black-sounding names in BM. That is, they are asked how many times a resume with a Black-sounding name had to be sent out on average to get one callback from an employer for an interview. Then, they are asked how many times

they think a resume with a White-sounding name had to be sent out on average to get one callback from an employer for an interview. See Figure 1 for a screenshot. From this round, I calculate participants' baseline beliefs about racial discrimination in hiring.

Figure 1: Round 1 Screenshot

Round 1 (of 5)

Experiment A: Your Best Guess

Researchers conducted an experiment to study **racial discrimination in the labor market**. They did so by sending out **fake resumes** to help-wanted ads. The resumes were exactly the same except for one thing: the name of the job applicant. Half of the resumes had typically **White-sounding names**, and the other half had typically **Black-sounding names**. The resumes were **otherwise identical** in terms of education and other qualifications. But, employers could use applicants' names to infer whether they were White or Black.

How many times do you think resumes with **Black-sounding names** on average had to be sent out to get one callback?
I think that a resume with a Black-sounding name on average had to be sent out times to get a callback for an interview.

How many times do you think resumes with **White-sounding names** on average had to be sent out to get one callback?
I think that a resume with a White-sounding name on average had to be sent out times to get a callback for an interview.

Next

Round 2: Participants are told the callback rate for applicants with Black-sounding names from BM. That is, they are told that a resume with a Black-sounding name had to be sent out 15 times on average to get one callback for an interview. Participants are then asked again for their best guess of the number of times that a resume with a White-sounding name had to be sent out on average to get one callback for an interview in BM. See Figure 2 for a screenshot.

Figure 2: Round 2 Screenshot

Round 2 (of 5)

Experiment A: Your Best Guess

Researchers conducted an experiment to study **racial discrimination in the labor market**. They did so by sending out **fake resumes** to help-wanted ads. The resumes were exactly the same except for one thing: the name of the job applicant. Half of the resumes had typically **White-sounding names**, and the other half had typically **Black-sounding names**. The resumes were **otherwise identical** in terms of education and other qualifications. But, employers could use applicants' names to infer whether they were White or Black.

Resumes with **Black-sounding names** had to be sent out on average **15 times** to get one callback for an interview.

How many times do you think resumes with **White-sounding names** on average had to be sent out to get one callback?
I think that a resume with a White-sounding name on average had to be sent out times to get a callback for an interview.

Next

Round 3: Participants are told that Black full-time workers in the US earn on average \$844 per week, and asked for their best guess of the average weekly earnings for White full-time workers in the US. Then, participants are told that on average, White full-time workers in the US earn on average \$1085 per week. Participants are then asked again for their best guess of the number of times that a resume with a White-sounding name had to be sent out on average to get one callback for an interview in BM.

Round 4: Participants are asked how much (in %) of the Black-White wage gap they think is driven by (1) differences in educational attainment between Black and White workers and (2) employer discrimination against Black workers. Then, participants are told that statisticians estimate that 12% of the Black-White wage gap is driven by differences in educational attainment. Participants are then asked again for their best guess of the number of times that a resume with a White-sounding name had to be sent out on average to get one callback for an interview in BM. Finally, participants state their updated belief about how much (in %) of the Black-White wage gap they think is driven by employer discrimination against Black workers.

Round 5: Participants are presented with the callback rates for applicants with White-sounding names and Black-sounding names from Jacquemet and Yannelis (2012)’s fake resume study. Participants are then asked again for their best guess of the number of times that a resume with a White-sounding name had to be sent out on average to get one callback for an interview in BM. Participants are then told that a resume with a White-sounding name had to be sent out 10 times on average to get one callback for an interview in BM.

At the end of the study, participants are asked unincentivized questions about their thoughts on the BM study, their political views, and a couple of math questions. See Appendix A for screenshots of the study.

3.2 Incentives

All participants receive a participation payment of at least \$3 for finishing this study¹. In addition, participants have the opportunity to earn a \$2 bonus based on their answers. At the end of the study, one of the eligible questions is randomly selected to determine whether the participant receives the bonus. If the participant’s guess is close enough to the correct answer on this randomly selected question, then they earn the bonus.

¹The participation payment was increased from \$3 to \$3.75 for the final third of data collection due to grant requirements. Within each participation payment amount, the sample is balanced by Democrats and Republicans.

Eight questions are eligible to be selected for the bonus. In each of the five rounds, participants are asked the number of times a resume with a White-sounding name had to be sent out to receive one callback in BM. Participants' answers to this question in each round are eligible to be selected for the bonus, and if selected, participants receive the bonus if they are within one unit of the correct answer. In Round 1, participants are asked the number of times a resume with a White-sounding name had to be sent out to receive one callback in BM. This question is also eligible, and if selected, participants receive the bonus if they are within one unit of the correct answer. In Round 3, participants are asked their best guess of average weekly earnings for White full-time workers in the US is eligible. This question is also eligible, and if selected, participants receive the bonus if they are within \$100 of the correct answer. In Round 4, participants are asked their best guess of the percent of the Black-White wage gap that is explained by differences in educational attainment. This question is also eligible, and if selected, participants receive the bonus if they are within five percentage points of the correct answer.

The only questions in Rounds 1-5 that are not eligible to be selected for the bonus are about how much of the Black-White wage gap participants believe are driven by employer discrimination against Black workers in Rounds 3, 4, and 5. These questions cannot be incentivized because we do not currently have methods to calculate this number. Each time this question is asked, participants are told that this question is hypothetical and not eligible for a bonus. Analysis of these unincentivized questions is presented in Appendix B.

4 Hypotheses

In this section, I outline the main hypotheses on beliefs about racial hiring discrimination for each round.

4.1 Round 1

In Round 1, I ask participants their best guesses of the callback rates from BM: the number of times a resume with a Black-sounding name had to be sent out to get one callback and the number of times a resume with a White-sounding name had to be sent out to get one callback. From their responses, I calculate each participant's baseline belief about racial

discrimination in hiring as follows.

$$D_{1,i} = \log(\widehat{B}_i) - \log(\widehat{W}_{1,i}) \quad (1)$$

where \widehat{B}_i is participant i 's prediction of the number of times resumes with Black-sounding names had to be sent out to receive one callback in BM, and $\widehat{W}_{1,i}$ is participant i 's Round 1 prediction of the number of times resumes with White-sounding names had to be sent out to receive one callback in BM.

In this round, I evaluate whether Democrats and Republicans disagree about the extent of discrimination in hiring against Black workers. Findings from the literature (Haaland and Roth, 2021; Alesina et al., 2021) suggest that Democrats believe there is more racial discrimination in hiring than Republicans do. I seek to replicate this finding in Round 1 of my study. I test directly whether Democrats' and Republicans' mean beliefs about racial discrimination in hiring statistically differ. I also test belief differences between Democrats and Republicans across the distribution of responses nonparametrically using a Kolmogorov-Smirnov test.

4.2 Round 2

In Round 2, I tell participants the number of times that resumes with Black-sounding names in BM had to be sent out to get one callback for an interview. Given that participants know the callback rate for resumes with Black-sounding names from Round 2 onward, I adjust the calculation of their beliefs about racial discrimination in hiring as follows for Rounds 2-5.

$$D_{j,i} = \log(\overline{B}) - \log(\widehat{W}_{j,i}) \quad (2)$$

where $D_{j,i}$ is participant i 's calculated belief about hiring discrimination in Round $j \in \{2, 5\}$, \overline{B} is the actual number of times resumes with Black-sounding names had to be sent out to receive one callback from BM (15), and $\widehat{W}_{j,i}$ is participant i 's Round $j \in \{2, 5\}$ prediction of the number of times resumes with White-sounding names had to be sent out to receive one callback from BM.

In Round 2, I test how participants update their beliefs about racial discrimination in hiring in response to the callback rate for Black-sounding names in BM. If participants interpret this information purely as benchmarking information (i.e., to get a sense of average callback rates in BM), they may not update their beliefs about racial discrimination. That is, they

may update their predicted callback rate for applicants with White-sounding names such that their prediction of racial discrimination in hiring is unchanged. Participants may, on the other hand, use the callback rate for Black applicants in BM as a signal of racial discrimination in hiring. Suppose, for example, a participant finds out that Black applicants in BM received fewer callbacks than they anticipated. The participant may interpret this low callback rate as a signal that there is more racial discrimination in hiring than they thought. To calculate participants' changes in beliefs about racial discrimination in hiring between Round 1 and 2, I calculate the following.

$$\Delta D_{1,2,i} = ihs(D_{2,i}) - ihs(D_{1,i}) \quad (3)$$

where $ihs()$ is the inverse hyperbolic sine function. This function approximates the log function, while allowing for zeroes. Therefore, if participants believe there is no racial discrimination in hiring, this function allows me to calculate their belief updates, unlike the log function which would exclude their responses.

I calculate participants' errors on the number of times that resumes with Black-sounding names had to be sent out to receive one callback for an interview as follows:

$$Error_B_i = \log(\overline{B}) - \log(\hat{B}_i) \quad (4)$$

where \overline{B} is the true average number of times resumes with Black-sounding names had to be sent out to receive a callback in BM.

Then, I test how participants update their beliefs between Round 1 and 2 in response to the Black callback rate in BM as follows.

$$\Delta D_{1,2,i} = \mu + \delta_1 Rep_i Error_B_i + \delta_2 Dem_i Error_B_i + \eta_i \quad (5)$$

where $Rep_i = 1$ if participant i is a Republican and 0 otherwise, and $Dem_i = 1$ if participant i is a Democrat and 0 otherwise.

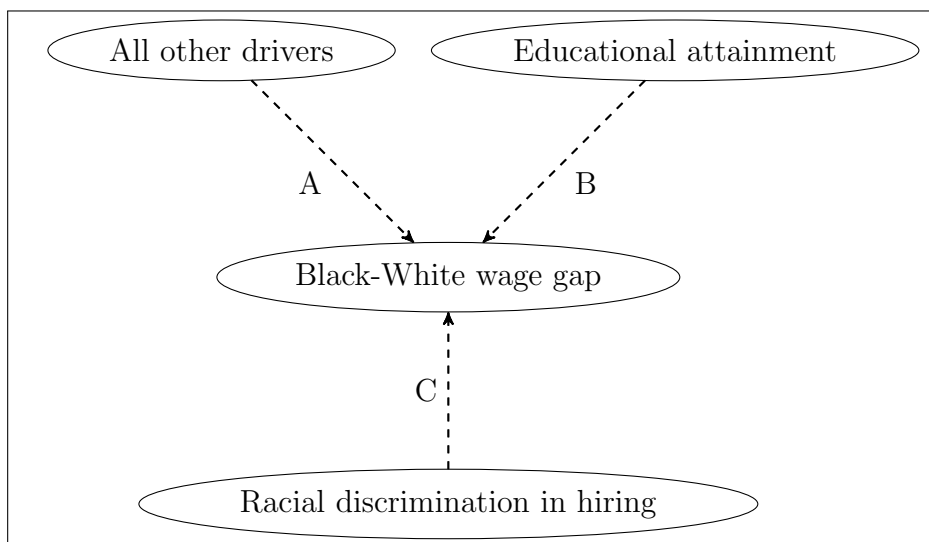
From δ_1 and δ_2 , I identify if Republicans and Democrats, respectively, update their beliefs about racial discrimination in hiring in response to the Black callback rate in BM. If $\delta_1 = 0$ ($\delta_2 = 0$), then this would suggest that Republicans (Democrats) do not update their beliefs about racial discrimination and treat the Black callback rate as purely benchmarking information.

4.3 Round 3

In Round 3, participants are told (after stating their priors) that White full-time workers in the US earn on average \$1085 per week, while Black full-time US workers earn on average \$844 per week. Participants then state their updated best guess of the number of times that resumes with White-sounding names had to be sent out to receive one callback in BM.

In Round 3, I test whether participants update their beliefs about racial discrimination in hiring in response to information about the Black-White wage gap. Figure 3 is a directed acyclic graph (DAG) summarizing how participants may think about the relationship between racial discrimination in hiring and the Black-White wage gap. Arrows indicate the direction of causality.

Figure 3: Potential drivers of the Black-White wage gap



Notes. The figure above is a directed acyclic graph (DAG) summarizing the relationship between the Black-White wage gap for full-time workers in the US and various potential drivers. Arrows indicate the direction of causality. Dashed arrows represent pathways that participants may or may not believe exist. From participants' responses in my study, I can test whether participants believe arrows B and C are prominent contributors to the Black-White wage gap.

There are many possible drivers of the Black-White wage gap. I highlight two in Figure 3: educational attainment differences between Black and White workers in the US and racial discrimination in hiring. All other drivers of the wage gap that participants may think of are encapsulated in the category “All other drivers.” In Round 3, I test directly whether arrow C holds. That is, I test whether participants believe that racial discrimination in hiring is a driver of the Black-White wage gap.

If participants do not believe that racial discrimination in hiring is a driver of the Black-White wage gap, then we would expect the update in their belief about racial discrimination in hiring between Round 2 and 3 to be uncorrelated with their error on the Black-White wage gap. If, on the other hand, participants believe that racial discrimination in hiring is a driver of the Black-White wage gap, then we may expect participants to update their beliefs about racial discrimination in hiring in response to information on the Black-White wage gap. That is, participants who overestimate the Black-White wage gap may decrease their belief about the extent of racial discrimination in hiring, and those who underestimate the Black-White wage gap may increase their belief about the extent racial discrimination in hiring.

To test whether participants update in response to the Black-White wage gap, I first calculate their belief update about racial discrimination in hiring as follows.

$$\Delta D_{2,3,i} = ihs(D_{3,i}) - ihs(D_{2,i}) \quad (6)$$

where $ihs()$ is the inverse hyperbolic sine function, which approximates the natural log function while allowing for zeroes.

I then calculate participants' errors on White average weekly earnings is calculated as follows.

$$Error_WE_i = \log(\overline{WE}) - \log(\widehat{WE}_i) \quad (7)$$

where \overline{WE} is the true average White weekly earnings (\$1085), and \widehat{WE}_i is participant i 's prediction of White weekly average earnings. Because participants are first told Black average weekly earnings, this measure indicates their beliefs about the Black-White wage gap.

I then test whether participants' belief updates are correlated with their error on average weekly earnings for White full-time workers. Findings from Alesina et al. (2021) suggest that Democrats are more likely than Republicans to believe racial disparities are driven more by systemic factors, including racial discrimination. So, I test the relationship separately for Democrats and Republicans, as follows.

$$\Delta D_{2,3,i} = \alpha + \beta_1 Rep_i Error_WE_i + \beta_2 Dem_i Error_WE_i + \epsilon_i \quad (8)$$

where $Rep_i = 1$ if participant i is a Republican and 0 otherwise, and $Dem_i = 1$ if participant i is a Democrat and 0 otherwise.

β_1 and β_2 inform whether Republicans and Democrats, respectively, update their beliefs about racial discrimination in hiring in response to the Black-White wage gap.

4.4 Round 4

In Round 4, participants are told (after stating their priors) that 12% of the Black-White wage gap for full-time workers in the US is explained by differences in educational attainment between Black and White workers. They then state their updated best guess of the BM White callback rate.

In thinking about how information on the explanatory power of educational attainment may affect participants' beliefs about racial discrimination in hiring, we turn again to Figure 3. Because the categories are all-encompassing, all three arrows (A, B, and C) must together explain 100% of the Black-White wage gap. Consider a participant who overestimates the percent of the wage gap that is explained by educational attainment. This participant would then have leftover weight that must be spread between arrows A and C. If the participant believes that racial discrimination in hiring is a driver of the Black-White wage gap, then they may assign some of the weight to arrow C. If the participant does not believe that racial discrimination is a driver, then we would not expect them to add any weight to arrow C.

I calculate participants' Round 4 updates in beliefs about racial discrimination in hiring as follows:

$$\Delta D_{3,4,i} = ihs(D_{4,i}) - ihs(D_{3,i}) \quad (9)$$

where $ihs()$ is the inverse hyperbolic sine function, which approximates the log function while allowing for zeroes.

I calculate participants' errors on how much of the wage gap is explained by educational attainment as follows.

$$Error_EA_i = ihs(\overline{EA}) - ihs(\widehat{EA}_i) \quad (10)$$

where \overline{EA} is the calculation of the amount of the wage gap explained by differences in educational attainment (12%), and \widehat{EA}_i is participant i 's prediction of this percent.

To investigate whether participants update their beliefs about racial hiring discrimination in response to information about the explanatory power of educational attainment, I run the following regression.

$$\Delta D_{3,4,i} = \phi + \gamma_1 Rep_i Error_EA_i + \gamma_2 Dem_i Error_EA_i + v_i \quad (11)$$

where $Rep_i = 1$ if participant i is a Republican and 0 otherwise, and $Dem_i = 1$ if participant i is a Democrat and 0 otherwise.

γ_1 and γ_2 inform whether Republicans and Democrats, respectively, update their beliefs about racial discrimination in hiring in response to the explanatory power of educational attainment. If $\gamma_1 < 0$ and $\gamma_2 < 0$, then this would suggest that Democrats and Republicans, respectively, increase the weight on arrow C in Figure 3 upon finding out that educational attainment explains less of the wage gap than they thought.

4.5 Round 5

In Round 5, participants are told the callback rates for applicants with White-sounding names and for applicants with Black-sounding names from the fake resume study in Jacquemet and Yannelis (2012). Participants then state their final best guess of the callback rate for applicants with White-sounding names in BM.

The purpose of Round 5 is to show that the belief gap between Democrats and Republicans in my sample can indeed be closed using information. A closing of the belief gap between Democrats and Republicans would replicate a finding from Haaland and Roth (2021) that information on results from experiments designed to measure discrimination can successfully close the partisan belief gap about hiring discrimination.

To examine if the belief gap persists in Round 5, I test directly whether Democrats' and Republicans' mean Round 5 beliefs about racial discrimination in hiring statistically differ. I also test belief differences between Democrats and Republicans across the distribution of responses nonparametrically using a Kolmogorov-Smirnov test.

I also test if Democrats and Republicans significantly update their beliefs about racial discrimination in hiring between Round 4 and Round 5. To do so, I calculate participants' changes in beliefs between Round 4 and 5 as follows.

$$\Delta D_{4,5,i} = ihs(D_{5,i}) - ihs(D_{4,i}) \quad (12)$$

To test if Democrats and Republicans significantly update their beliefs, I regress their belief update on their political affiliation.

$$\Delta D_{4,5,i} = \psi + \chi Rep_i + \rho_i \quad (13)$$

where Rep_i is a dummy variable indicating if participant i is Republican.

The constant term ψ indicates if Democrats update significantly in Round 5, and $\psi + \chi$ indicates if Republicans update significantly.

5 Results

In this section, I review study results. Subsection 5.1 describes the sample in terms of demographic characteristics and baseline interpretations of BM. In subsection 5.2, I describe participants' baseline beliefs about racial hiring discrimination. In subsection 5.3, I investigate belief-updating about hiring discrimination in response to the Black callback rate in BM. Subsection 5.4 investigates belief-updating about hiring discrimination in response to information on the Black-White wage gap. In subsection 5.5, I investigate belief-updating about hiring discrimination in response to information on the role of educational attainment in explaining the Black-White wage gap. In subsection 5.6, I examine how participants update their beliefs in response to results from another fake resume study. Subsection 5.7 compares participants' endline interpretations of BM to their baseline interpretations, and compares responses by political affiliation.

5.1 Sample

The study was administered on Prolific, a widely used online survey platform among social scientists, from April - August 2023. My sample consists of 1100 self-reported Democrats and 1100 self-reported Republicans in the US with accounts on Prolific. I ensured the sample is split evenly by gender, with 50% female and 50% male participants. Respondents are on average 40 years old, with Democrats being slightly younger (37) than Republicans (43). Overall, the sample is more White than the general US population, with 77% of my sample identifying as White and only 7% identifying as Black. Democrats skew less White and more Black than Republicans. See Table 1 for more demographic details. On average, participants took approximately 13 minutes to complete the study, and 21% of participants earned the \$2 bonus.

One concern with using an online survey platform for my study is that participants lean more liberal than the general US population. Indeed, the total available sample of self-identified Democrats on Prolific is approximately 12,000 people, compared to only approximately 3,000 Republicans. While both groups are large enough for my sample size, one may be concerned

that Republicans on this platform are more ideologically moderate than those of the general US population. To check, I ask participants two questions at the end of the study. First is their self-reported ideology on a standard seven-point scale from “Extremely Liberal” to “Extremely Conservative”. Second is the probability they will vote for the Republican or Democratic candidate in the 2024 presidential election, conditional on voting. Figure 4 reports participants’ responses to these questions.

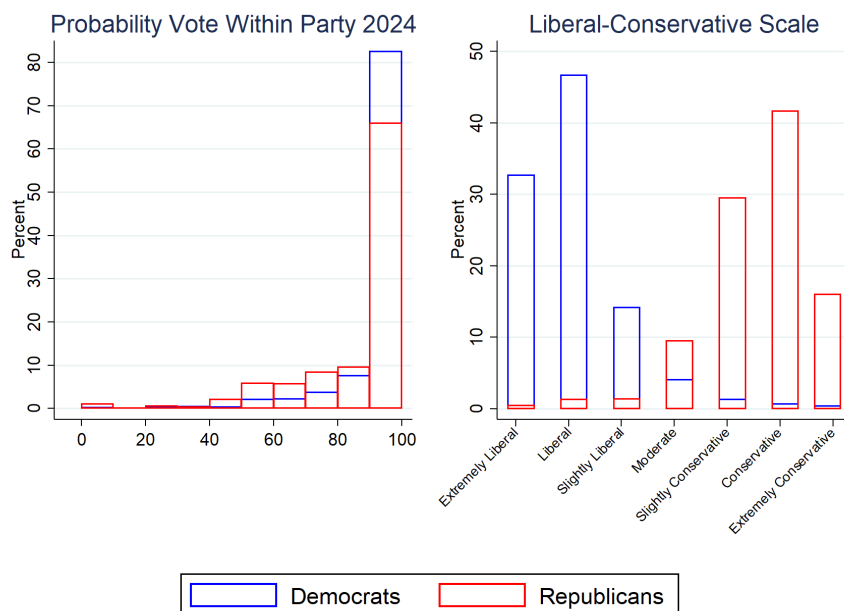
Table 1: Sample Demographics by Political Affiliation

	Democrats	Republicans
Male	0.50 (0.50)	0.51 (0.50)
White	0.70 (0.46)	0.84 (0.36)
Black	0.10 (0.30)	0.04 (0.19)
Asian	0.09 (0.29)	0.04 (0.21)
Other Race	0.10 (0.30)	0.07 (0.26)
Born in US	0.94 (0.24)	0.95 (0.22)
Employed Full-time	0.41 (0.49)	0.53 (0.50)
Employed Part-time	0.13 (0.34)	0.13 (0.34)
Unemployed	0.11 (0.31)	0.07 (0.26)
Observations	1100	1100

Participants’ responses to both questions indicate that Republicans are indeed more moderate than Democrats. Approximately 58% of Democrats state there is a 100% probability that they will vote for the Democratic nominee in the 2024 presidential election, while approximately 45% of Republicans in my sample state there is a 100% probability that they will vote for the Republican nominee. A substantial portion of Republicans do self-report being

“Extremely Conservative” (16%), but this proportion is significantly smaller than Democrats who self-report being “Extremely Liberal” (33%). Given that my primary analysis is in evaluating differences between Democrats and Republicans, having a more moderate sample of Republicans than the general US population biases me away from finding differences between Democrats and Republicans.

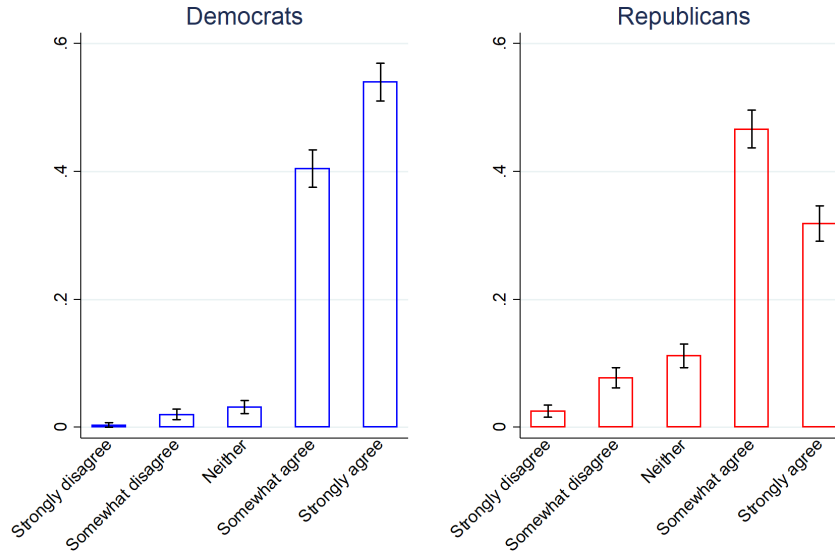
Figure 4: Self-Reported Degree of Conservativeness and Liberalness



Notes. The left panel displays the distribution of participants’ self-reported probability they will vote for their political party candidate in the 2024 presidential election, conditional on voting. That is, Democrats report the likelihood they will vote for the Democratic presidential candidate in 2024, and Republicans report the likelihood they will vote for the Republican presidential candidate in 2024, conditional on voting in the election. The right panel displays participants’ responses about their political ideology, on a seven-point scale from “extremely liberal” to “extremely conservative.” For both panels, the distribution of Democrats’ responses is shown in blue, and Republican responses are in red.

Before beginning Round 1, I explain BM to participants. I then ask participants if they believe that a difference in callback rates between applicants with Black-sounding names and applicants White-sounding names reflects that employers base their callback decisions in part on the race of the applicant. If participants do not agree with this interpretation, then it would not be appropriate for me to interpret their beliefs about the study findings as their beliefs about racial discrimination in hiring. Figure 16 reports the distributions of participants’ agreement with this statement, on a scale from “Strongly Agree” to “Strongly Disagree.”

Figure 5: Agree BM tests whether employers use race in callback decisions



Notes. The figures show the distributions of participants’ responses on a scale from “strongly disagree” to “strongly agree” to the following statement. “If the researchers find a difference in callback rates between applicants with Black-sounding names and applicants with White-sounding names in Experiment A [BM], this would reflect that employers base their callback decisions in part on the race of the applicant.” The left panel restricts my sample to Democrats, and the right panel restricts to Republicans.

In my sample, 94% of Democrats and 79% of Republicans either “somewhat agree” or “strongly agree” that any difference in callback rates between applicants with Black-sounding and White-sounding names would indicate that employers base their callback decisions in part on the race of the applicant. While Democrats are more likely to “strongly agree” than Republicans (54% of Democrats vs. 32% of Republicans), I find it promising that the majority of my sample from both parties generally agree that the results are driven by employers using applicants’ races in making their callback decisions.

5.2 Round 1: Baseline beliefs about racial discrimination in hiring

In the first round, participants state their baseline beliefs about racial discrimination in hiring. That is, they state the number of times they think a resume with a White-sounding name had to be sent out to get one callback for an interview in BM, and the number of times they think a resume with a Black-sounding name had to be sent out to get one callback for an interview in BM.

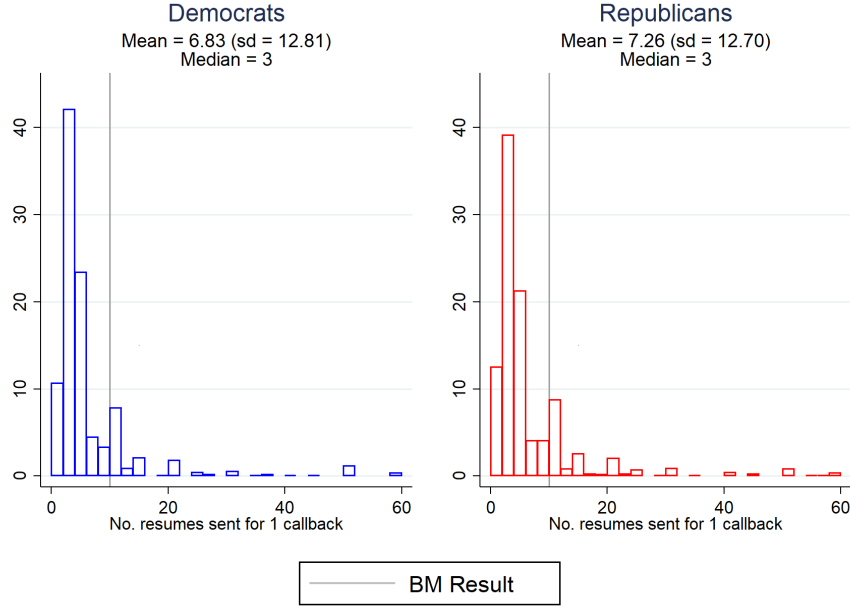
Figure 6 shows participants’ baseline beliefs for White-sounding names, split by political affiliation. Responses greater than 60 are excluded (1.3% of responses) from the graph for visual purposes. The median response among both Democrats and Republicans is that resumes with White-sounding names had to be sent out an average of 3 times to get one callback for an interview. Using a Kolmogorov-Smirnov test for equality of distributions, I cannot reject the null hypothesis that Democrats’ responses and Republicans’ responses come from the same underlying distribution ($p = 0.46$). Both groups underestimate the number of times resumes with White-sounding names had to be sent out, as BM finds they had to be sent out 10 times to get a callback.

Figure 7 shows participants’ baseline beliefs on the callback rate for applicants with Black-sounding names in BM, split by political affiliation. Responses greater than 60 are excluded (2% of responses) from the graph for visual purposes. Democrats’ median prediction is that resumes with Black-sounding names had to be sent out 8 times to get one callback. Republicans’ median response is 6 times. Average callback beliefs about the Black callback rate are significantly different between Democrats and Republicans ($p = 0.01$), and a Kolmogorov-Smirnov test rejects the null hypothesis that these responses come from the same underlying distribution ($p < 0.001$). Both groups underestimate the number of times resumes with Black-sounding names had to be sent out, as BM finds they had to be sent out 15 times to get one callback.

To calculate participants’ baseline beliefs about racial discrimination in hiring, I take the log difference of their predictions of callback rates, as in Equation 1. Figure 8 reports the cumulative distribution function of participants’ baseline beliefs about racial discrimination in hiring in Round 1 split by political affiliation. Across the distribution, Democrats believe there is more racial discrimination in hiring than Republicans do. Distributions are significantly different by political affiliation ($p < 0.001$), according to the Kolmogorov-Smirnov test. Relative to BM results, both Democrats and Republicans overestimate the amount of discrimination.

Result 1: *At baseline, Democrats believe there is more racial discrimination in hiring than Republicans do.*

Figure 6: Priors on White callback rate in BM



Notes. The figures show the distributions of participants' baseline predictions of the number of resumes applicants with White-sounding names had to be sent out to employers to get one callback for an interview in Bertrand and Mullainathan (2004). The left panel restricts my sample to Democrats, and the right panel restricts to Republicans. The actual number of times resumes with White-sounding names had to be sent out to receive one callback was 10 times, as depicted with the grey vertical line on each panel.

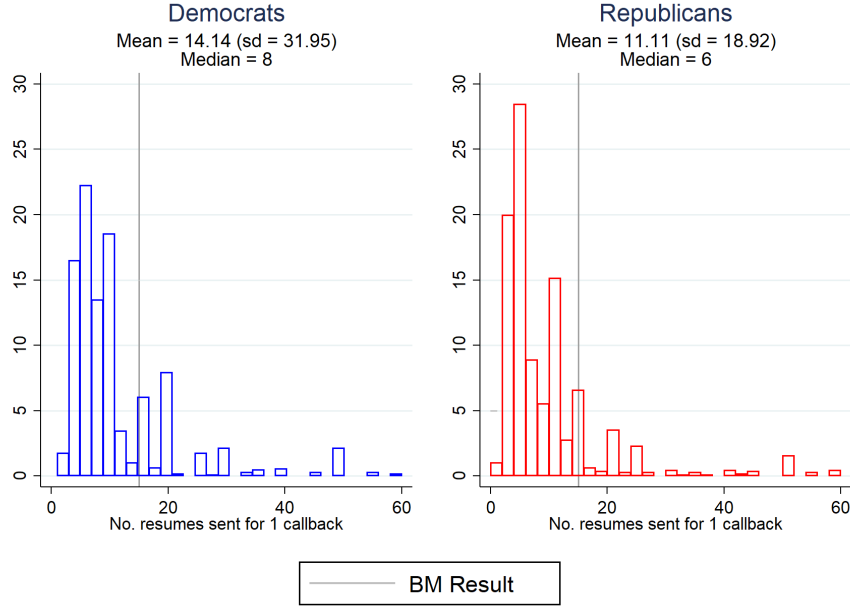
5.3 Round 2: Hiring discrimination beliefs in response to BM Black callback rate

In Round 2, participants are told the number of times that resumes with Black-sounding names had to be sent out to get one callback for an interview in BM. They then state their updated beliefs about the number of times that resumes with White-sounding names had to be sent out for a callback in BM. From Round 2 onward, I calculate participants' beliefs about racial hiring discrimination as in Equation 2. That is, I take the log difference between the actual callback rate for applicants with Black-sounding names in BM, and participants' predictions of the callback rate for applicants with White-sounding names.

Figure 9 shows participants' beliefs about racial discrimination in hiring in Round 2 split by political affiliation. The dashed lines depict participants' Round 1 beliefs, and the solid lines depict participants' Round 2 beliefs.

Relative to Round 1, both Democrats and Republicans increase their hiring discrimination

Figure 7: Priors on Black callback rate in BM

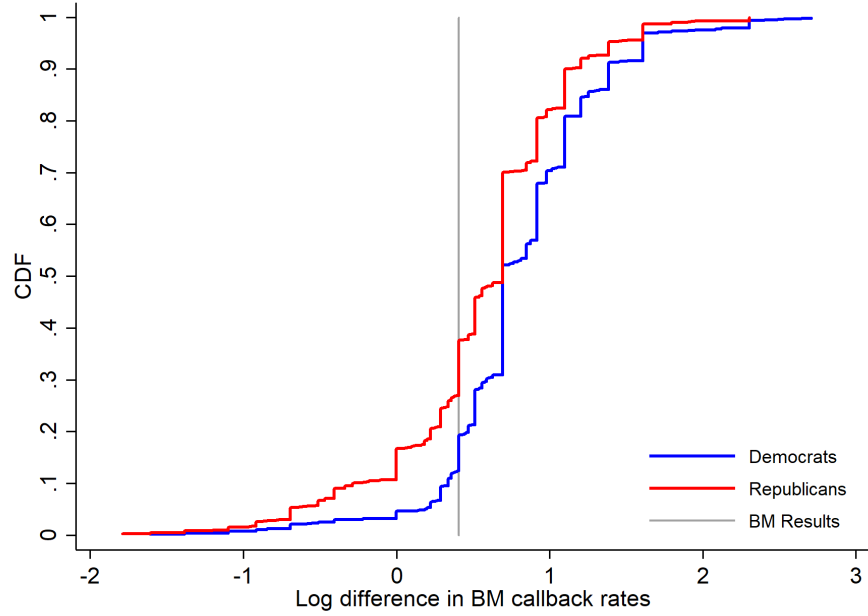


Notes. The figures show the distributions of participants' baseline predictions of the number of resumes applicants with Black-sounding names had to be sent out to employers to get one callback for an interview in Bertrand and Mullainathan (2004). The left panel restricts my sample to Democrats, and the right panel restricts to Republicans. The actual number of times resumes with Black-sounding names had to be sent out to receive one callback was 15 times, as depicted with the grey vertical line on each panel.

beliefs in response to the Black callback rate from BM. The gap between Democrats' and Republicans' beliefs about racial discrimination in hiring decreases ($p < 0.001$), as Republicans update more positively than Democrats. This is in line with Bayesian updating, as Republicans overestimated the frequency of callbacks for Black applicants more than Democrats did. I reject that Democrats' and Republicans' beliefs come from the same underlying distribution ($p < 0.001$), according to the Kolmogorov-Smirnov test.

In Table 2, I directly test the relationship between participants' errors on the BM Black callback rate and their updating behavior. I calculate participants' belief changes about hiring discrimination between Round 1 and Round 2 as in Equation 3, and their error on the BM Black callback rate as in Equation 4.

Figure 8: Round 1 Beliefs about racial discrimination in hiring



Notes. This figure shows the cumulative distribution functions of participants' baseline beliefs about racial discrimination in hiring in Round 1, split by political affiliation. Beliefs are measured as the log difference between participants' predictions of the number of times resumes with Black-sounding names had to be sent out to receive one callback for an interview in Bertrand and Mullainathan (2004) and the number of times resumes with White-sounding names had to be sent out to receive one callback. The actual log difference in callback rates from BM is depicted by the vertical grey line. Democrats' beliefs are shown in blue, and Republicans' beliefs are in red.

Table 2: Hiring Discrimination Belief Updates to BM Black Callback Rate

	(1) Belief Update: R2-R1	(2) Belief Update: R2-R1	(3) Belief Update: R2-R1
Error: Black Callbacks	0.214*** (0.0132)		
Overestimate \times Error: Black Callbacks		0.0769** (0.0374)	
Underestimate \times Error: Black Callbacks		0.286*** (0.0181)	
Democrat \times Overestimate \times Error: Black Callbacks			0.0768 (0.0504)
Democrat \times Underestimate \times Error: Black Callbacks			0.256*** (0.0217)
Republican \times Overestimate \times Error: Black Callbacks			0.0862* (0.0462)
Republican \times Underestimate \times Error: Black Callbacks			0.299*** (0.0197)
Constant	0.0469*** (0.0109)	-0.0248* (0.0150)	-0.0200 (0.0151)
Observations	2190	2190	2190

Notes. The table shows regressions of participants’ changes in beliefs about racial discrimination in hiring between rounds 1 and 2. Round 1 beliefs are calculated as the log difference in participants’ predicted callback rates for applicants with White-sounding names and for applicants with Black-sounding names in BM. Round 2 beliefs are calculated as the log difference between participants’ predicted White callback rates and the actual Black callback rate in BM. Changes in beliefs between Round 1 and Round 2 are calculated using the inverse hyperbolic sine function difference. “Error: Black Callbacks” is the inverse hyperbolic sine difference between participants’ priors on the Black callback rate and the actual Black callback rate in BM. “Underestimate” (“Overestimate”) includes only participants who underestimate (do not underestimate) the number of times Black resumes had to be sent out to get a callback in BM. “Democrat” (“Republican”) includes only participants who identify as Democrats (Republicans). Robust standard errors are in parentheses.

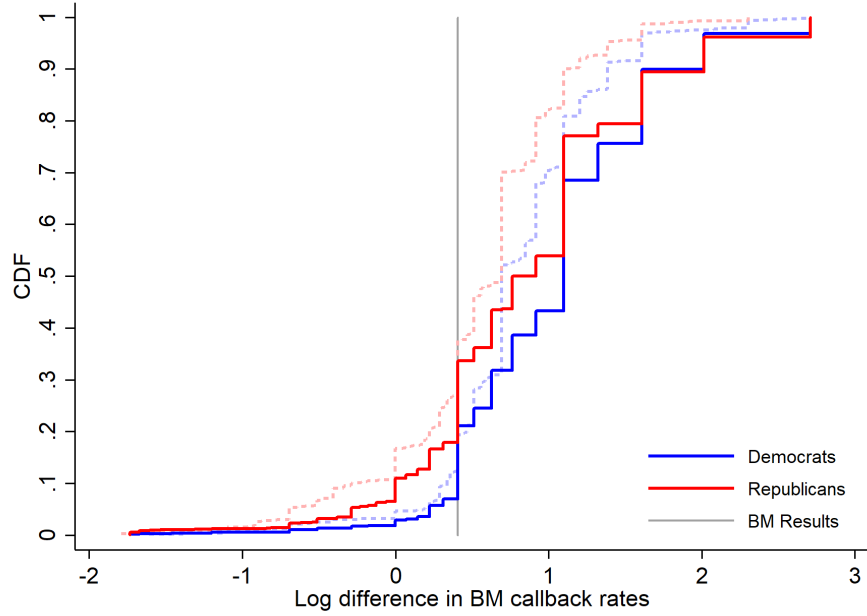
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Model 1 of Table 2 regresses participants’ changes in discrimination beliefs between rounds 2 and 1 on their errors on the Black callback rate, as in Equation 5. Coefficients can be thought of as elasticities, where a coefficient of 1 would indicate that participants update entirely on racial hiring discrimination, and a coefficient of 0 would indicate that participants update entirely on the White callback rate. The coefficient of 0.214 means that a 100% error in the callback rate for applicants with Black-sounding names translates to a 21.4% increase in beliefs about hiring discrimination.

Model 2 of Table 2 interacts participants’ errors on the Black callback rate with an indicator for whether participants overestimate or underestimate the Black callback rate. This shows that the relationship between participants’ errors and their updating behavior is driven by those who underestimate the frequency of callbacks for resumes with Black-sounding names. That is, participants who find out Black resumes had to be sent out *more* times than they thought update on hiring discrimination, while those who find out Black resumes had to be sent out *fewer* times than they thought do not update on hiring discrimination.

Model 3 of Table 2 interacts each of the terms from model 2 with political affiliation. Both groups update positively on discrimination when they find out Black resumes had to be sent out more times to get a callback than they had initially predicted. Among those who overestimate the number of times that Black resumes had to be sent out to get a callback, I find no evidence that Democrats and Republicans update significantly differently from each other ($p = 0.88$). Among those who underestimate the number of times that Black resumes had to be sent out to get a callback, Republicans update their beliefs about racial discrimination in hiring more than Democrats ($p = 0.03$).

Figure 9: Round 2 Beliefs about racial discrimination in hiring



Notes. This figure shows the cumulative distribution functions of participants' beliefs about racial discrimination in hiring in Round 2 (bolded solid lines), split by political affiliation. Participants' Round 1 beliefs are shown as dashed lines for ease of comparison. In Round 2, participants are told the number of times resumes with Black-sounding names had to be sent out to receive one callback for an interview. Beliefs in Round 2 are measured as the log difference between the actual number of times resumes with Black-sounding names had to be sent out to receive one callback (15) in Bertrand and Mullainathan (2004) and participants' predictions of the number of times resumes with White-sounding names had to be sent out to receive one callback in BM. The actual log difference in callback rates from BM is depicted by the vertical grey line. Democrats' beliefs are shown in blue, and Republicans' beliefs are in red.

5.4 Round 3: Hiring discrimination beliefs in response to Black-White wage gap

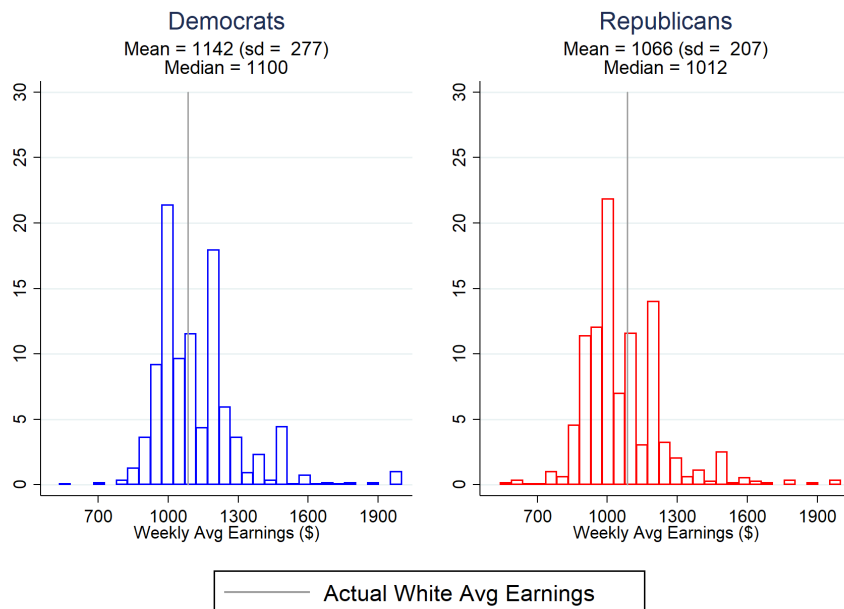
In Round 3, participants are told average weekly earnings for Black full-time workers in the US (\$844)², and asked for their best guess of average weekly earnings for White full-time workers in the US. Participants are then told median weekly earnings for White full-time workers in the US (\$1085). Then, participants again state their best guess of the number of times a resume with a White-sounding name had to be sent out on average to get one callback for an interview in BM.

Figure 10 shows Democrats' (left panel) and Republicans' (right panel) distributions of

²This statistic was gathered from the Current Population Survey 2021 median earnings for Black full-time workers in the US.

priors on average weekly earnings for White full-time workers in the US. Average weekly earnings among White full-time workers in the US was \$1085 according to the 2021 Current Population Survey. The median prediction among Democrats was \$1142, which was larger than Republicans' median estimate of \$1066 ($p < 0.001$), implying that Democrats think the wage gap is larger than Republicans do. Overall, 46% of Democrats underestimate the wage gap, compared to 59% of Republicans.

Figure 10: Priors on White average weekly earnings

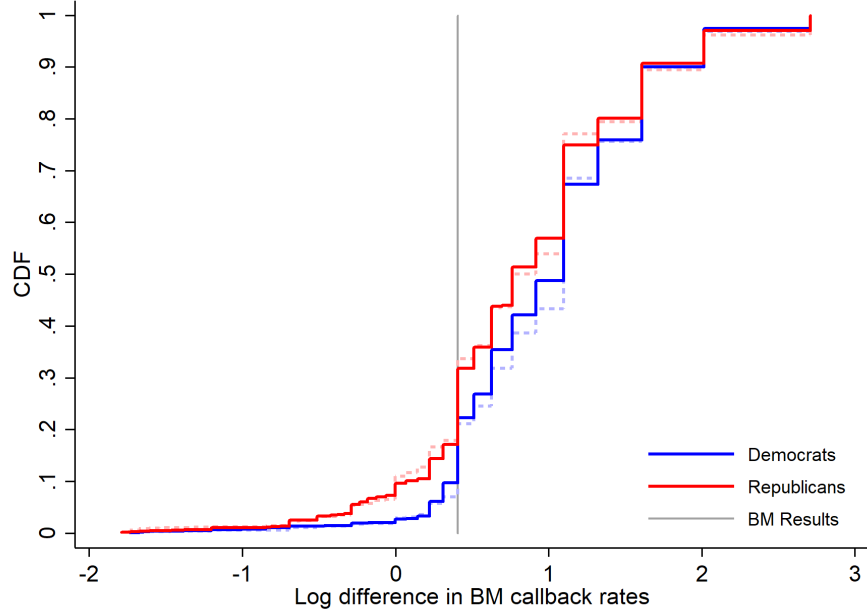


Notes. The figures show the distributions of participants' priors about average weekly earnings among White full-time workers in the US. Before responding, participants are first told the average weekly earnings for Black full-time workers (\$844) in the US according to the US Bureau of Labor Statistics. The left panel restricts my sample to Democrats, and the right panel restricts to Republicans. The true average weekly earnings for White full-time workers in the US according to the US Bureau of Labor Statistics is \$1085, as depicted by the grey vertical line on each panel.

On average, Democrats' beliefs about racial discrimination in hiring decrease slightly, but not statistically significantly between rounds 2 and 3 ($p = 0.237$). Republicans' beliefs do not significantly change ($p = 0.833$). As seen in Figure 11, Democrats experience a slight distributional shift in beliefs in Round 3 (Kolmogorov-Smirnov test: $p = 0.08$), but Republicans do not (Kolmogorov-Smirnov test: $p = 0.70$). The average gap between Democrats' and Republicans' beliefs decreases slightly but not significantly ($p = 0.11$).

To evaluate how participants respond to wage gap information in this round, I regress their changes in beliefs about hiring discrimination on their error in White average earnings in

Figure 11: Round 3 Beliefs about racial discrimination in hiring



Notes. This figure shows the cumulative distribution functions of participants' beliefs about racial discrimination in hiring in Round 3 (bolded solid lines), split by political affiliation. Participants' Round 2 beliefs are shown as dashed lines for ease of comparison. In Round 3, participants are told the Black-White wage gap for full-time workers in the US. Beliefs are measured as the log difference between the actual number of times resumes with Black-sounding names had to be sent out to receive one callback (15) in Bertrand and Mullainathan (2004) and participants' predictions of the number of times resumes with White-sounding names had to be sent out to receive one callback in BM. The actual log difference in callback rates from BM is depicted by the vertical grey line. Democrats' beliefs are shown in blue, and Republicans' beliefs are in red.

Table 3 as shown in Equation 8). The outcome variable, the change in beliefs about hiring discrimination, is calculated as in Equation 6. Participants' errors on the average weekly earnings for White full-time workers in the US are calculated as in Equation 7. I exclude extreme outliers from participants who submit best guesses of the average weekly White earnings that are an order of magnitude off from the correct answer: observations less than or equal to \$100 or greater than or equal to \$10,000. This includes 21 participants in total (1% of my sample).

As can be seen in model 1 of Table 3, there does not seem to be strong relationship between wage gap information and beliefs about hiring discrimination. When we split the sample by Democrats and Republicans in model 2, however, Democrats update their beliefs about racial discrimination in hiring in response to the Black-White wage gap, while Republicans do not.

Result 2: *Democrats update their beliefs about racial discrimination in hiring in response to information about the Black-White wage gap, while Republicans do not.*

Splitting the sample by those who overestimated and underestimated White average earnings in model 3, I find that Democrats who overestimate White earnings seem to be driving the effect, not Democrats who underestimate White earnings. Republicans, on the other hand, do not seem to use the Black-White wage gap to update their beliefs about racial discrimination in hiring regardless of whether they overestimate or underestimate White earnings.

Table 3: Hiring Discrimination Belief Updates to Black-White Wage Gap

	(1)	(2)	(3)
	Belief Update: R3-R2	Belief Update: R3-R2	Belief Update: R3-R2
Error: White Earnings	0.0440 (0.0413)		
Democrat \times Error: White Earnings		0.0895** (0.0434)	
Republican \times Error: White Earnings		-0.00274 (0.0710)	
Democrat \times Overestimate \times Error: White Earnings			0.231*** (0.0452)
Democrat \times Underestimate \times Error: White Earnings			-0.108 (0.0864)
Republican \times Overestimate \times Error: White Earnings			0.0894 (0.110)
Republican \times Underestimate \times Error: White Earnings			-0.0615 (0.101)
Constant	-0.0114** (0.00556)	-0.00986* (0.00576)	0.00616 (0.00817)
Observations	2171	2171	2171

Notes. The table shows regressions of participants' changes in beliefs about racial discrimination in hiring between rounds 2 and 3. Beliefs about racial hiring discrimination are calculated as the log difference between participants' predicted White callback rates and the actual Black callback rate in BM. Changes in beliefs between Round 2 and Round 3 are calculated using the inverse hyperbolic sine function difference. "Error: White Earnings" is the log difference between participants' priors of average White weekly earnings for full-time US workers (after learning Black weekly earnings) and actual weekly earnings for White full-time US workers. "Democrat" ("Republican") includes only participants who identify as Democrats (Republicans). "Underestimate" ("Overestimate") includes only participants who underestimate (do not underestimate) median White weekly earnings. Robust standard errors are in parentheses.

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

5.5 Round 4: Hiring discrimination beliefs in response to role of educational attainment on wage gap

In Round 4, participants state how much (in %) of the Black-White wage gap they think is driven by differences in educational attainment between Black and White full-time workers. Participants are told that statisticians have developed methods of calculating this number, and if this question is selected for a bonus, they earn the \$2 bonus if they guess within 5 percentage points of the correct answer (12%).

Participants are then told that statisticians estimate 12% of the Black-White wage gap is explained by differences in educational attainment³. The vast majority of the sample (89%) overestimates how much of the wage gap is explained by differences in educational attainment, as shown in Figure 12. 91% of Republicans and 86% of Democrats overestimate the role of educational attainment in explaining the wage gap do ($p < 0.001$).

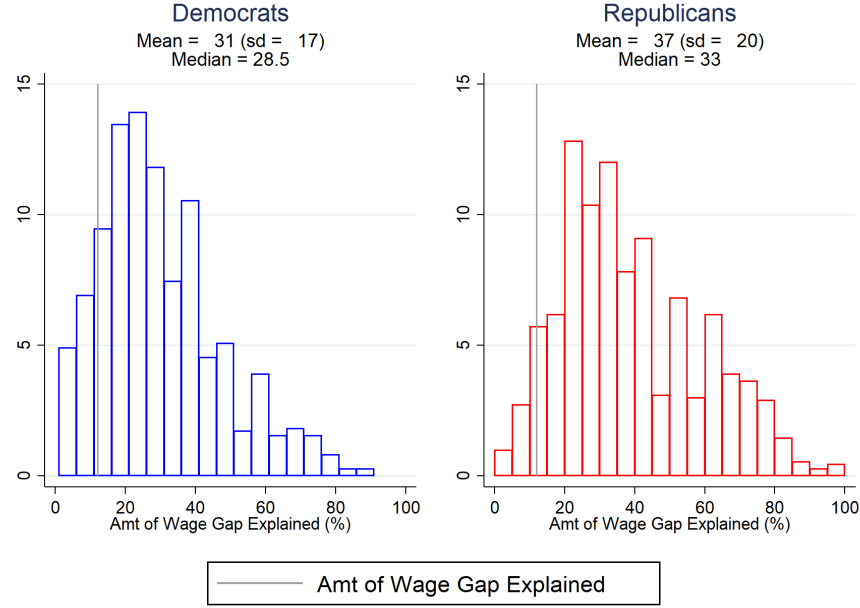
Participants are then asked again their best guess of the callback rate for applicants with White-sounding names in BM. Between Rounds 3 and 4, Democrats' beliefs about racial discrimination in hiring increase ($p = 0.020$), while Republicans' beliefs do not ($p = 0.250$). Democrats update, on average, more in Round 4 than Republicans do, leading to a slight increase in the belief gap about racial discrimination in hiring relative to Round 3 ($p = 0.069$), as shown in Figure 15.

In Figure 13, I compare belief distributions about racial discrimination in hiring between Rounds 3 and 4. While the distribution for Democrats appear to shift rightward, I cannot reject that Democrats' Round 3 and 4 beliefs about racial discrimination come from the same distributions ($p = 0.16$). I also cannot reject that the distribution of Republicans' beliefs between Round 3 and 4 come from the same distribution ($p = 0.44$).

Table 4 reports regression analysis of participants' changes in hiring discrimination beliefs from Rounds 3 to 4 on their error in the explanatory power of educational attainment on the Black-White wage gap (Equation 11). I calculate participants' updates to their beliefs about racial discrimination in hiring as in Equation 9. I calculate participants' errors on how much of the wage gap is explained by educational attainment as in Equation 10.

³This statistic was calculated using the Oaxaca-Blinder decomposition using 2021 earnings and education data from the Census Bureau for full-time workers in the US.

Figure 12: Priors on educational attainment



Notes. The figures show the distributions of participants' priors about the percentage of the Black-White wage gap among full-time workers in the US that is explained by differences in educational attainment between Black and White workers. The left panel restricts my sample to Democrats, and the right panel restricts to Republicans. The actual amount of the wage gap explained by differences in educational attainment according to a Oaxaca-Blinder decomposition using data from the Bureau of Labor Statistics is 12%, as depicted by the grey vertical line on each panel.

Table 4: Hiring Discrimination Belief Updates to Role of Edu on Black-White Wage Gap

	(1)	(2)	(3)
	Belief Update: R4-R3	Belief Update: R4-R3	Belief Update: R4-R3
Error: Pct EA Explains	-0.00939 (0.00773)		
Underestimate \times Error: Pct EA Explains		0.0244 (0.0214)	
Overestimate \times Error: Pct EA Explains		-0.0208** (0.0100)	
Democrat \times Underestimate \times Error: Pct EA Explains			0.0346 (0.0250)
Democrat \times Overestimate \times Error: Pct EA Explains			-0.0319*** (0.0107)
Republican \times Underestimate \times Error: Pct EA Explains			0.0166 (0.0339)
Republican \times Overestimate \times Error: Pct EA Explains			-0.0156 (0.0113)
Constant	0.0274*** (0.00797)	0.0150 (0.0101)	0.0128 (0.0101)
Observations	2193	2193	2193

Notes. The table shows regressions of participants’ changes in beliefs about racial hiring discrimination between rounds 3 and 4. Beliefs about racial hiring discrimination are calculated as the log difference between participants’ predicted White callback rates and the actual Black callback rate in BM. Changes in beliefs between Round 3 and 4 are calculated using the inverse hyperbolic sine function difference. “Error: Pct EA Explains” is the inverse hyperbolic sine difference between participants’ priors of how much of the Black-White wage gap is explained by educational attainment and an actual estimate of the amount (12%). “Overestimate” (“Underestimate”) includes all participants who overestimate (do not overestimate) the role of educational attainment. “Democrat” (“Republican”) includes only participants who identify as Democrats (Republicans). Robust standard errors are in parentheses.

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

Model 1 shows an insignificant relationship between participants’ beliefs about discrimination and the role of educational attainment on the wage gap. Splitting the sample in model 2 by those who underestimate vs. overestimate the role of educational attainment, however, shows that participants who overestimate the role of educational attainment increase their beliefs about racial discrimination in hiring. Participants who overestimate by 100%, increase their discrimination beliefs by 2%, on average.

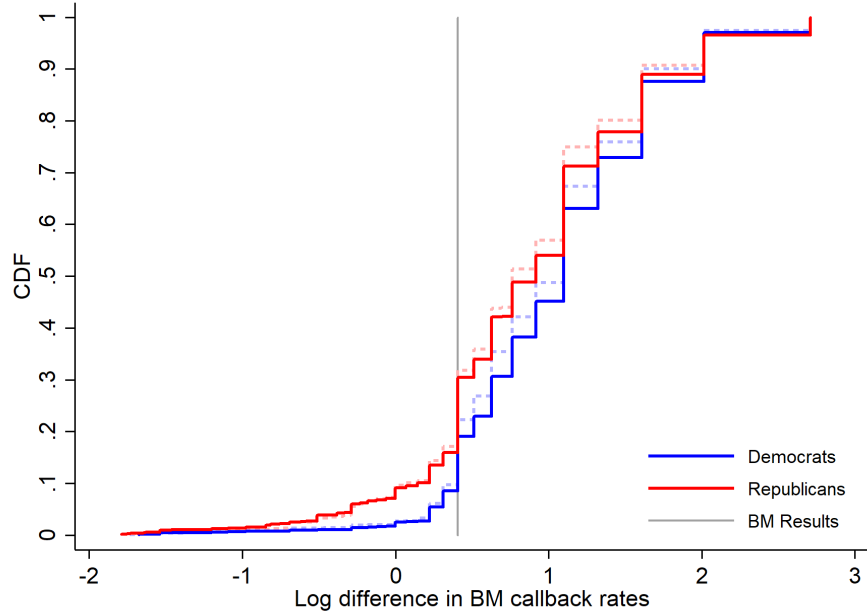
In model 3, I split updating behavior by political affiliation. The relationship between hiring discrimination beliefs and overestimating the role of educational attainment holds for Democrats in this regression, but not for Republicans. That is, Democrats tend to increase their beliefs about how much discrimination drives the wage gap after learning that educational attainment explains less than they thought, while Republicans do not.

Result 3: *In response to information on the role of educational attainment on the Black-White wage gap, Democrats update their beliefs about racial discrimination in hiring while Republicans do not.*

5.6 Round 5: Hiring discrimination beliefs in response to results from another fake resume study

In Round 5, participants are shown callback rates from another fake resume study, Jacquemet and Yannelis (2012). That is, they are told Jacquemet and Yannelis (2012) found that applicants with White-sounding names had to send out on average 4 applications to receive one callback for an interview, and applicants with Black-sounding names had to send out on average 6 applications to receive one callback for an interview.

Figure 13: Round 4 Beliefs about racial discrimination in hiring



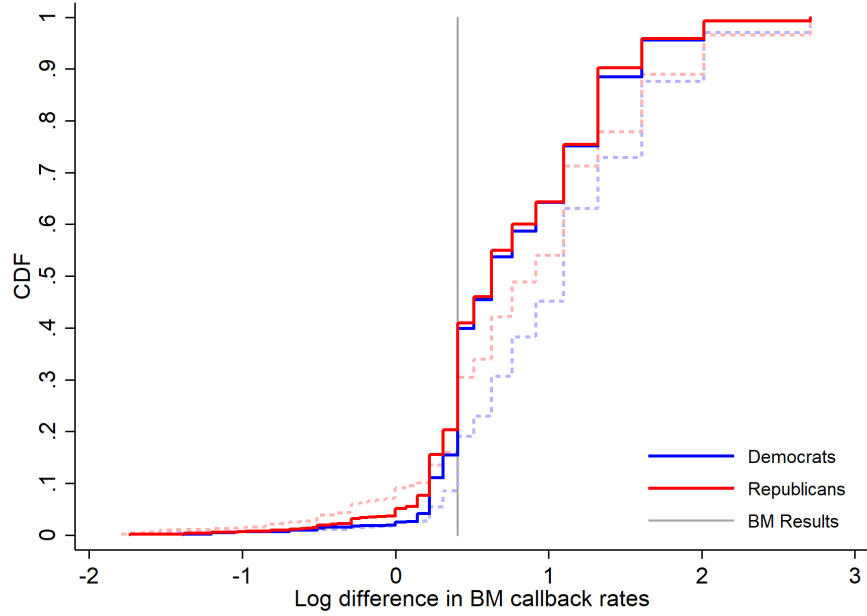
Notes. This figure shows the cumulative distribution functions of participants' beliefs about racial discrimination in hiring in Round 4 (bolded solid lines), split by political affiliation. Participants' Round 3 beliefs are shown as dashed lines for ease of comparison. In Round 4, participants are told the percent of the Black-White wage gap that is explained by differences in educational attainment between Black and White workers. Beliefs are measured as the log difference between the actual number of times resumes with Black-sounding names had to be sent out to receive one callback (15) in Bertrand and Mullainathan (2004) and participants' predictions of the number of times resumes with White-sounding names had to be sent out to receive one callback in BM. The actual log difference in callback rates from BM is depicted by the vertical grey line. Democrats' beliefs are shown in blue, and Republicans' beliefs are in red.

The purpose of this final round is to replicate a finding from Haaland and Roth (2021) that results from experiments designed to measure discrimination can successfully close the belief gap between Democrats and Republicans. In Figure 14, the distribution of Democrats' beliefs and the distribution of Republicans' beliefs shift to the left in Round 5 ($p < 0.001$ for both groups).

As shown in Figure 15, Round 5 is the only round in which the average gap in beliefs about racial discrimination in hiring between Democrats and Republicans is closed ($p = 0.13$). Furthermore, I cannot reject that Democrats' and Republicans' beliefs come from the same distribution ($p = 0.14$).

Table 5 reports these findings in a regression, with the outcome variable calculated as in Equation 12. Participants did not state their priors for this outcome, so I regress belief

Figure 14: Round 5 Beliefs about racial discrimination in hiring

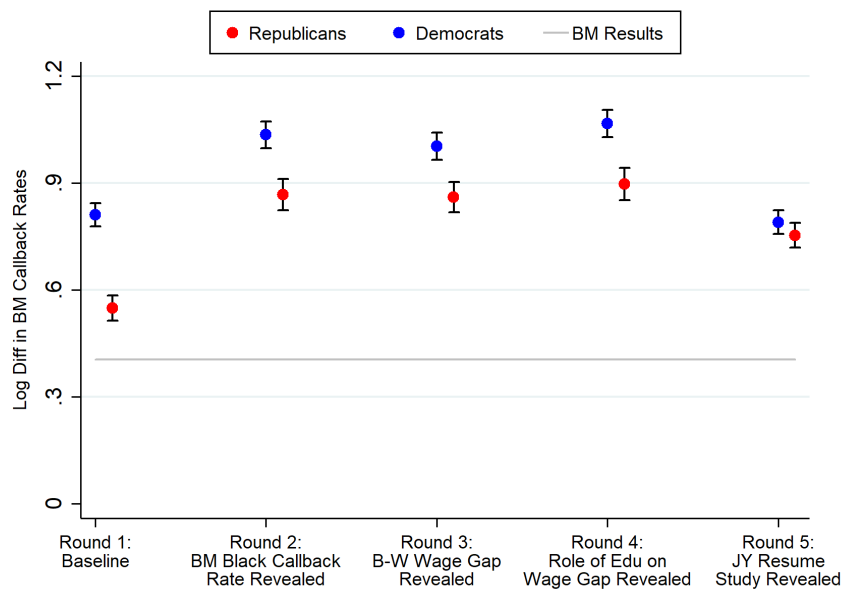


Notes. This figure shows the cumulative distribution functions of participants' beliefs about racial discrimination in hiring in Round 5 (bolded solid lines), split by political affiliation. Participants' Round 4 beliefs are shown as dashed lines for ease of comparison. In Round 5, participants are told the callback rates for applicants with Black-sounding names and for applicants with White-sounding names from the fake resume study in Jacquemet and Yannelis (2012). Beliefs are measured as the log difference between the actual number of times resumes with Black-sounding names had to be sent out to receive one callback (15) in Bertrand and Mullainathan (2004) and participants' predictions of the number of times resumes with White-sounding names had to be sent out to receive one callback in BM. The actual log difference in callback rates from BM is depicted by the vertical grey line. Democrats' beliefs are shown in blue, and Republicans' beliefs are in red.

updates about hiring discrimination on political affiliation and a constant, as shown in Equation 13. Democrats' beliefs about racial discrimination in hiring drop by approximately 19%, while Republicans' drop by approximately 9%. While the gap does close between Democrats and Republicans, beliefs do not converge on the results from BM (shown by the horizontal gray line in Figure 15), even though both studies found the same ratio of callback rates between the two groups.

Result 4: *Results from another fake resume study successfully close the gap in beliefs about racial discrimination in hiring between Democrats and Republicans.*

Figure 15: Beliefs about racial discrimination in hiring across rounds



Notes. This figure shows participants’ average beliefs about racial discrimination in hiring with 95% confidence intervals in each of the five rounds of the study, split by political affiliation. Beliefs in Round 1 are measured as the log difference between participants’ predictions of the number of times resumes with Black-sounding names had to be sent out to receive one callback for an interview in Bertrand and Mullainathan (2004) and the number of times resumes with White-sounding names had to be sent out to receive one callback. Beliefs in Round 2 to Round 5 are measured as the log difference between the actual number of times resumes with Black-sounding names had to be sent out to receive one callback (15) in Bertrand and Mullainathan (2004) and participants’ predictions of the number of times resumes with White-sounding names had to be sent out to receive one callback in BM. The actual log difference in callback rates from BM is depicted by the horizontal grey line. Democrats’ beliefs are shown in blue, and Republicans’ beliefs are in red.

5.7 Interpretations of BM results

In this subsection I present results on participants’ interpretations of BM. The questions analyzed in subsections 5.7.1 and 5.7.2 were the only questions in the study that were asked at both baseline and endline. These analyses were not incentivized nor pre-registered, and may be considered exploratory.

5.7.1 Do BM results reflect that employers use race in callback decisions?

After introducing BM and before rounds begin (baseline), I ask participants how much they agree on a 5-point scale from “Strongly disagree” to “Strongly agree” with the following

Table 5: Hiring Discrimination Belief Updates to JY Resume Study Results

	(1)
	Belief Update: R5-R4
Republican	0.107*** (0.0168)
Constant	-0.194*** (0.0107)
Observations	2196

Notes. The table shows regressions of participants’ changes in beliefs (between rounds 4 and 5) about racial hiring discrimination in response to results from another fake resume study. Beliefs about racial hiring discrimination are calculated as the log difference between participants’ predicted White callback rates and the actual Black callback rate in BM. Changes in beliefs between Round 3 and 4 are calculated using the inverse hyperbolic sine function difference. “Republican” includes only participants who list their political affiliation as “Republican” on their Prolific account. Robust standard errors are in parentheses.

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

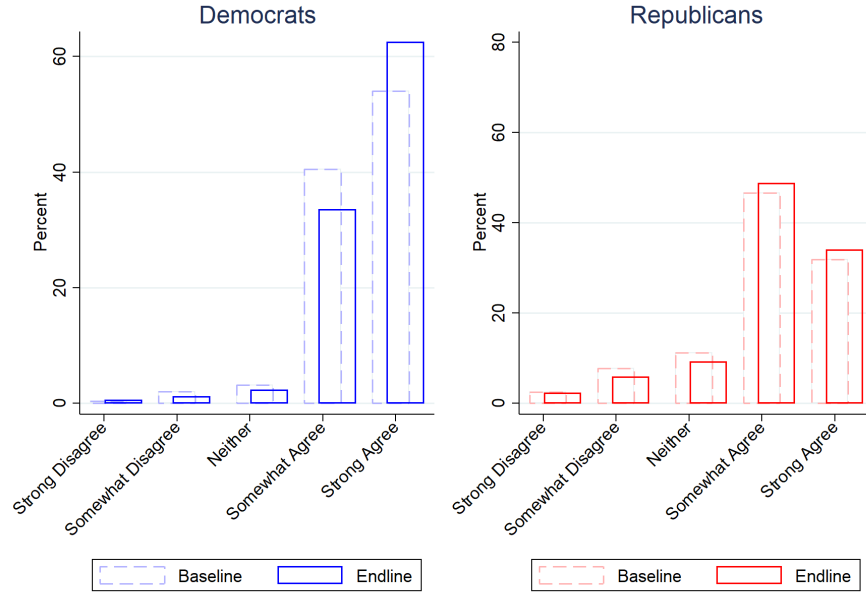
statement. “If the researchers find a difference in callback rates between applicants with Black-sounding names and applicants with White-sounding names in Experiment A⁴, this would reflect that employers base their callback decisions in part on the race of the applicant.”

After all rounds are completed and participants have learned the results from BM (endline), I ask participants how much they agree (on the same scale) with the following statement. “The difference in callback rates between applicants with Black-sounding names and applicants with White-sounding names in Experiment A reflects that employers base their callback decisions in part on the race of the applicant.”

Figure 16 shows participants’ responses at baseline (dashed lines) and endline (solid lines), split by political affiliation. At baseline, Democrats on average score 4.5 on the scale from 1 (“Strongly disagree”) to 5 (“Strongly agree”). At baseline, Republicans on average score lower than Democrats ($p < 0.001$) at 4.0. I reject the null hypothesis that responses come from the same underlying distribution, according to the Kolmogorov-Smirnov test ($p < 0.001$).

⁴BM was referred to as “Experiment A” to participants throughout the study.

Figure 16: Agree BM tests whether employers use race in callback decisions



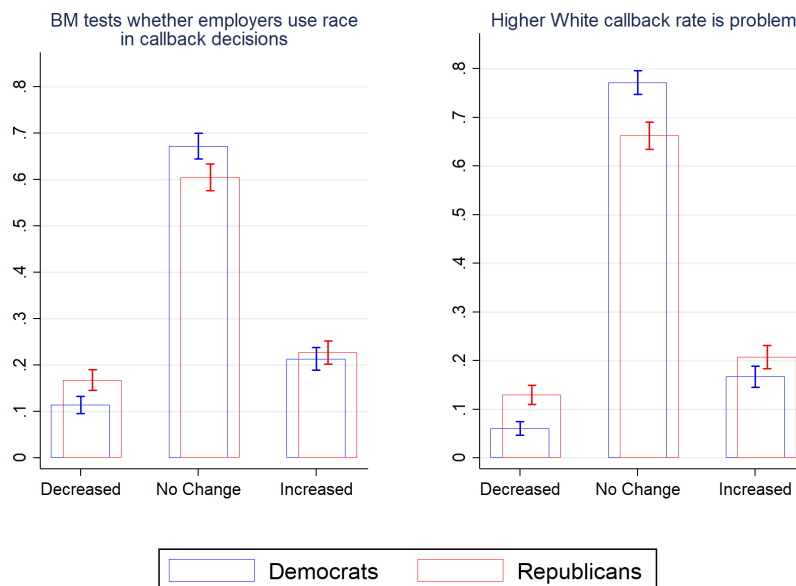
Notes. The figures show the distributions of participants’ responses on a scale from “strongly disagree” to “strongly agree” at baseline and endline about the interpretation of BM. At baseline (depicted by dashed lines), participants are asked how much they agree with the following statement. “If the researchers find a difference in callback rates between applicants with Black-sounding names and applicants with White-sounding names in Experiment A⁵, this would reflect that employers base their callback decisions in part on the race of the applicant.” At the end of the study (depicted by solid lines), participants are asked how much they agree with the following statement. “The difference in callback rates between applicants with Black-sounding names and applicants with White-sounding names in Experiment A reflects that employers base their callback decisions in part on the race of the applicant.” The left panel restricts my sample to Democrats, and the right panel restricts to Republicans.

At baseline, 54% of Democrats and 32% of Republicans ($p < 0.001$) selected the maximum response (“Strongly agree”) and therefore cannot increase their response further at endline. Mechanically, therefore, Republicans have more room to increase their beliefs than Democrats. Only 0.4% of Democrats and 2.5% of Republicans ($p < 0.001$) selected the minimum response (“Strongly disagree”) at baseline, so there is less of a concern of participants being unable to decrease their agreement at endline relative to baseline.

At endline, both Democrats’ ($p < 0.001$) and Republicans’ ($p = 0.002$) agreement levels shift upwards on average relative to their baseline responses. I also calculate the probability within political party that participants change their level of agreement between baseline and endline. As shown in the left panel of Figure 17, Democrats (21%) and Republicans (23%) are equally likely to increase their level of agreement relative to their response at baseline

($p = 0.44$). Republicans (17%) are more likely than Democrats (11%) to decrease their agreement at endline relative to their baseline agreement ($p < 0.001$).

Figure 17: Consistency of participants' interpretations: Baseline vs. Endline



Notes. The figures show the proportion of Democrats (blue) and Republicans (red) who increase, decrease, and do not change their agreement on a scale from “strongly disagree” to “strongly agree” at baseline and endline about the interpretation of BM (left panel) and whether the BM results are a problem (right panel). Participants who decrease their agreement (i.e., select a lower level of agreement at endline relative to baseline) are included in the “Decreased” group. Participants who give the same response at baseline and endline are included in the “No change” group. Participants who increase their agreement (i.e., select a greater level of agreement at endline relative to baseline) are included in the “Increased” group. See figure notes in Figure 16 and Figure 18 for the question wordings about the interpretation of BM and whether the BM results are a problem, respectively.

5.7.2 Are BM results a problem?

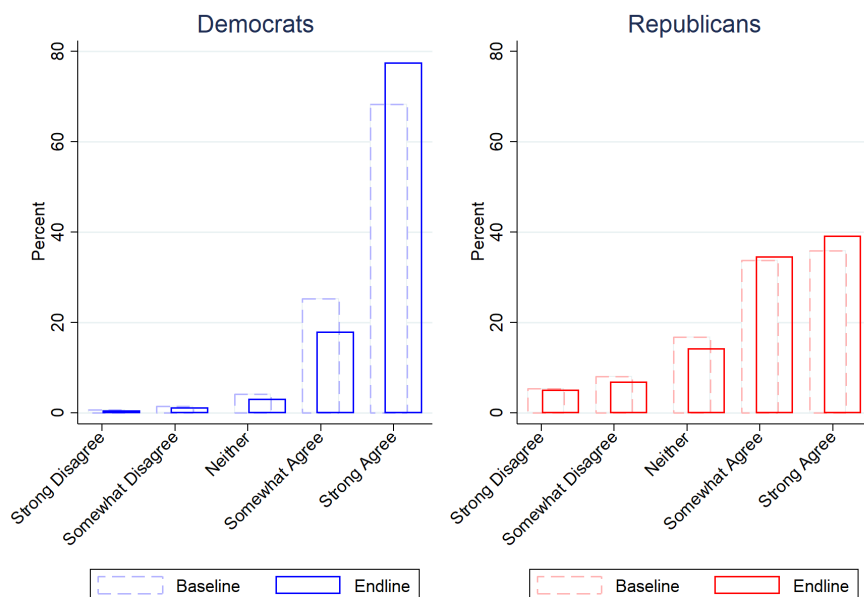
After introducing BM and before rounds begin (baseline), I ask participants how much they agree on a 5-point scale from “Strongly disagree” to “Strongly agree” with the following statement. “If the researchers find that applicants with White-sounding names get callbacks more often than those with Black-sounding names, this would be a problem that should be solved.”

After Round 5 is completed and participants have learned the BM results (endline), I ask participants how much they agree on the same scale with the following statement. “The

difference in callback rates is a problem that should be solved.”

Figure 18 shows participants’ responses at baseline (dashed lines) and endline (solid lines), split by political affiliation. At baseline, Democrats’ average response at 4.6 is greater than Republican’ average score of 3.9 ($p < 0.001$). I reject the null hypothesis that these responses come from the same distribution, according to the Kolmogorov-Smirnov test ($p < 0.001$).

Figure 18: Agree that higher White callback rate in BM is a problem



Notes. The figures show the distributions of participants’ responses on a scale from “strongly disagree” to “strongly agree” at baseline and endline about whether the BM results are a problem. At baseline (depicted by dashed lines), participants are asked how much they agree with the following statement. “If the researchers find that applicants with White-sounding names get callbacks more often than those with Black-sounding names, this would be a problem that should be solved.” At the end of the study (depicted by solid lines), participants are asked how much they agree with the following statement. “The difference in callback rates is a problem that should be solved.” The left panel restricts my sample to Democrats, and the right panel restricts to Republicans.

Note that 68% of Democrats and 36% of Republicans ($p < 0.001$) selected the maximum response (“Strongly agree”) and therefore cannot increase their agreement any further at endline. Mechanically, therefore, Republicans have more room to increase their beliefs than Democrats at endline. Only 0.7% of Democrats and 5.4% of Republicans ($p < 0.001$) selected the minimum response (“Strongly disagree”) at baseline, so there is less of a concern of participants being unable to decrease their agreement at endline.

At endline, both Democrats’ ($p < 0.001$) and Republicans’ ($p = 0.001$) agreement levels shift

upwards on average relative to their baseline responses. As shown in the right panel of Figure 17, 21% of Republicans and 17% of Democrats increase their agreement at endline, relative to their response at baseline ($p = 0.02$). Given that a strong majority of Democrats could not increase their level of agreement relative to baseline, this difference may be mechanical. That is, Democrats who may have otherwise increased their level of agreement were not able to.

Republicans (13%) are also more likely than Democrats (6%) to decrease their agreement level at endline relative to their agreement at baseline ($p < 0.001$). This is less likely to be mechanical, as the vast majority of both groups had the ability to decrease their agreement level relative to their baseline response.

Result 5: *At endline, Republicans are more likely than Democrats to decrease their agreement (relative to baseline) that (1) BM results reflect that employers base callback decisions in part on applicant race and (2) a higher White callback rate in BM is a problem.*

6 Discussion

Across five rounds, I evaluate how participants' beliefs about racial discrimination in hiring respond to various pieces of information. In this section, I synthesize what we learn from the results in each round.

I find that Democrats and Republicans disagree about how informative some signals are about racial discrimination in hiring. Democrats update their hiring discrimination beliefs in response to the Black-White wage gap, while Republicans do not. Similarly, when presented with the role of educational attainment on the wage gap, Democrats update their beliefs about hiring discrimination, while Republicans do not.

One potential explanation for Republicans updating less than Democrats in response to both pieces of wage gap information is that Republicans have stronger priors, and thus less movable beliefs about racial discrimination in hiring than Democrats do. However, Republicans update their beliefs about racial discrimination in hiring *more* than Democrats in Round 2 after presented with the BM callback rate for applicants with Black-sounding names. This suggests that the observed differences in updating patterns between Democrats and Republicans to wage gap information are not due to Republicans having less movable beliefs, and instead may be due to differences in beliefs about the relationship between wage gaps and discrimination.

The findings demonstrate that when groups disagree about the relevance of information, then it may risk increasing belief polarization. In my context, information on the role of educational attainment in explaining the wage gap marginally increased the belief gap between Democrats and Republicans about hiring discrimination. This resulted from Democrats overestimating how much of the wage gap driven by educational attainment and, upon learning the true estimate, subsequently increasing their beliefs about hiring discrimination.

I also find evidence that even when Democrats and Republicans are given information that leads to agreement about the extent of racial hiring discrimination, they may change their beliefs about whether the observed discrimination is a problem. At baseline, I ask participants whether they agree that (1) a difference in callback rates between applicants with Black-sounding names and applicants with White-sounding names would reflect that employers use race in making their callback decisions, and (2) a higher White callback rate in Bertrand and Mullainathan (2004) would be a problem. Then, after presenting participants with the result that the callback rate for White applicants was 50% higher than for Black applicants, I ask participants if they believe the difference in callback rates (1) reflects that employers base their callback decisions on applicant race, and (2) is a problem. Relative to their baseline responses, Republicans are more likely than Democrats to decrease their agreement to both questions.

In thinking about why Republicans decreased their agreement with these statements, perhaps the amount of hiring discrimination found in BM was small enough such that Republicans decrease their concern about the difference in callback rates being a problem. While Republicans did indeed overestimate the gap in callback rates at baseline, Democrats overestimated the gap even more. So, Democrats should be more likely to decrease their agreement at end line if this were the driving mechanism.

A remaining explanation is preference-biased updating (Benjamin, 2019). Because both groups want to believe they live in a world consistent with their political views (as demonstrated in Thaler (2019)), they may update more strongly to information aligning with their preferred state of the world. Even though Democrats learn they overestimated racial hiring discrimination, they remain consistent that discrimination is a problem. Republicans, conversely, use the fact that there is less racial hiring discrimination than they thought to update downward on discrimination being a problem. Biased updating on these unincentivized questions is in line with evidence suggesting that people are more likely to exhibit motivated updating when they face no monetary incentive for accuracy (Prior et al., 2015). This finding highlights an avenue through which belief convergence about the extent of racial hiring discrimination may not translate to a convergence in policy demand.

These findings contribute to empirical literature showing that information dissemination may not be successful at closing polarization in political preferences or policy demand (Haaland and Roth, 2021; Marino et al., 2023). I contribute by demonstrating two channels through which this occurs: (1) differences in information processing that prevent belief convergence, and (2) preference-biased updating on whether the information suggests a problem.

Much of the theoretical literature on belief polarization explores channels through which people may be exposed to differing sets of information, including selective information sharing (Levy and Razin, 2018; Bowen et al., 2023) and biased news sources (Mullainathan and Shleifer, 2005; Levendusky, 2013; Perego and Yuksel, 2022). An exception is Andreoni and Mylovanov (2012) in which the authors identify a channel through which disagreements persist in the face of common information when that information is multi-dimensional. This finding may be particularly relevant when the information is open to interpretation and requires processing based on one’s worldview.

Interestingly, Democrats and Republicans throughout the study consistently overestimate racial hiring discrimination relative to BM. In the final round, if participants were to fully update on the extent of racial hiring discrimination based on the results from Jacquemet and Yannelis (2012), then they would correctly predict the BM results, as both studies found the same ratio in callback rates between applicants with White-sounding and Black-sounding names. However, the average callback rates in these two studies were quite different. While BM found that applicants with Black-sounding names had to be sent out 15 times to get one callback, Jacquemet and Yannelis (2012) found that applicants with Black-sounding names had to be sent out only 6 times. Participants may have viewed the low Black callback rate in BM as a signal of hiring discrimination, leading them to overestimate the observed discrimination in BM even in the final round of the study.

7 Conclusion

I conduct an experiment to investigate how information affects belief polarization among 1100 Democrats and 1100 Republicans about racial discrimination in hiring. I measure participants’ beliefs about racial hiring discrimination using an incentivized and quantified method from Haaland and Roth (2021) in which participants state their predictions of racial differences in callback rates from the fake resume study in Bertrand and Mullainathan (2004).

I first establish that Democrats believe there is more racial discrimination in hiring than Republicans do at baseline. I then explore how beliefs about racial discrimination in hiring

respond to varying pieces of information. I find that Democrats update their beliefs in response to the Black-White wage gap and in response to the role of educational attainment in explaining the wage gap. Republicans, on the other hand, do not significantly update their beliefs in either of these cases, likely due to differing views on the relationship between wage gap information and labor market discrimination. The divergent interpretations of this information between Democrats and Republicans prevents the information from reducing belief polarization, and even risks increasing it.

Even when Democrats and Republicans eventually agree about the extent of racial discrimination in a fake resume study, they may exhibit biased reasoning in their interpretations. After learning the results of BM, Republicans are more likely than Democrats to decrease, relative to their baseline response, their beliefs that (1) BM is designed to measure racial discrimination in hiring, and (2) the higher White callback rate in BM is a problem. This finding demonstrates a channel through which convergence in beliefs may not yield convergence in policy demand.

The main findings in this paper expose key drawbacks in using information to decrease belief polarization. When information requires processing based on one's world view, belief polarization may fail to decrease in response, and may even increase. Furthermore, even when groups agree on the facts surrounding a political topic, they may change their beliefs in another dimension: whether the facts reflect a problem. As Democrats and Republicans increasingly view the world through different lenses, these risks may become more prevalent.

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