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Three Essays on Employer Decision Making, Workplace Inequality, and Organizational Attraction

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Princeton, NJ : Princeton University

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THREE ESSAYS ON EMPLOYER DECISION MAKING, WORKPLACE INEQUALITY, AND ORGANIZATIONAL ATTRACTION

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Abstract

Racial and gender inequality in the workplace has many causes. On the supply side, factors like applicant pool diversity and differences in educational attainment, skills, and credentials contribute to racial and gender inequality. On the demand side, it can be influenced by individual decision-makers, organizations, and broader social forces. This dissertation focuses on how organizational practices can contribute to inequality. The first paper examines how workplace inclusion efforts inform organizational attraction. In a within-subjects experiment with a nationally representative sample (n = 500), only 42.6% chose the company with inclusion efforts; however, Black participants, Democrats (and Independents), and women were more likely to select workplaces with inclusion efforts than White participants, Republicans, and men, respectively. Using a quota sample (n = 598), I found evidence that all demographic subgroups, except White Republican women, preferred companies with inclusion efforts more than White Republican men did. The second paper asks how the design of hiring processes affects the racial composition of selected applicants. Drawing on a survey experiment with participants who have hiring experience (n = 1,265; 1,729 decisions), I found that neither collective nor simulated collective hiring contexts significantly increased the selection of Black applicants compared to an isolated context. However, Black applicants were 20% more likely to be selected in the simulated collective condition than in the collective condition. Additionally, Black participants and Democrats selected Black applicants at higher rates than White participants and Republicans. The third paper explores whether increasing clarity in reward allocation criteria can reduce gender inequality in bonuses and promotions. Using a survey experiment with participants who have management experience (n = 1,626; 8,130 bonus and 1,626 promotion decisions), I found that the ambiguous condition amplified disparities: women, but not men, allocated higher bonuses to women (by 7.69%) and were 5.6 percentage points more likely (equal to 28% of the expected baseline rate) than men to promote a woman. There was insufficient evidence of similar disparities in the clear condition. Combined, these three papers demonstrate how organizational practices can shape inequality in attracting, hiring, and rewarding employees, and how these effects vary across demographic groups.

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1 Introduction

Substantial progress has been made in the last fifty years in reducing racial and gender inequalities in the workplace; however, these inequalities persist, with racial/ethnic minorities and women being overrepresented in precarious and low-paying work and underrepresented in high-paying and prestigious work (Friedman, 2019; P. Vallas & Kalleberg, 2017). Inequality in the workplace has been documented in a variety of domains, including in earnings and unemployment rates (Labor Statistics, 2020, 2022a),[1] as well as in key employment processes such as hiring (Pager, 2003; Quillian, Pager, Hexel, et al., 2017; Gaddis, 2015; Bertrand & Mullainathan, 2004; Park & Oh, 2025), evaluation (Correll, Weisshaar, Wynn, et al., 2020; Rivera & Tilcsik, 2019; Wynn & Carian, 2023), and reward allocation (Castilla, 2008, 2015; Joshi, Son, & Roh, 2015) of employees.

Racial and gender inequalities in the workplace have many causes. On the supply side, factors like applicant pool diversity and group differences in educational attainment, skills, and credentials contribute to racial and gender inequality. On the demand side, racial and gender inequality can be influenced by individual agents (e.g., racial and gender bias), organizations, and broader social forces. Workplaces, a type of organization, can contribute to racial and gender inequalities through a variety of policies and practices, including, but not limited to, hiring decisions (Rivera, 2020) and reward allocation systems (Castilla, 2008, 2015). Researchers (Karpowitz, O'Connell, Preece, et al., 2024; Bohnet, 2016; Goldin & Rouse, 2000) have found evidence that approaches to address inequality benefit from targeting organizational practices, such as processes and policies for attracting, hiring, evaluating, and rewarding employees. This dissertation examines inequality in the workplace, and

[1]The unemployment rate in 2020 for men 16 years of age and older was 7.0% for White men, yet 12.1% for Black men, 9.7% for Hispanic men, and 7.8% for Asian men (Labor Statistics, 2020). Similar disparities are observed for women, with the unemployment rate in 2020 for women 16 years of age and older being 7.6% for White women, 10.9% for Black women, 9.6% for Asian women, and 11.4% for Hispanic women (Labor Statistics, 2020). Disparities have also been documented in the median weekly earnings of the 117.5 million full-time wage and salary employees in the United States (Labor Statistics, 2022a). Median weekly earnings for women in the first quarter of 2022 were $939, while the median weekly earnings for men were $1,128 (Labor Statistics, 2022a). Median weekly earnings in the first quarter of 2022 varied by racial and ethnic groups as well, with earnings for Black ($840) and Hispanic ($799) adults being lower than White ($1,064) and Asian ($1,362) adults (Labor Statistics, 2022a).

the role organizations can play in decreasing it (or increasing it when not careful). While recognizing that workplaces are a type of organization, I sometimes use the term "organizations" in reference to workplaces in this dissertation. I adopt the definition for organizations used by Avent-Holt and Tomaskovic-Devey: "socially constructed spaces in which individuals' efforts are coordinated to jointly accomplish a set of tasks to fulfill some goal or set of linked goals" (2019, p. 2).

What workplaces can do to address racial and gender inequalities has garnered the attention of the public, politicians, and researchers, with many interested in how efforts for diversity, equity, and inclusion (DEI) affect society. Data collected by the Pew Research Center in February 2023 found that 56% of workers believe that focusing on increasing DEI in the workplace is predominantly a good thing (Minkin, 2023). Despite worker interest and recent social movements advocating for increased equality, corporations and politicians have begun targeting DEI: DEI workers are being laid off; dozens of states have proposed or passed bills targeting DEI statements, offices, programs, and education in institutions of higher education; and, as of 2025, the federal government has also begun targeting efforts related to diversity and inclusion. Organizations, however, remain committed to following anti-discrimination law and creating workplaces that are diverse and inclusive. The amount of money spent on DEI-related initiatives was estimated to be $7.5 billion for the year 2020 and was projected to more than double by 2026 (Forum & Company, 2023). Not only have DEI efforts caught the attention of the public, employees/employers, and politicians, but social scientists as well, with ever-increasing pushes to focus on evidence-based efforts (Dobbin & Kalev, 2022d) that can address the inequalities social scientists have so elaborately documented over the course of many decades.

The efforts of organizations are just one component of a larger puzzle, which includes individual biases and social forces[2] as well. The studies in this dissertation focus on addressing examples in which organizations shape inequality through their programs, practices, and policies.

[2]Examples of social forces include who is encouraged to pursue certain vocations, who is encouraged to study in certain fields, economic trends and salaries in certain fields, social and political pressures to adopt policies and hire DEI officers, government policies to cut DEI efforts and offices/officers, and recessions (which can lead to cuts of DEI efforts and offices/officers).

The first paper in this dissertation explores how workplace inclusion efforts inform workplace attraction, and tests for significant differences across demographic groups. It highlights the polarizing nature of organizational inclusion efforts with efforts simultaneously attracting some groups and repelling others. The second paper examines how the design of hiring processes affects the racial composition of selected candidates. It has implications for how organizations structure the context in which their selection decisions, whether in isolation or as a collection of choices, are made. The third paper investigates whether increasing the clarity in performance-based reward allocation criteria can mitigate gender inequality in the allocation of bonuses and promotions to employees. It provides insight into how organizations can increase clarity in reward allocation criteria to address workplace differences in reward allocation. Combined, the three studies in this dissertation inform how organizational practices in attracting, hiring, and rewarding employees can foster or mitigate inequality, and how these effects vary across demographic groups.

2 Diversity at Work: The Heterogeneous Impact of Inclusion Efforts on Organizational Attraction

Abstract: This study investigates how workplace inclusion efforts inform organizational attraction and whether there are significant differences across demographic groups. Using a within-subjects experimental design, 1,098 participants chose between a company that included information about inclusion efforts in its description and one that did not. The study included both a nationally representative sample (n = 500) and a quota sample stratified by race, gender, and political affiliation (n = 598). In the nationally representative sample, only 42.6% of participants selected the company with inclusion efforts, which was significantly different from the expected 50% split and suggested a general preference for companies without diversity and inclusion messaging. However, this pattern was not uniform across groups. Using the nationally representative sample, I found evidence that Black participants and Democrats were, on average, significantly more likely (than White participants and Republicans respectively) to choose the workplace with inclusion efforts. Notably, the difference in predicted probabilities between Democrats and Republicans (34.0 percentage points) is even larger than the difference in predicted probabilities between Black and White participants (23.7 percentage points). This 10.3 percentage point difference in differences highlights the stronger association between political affiliation (an achieved status) and selection of workplaces with inclusion efforts compared to race (an ascribed status). Women similarly showed a somewhat higher probability (marginal statistical significance) of selecting the company with inclusion efforts than men. Subgroup analyses using the quota sample further underscored this heterogeneity: with White Republican men as the reference group, all other subgroups except for White Republican women (i.e., Black Republican women, Black Republican men, Black Democrat men, White Democrat men, Black Democrat women, and White Democrat women) were significantly more likely to prefer workplaces with inclusion efforts. In the quota sample, 63.0% of White Democrat women selected the company with inclusion efforts, while only 38.7% of White Republican men chose the company with inclusion

efforts. Participants also rated companies on belonging, value alignment, compensation, and career opportunity. Across these domains, companies without inclusion efforts consistently received higher ratings (statistically significant for all except for sense of belonging), potentially suggesting concerns about possible trade-offs associated with companies that include messaging about inclusion efforts in their descriptions. Overall, this study highlights the polarizing nature of organizational inclusion efforts. While such efforts attract certain groups, they may repel others, pointing to the complex and often conflicting dynamics organizations must navigate in their strategies regarding diversity and inclusion.

2.1 Introduction

This study assesses whether organizational attraction is affected by workplace inclusion efforts. Data collected by the Pew Research Center in 2024 suggest that a little over half (52%) of workers believe that focusing on diversity, equity, and inclusion (DEI) in the workplace is predominantly good (a decrease from 56% in early 2023), while the proportion who believe that focusing on DEI in the workplace is primarily bad has increased from 21% in 2023 to 26% in 2024 (Minkin, 2024). However, how do these views influence the organizational attractiveness of workplaces engaged in inclusion efforts?

Organizational attractiveness can be measured in many ways. Direct, behavioral measures include attending informational sessions, applications to workplaces, and the ultimate selection of a company if a job offer is extended (Highhouse, Lievens, & Sinar, 2003). Isolating the influence of a specific company characteristic on organizational attractiveness is ethically and logistically challenging when using behavioral measures. Therefore, researchers often assess organizational attraction through other measures, such as general company attractiveness, behavioral intentions regarding a company, and beliefs about a company's prestige (Highhouse, Lievens, & Sinar, 2003). In this study, the term "organizational attraction" is used in two ways: (1) to refer to participants' explicit selection of the workplace they would prefer to work for and (2) more broadly, to describe participants' interest in and favorability toward a particular organization.

To examine the attractiveness of workplace inclusion efforts, this study uses a within-subjects experimental design that manipulates the presence of inclusion efforts and asks participants to select between two companies: one that mentions inclusion efforts and one that does not. In doing so, participants made choices that shed light on how information about inclusion efforts works as a force of either attraction or repulsion. Recognizing how attitudes toward diversity and inclusion are not monolithic and are instead heterogeneous across demographic groups (Minkin, 2024, 2023), this study additionally disaggregated findings by race, gender, political affiliation, and educational attainment. A total of 1,098 participants, 500 in a nationally representative sample (based on age, gender, race, and political affiliation in the United States) and 598 in a quota sample (stratified by race, gender, and political affiliation), completed 1,098 company choices. In comparing interest in workplaces with or without inclusion efforts, and by disaggregating these findings based on demographic characteristics, this study illuminates how information about organizations' inclusion efforts shapes interest in joining those organizations. This study also collected data on participants' attitudes toward the two company options, and tests for differences in these attitudes depending on whether the workplace descriptions included information about inclusion efforts. This research adds to the literature on how inclusion efforts affect organizational attraction (Georgeac & Rattan, 2023; Starck, Sinclair, & Shelton, 2021; Trawalter, Driskell, & Davidson, 2016; Scarborough, Lambouths, & Holbrook, 2019; Lievens & Slaughter, 2016; Choi, Pacelli, Rennekamp, et al., 2023; Krivoshchekov, Graf, & Sczesny, 2024), an area of high research and practical importance due to increased scrutiny from researchers, employers, the public, and the government.

2.2 Theoretical Background

2.2.1 Inclusion Efforts

The term "inclusion efforts" in this study refers to organizations' diversity statements and programs, each of which is discussed in more detail below.

2.2.1.1 Diversity Statements

Diversity statements are a way for organizations to communicate their support for diversity and inclusion through a variety of rationales. Many terms have been developed to describe the explanations organizations provide for their support for diversity: the "diversity is good for organizations" frame vs. the "diversity is fair" frame (Trawalter, Driskell, & Davidson, 2016), the business case vs. the fairness case (Georgeac & Rattan, 2023), and the instrumental diversity rationale vs. the moral diversity rationale (Starck, Sinclair, & Shelton, 2021) to name a few. This study adopts the use of the terms business case and fairness case (Georgeac & Rattan, 2023). The business case justifies supporting diversity because it is imperative for the performance of an organization. This rationale sees diversity as an asset that helps organizations meet their objectives. It therefore makes the diversity statement an instrumental rhetoric (Georgeac & Rattan, 2023; Starck, Sinclair, & Shelton, 2021). The fairness case, on the other hand, is a non-instrumental rhetoric that emphasizes the intrinsic values and principles that motivate supporting diversity out of concern for human dignity and to combat discrimination. Support for diversity through the fairness case stems out of values for fairness and what is deemed as the right thing to do (Georgeac & Rattan, 2023; Starck, Sinclair, & Shelton, 2021). It is important to note that organizations, in expressing support for diversity and inclusion, often use a combination of both the business and fairness cases for diversity.

Much of the previous literature on diversity rationales has focused on the workplace (Herring, 2009; Trawalter, Driskell, & Davidson, 2016; Georgeac & Rattan, 2023). Using survey experiments, Trawalter, Driskell, and Davidson found evidence that White participants prefer a "diversity as good for organizations" frame, as opposed to a "diversity is fair" frame (2016). Furthermore, under the former frame, White participants adopted a broad definition of diversity that de-emphasized racial diversity and led to lower rankings of Black applicants in hiring scenarios (Trawalter, Driskell, & Davidson, 2016). In a different study that used algorithmic classification and focused on Fortune 500 companies, Georgeac and Rattan found that the business case for diversity is more commonly utilized than the fairness case (2023). Georgeac and Rattan also found that the business case for diversity activates social identity threat and undermines sense of belonging for LGBTQ+ individuals, women

in STEM, and African Americans (2023). In an interesting last example, the use of positive and strongly emotional language (e.g., happy, passionately, wholeheartedly, etc.) in diversity statements has been found to play a crucial role in enhancing an organization's attractiveness to potential employees in the United Kingdom (Krivoshchekov, Graf, & Sczesny, 2024).

Diversity statements allow workplaces to signal their values and to provide a rationale for why they believe those values are important. However, diversity statements are not the same as organizational programs that are put in place to support diversity and inclusion. The next section examines these diversity programs.

2.2.1.2 Diversity Programs

Despite current turmoil,[3] many organizations remain committed to following anti-discrimination law and creating workplaces that are diverse and inclusive. The amount of money spent on DEI-related programs was estimated to be $7.5 billion for the year 2020 and was projected to more than double by 2026 (Forum & Company, 2023). Though these projections are likely now inaccurate due to recent backlash against DEI programs, researchers at Stanford VMware Women's Leadership Innovation Lab argue that this work will likely continue in a "period of what social movement scholars call 'closed doors,' where the obvious route for change is no longer easily accessible" (Mackenzie, Soule, Correll, et al., 2024).

A robust and wide array of workplace diversity programs exist. Examples of diversity programs include employees resource groups, diversity task forces, and mentoring programs, all of which are described in more detail below to provide information about the programs that are mentioned in the survey instrument. First, employee resource groups (ERGs) facilitate the advancement of women and people of color within organizations by enhancing their professional networks and increasing their visibility within a company (Dobbin & Kalev, 2022c). Research conducted by Dobbin and Kalev

[3]Layoffs of DEI workers have been accelerating; organizations are ending and cutting DEI-related programs (Mackenzie, Soule, Correll, et al., 2024); and dozens of states along with the federal government have proposed or passed bills that target DEI statements, offices, programs, and education in higher education institutions.

indicates that ERGs are particularly effective when implemented alongside targeted recruitment initiatives and referral incentive programs. Additionally, these groups can play a significant role in advocating for organizational policies. However, if not carefully managed, ERGs may inadvertently reinforce workplace silos and contribute to segregation. Moreover, participation in these groups often entails substantial (and frequently uncompensated) labor, which can result in excessive workloads for members. Furthermore, ERGs may unintentionally shift the responsibility of discussing DEI issues away from White men (Dobbin & Kalev, 2022c).

Another prominent diversity program is the diversity task force. Using data from interviews, Dobbin and Kalev argue that effective diversity task forces should be demographically diverse, organizationally diverse (i.e., consisting of leaders from various departments), and formally endorsed by top management (Dobbin & Kalev, 2022b). These task forces require a close partnership with human resources to access relevant data and are typically responsible for generating strategies, fostering managerial accountability for diversity efforts, and monitoring key metrics to assess progress and identify areas requiring additional support. The impact of these task forces on increasing diversity in managerial roles is substantial and consistent, matched only by that of mentoring programs (Dobbin & Kalev, 2022b).

The final diversity program relevant to this study is the implementation of mentoring programs. Research by Dobbin and Kalev (Dobbin & Kalev, 2022c) highlights the effectiveness of mentoring programs in enhancing protégés' performance, attitudes, motivation, and skill development. These programs expand protégés' professional networks and increase their visibility to senior leadership. Moreover, mentoring benefits not only protégés but also mentors, as both groups are more likely to be promoted. Participation in mentoring programs is also associated with reduced turnover, as mentors and protégés are less likely to leave the organization. However, for mentoring programs to effectively contribute to managerial diversity, organizations must employ a sufficient number of women and people of color, maintain a pool of non-managers with the necessary credentials for promotion (e.g., college degrees), and have available management positions. Consequently, mentoring is most effective in industries with highly skilled workers. In sectors with a predominantly low-skilled

workforce, organizations seeking to diversify management may need to invest in programs that provide employees with the credentials necessary for career advancement (Dobbin & Kalev, 2022c).

2.2.2 Inclusion Efforts and Group Differences in Organizational Attraction

Sociologists have traditionally focused research efforts on workplace diversity programs (and, to a limited extent, diversity statements) and their efficacy in ameliorating inequality; however, greater attention is needed on how individuals and groups respond to these organizational inclusion efforts. Scholars in neighboring disciplines have examined this issue and found that an organization's demonstrated commitment to diversity is a key determinant of racial differences in workplace attraction (Avery & McKAY, 2006). In a survey experiment with a nationally representative sample of 1,862 respondents (755 White, 526 Black, and 581 Latino), Scarborough et al. (2019) found that support for diversity policies was highest among Black respondents, followed by Latino respondents, with White respondents expressing the lowest levels of support. They also found that women are more supportive of diversity policies than men (Scarborough, Lambouths, & Holbrook, 2019). As another example of an organization's demonstrated commitment to diversity working as a key determinant of racial differences in workplace attraction, findings from a field experiment suggest that diversity messages increased African American and Hispanic student interest and application rates to a financial services company without dissuading White and Asian American students (Flory, Leibbrandt, Rott, et al., 2021). However, this evidence is to be considered with caution due to comparisons relying on a small sample size in the control group (e.g., there were approximately 25 African American and Hispanic students in the control group).

Information about an organization's demographic composition can influence organizational attractiveness as well. In one study, researchers found evidence that, when given information about a company's workforce diversity, job seekers expressed higher interest (operationalized as clicking on a job posting) in organizations with higher workforce diversity (Choi, Pacelli, Rennekamp, et al., 2023). Similarly, research on representation of workplace diversity in organizational images and promotional materials has shown that this practice is widespread (Cober, Brown, Levy, et al., 2003),



Figure 1. Varying Impact of Inclusion Efforts on Organizational Attraction
Note: This figure illustrates the hypothesized pattern in which some groups are more interested than others in inclusion efforts, and how these inclusion efforts can function as a source of organizational attraction for these groups.

and that racial minorities and women respond positively to diverse representation in such images (Avery, 2003).

Across these examples, the evidence suggests that some groups are more interested than others in inclusion efforts, and that these inclusion efforts can function as a source of organizational attraction for these groups. This conceptual model is illustrated in **Figure 1**.

2.2.3 The Increasingly Polarizing Impact of Inclusion Efforts on Organizational Attraction

Across these studies on diversity statements, the efficacy of diversity programs, and responses to organizations' inclusion efforts, an area requiring increased scrutiny is apparent: researchers have scantly studied how the relationship between organizational attractiveness and workplace inclusion efforts varies among groups with different achieved statuses. An achieved status refers to a characteristic or social position that is earned, attained, accomplished, or chosen (Linton, 1936). Examples include education and political affiliation. In contrast, an ascribed status indicates a trait that is involuntarily assigned and is typically beyond personal control (Linton, 1936), such as

race, ethnicity, and gender. 2024 data from the Pew Research Center suggest that we might expect differences in the effect of information about inclusion efforts on organizational attraction along dimensions of achieved status, and not just ascribed statuses. These differences are likely as large, if not larger than those for ascribed statuses. Survey data collected by the Pew Research Center in 2024 found that 78% of Democrat and Democrat-leaning adult workers (compared to 27% of Republican and Republican-leaning adult workers) believed that focusing on increasing DEI in the workplace is a good thing (Minkin, 2024). As a contrast, 42% of Republican and Republican-leaning adult workers (compared to 4% of Democrat and Democrat-leaning adult workers) indicated that focusing on DEI is a bad thing (Minkin, 2024). Collecting data on between-group variation in workplace attraction based on race, gender, and political affiliation in one study presents the unique and important opportunity for immediately comparable differences in effect sizes.

Beyond examining how inclusion efforts impact organizational attractiveness and how this varies across demographic characteristics (both achieved and ascribed), this study contributes to the literature by revisiting these topics at a time when public opinion on inclusion efforts is rapidly changing. For example, while 21% of workers indicated that focusing on DEI is a bad thing in 2023, 26% indicated it was bad in 2024 (Minkin, 2024), with Republican and Republican-leaning workers who expressed this focus being a bad thing increasing by 12 percentage points during this short time frame. This rapidly evolving landscape suggests that sociologists, and social scientists more broadly, should examine not only the effectiveness of inclusion efforts, but also how workers perceive these efforts, as such perceptions are increasingly influencing whether these initiatives exist at all.

2.3 Research Questions and Hypotheses

2.3.1 Research Questions

1. How do workplace inclusion efforts affect organizational attraction?

2. How does this organizational attraction vary by race, gender, and political affiliation?

2.3.2 Hypotheses

1. The proportion of participants selecting the workplace with inclusion efforts will not be significantly different from 0.5, indicating no overall preference between workplaces with or without inclusion efforts.

2. Black participants, women, and Democrats (compared to White participants, men, and Republicans, respectively) will be more likely to select workplaces that provide information about inclusion efforts.

2.4 Data and Methods

2.4.1 Design

To investigate how inclusion efforts affect organizational attractiveness, this study employed a within-subjects experimental design. Participants were presented with two job postings and asked to choose between them, thereby indicating their preferred employer. Given the within-subjects design, all participants were exposed to both conditions (one company mentioning inclusion efforts and one not) rather than being assigned to separate treatment groups. The design of this study is illustrated in **Figure 2**.

The primary independent variable in this study was the company information provided to participants. One of the two company descriptions included information about inclusion efforts, while the other did not, with the presentation order randomized. The information about inclusion efforts consisted of a diversity statement, incorporating elements of both the business case and the fairness case, along with details about the company's diversity programs.

The primary dependent variable of interest was whether the participant selected the company that mentioned inclusion efforts. Each participant made only one selection between the two company descriptions. Participants were specifically asked, "Which of these two companies would you rather work for as an employee?"

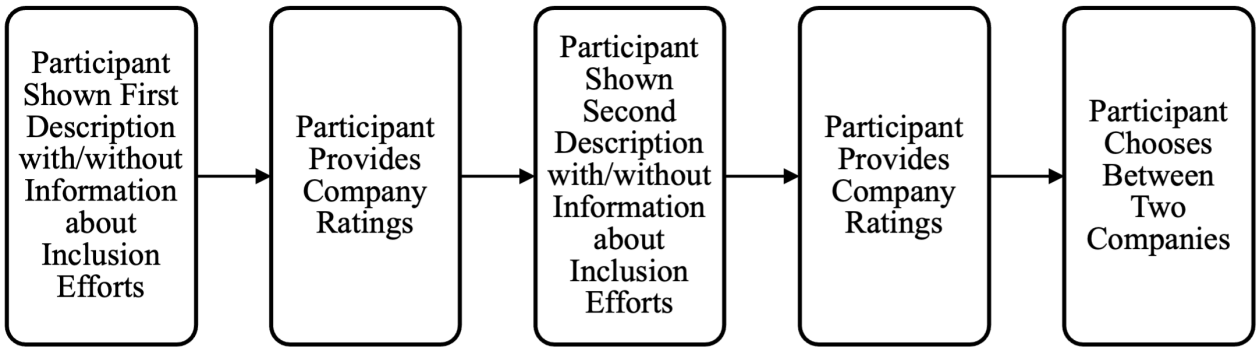


Figure 2. Design Testing the (Heterogeneous) Effect of Company Inclusion Efforts on Organizational Attraction
Note: This figure illustrates the study's experimental design and outlines the data collection process from participants' perspective based on their treatment assignment.

Participants also rated each workplace on a seven-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree," in response to the following statements: (1) "I would feel accepted at this company." (2) "This company's values align well with my personal values." (3) "This company would offer great financial compensation." (4) "This company would offer many career opportunities."

2.4.2 Participants

The samples were obtained using Prolific ("Prolific", 2014), which was selected due to its strong performance in prior research. Researchers have found that participants recruited through Prolific and CloudResearch tend to provide higher data quality (i.e., more likely to maintain consistent IP addresses and geolocations, follow instructions, retain information, pass attention checks, provide thoughtful responses, and complete surveys at an appropriate speed) than those recruited from MTurk, Qualtrics, or undergraduate samples (Douglas, Ewell, & Brauer, 2023). Douglas, Ewell, and Brauer (2023) also found that the cost per high-quality respondent was lower on Prolific than on CloudResearch, MTurk, or Qualtrics. Prolific was particularly suitable for online

data collection because it allowed filtering based on participants' prior survey experience, thereby reducing non-naivety by excluding individuals who had completed thousands of surveys (Prolific, 2024).

To participate in this study, respondents were required to have completed at least 10, but no more than 500, surveys and to have an approval rating of at least 95%. Participants also had to reside in the United States at the time of survey completion. Survey submissions from participants who completed the study exceptionally quickly, defined as three standard deviations below the mean according to Prolific's protocol, were subject to exclusion; however, this resulted in no exclusions. Respondents who failed attention checks twice (i.e., incorrectly answered the same attention check question twice in a row) were asked to return their submissions. Lastly, participants who did not complete the study were excluded from the data analysis as they did not provide a response to the main study question regarding which company they would prefer to work for.

Data were obtained from two samples. The first sample was a nationally representative sample of 500 based on the population in the United States. Prolific helped obtain a nationally representative sample based on age, sex, race/ethnicity, and political affiliation. A quota sample was also collected because one of the main research questions of this study considered differences between groups of participants. Quota sampling, a non-probability sampling method, was used to ensure sufficient representation of these different groups. The quota sample consisted of 598 participants[4] that were recruited based on race (Black or White), gender (woman or man), and political affiliation (Democrat or Republican). The quota sample was key to recruiting larger pools of participants from smaller subgroups (2 racial groups $\times$ 2 gender groups $\times$ 2 political affiliation groups = 8 subgroups) that would have otherwise been financially unfeasible to obtain from a nationally representative sample (since some subgroups are a very small proportion of the population, a much larger nationally representative sample would have been needed for analyses with these subgroups to have sufficient power).

[4]It was meant to be 600, but due to two participants attempting a second submission, the total number of unique participants came down to 598.

Data collection for both the nationally representative sample and the quota sample took place in March 2025. **Table 1** presents the demographic characteristics of participants in both samples. A total of 1,098 participants completed the study (500 in the nationally representative sample and 598 in the quota sample), resulting in 1,098 choices between company descriptions with or without inclusion efforts. Participants in the nationally representative sample had a median survey completion time of three minutes and 23 seconds, whereas participants in the quota sample took slightly longer, with a median completion time of four minutes and 49.5 seconds. On average, participants in the nationally representative sample were older (45.78) than those in the quota sample (38.76).

As to be expected due to the different sampling strategies, there were some differences in the educational attainment of the two samples. 35.00% of participants in the nationally representative sample indicated having a bachelor's degree (43.31% in the quota sample), 20.40% a graduate degree (28.76% in the quota sample), 20.20% had some college credit with no degree (13.55% in the quota sample), 13.20% had a high school diploma or equivalent (7.19% in the quota sample), 10.80% had an associate's degree (6.69% in the quota sample), and 0.40% had less than a high school diploma or equivalent (0.50% in the quota sample).

For the quota sample, the gender (man or woman in this sample), political affiliation (Democrat or Republican in this sample), and race (Black or White in this sample) of participants all hovered near 50%, as to be expected due to the nature of a quota sample. For the nationally representative sample, 42.40% of participants identified as Independents, 29.60% identified as Democrats, and 28.00% identified as Republicans. 51.00% of participants in the nationally representative sample identified as women, while 49.00% identified as men. Regarding racial identity of the nationally representative sample, the majority of respondents self-identified as White (67.00%), followed by Black or African American (13.00%), and then Asian or Asian American (7.20%). In response to the question, "Are you of Hispanic, Latino, or Spanish origin?", a larger percentage answered yes in that nationally representative sample than in the quota sample. The remaining demographic characteristics of participants for each of the two samples are presented in **Table 1**.

Table 1. Participant Demographic Characteristics for Nationally Representative Sample and Quota Sample

Descriptive Statistic	Nationally Representative Sample	Quota Sample
Sample Size	500 (100.00%)	598 (100.00%)
Mean Age	45.78	38.76
Educational Attainment		
Less than high school diploma or equivalent	2 (0.40%)	3 (0.50%)
High school diploma or equivalent	66 (13.20%)	43 (7.19%)
Some college credit, no degree	101 (20.20%)	81 (13.55%)
Associate's degree	54 (10.80%)	40 (6.69%)
Bachelor's degree	175 (35.00%)	259 (43.31%)
Graduate degree	102 (20.40%)	172 (28.76%)
Political Affiliation		
Republican	140 (28.00%)	300 (50.17%)
Independent	212 (42.40%)	0 (0.00%)
Democrat	148 (29.60%)	298 (49.83%)
Gender		
Man	245 (49.00%)	300 (50.17%)
Woman	255 (51.00%)	298 (49.83%)
Hispanic, Latino, or Spanish?		
Hispanic, Latino, or Spanish	81 (16.20%)	60 (10.03%)
Not Hispanic, Latino, or Spanish	419 (83.80%)	538 (89.97%)
Race		
White	335 (67.00%)	298 (49.83%)
Black or African American	65 (13.00%)	300 (50.17%)
Asian or Asian American	36 (7.20%)	0 (0.00%)
American Indian or Alaska Native	9 (1.80%)	0 (0.00%)
Native Hawaiian or Other Pacific Islander	4 (0.80%)	0 (0.00%)
Middle Eastern, Arab American, or North African	4 (0.80%)	0 (0.00%)
Multiracial	37 (7.40%)	0 (0.00%)
A race not listed	10 (2.00%)	0 (0.00%)

Note. The nationally representative sample was based on age, sex, race/ethnicity, and political affiliation. The quota sample was collected based on race (Black or White), gender (woman or man), and political affiliation (Democrat or Republican).

2.4.3 Survey Instrument and Data Collection Procedure

The survey was created and administered using Qualtrics' survey design software ("Qualtrics", 2005), and was distributed to participants recruited via Prolific. Workplace descriptions used in the study did not include information about salaries or any other quantitative data. This decision was based on research indicating that individuals systematically favor options that perform better on quantified dimensions (Chang, Kirgios, Mullainathan, et al., 2024). Specifically, prior findings provide evidence of quantification fixation, a phenomenon in which, when making trade-off decisions involving both qualitative and quantitative attributes, individuals tend to prioritize quantitative information. This bias affects decision making across various domains, leading people to prefer options that excel on numerically expressed criteria (Chang, Kirgios, Mullainathan, et al., 2024). Given that the study design required participants to make a single choice, it was therefore crucial to exclude information about salaries or any other quantitative data.

Participants first provided informed consent before beginning the study. They were then presented with a description of the first workplace, which either included or omitted information about inclusion efforts. To ensure that participants read and understood the workplace description, participants completed a manipulation check question, for which they had up to two attempts to provide a correct response. Participants then rated each workplace on a seven-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree," in response to the following statements: (1) "I would feel accepted at this company." (2) "This company's values align well with my personal values." (3) "This company would offer great financial compensation." (4) "This company would offer many career opportunities."

Next, participants were shown a description of a second workplace. If the first workplace description included information about inclusion efforts, the second did not, and vice versa. Again, participants completed a manipulation check question, with two attempts to confirm their comprehension of the description. Afterward, they answered the same questions, randomly ordered, about their attitudes toward the second workplace.

Participants then made a forced-choice decision between the two workplaces, selecting the one they would prefer to work for by answering the question: "Which of these two companies would you rather work for as an employee?" Finally, participants answered demographic questions, including items on race and ethnicity, gender, political affiliation, and educational attainment. The complete survey instrument, including all questions and materials shown to participants, can be found in **Appendix A: Survey Instrument for Diversity at Work Study**.

2.4.4 Statistical Methods

The study design and data analysis plan were pre-registered with the Open Science Foundation. All data processing (including cleaning, statistical analyses, model estimations, and data visualizations) was carried out using R statistical software (Team, 2024).

2.4.4.1 Testing Study Hypotheses

To address the first hypothesis (the proportion of participants selecting the workplace with inclusion efforts will not be significantly different from 0.5, indicating no overall preference between workplaces with or without inclusion efforts), a two-tailed, one-sample proportion test was conducted with the data collected from the nationally representative sample. This test compared the observed proportion of participants selecting the workplace with inclusion efforts to the expected proportion of 0.5, given that one of the two workplaces mentioned inclusion efforts while the other did not. The test statistic for the one-sample proportion test was:

$$Z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}} \tag{1}$$

where $\hat{p}$ is the observed proportion of the time the company with inclusion efforts was selected, p_0 (which is equal to 0.5) is the expected proportion under the null hypothesis, and n is the total number of company choices made.

To address the second hypothesis (Black participants, women, and Democrats [compared to White participants, men, and Republicans, respectively] will be more likely to select workplaces that provide information about inclusion efforts), a linear probability model with robust standard errors was estimated. For analyses involving a binary outcome variable, linear regression was used instead of logistic regression. Prior research (Gomila, 2021) has shown that, in many cases, linear regression offers an effective approach for estimating non-causal probabilities associated with different participant characteristics and a dichotomous outcome. The binary outcome variable was coded as 1 if the workplace with inclusion efforts was chosen and 0 otherwise. As such, each participant contributed one observation to the model. A series of indicator variables were included for participant demographic characteristics, specifically race (White participants as the reference group), ethnicity (non-Hispanic, Latino, or Spanish origin as the reference group), gender (men as the reference group), political affiliation (Republicans as the reference group), and educational attainment (less than a bachelor's degree as the reference group). This statistical analysis was conducted using the nationally representative sample due to sufficient representation of minority groups to run models with no interaction terms. The first model included only ascribed identities, while the second model included only achieved identities. The first full model included all participant characteristics. All three of these models are shown below:

$$DiversityWorkplace_i = \beta_0 + \beta_1 \text{Race}_i + \beta_2 \text{Ethnicity}_i + \beta_3 \text{Gender}_i + \epsilon_i \tag{2}$$

$$DiversityWorkplace_i = \beta_0 + \beta_1 \text{PoliticalAffiliation}_i + \beta_2 \text{EducationalAttainment}_i + \epsilon_i \tag{3}$$

$$\begin{aligned} DiversityWorkplace_i = \beta_0 + \beta_1 \text{Race}_i + \beta_2 \text{Ethnicity}_i + \beta_3 \text{Gender}_i \\ + \beta_4 \text{PoliticalAffiliation}_i + \beta_5 \text{EducationalAttainment}_i + \epsilon_i \end{aligned} \tag{4}$$

Lastly, I included interaction terms to the full model mentioned previously as an exploratory analysis and then estimated all of the prior models again using logistic regression models as a robustness check.

2.4.4.2 Exploratory Analyses

As an exploratory analysis, I used the data from the quota sample and estimated a linear probability model (with robust standard errors) for whether the workplace with inclusion efforts was chosen with a series of seven indicator variables (with White Republican men as the reference group) for the following subgroups: White Republican women, White Democrat men, White Democrat women, Black Republican men, Black Republican women, Black Democrat men, and Black Democrat women. Because of the nature of the quota sample, each of these subgroups consisted of 75 participants, except for White Democrat women (which consisted of 73 participants). An analysis of this sort was possible with the quota sample, but not with the nationally representative sample for which representation in some of these groups (e.g., Black Republican women) would have been too small for modeling due to issues with statistical power. This model is shown below.

$$\begin{aligned} DiversityWorkplace_i = \beta_0 + \beta_1 \text{WhiteRepublicanWomen}_i + \beta_2 \text{WhiteDemocratMen}_i + \\ \beta_3 \text{WhiteDemocratWomen}_i + \beta_4 \text{BlackRepublicanMen}_i + \\ \beta_5 \text{BlackRepublicanWomen}_i + \beta_6 \text{BlackDemocratMen}_i + \\ \beta_7 \text{BlackDemocratWomen}_i + \epsilon_i \end{aligned} \quad (5)$$

I additionally ran a series of one-tailed, one-sample proportion tests for each of the eight subgroups in the quota sample to examine whether the observed proportion of participants selecting the workplace with inclusion efforts differed from the expected proportion of 0.5.

Lastly, I analyzed the data collected on company ratings for four statements: (1) "I would feel accepted at this company," (2) "This company's values align well with my personal values," (3) "This company would offer great financial compensation," and (4) "This company would offer many

career opportunities." Differences in ratings between workplaces with inclusion efforts and those without inclusion efforts were assessed using Wilcoxon Signed-Rank Tests (Woolson, 2005). The Wilcoxon Signed-Rank Tests allowed me to compare two related samples (each participant rated two companies across four statements) to determine if their median difference is significantly different from zero. This test was appropriate due to the paired design (each participant rated two companies, one with inclusion efforts and one without), the ordinal nature of the data (Likert scale ratings), and the nonparametric nature of the Wilcoxon Signed-Rank Test (which does not assume a normal distribution). Separate Wilcoxon Signed-Rank Tests were conducted for each statement to determine whether significant differences existed between the rating of the workplace with inclusion efforts and the rating of the workplace without inclusion efforts.

The Wilcoxon Signed-Rank Test procedures (Woolson, 2005) were applied to the data from the nationally representative sample. I first computed the difference between the ratings for each participant and each statement. Second, if a participant rated both companies the same for one of the statements, that observation was removed because it did not contribute to ranking. Third, I took the absolute values of the differences, ranked these from smallest to largest, and if multiple differences had the same absolute value, assigned them the average rank. Fourth, if original differences (i.e., before taking the absolute value) were positive, ranks were kept positive. If original differences were negative, the rank was given a negative value. Next, all positive ranks were added together and then all negative ranks were added together separately. Finally, the smaller of the two rank sums (absolute value of each was taken) was used as the test statistic. Since the sample is large, the standard normal distribution Z served as an approximation for assessing differences in ratings (Woolson, 2005).

2.5 Results

2.5.1 Which Company is Selected More Often?

To test the first hypothesis (the proportion of participants selecting the workplace with inclusion efforts will not be significantly different from 0.5, indicating no overall preference between

workplaces with or without inclusion efforts), I conducted a two-tailed one-sample proportion test and found evidence that the observed proportion of participants who selected the workplace with inclusion efforts in the nationally representative sample (213 out of 500; $\hat{p} = 0.426$) is statistically different than the expected proportion ($p_0 = 0.500$), $z = -3.309$, $p = 0.001$. Therefore, the findings do not support the hypothesis that the proportion of participants selecting the workplace with inclusion efforts will not be significantly different from 0.5 and instead suggests an overall preference for workplaces without information about inclusion efforts. With a one-tailed one-sample proportion test, I found evidence that the observed proportion of participants who selected the workplace without inclusion efforts ($\hat{p} = 0.574$) is significantly higher than the expected proportion ($p_0 = 0.500$), $z = 3.309$, $p < 0.001$. Expectedly, the findings from an additional one-tailed one-sample proportion test also suggest that the observed proportion of participants who selected the workplace with inclusion efforts ($\hat{p} = 0.426$) is significantly lower than the expected proportion ($p_0 = 0.500$), $z = 3.309$, $p < 0.001$. Participants' company choices are visualized in **Figure 3**, which demonstrates that a larger proportion of participants were attracted to the workplace without information about inclusion efforts than the workplace with information about inclusion efforts.

2.5.2 Comparing Differences in Organizational Attraction between Ascribed and Achieved Statuses

Using the nationally representative sample based on age, sex, race, and political affiliation in the United States, I first documented the proportion choosing the company with inclusion efforts, disaggregated by key participant characteristics. **Figure 4** shows the observed selection rates for each of the key groups for this study. Approximately 61.5% of Black participants chose the company with inclusion efforts, compared to 37.3% of White participants (a difference of 24.2 percentage points). About the same proportion of Hispanic and non-Hispanic participants chose the company with inclusion efforts (42.0% and 42.7% respectively). Women in the nationally representative sample chose the company with inclusion efforts 6.7 percentage points more than men (45.9% and 39.2% respectively). A much larger proportion of Democrats chose the company with inclusion efforts

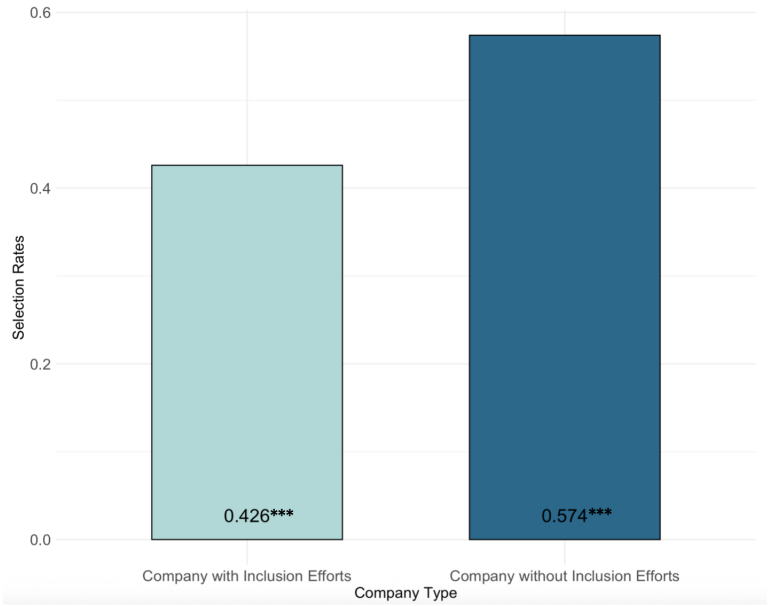


Figure 3. Nationally Representative Sample's Company Choices
Note. + $p < 0.1$ ∗ $p < .05$; ∗∗ $p < .01$; ∗ ∗ ∗ $p < .001$. Symbols indicate the level of significance of one-tailed one-sample proportion tests comparing whether the observed selection rate is lower (for companies with inclusion efforts) or higher (for companies without inclusion efforts) than the expected 0.5.

(60.1%) than Republicans (25.7%). This difference amounts to 34.4 percentage points. A larger proportion of Independents (41.5%) chose the company with inclusion efforts than Republicans as well. Lastly, 50.0% of participants with graduate degrees chose the company with inclusion efforts, which was higher than the 38.9% of participants with bachelor's degrees and the 42.2% of participants with less than a bachelor's degree that did.

To test whether these differences are statistically significant, I estimated a series of linear probability models with the outcome variable being whether the workplace with inclusion efforts was chosen and participants' ascribed statuses (i.e., indicator variables for race, ethnicity, and gender) as the independent variables. The findings are shown in **Table 2**. **Model 1** includes indicator variables for race, with White participants serving as the reference group. **Model 2** includes an indicator variable for Hispanic, Latino, or Spanish origin (with non-Hispanic, Latino, or Spanish origin serving as the reference group). **Model 3** includes an indicator variable for women, with men serving as the reference group. Lastly, **Model 4** includes all of these indicator variables. **Model 4** suggests that, on

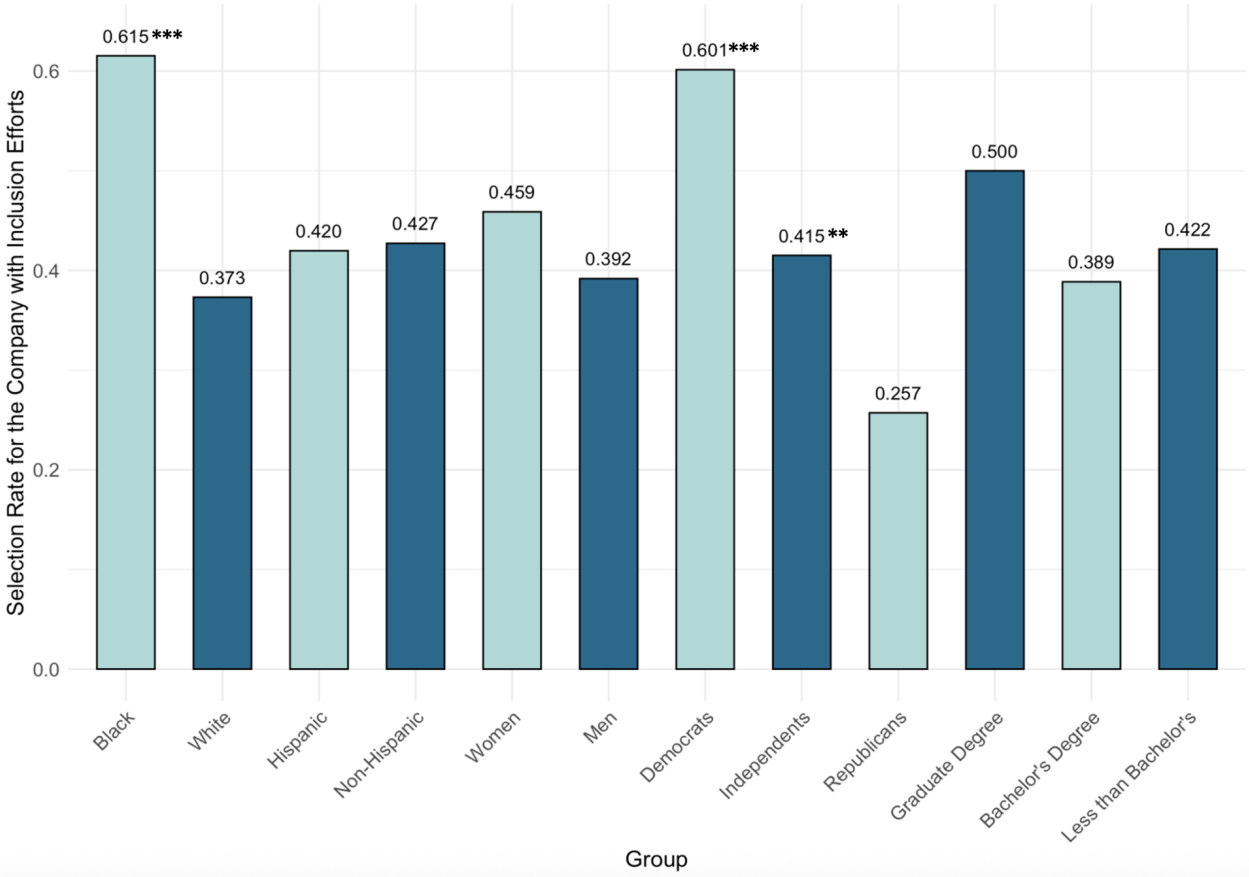


Figure 4. Selection Rate for the Company with Inclusion Efforts, Disaggregated by Participant Characteristics for Nationally Representative Sample

Note. + $p < 0.1$ ∗ $p < .05$; ∗∗ $p < .01$; ∗ ∗ ∗ $p < .001$. Symbols indicate the level of significance of the differences in the observed selection rate for the company with inclusion efforts by Black compared to White participants, Hispanic compared to non-Hispanic participants, women compared to men, Democrats and Independents compared to Republicans, and graduate degree holders and bachelor's degree holders compared to those with less than a bachelor's degree in educational attainment. Symbols for level of significance are based on corresponding linear probability models in which group differences within only one characteristic (e.g., race, political affiliation, etc.) are modeled. These models are in **Table 2** and **Table 3**.

average, Black participants are more likely than White participants (the reference group) to choose the workplace with inclusion efforts ($\beta_{Black/AfricanAmerican} = 0.241$, $t(494) = 3.658$, $p < 0.001$). I found insufficient evidence that the probability of Asian / Asian American participants choosing the company with inclusion efforts is significantly different than White participants. Similarly, I found insufficient evidence that the probability of Hispanic, Latino, or Spanish origin participants choosing the company with inclusion efforts is significantly different than non-Hispanic, Latino, or Spanish origin participants. Lastly, the findings suggest that there is insufficient evidence that, after accounting for race and ethnicity, women are more/less likely than men to select the company with inclusion efforts.

I then ran the same models shown in **Table 2**, but for achieved statuses (i.e., indicator variables for political affiliation and educational attainment). The findings are shown in **Table 3**. **Model 1** includes indicator variables for political affiliation, with Republicans serving as the reference group. **Model 2** includes indicator variable for educational attainment (with participants with less than a bachelor's degree as the reference group). **Model 3** includes all of these indicator variables and provides evidence that, on average, Democrats are more likely than Republicans (the reference group) to choose the workplace with inclusion efforts ($\beta_{Democrat} = 0.346$, $t(495) = 6.367$, $p < 0.001$). I found evidence that Independents too are more likely than Republicans to choose the workplace with inclusion efforts ($\beta_{Independent} = 0.164$, $t(495) = 3.303$, $p = 0.001$). However, I found insufficient evidence that the probability of participants with either graduate degrees or bachelor's degrees choosing the company with inclusion efforts is significantly different than participants with less than a bachelor's degree.

To test the second hypothesis (Black participants, women, and Democrats [compared to White participants, men, and Republicans, respectively] will be more likely to select workplaces that provide information about inclusion efforts), I used the **All Characteristics Model** in **Table 4**. This model is similar to those in **Table 3** and **Table 2**, but is different in that it includes indicator variables for all characteristics (i.e., both achieved and ascribed statuses), which is why it is the preferred model. In support of the hypothesis, the findings provide evidence that Black participants,

Table 2. Association between Selection of Company with Inclusion Efforts and Ascribed Statuses

	Model 1	Model 2	Model 3	Model 4
Intercept	0.373***	0.427***	0.392***	0.348***
	(0.026)	(0.024)	(0.031)	(0.035)
Black / African American	0.242***			0.241***
	(0.066)			(0.066)
Asian / Asian American	0.016			0.008
	(0.085)			(0.086)
Hispanic, Latino, or Spanish origin		-0.007		-0.040
		(0.060)		(0.061)
Woman			0.067	0.062
			(0.044)	(0.043)
Num.Obs.	500	500	500	500
R2	0.033	0.000	0.005	0.038
R2 Adj.	0.027	-0.002	0.003	0.028
AIC	708.0	720.7	718.4	709.5
BIC	729.0	733.3	731.1	739.0
RMSE	0.49	0.49	0.49	0.49
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001				

Note. Linear probability models with robust standard errors in parentheses. Models use data collected from nationally representative sample.

Table 3. Association between Selection of Company with Inclusion Efforts and Achieved Statuses

	Model 1	Model 2	Model 3
Intercept	0.257***	0.422***	0.257***
	(0.037)	(0.033)	(0.043)
Democrat	0.344***		0.346***
	(0.055)		(0.054)
Independent	0.158**		0.164**
	(0.050)		(0.050)
Graduate degree (for example: MA, MS, MD, JD, PhD)		0.078	0.068
		(0.060)	(0.059)
Bachelor's degree (for example: BA, BS)		-0.033	-0.047
		(0.050)	(0.047)
Num.Obs.	500	500	500
R2	0.070	0.007	0.077
R2 Adj.	0.066	0.003	0.070
AIC	686.4	719.4	686.6
BIC	703.2	736.3	711.9
RMSE	0.48	0.49	0.48

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note. Linear probability models with robust standard errors in parentheses. Models use data collected from nationally representative sample.

on average, are more likely than White participants to choose the workplace with inclusion efforts ($\beta_{Black/AfricanAmerican} = 0.237$, $t(490) = 3.377$, $p < 0.001$). Unlike prior models, after accounting for all participant characteristics, I found some evidence that women, on average, choose the workplace with inclusion efforts at a somewhat higher probability (marginal statistical significance) than men ($\beta_{Woman} = 0.070$, $t(490) = 1.664$, $p = 0.097$). Lastly, the model provides evidence (in support of the hypothesis) that Democrats, on average, are more likely than Republicans to choose the workplace with inclusion efforts ($\beta_{Democrat} = 0.340$, $t(490) = 6.313$, $p < 0.001$). I also found evidence that Independents are more likely than Republicans to choose the workplace with inclusion efforts ($\beta_{Independent} = 0.164$, $t(490) = 3.260$, $p = 0.001$). As a robustness check, I reran all the models in **Table 2**, **Table 3**, and **Table 4** as logistic regression models (the findings are shown in **Appendix B: Logistic Regression Models for Nationally Representative Sample**) and found that none of the previously described results change in directionality or statistical significance.

The **All Characteristics Model** in **Table 4** supports the second hypothesis and provides evidence of significant differences in the selection of workplaces with inclusion efforts across groups with different ascribed and achieved statuses. Notably, the difference in predicted probabilities between Democrats and Republicans (34.0 percentage points) is even larger than the difference in predicted probabilities between Black and White participants (23.7 percentage points). This 10.3 percentage point difference in differences highlights the stronger association between political affiliation (an achieved status) and selection of workplaces with inclusion efforts compared to race (an ascribed status).

The **Interaction Model** in **Table 4** consists of an exploratory analysis in which I added interaction terms between the indicator variables $Black/AfricanAmerican$, $Women$, and $Democrat$ to identify whether some groups experience amplified or mitigated effects based on overlapping characteristics. These characteristics were selected for the interaction terms because (1) they are the characteristics the second study hypothesis was based on and (2) the strata in the quota sample were constructed based on race (White or Black), gender (woman or man), and political affiliation (Democrat or Republican). The **Interaction Model** suggests a diminishing association

Table 4. Association between Selection of Company with Inclusion Efforts and All Participant Characteristics

	All Characteristics Model	Interaction Model
Intercept	0.185***	0.144**
	(0.048)	(0.049)
Black / African American	0.237***	0.431***
	(0.070)	(0.105)
Asian / Asian American	0.037	0.036
	(0.081)	(0.082)
Hispanic, Latino, or Spanish origin	-0.033	-0.035
	(0.060)	(0.058)
Woman	0.070+	0.119*
	(0.042)	(0.051)
Democrat	0.340***	0.451***
	(0.054)	(0.075)
Independent	0.157**	0.157**
	(0.048)	(0.048)
Graduate degree (for example: MA, MS, MD, JD, PhD)	0.059	0.069
	(0.059)	(0.058)
Bachelor's degree (for example: BA, BS)	-0.059	-0.062
	(0.047)	(0.047)
Black / African American * Woman		-0.161
		(0.151)
Black / African American * Democrat		-0.548**
		(0.212)
Democrat * Woman		-0.116
		(0.098)
Black / African American * Woman * Democrat		0.229
		(0.297)
Num.Obs.	500	500
R2	0.112	0.133
R2 Adj.	0.096	0.110
AIC	677.1	673.3
BIC	723.4	736.5
RMSE	0.47	0.46

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note. Linear probability models with robust standard errors in parentheses. Models use data collected from nationally representative sample.

for Black / African American Democrats in which their combined probability to select a workplace with inclusion efforts is weaker than expected had the probabilities been solely additive ($\beta_{Black/AfricanAmerican*Democrat} = -0.548$, $t(486) = -2.591$, $p = 0.010$). This is likely because Democrats and Black / African American participants both already strongly prefer workplaces with inclusion efforts, so the difference associated with being Black among Democrats is smaller compared to the difference associated with being Black among Republicans or Independents. However, it is important to note that interpretation of the interaction terms in this model (or any other interaction terms in this model were they to be added) should be approached with caution due to small sample sizes for some of these subgroups. For example, in the nationally representative sample, there are only 33 Black / African American women.

2.5.3 Comparing Differences in Organizational Attraction between Subgroups

As an exploratory and supplementary approach to examine subgroup[5] differences in organizational attraction to companies with or without inclusion efforts, I estimated a linear probability model with robust standard errors using the quota sample. The outcome was whether participants selected the workplace with inclusion efforts. The model included seven indicator variables (White Republican women, White Democrat men, White Democrat women, Black Republican men, Black Republican women, Black Democrat men, and Black Democrat women) representing different subgroups constructed through a combination of race, political affiliation, and gender. I used the White Republican men subgroup as the reference category. Each subgroup in the quota sample consisted of 75 participants, except for White Democrat women ($n = 73$). The findings from this model are shown in **Table 5**.

Looking at **Table 5**, the findings provide evidence that all subgroups, except for White Republican women, are on average more likely than White Republican men to choose the workplace

[5]I use the term "subgroup" to refer to participant segments defined by a combination of race, political affiliation, and gender.

Table 5. Differences in Selection of Company with Inclusion Efforts across Participant Subgroups

	Subgroup Model
Intercept	0.387***
	(0.056)
White Republican Women	0.040
	(0.080)
White Democrat Men	0.187*
	(0.080)
White Democrat Women	0.243**
	(0.080)
Black Republican Men	0.173*
	(0.080)
Black Republican Women	0.173*
	(0.080)
Black Democrat Men	0.187*
	(0.080)
Black Democrat Women	0.200*
	(0.080)
Num.Obs.	598
R2	0.025
R2 Adj.	0.013
AIC	867.7
BIC	907.3
RMSE	0.49
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001	

Note. Linear probability models with robust standard errors in parentheses. Models use data collected from quota sample. The subgroup used as the reference category is White Republican men.

with inclusion efforts. Looking more closely at the findings, I found insufficient evidence that the probability of White Republican women choosing the company with inclusion efforts is significantly different than White Republican men ($\beta_{WhiteRepublicanWomen} = 0.040$, $t(590) = 0.499$, $p = 0.618$). I did, however, find evidence that Black Republican women and Black Republican men, on average, are both more likely than White Republican men to choose the workplace with inclusion efforts ($\beta_{BlackRepublicanWomen} = 0.173$, $t(590) = 2.159$, $p = 0.031$; $\beta_{BlackRepublicanMen} = 0.173$, $t(590) = 2.159$, $p = 0.031$). The findings similarly suggest that the probability of Black Democrat men and White Democrat men choosing the company with inclusion efforts is significantly higher than the probability of White Republican men choosing the company with inclusion efforts ($\beta_{BlackDemocratMen} = 0.187$, $t(590) = 2.329$, $p = 0.020$; $\beta_{WhiteDemocratMen} = 0.187$, $t(590) = 2.329$, $p = 0.020$). Lastly, the largest differences were for Black Democrat women and White Democrat women. The evidence suggests that both Black Democrat women and White Democrat women are more likely than White Republican men to choose the workplace with inclusion efforts ($\beta_{BlackDemocratWomen} = 0.200$, $t(590) = 2.501$, $p = 0.013$; $\beta_{WhiteDemocratWomen} = 0.244$, $t(590) = 3.054$, $p = 0.002$). The observed selection rates for the company with inclusion efforts, disaggregated by participant subgroups for the quota sample, are shown in **Figure 5** and range from 38.7% for White Republican men to 63.0% for White Democrat women.

This analysis was feasible using the quota sample but would not have been possible with the nationally representative sample, where some subgroups (e.g., Black Republican women) would have been too small to ensure sufficient statistical power. Though the inclusion of interaction terms in a linear probability model is possible with the quota sample (**Appendix C: Linear Probability Models for Quota Sample** includes the results from fitting all of the same models from **2.5.2 Comparing Differences in Organizational Attraction between Ascribed and Achieved Statuses**, but with the quota sample; the **Interaction Model** specifically includes interaction terms), I took the approach of modeling subgroups in order to directly compare the likelihood of choosing the workplace with inclusion efforts across different subgroups. This comes at the cost of not being able to explicitly capture how the different factors (i.e., race, gender, and political affiliation) interact

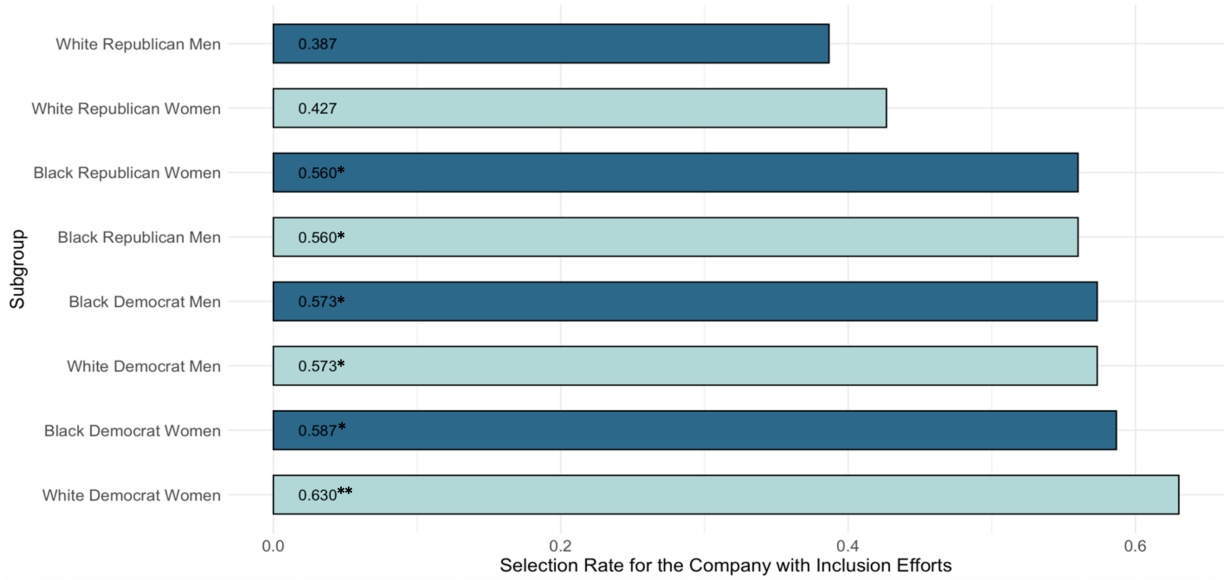


Figure 5. Selection Rate for the Company with Inclusion Efforts, Disaggregated by Participant Subgroups for Quota Sample

Note. Observed selection rates for the company with inclusion efforts for different subgroups in the quota sample are shown. + $p < 0.1$ ∗ $p < .05$; ∗∗ $p < .01$; ∗ ∗ ∗ $p < .001$. Symbols indicate the level of significance of the differences in the observed selection rate for the company with inclusion efforts by different subgroups compared to White Republican men. Symbols for level of significance are based on the linear probability model in **Table 5**.

with each other in a potentially amplifying or diminishing manner. Future work should examine this area of inquiry with a large enough nationally representative sample to investigate questions about how these different characteristics interact.

Next, as an additional exploratory analysis, I ran a series of one-tailed, one-sample proportion tests for each of the eight subgroups in the quota sample to examine whether the observed proportion of participants selecting the workplace with inclusion efforts differed from the expected proportion of 0.5. I found evidence that the observed proportion of White Republican men who selected the workplace with inclusion efforts in the quota sample ($\hat{p} = 0.387$) is significantly lower than the expected proportion ($p_0 = 0.500$), $z = -1.963$, $p = 0.025$. Additionally, I found evidence that the observed proportion of White Democrat women who selected the workplace with information about inclusion efforts in the quota sample ($\hat{p} = 0.630$) is significantly higher than the expected proportion ($p_0 = 0.500$), $z = 2.224$, $p = 0.013$. Lastly, I found weak evidence that the observed proportion of Black Democrat women who selected the workplace with information about inclusion efforts in

the quota sample ($\hat{p} = 0.587$) is significantly higher than the expected proportion ($p_0 = 0.500$), $z = 1.501$, $p = 0.067$. For all other subgroups, I found insufficient evidence that the observed proportion who selected the workplace with inclusion efforts in the quota sample is statistically different than the expected proportion ($p_0 = 0.500$).

2.5.4 Differences in Attitudinal Measures

Besides selecting the company they would prefer to work for, participants were also asked to rate companies on a seven-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree," in response to the following statements: (1) "I would feel accepted at this company," (2) "This company's values align well with my personal values," (3) "This company would offer great financial compensation," and (4) "This company would offer many career opportunities." As an exploratory analysis, I examined whether there were differences in these ratings between companies with or without information about inclusion efforts for participants in the nationally representative sample. After assigning numerical values to these Likert scale ratings, I first compared the average ratings for the various statements between companies with or without information about inclusion efforts. These observed average ratings can be seen in **Figure 6**.

When asked to rate how much they agreed with the statement "I would feel accepted at this company," the average participant rating in the nationally representative sample was 5.542 for the company with inclusion efforts and a slightly higher (by 2.201%) 5.664 for the company without inclusion efforts. For the statement "This company's values align well with my personal values," the company with inclusion efforts received an average rating of 5.368, while the company without inclusion efforts received a higher (by 6.781%) average rating of 5.732. The largest difference was for the average participant rating for the statement "This company would offer great financial compensation." The average participant rating was 4.704 for the company with inclusion efforts and 5.172 for the company without inclusion efforts (which is 9.949% higher). Lastly, the average participant rating was similarly higher for the company without inclusion efforts when participants were asked to rate how much they agreed with the statement "This company would offer many career

opportunities" (by 9.140%; average rating of 5.684 for the company without inclusion efforts and 5.208 for the company with inclusion efforts).

To test whether differences in ratings between workplaces with inclusion efforts and those without inclusion efforts were statistically significant, I used Wilcoxon Signed-Rank Tests (Woolson, 2005). I determined that the Wilcoxon Signed-Rank Tests were appropriate for this analysis after I tested if the differences between paired ratings were normally distributed with Shapiro-Wilk tests (results in **Figure 7**) and found evidence that the data (the differences between paired ratings) significantly deviate from normality. Since paired t-tests assume normality of differences between paired observations, the Wilcoxon Signed-Rank Test is more appropriate. However, as a robustness check, I also ran paired t-tests for the ratings for all of the statements and found no difference in the statistical significance of the results (results in **Figure 7**). Focusing on the Wilcoxon Signed-Rank Test results for the statement "I would feel accepted at this company," the results indicated a non-significant difference in ratings between workplaces with inclusion efforts and those without inclusion efforts ($V = 16873.5, z = -0.600, p = 0.540$).[6] Regarding the statement, "This company's values align well with my personal values," the Wilcoxon Signed-Rank Test provided evidence for a significant difference in ratings between workplaces with and without inclusion efforts ($V = 14103.5, z = -3.774, p < 0.001$). For the third statement, "This company would offer great financial compensation," I once again found evidence for a significant difference in ratings ($V = 7373, z = -7.461, p < 0.001$). Finally, for the last statement, "This company would offer many career opportunities," the Wilcoxon Signed-Rank Test similarly provided evidence for a significant difference in ratings between workplaces with and without inclusion efforts ($V = 8159, z = -6.922, p < 0.001$).

[6]Due to large sample size, the distribution of V is approximated using the normal distribution; the p-value is calculated using the Z-score derived from the V statistic.

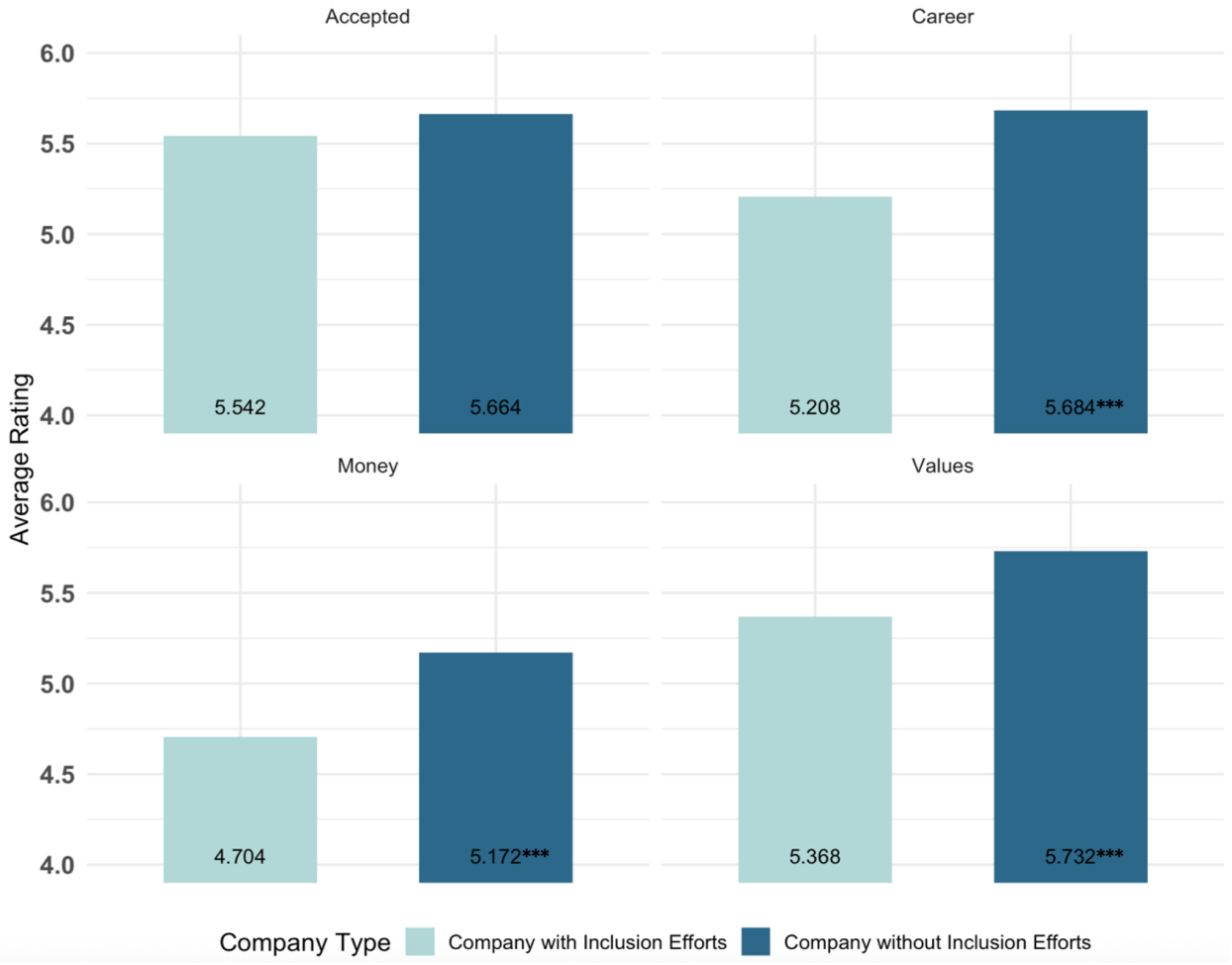


Figure 6. Comparison of Average Ratings for Various Statements Between Companies with or without Inclusion Efforts

Note. Observed average ratings from participants in the nationally representative sample are shown. Participants rated how much they agreed with the following statements: (1) "I would feel accepted at this company," (2) "This company's values align well with my personal values," (3) "This company would offer great financial compensation," and (4) "This company would offer many career opportunities." + $p < 0.1$ $*$ $p < .05$; $**$ $p < .01$; $***$ $p < .001$. Symbols indicate the level of significance of the differences in ratings between workplaces with inclusion efforts and those without inclusion efforts based on Wilcoxon Signed-Rank Tests.

Statement	Shapiro-Wilk Test	Wilcoxon Signed-Rank Test	Paired t-Test
I would feel accepted at this company	< 0.001	0.54	0.11
This company's values align well with my personal values	< 0.001	< 0.001	< 0.001
This company would offer great financial compensation	< 0.001	< 0.001	< 0.001
This company would offer many career opportunities	< 0.001	< 0.001	< 0.001

Figure 7. Shapiro-Wilk Test, Wilcoxon Signed-Rank Test, and Paired t-Test Results for Ratings of Various Statements
Note. Results are based on data from the nationally representative sample.

2.6 Discussion

2.6.1 Summary of Key Findings

I found evidence that participants significantly deviated from the expected 50% split in the choice of companies with or without inclusion efforts. In the nationally representative sample, only 42.6% of participants selected the workplace with inclusion efforts, a proportion that was significantly lower than the expected 50% ($z = -3.309$, $p = 0.001$). 57.4% selected the workplace without inclusion efforts, which was significantly higher than the expected 50% ($z = 3.309$, $p < 0.001$). These findings indicate an overall preference to work for companies without inclusion efforts, thereby rejecting the hypothesis of no overall preference between workplaces with or without inclusion efforts.

Using a nationally representative sample based on age, sex, race, and political affiliation, I documented the proportion of participants selecting the workplace with inclusion efforts across key demographic categories and observed that 61.5% of Black participants chose the workplace with inclusion efforts compared to 37.3% of White participants, while nearly identical proportions were observed for Hispanic (42.0%) and non-Hispanic (42.7%) participants. Women chose the company with inclusion efforts more often than men by 6.7 percentage points. A substantial 34.4 percentage point difference emerged between Democrats (60.1%) and Republicans (25.7%), with

Independents (41.5%) also favoring the company with inclusion efforts more than Republicans. To test the hypothesis that Black participants, women, and Democrats would be more likely to prefer workplaces with inclusion efforts, I employed a linear probability model with robust standard errors estimating the selection of the company with inclusion efforts which included indicator variables for both ascribed and achieved statuses. The model provided evidence supporting the hypothesis, with Black participants ($\beta_{Black/AfricanAmerican} = 0.237$, $t(490) = 3.377$, $p < 0.001$) and Democrats ($\beta_{Democrat} = 0.340$, $t(490) = 6.313$, $p < 0.001$) on average being significantly more likely (than White participants and Republicans respectively) to choose the workplace with inclusion efforts, while women showed a somewhat higher probability (marginal statistical significance) of selecting the company with inclusion efforts than men ($\beta_{Woman} = 0.070$, $t(490) = 1.664$, $p = 0.097$). Findings from robustness checks using logistic regression supported the direction and statistical significance of these findings. Notably, the difference in predicted probabilities between Democrats and Republicans (34.0 percentage points) is even larger than the difference in predicted probabilities between Black and White participants (23.7 percentage points), highlighting a larger association between political affiliation and preference for workplaces with inclusion efforts than between race and workplaces with inclusion efforts.

In an exploratory analysis of subgroup differences (defined as participant segments based on race, political affiliation, and gender), I found evidence that, except for White Republican women (for whom $\beta_{WhiteRepublicanWomen} = 0.040$, $t(590) = 0.499$, $p = 0.618$), all subgroups were significantly more likely than White Republican men to select the workplace with information about inclusion efforts ($\beta_{BlackRepublicanWomen} = 0.173$, $t(590) = 2.159$, $p = 0.031$; $\beta_{BlackRepublicanMen} = 0.173$, $t(590) = 2.159$, $p = 0.031$; $\beta_{BlackDemocratMen} = 0.187$, $t(590) = 2.329$, $p = 0.020$; $\beta_{WhiteDemocratMen} = 0.187$, $t(590) = 2.329$, $p = 0.020$; $\beta_{BlackDemocratWomen} = 0.200$, $t(590) = 2.501$, $p = 0.013$; $\beta_{WhiteDemocratWomen} = 0.2435$, $t(590) = 3.054$, $p = 0.002$). Overall, the proportions choosing the workplace with information about inclusion efforts ranged from 38.7% for White Republican men to 63.0% for White Democrat women. Additionally, one-tailed one-sample proportion tests indicated that the observed proportion for White Republican men ($\hat{p} = 0.387$) was

significantly lower than the expected 0.5 ($z = -1.963$, $p = 0.025$), the observed proportion for White Democrat women ($\hat{p} = 0.630$) was significantly higher ($z = 2.224$, $p = 0.013$), and there was weak evidence that Black Democrat women ($\hat{p} = 0.587$) exceeded the expected proportion ($z = 1.501$, $p = 0.067$). The remaining subgroups did not differ significantly from the expected proportion.

Participants also rated companies on a seven-point Likert scale in response to four statements: "I would feel accepted at this company," "This company's values align well with my personal values," "This company would offer great financial compensation," and "This company would offer many career opportunities." I compared the average ratings between companies with and without information about inclusion efforts and documented that the company without information about inclusion efforts received slightly higher ratings for feeling accepted (5.664 for the company without inclusion efforts versus 5.542 for the company with inclusion efforts) and markedly higher ratings for value alignment (5.732 versus 5.368), financial compensation (5.172 versus 4.704), and career opportunities (5.684 versus 5.208). Given that Shapiro–Wilk tests indicated the differences between paired ratings significantly deviated from normality, Wilcoxon Signed–Rank Tests were employed (with paired t–tests yielding similar significance levels as a robustness check). The test for "I would feel accepted at this company" was non–significant ($V = 16873.5$, $z = -0.600$, $p = 0.540$), whereas the tests for "This company's values align well with my personal values" ($V = 14103.5$, $z = -3.774$, $p < 0.001$), "This company would offer great financial compensation" ($V = 7373$, $z = -7.461$, $p < 0.001$), and "This company would offer many career opportunities" ($V = 8159$, $z = -6.922$, $p < 0.001$) all indicated statistically significant differences, with higher ratings consistently observed for companies without information about inclusion efforts.

2.6.2 Limitations, Implications, and Future Research

In examining the findings from this study, it is important to consider what they do and do not imply. A participants' selection of the company that does not include information about inclusion efforts does not necessarily imply distaste for corporate efforts for inclusion efforts. For example, this could be a result of participants perceiving the inclusion of information about inclusion efforts in a

workplace description as pandering or having ulterior motives. Looking at the case of how consumers (as opposed to potential employees) view companies, researchers have found evidence that explicitly promoting diversity in advertisements leads to less favorable consumer attitudes due to perceptions of corporate pandering (Ding, Yu, & Cowart, 2022). Therefore, overt messaging about a company's inclusion efforts can backfire while subtle messaging can be associated with more positive responses. Additionally, research on participants from the United Kingdom has found evidence that groups who often face discrimination in the labor market are more likely to believe that workplace use of equality, diversity, and inclusion information is to maintain appearances / for public relations purposes (Heath, Carlsson, & Agerström, 2023b).[7] Furthermore, researchers have found evidence supporting skepticism toward companies' disclosures about their inclusion efforts: researchers have found that ethnoracial minorities engage in relatively little "résumé whitening" when applying for a job with an employer with an organizational diversity statement. However, audit study data suggest that organizational diversity statements are not associated with a decreased prevalence of discrimination against "unwhitened résumés" (Kang, DeCelles, Tilcsik, et al., 2016). In other words, places of work that have explicitly committed themselves to diversity and nondiscriminatory hiring practices show no signs of behavioral change.

Several design choices in this study required tradeoffs, including the construction of a foil for a company with information about inclusion efforts and the use of manipulation checks. First, to assess attraction to companies with inclusion efforts, I needed to construct a workplace without such information. Both descriptions included randomly assigned general company information along with a treatment. The treatment consisted of either (1) a brief statement about the company's inclusion efforts or (2) a similar-length statement about company values without mentioning diversity. This approach made it so participants were not choosing between information about inclusion efforts and its absence, but rather between inclusion efforts and alternative (potentially appealing) information. This design choice maintained equal description length, though an alternative design could have

[7] However, considering current trends in how work on inclusion efforts is framed, people's attitudes toward companies presenting inclusion efforts in their public materials may shift as it may be seen as more authentic during a time when these efforts are being heavily scrutinized.

framed inclusion efforts as an addition rather than as a zero-sum trade-off. Second, a manipulation check was included after each company description to ensure that participants were reading the company descriptions and understanding whether these included information about inclusion efforts (the independent variable). This design choice has a trade-off: manipulation checks can act as an intervention themselves, potentially triggering new cognitive processes (Hauser, Ellsworth, & Gonzalez, 2018). They may enhance, counteract, or alter the effects of the original manipulation (Hauser, Ellsworth, & Gonzalez, 2018).

The external validity of this study is limited by how workplaces and information about inclusion efforts were operationalized. To capture broadly occurring processes, workplace descriptions were not tied to a specific industry, which may obfuscate industry-specific differences in the appeal of inclusion efforts. Additionally, while diversity is one of many factors that influences organizational attraction, this study isolates its effect, limiting insight into the trade-offs individuals might consider when evaluating companies with strong or weak diversity signals (a discrete choice experiment could better address these questions). Lastly, this study examines only one treatment for information about inclusion efforts. In reality, companies engage in various inclusion efforts, such as statements and programs, which may have different effects. For instance, individuals might respond positively to diversity programs but negatively to diversity statements. Additional research is needed to disentangle these potential differences.

Another consideration is that self-reports do not always align with behaviors. Research on this relationship (LaPiere, 1934; Pager & Quillian, 2005; Jerolmack & Khan, 2014) suggests that the link can be tenuous, particularly in studies about diversity and inclusion. Future research should build on Flory et al.'s (2021) efforts by examining how behaviors (such as opening applications, applying for jobs, and accepting job offers) are influenced by companies' inclusion efforts. However, studying stated attitudes toward inclusion efforts remains valuable on its own, as these attitudes can influence broader political and economic decisions beyond the workplace.

I found evidence for a preference for workplaces without information about inclusion efforts. However, it remains unclear whether this trend is increasing and whether the findings hold across

different study designs and operationalizations of workplace inclusion efforts. Replication studies are therefore necessary. Additionally, my findings indicate that different groups respond differently to companies' diversity statements and programs, with important implications for workplace recruitment strategies. In particular, differences among Republicans, Democrats, and Independents suggest a need for further theoretical and empirical work on achieved statuses and their relationship to attitudes toward workplace inclusion efforts. Future research should also explore how characteristics such as race, gender, and political affiliation interact in ways that may amplify or mitigate these effects. A larger, nationally representative sample would be crucial for advancing this line of inquiry.

Lastly, future research should further explore the factors shaping the relationship between organizational attraction and inclusion efforts. I found that participants rated workplaces without information about inclusion efforts more favorably in terms of value alignment, financial compensation, and career opportunities. However, it remains unclear whether these attitudes are specific to this study's operationalization of inclusion efforts or if they reflect broader attitudes toward workplace inclusion efforts. Prior research in the United Kingdom suggests that men and White respondents who report higher past experiences of sex-based and ethnic discrimination (respectively) are less supportive of employment equality monitoring (i.e., collecting data on legally protected characteristics), indicating that diversity and inclusion efforts may be perceived as a threat to self-interest (Heath, Carlsson, & Agerström, 2023a). Additionally, attitudes toward inclusion efforts may be influenced by the politicization of terms such as "diversity," "inclusion," "equity," and "DEI." It is possible that while workers support the underlying efforts and programs, they react negatively when these efforts are explicitly labeled as such.

Using both a nationally representative sample and a quota sample, this study examines whether workplace attraction is influenced by the presentation of organizational inclusion efforts. It also disaggregates findings by worker characteristics (such as race, gender, and political affiliation) to highlight group differences in organizational attraction to workplaces with information about inclusion efforts. These insights are valuable for workplaces (which allocate financial resources and personnel to these efforts), researchers seeking to understand how inclusion efforts affect

organizational attraction, and the public amid ongoing national and political debates about the role of diversity and inclusion in the workplace.

3 Simulating Collective Choices: Can the Benefits of Collective Choices be Replicated for Isolated Choices?

Abstract: Racial inequality in hiring remains a persistent feature of the labor market, yet much of the sociological literature has focused on individual bias rather than the organizational structures that shape selection outcomes. This study investigates how the design of hiring processes (specifically whether decisions are made in isolated, collective, or simulated collective contexts) affects the racial composition of selected candidates. Using data from a preregistered survey experiment with participants with hiring experience (n = 1,265 participants; 1,729 selection decisions), this study evaluates whether hiring context influences the likelihood that Black applicants are selected for interview and explores heterogeneity in selection patterns by participant characteristics. Contrary to findings in prior research, I found insufficient evidence that either simulated collective or collective hiring contexts significantly increase the selection of Black applicants relative to isolated choices, posing questions about how prior findings may be constrained to design choices. However, a surprising pattern was observed: participants were approximately 20% more likely to select Black applicants in the simulated collective choice condition than in the collective choice condition. I also found meaningful variation across groups of participants. Black participants selected Black applicants about 24% more often than White participants, while Asian participants were somewhat less likely to do so (marginally statistically significant). Political affiliation also played a role, with Democrats selecting Black applicants approximately 19% more often than Republicans. Looking at the association between the experience level of the selected applicant and the likelihood that the selected applicant is Black, I found evidence that Black applicants were more likely to be selected when they had medium, rather than low, experience, though this finding was only marginally significant. Lastly, when making their selection decisions, most participants reported considering

company success and applicant qualifications, but fewer than half considered the impact of their choices on company diversity. Exploratory analyses show that participants who did report considering diversity were significantly more likely to have selected Black applicants, especially in the simulated collective choice condition. This study underscores how organizational practices shape hiring outcomes and highlights the potential of simulating collective decision-making as an intervention to promote diversity in hiring.

3.1 Introduction

An often-studied source of workplace racial inequality occurs at the hiring stage (Pager, 2003; Quillian, Pager, Hexel, et al., 2017; Gaddis, 2015; Bertrand & Mullainathan, 2004). A factor that remains understudied, however, is the design of the selection process. One characteristic of the design of the selection process is whether workplaces make isolated or collective hiring decisions. Workplaces often make isolated hiring decisions, in which a single employee is hired at a given time. Researchers (Chang, Kirgios, Rai, et al., 2020; Luo, Zhou, & Song, 2022) have found evidence that isolated hiring choices are less likely to increase an organization's diversity than collective hiring choices (i.e., hiring multiple employees at a time). Researchers call this phenomenon the isolated choice effect, in which groups assembled through the selection of one individual at a time are less diverse than groups assembled through the simultaneous selection of multiple individuals (Chang, Kirgios, Rai, et al., 2020).

Using data collected from a survey experiment with 1,265 participants that made 1,729 selection decisions, this study builds on the literature on the role of organizational practices in differences in the hiring and evaluation of job candidates with different identities (Bohnet, Van Geen, & Bazerman, 2016; Chang, Kirgios, Rai, et al., 2020; Rivera & Tilcsik, 2019). Studied in psychology, management science, and economics, organizational practices remain understudied in sociology as both a source of inequality and as potential levers for intervention. Specifically, this study examines variation in the racial diversity of job candidates selected in hiring scenarios constructed to elicit either isolated, collective, or a simulated collective hiring context. I build on the existing literature

by examining whether prior findings are generalizable after addressing methodological concerns of prior research and by testing whether isolated decisions can be simulated to feel like collective choices.

3.2 Theoretical Background

3.2.1 Organizational Practices

Based on prior work by Mario Small (2009) and Richard Scott (2013), Devah Pager and Mario Small define organizations as "loosely coupled set[s] of people and institutional practices formally organized around a global purpose" (2020). Institutional practices, called organizational practices in this paper, are stable, typically comprehended by the organization's members, and independent from specific individuals within the organization (Small & Pager, 2020). Organizational practices can create inequality by (dis)advantaging racial groups differently from one another. This can occur even if not intended in the development or enforcement of the practice or if individual agents (e.g., managers and employees) within the organization are not driven by prejudice (Small & Pager, 2020).

Researchers have documented many examples of how organizational practices can create workplace inequality. As an example, Rivera and Tilcsik's (2019) research findings demonstrate that the scale granularity (i.e., number of scale points) of faculty teaching evaluation tools significantly affects the observed gender gap in evaluation outcomes. In their study, Rivera and Tilcsik (2019) first used a quasi-natural experiment in which faculty teaching evaluations at one of the professional schools of a big university in North America changed from using a ten-point scale to using a six-point scale. They found that this shift from using a ten-point scale to using a six-point scale significantly reduced the gender gap in evaluations within male-dominated fields of instruction. Rivera and Tilcsik (2019) complemented these findings with a survey experiment, presenting participants with identical lecture transcripts while varying both the signaled gender of the instructor and the number of scale points in the evaluation tool. The experiment replicated the quasi-natural experiment's results, showing that the gender gap in evaluations favoring men was significantly smaller when a

six-point scale was used. Through having participants rate lecturers on a variety of job-related skills and traits, Rivera and Tilcsik (2019) were able to hypothesize that this effect is motivated by the ways in which gendered stereotypes of brilliance are expressed in evaluations.

Another example comes from work conducted by Emilio Castilla (2008), in which he used longitudinal data from one workplace and 8,898 employees to test for performance-reward bias, in which employees, even after having the same performance evaluations in seemingly merit-based reward systems, are rewarded differently depending on their race and gender. Castilla tested for performance-reward bias, "whereby women and minorities receive less compensation than [W]hite men with equal scores on performance evaluations," and found that salary growth is slower for women than men, and slower for African Americans and Latinos when compared to White employees (2008). This finding held even after accounting for years of experience, education, and performance evaluations. In a follow-up to this study, Castilla (2015) looked at how changes to increase transparency and accountability reduced the observed pay gap at this organization. In one last classic example of how an organizational practice can shape inequality, Goldin and Rousse (2000) documented how the practice of having candidates for a symphony orchestra audition behind a screen (and thus conceal candidates' identities) increased the probability of women being selected. All of these examples show how organizational practices can have an effect on gender and/or racial inequality in a workplace.

3.2.2 Isolated and Collective Choice Effects in Joint Evaluation Conditions

One organizational practice is to make either isolated or collective hiring choices. The literature on isolated and collective hiring choices has focused on joint evaluation of candidates, as opposed to separate evaluation. Joint evaluation of multiple candidates, in which job candidates are assessed comparatively (instead of evaluating each candidate separately), reduces bias in decision making (Bohnet, Van Geen, & Bazerman, 2016). In one study, Bohnet, Van Geen, and Bazerman (2016) found evidence that evaluators in joint evaluation conditions (in which candidates are assessed side



Figure 8. Isolated Choice Effect
Note: This figure illustrates job applicants being selected from a broader pool through isolated hiring decisions, a process that can lead to less diverse organizations. This pattern is known as the isolated choice effect.

by side) are more likely to focus on individual performance, whereas those in separate evaluation conditions tend to rely more on group stereotypes (likely due to the lack of direct comparison points).

When focusing on joint evaluation conditions, previous work has found evidence for the isolated choice effect. Using joint evaluation and a series of six experiments, Chang, Kirgios, Rai, and Milkman (2020) examined the effect on group diversity of isolated hiring choices compared to sets of hiring choices (i.e., collective hiring choices), and found that participants create more gender-diverse groups (in reference to the proportion of women and men selected) when collective hiring choices are made as opposed to isolated hiring choices. Chang, Kirgios, Rai, and Milkman (2020) named this tendency for isolated hiring choices to create less diverse groups the isolated choice effect. This process is depicted in **Figure 8**. Chang et al. argue that "people do not attend as much to diversity when making isolated selection choices, which drives this effect" (Chang, Kirgios, Rai, et al., 2020). The converse of the isolated choice effect is what I call the collective choice effect, in which making multiple, simultaneous hires produces more diverse groups. In a similar study, researchers replicated these findings with race and found that the racial diversity, focusing on Black and White job applicants (Luo, Zhou, & Song, 2022), of the selected group increased (i.e., a larger proportion of Black applicants was selected) when hiring choices were made as sets as opposed to in isolation.

3.2.3 Increasing Feasibility: Simulated Collective Choices

What motivates the isolated choice effect? Chang et al. (2020) theorize that individuals making a hiring decision (or a selection decision more generally) are less likely to think about how their decisions affects the diversity of a group than when making multiple hiring decisions (or selection decisions) at the same time. Because diversity is a property that emerges at the group level (Harrison & Klein, 2007), Chang et al. (2020) hypothesize that the notion of diversity is less salient to individuals making only one selection decision compared to individuals making collections of selection decisions. This drives the isolated choice effect, while the increased salience of diversity when making a set of selection decisions can motivate a collective choice effect. Chang et al. (2020) found evidence supporting the idea that diversity is less salient to participants when making isolated choices, as opposed to collections of choices, and that this reduced salience mediates the isolated choice effect on the gender diversity of selected candidates.

Prior work (Chang, Kirgios, Rai, et al., 2020; Luo, Zhou, & Song, 2022) has not tested whether the collective choice effect, which increases organizational diversity by making collective hiring choices as opposed to isolated hiring choices, is reproducible when isolated choices are made to feel like or simulated to feel like collective hiring choices. It is crucial to test whether this intervention can have similar effects when collective hiring choices are simulated, as this intervention could otherwise be hard to implement in some contexts or workplaces, as acknowledged by Chang et al. (2020). To simulate collective choices, an isolated decision can be made to feel collective by informing or reminding the decision-maker about recent selections or hires made by an organization. This sets the stage for how this project adds to the literature. Using a survey experiment, I examine whether collective choice effects can be simulated for isolated hiring choices. The hypothesized process is depicted in **Figure 9**.



Figure 9. Collective Choice Effect
Note: This figure illustrates the hypothesized process by which selecting job applicants from a broader pool through collective or simulated collective hiring decisions may lead to more diverse organizations. This pattern is referred to as the collective choice effect.

3.2.4 Methodological Limitations of Prior Work

Prior work (Chang, Kirgios, Rai, et al., 2020; Luo, Zhou, & Song, 2022) poses methodological concerns regarding (1) the samples used, (2) the limited information provided about job applicants in the hiring scenario, and (3) a design decision that limited the experience of candidates signaled to be women (Chang, Kirgios, Rai, et al., 2020) or Black (Luo, Zhou, & Song, 2022). Firstly, regarding the sample of participants, both Chang et al. and Luo et al. rely on samples obtained from Amazon Mechanical Turk and did not require participants to have experience making hiring decisions. This design choice poses concerns about external validity since those with hiring experience may approach hiring decisions differently due to training and prior experience. Those with hiring experience may also have different demographic characteristics than those without hiring experience. Secondly, both studies show a limited amount of information about job candidates to participants. Chang et al. show participants photos of candidates along with candidates' years of experience and the name of the applicant's previous position. Similarly, Luo et al. show participants candidate photos, years of experience, and candidates' ages. This presents a limitation to external validity, given that hiring decisions in real-world settings typically involve access to more extensive information and data points about applicants. This complexity is lost in the design of previous studies. Lastly, and most interestingly, both Chang et al. and Luo et al. (in the experiments in their studies that focus on

hiring scenarios) take the approach of limiting minority candidates (women for Chang et al. and Black candidates for Luo et al.) to never having the most nor the least amount of experience. These researchers were motivated to take this approach "to avoid ceiling effects that might arise from social desirability concerns in experiments" (Chang, Kirgios, Rai, et al., 2020). However, this is a threat to external validity as it does not reflect the experience of Black job applicants and of women applying to jobs. It is unclear whether prior findings are a reflection of this methodological decision.

In order to address these methodological limitations, and to obtain stronger (though still flawed) external validity, this study (1) uses a sample of participants with hiring experience, (2) provides participants with job applicants' résumés, and (3) randomly assigns years of experience to job applicants.

3.3 Research Question and Hypotheses

3.3.1 Research Question

How does the probability of selecting a Black job candidate for an interview differ across isolated choices, collective choices, and simulated collective choices?

3.3.2 Hypotheses

1. The probability of selecting a Black job candidate will be higher in the simulated collective choice condition than in the isolated choice condition.

2. The probability of selecting a Black job candidate will be higher in the collective choice condition than in the isolated choice condition.

3. The probability of selecting a Black job candidate in the simulated collective choice condition will not be statistically different than in the collective choice condition.

3.4 Data and Methods

3.4.1 Design

This study employs a between-subjects experimental design with participants randomly assigned to make selection choices in one of three conditions: isolated choice condition, collective choice condition, or simulated collective choice condition. The two main independent variables in this study are: (1) how hiring choices are made (i.e., isolated, collective, or simulated collective) and (2) the signal for the race of the job candidate.

The first independent variable consists of participants being randomly assigned to make hiring choices in an isolated choice condition, a collective choice condition, or a simulated collective choice condition. The isolated choice condition (i.e., the control condition) consisted of participants being asked to read a job description for one of the five positions available within one company. The participants were then asked to select a candidate to interview (out of three) for that position. The collective choice condition (one of the treatment conditions) consisted of participants reading five job descriptions and being asked to select one candidate to interview for each of those five positions. All five decisions were shown on the same screen in the collective choice condition. In the simulated collective choice condition (one of the treatment conditions), participants made isolated choices made to feel like collective choices by showing participants the two employees most recently hired by the company. To balance the total number of hiring decisions across conditions, five times as many participants were assigned to the isolated choice and simulated collective choice conditions than to the collective choice condition. This design replicates (and extends) the design of the first study conducted by Chang, Kirgios, Rai, and Milkman (2020).

The second independent variable in this study is the signal of the race of the job candidate. Two different races were signaled: Black/African American or White. The racial identity of the job candidate was signaled by the job candidate's name and by a photo of the candidate. Ethnic and racial identities are often signaled by researchers using names (Bertrand & Mullainathan, 2004; Gaddis, 2015). The strength of the signal varies depending on the first (Gaddis, 2017a, 2017b) and

last (Crabtree & Chykina, 2018) names used, so careful attention to name selection was essential. The names selected for this study were tested by Gaddis (2017b) for their capacity to signal their intended group membership (i.e., White or Black/African American). Furthermore, none of the names selected for the study were names most commonly given by mothers in the lowest quartile (within race) of mother's education in order to minimize (though not eliminate) activating biases based on socioeconomic status. Along with names, participants were also provided with a picture of each candidate. These photos were taken from the Chicago Face Database (Ma, Correll, & Wittenbrink, 2015). These photos have been previously tested to create subjective norming data (e.g., subjective attractiveness, perceived age of individuals in photos, and perceived race of individuals in the photos). Photos were selected by choosing the photos of individuals who self-identified as White or Black males, had similar facial expressions (as categorized by the original research), and were rated by participants in prior research as having similar attractiveness (Ma, Correll, & Wittenbrink, 2015). Photos were removed if norming data suggested that more than 3% of participants who previously assessed the photos believed the photo to show a woman; if previous participants believed the photo to show an individual under the age of 25 or over the age of 35; and more than 3% of participants believed the photo to show an Asian, Latino, or multiracial individual. Researchers have argued that using names to signal race creates concerns of treatment validity due to signals of race being bundled with signals for the socioeconomic status of an individual (Crabtree, Gaddis, Holbein, et al., 2022). This, however, should not be interpreted as a reason to not use names (or other signals such as photos) to signal race, as signals for race are often bundled with signals for additional identities (e.g., photos signal race along with attractiveness, age, and other features). This study considers the correlation between race and social class perceptions both "a mechanism of inequality" and "a methodological problem to solve" (Crabtree, Gaddis, Holbein, et al., 2022), and attempts to address these issues by using previously validated names and photos that have been tested to signal the intended racial signal and that are relatively similar in regard to the additional characteristics they signal (e.g., selected photos had similar ages and perceived attractiveness based on previous research).

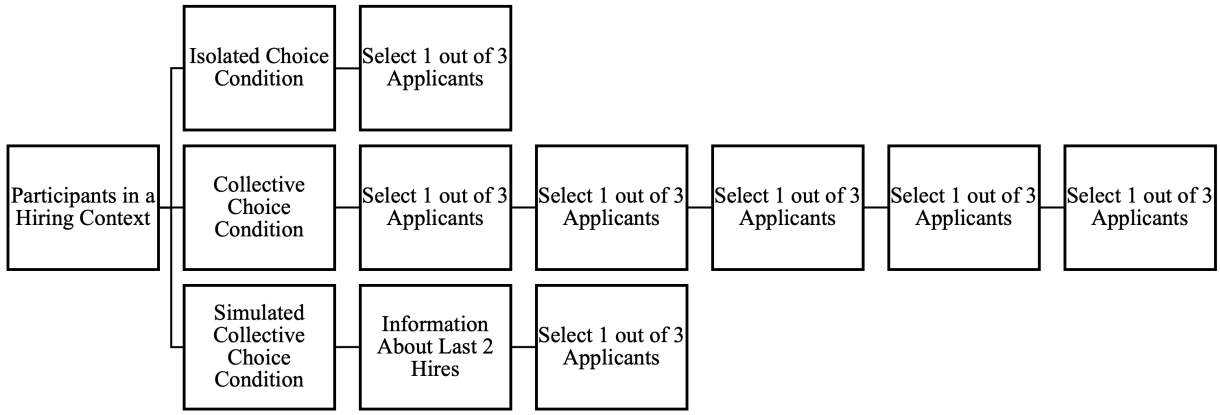


Figure 10. Experimental Design Comparing Isolated, Collective, and Simulated Collective Choice Effects in a Hiring Context
Note: This figure illustrates the study's experimental design and outlines the data collection process from participants' perspective based on their treatment assignment.

The main dependent variable of interest in this survey experiment is who is selected to be interviewed. There are two potential outcomes: either a Black applicant or a White applicant is selected. The design for this study is illustrated in **Figure 10**.

3.4.2 Participants

The sample was obtained using Prolific ("Prolific", 2014). Prolific was selected because researchers have found evidence that "compared to MTurk, Qualtrics, or an undergraduate student sample (i.e., SONA), participants on Prolific and CloudResearch were more likely to pass various attention checks, provide meaningful answers, follow instructions, remember previously presented information, have a unique IP address and geolocation, and work slowly enough to be able to read all the items" (Douglas, Ewell, & Brauer, 2023). Douglas, Ewell, and Brauer (2023) also found that the cost paid per high-quality participant (i.e., taking into account that not every participant will be a high-quality participant) was less expensive with Prolific than CloudResearch, MTurk, and Qualtrics.

The target population consisted of individuals who live in the United States, were 25 years of age or older at the time of taking the survey, and (most importantly for this study) had experience in making hiring decisions. To participate in this study, study participants needed to have previously completed at least 10 surveys (and no more than $5,000$) and have a previous submission approval rating of at least 95%. Additionally, survey submissions for participants who completed the study exceptionally fast, defined as three standard deviations below the mean as per Prolific protocol, were to be rejected. The determination of exceptionally fast survey submissions was done separately for submissions within each study condition (i.e., isolated choice condition, the collective choice condition, or the simulated collective choice condition). After checking for exceptionally fast submissions, 0 participants were excluded. Lastly, participants needed to correctly answer two attention check questions in order to participate in the study. As per Prolific protocol, participants were given two opportunities to answer each of these questions correctly (i.e., if they failed to answer the question correctly on their first attempt, they were given a second opportunity).

Data collection occurred in October of 2024 with a sample of participants with hiring experience. **Table 6** shows participants' demographic characteristics. The demographics characteristics are shown first for the entire sample and are then disaggregated based on the condition participants were assigned to. 1,265 participants completed the study (580 in the isolated condition, 116 in the collective condition, and 569 in the simulated collective condition) and made a total of 1,729 selection decisions. Respondents' median time taken to complete the survey was three minutes and 59 seconds ($25th$ percentile was two minutes and 52 seconds and $75th$ percentile was six minutes and eight seconds). For the isolated choice condition, the median time was three minutes and 28 seconds. For the collective choice condition, the median time was six minutes and five and a half seconds. And, for the simulated collective choice condition, the median time was four minutes and 15 seconds. Focusing on the entire sample, the mean age was 44.43.

In terms of education completed, 39.68% of participants indicated having a bachelor's degree, 24.03% a graduate degree, 18.50% had some college credit with no degree, 11.23% had an associate's degree, 6.40% had a high school diploma or equivalent, and 0.16% had less than a

Table 6. Participant Demographic Characteristics

Descriptive Statistic	All Participants	Isolated Condition	Collective Condition	Simulated Collective Condition
Sample Size	1265	580	116	569
Mean Age	44.43	44.20	44.66	44.61
Educational Attainment				
Less than high school diploma or equivalent	0.16%	0.17%	0.00%	0.18%
High school diploma or equivalent	6.40%	5.69%	6.03%	7.21%
Some college credit, no degree	18.50%	19.14%	19.83%	17.57%
Associate's degree	11.23%	11.03%	11.21%	11.42%
Bachelor's degree	39.68%	38.62%	37.93%	41.12%
Graduate degree	24.03%	25.34%	25.00%	22.50%
Political Affiliation				
Republican	22.21%	20.86%	21.55%	23.73%
Lean Republican	8.62%	9.48%	11.21%	7.21%
Independent	24.82%	23.79%	30.17%	24.78%
Lean Democrat	14.94%	15.69%	11.21%	14.94%
Democrat	28.54%	28.79%	25.86%	28.82%
A political affiliation not listed	0.87%	1.38%	0.00%	0.53%
Gender				
Man	45.06%	45.17%	47.41%	44.46%
Woman	53.60%	53.45%	52.59%	53.95%
A gender identity not listed	1.34%	1.38%	0.00%	1.58%
Hispanic, Latino, or Spanish				
Hispanic, Latino, or Spanish	13.36%	12.93%	18.10%	12.83%
Not Hispanic, Latino, or Spanish	86.64%	87.07%	81.90%	87.17%
Race				
White	71.78%	70.69%	67.24%	73.81%
Black or African American	16.05%	16.72%	19.83%	14.59%
Asian or Asian American	5.38%	6.38%	6.90%	4.04%
American Indian or Alaska Native	1.19%	1.55%	0.86%	0.88%
Native Hawaiian or Other Pacific Islander	0.24%	0.00%	0.00%	0.53%
Middle Eastern, Arab American, or North African	0.24%	0.34%	0.00%	0.18%
Multiracial	3.79%	3.45%	3.45%	4.22%
A race not listed	1.34%	0.86%	1.72%	1.76%

Note: To assess the success of random assignment, I tested for differences in participant demographic characteristics across experimental conditions (i.e., isolated, collective, and simulated collective conditions). I conducted an ANOVA for age and chi-squared tests for categorical variables including education, political affiliation, gender, ethnicity, and race. In addition, I ran logistic regressions with robust standard errors for each binary demographic variable (e.g., White as the outcome and the study conditions as the independent variables). None of the tests yielded statistically significant differences at the $p < .05$ level, suggesting successful random assignment.

high school diploma. When asked about political affiliation, 28.54% of participants indicated being Democrats (plus an additional 14.94% of participants indicated leaning toward the Democratic Party), 24.82% of participants indicated being Independents, and 22.21% of participants indicated being Republicans (along with an additional 8.62% of participants indicated leaning toward the Republican Party). 53.60% of participants indicated being women and 45.06% indicated being men. When asked "Are you of Hispanic, Latino, or Spanish origin?", 86.64% of respondents answered no and 13.36% indicated yes. In terms of racial identity, respondents mainly self-identified as White (71.78%), followed by Black or African American (16.05%) and Asian or Asian American (5.38%). The rest of the data on participants' demographic characteristics, broken down by which condition they were assigned to, can be found in **Table 6**.

3.4.3 Survey Instrument and Data Collection Procedure

Using Prolific to find participants, the survey was constructed and administered using Qualtrics' survey design software ("Qualtrics", 2005). From the participants' perspective, data collection consisted of providing informed consent, answering initial screening questions to confirm that they qualified to take the survey, and completing attention checks. If participants passed all of these stages, they were then randomly assigned to one of the following: the isolated choice condition, the collective choice condition, or the simulated collective choice condition. To ensure an equal number of hiring decisions across conditions, the isolated choice and simulated collective choice conditions included five times as many participants as the collective choice condition. Participants were informed that they would be selecting candidates to interview for a retail company hiring for five distinct positions: marketing coordinator, district manager, accountant, software engineer, and data scientist. Participants read brief job descriptions for the open positions at the company.

Participants in the isolated choice condition were then presented with résumés from three different candidates for one of the five (randomly assigned) positions. These candidates had different race signals and different work experiences in a relevant position (varying from 2 to 6 years in a similar role). Participants in the collective choice condition were presented with résumés from three

different candidates for each of the five positions. Just like in the isolated choice condition, these candidates had randomly assigned race signals and different work experiences in a related position (varying from two to six years in a similar role) as well. Participants in the simulated collective choice condition were shown the last two employees the company hired to fill the position for which they were randomly assigned to choose an applicant to interview. They were then presented with résumés from three different candidates for that position. Once again, these candidates had different race signals and different work experiences in a relevant position (varying from 2 to 6 years in a similar role). The three candidates for each of the five positions were held constant across the three conditions. Participants in the isolated choice condition and the simulated collective choice condition were asked to select one applicant to interview for the job posting. Participants in the collective choice condition were instructed to select one applicant for each of the five job postings concurrently, which consisted of presenting all five decisions on a single screen.

After completing their decisions, participants were asked a few questions about what factors they considered when making a decision on who to interview. At the end of the survey, participants were asked demographic questions, including race and ethnicity, gender, political affiliation, and educational attainment. The complete survey instrument, including all questions and materials shown to participants, can be found in **Appendix D: Survey Instrument for Simulating Collective Choices Study**.

3.4.4 Statistical Methods

Both the design and data analysis plan for this study were pre-registered with the Open Science Foundation. All data cleaning, statistical analyses and models, and data visualizations were implemented and created using R statistical software (Team, 2024). Prior work (Gomila, 2021) has argued that linear regression is usually a better strategy than logistic regression to estimate causal effects of treatments on dichotomous outcomes. Gomila (2021) finds that linear regression (1) has coefficients which can be interpreted in terms of probabilities and (2) when it comes to a binary dependent variable, produces unbiased estimates of treatment effects.

The first model employed used the same approach as Chang et al. (2020): an ordinary least squares regression model with robust standard errors clustered at the participant level. The outcome is whether a Black applicant was selected to be interviewed ($BlackApplicantSelected_{ij}$). The model uses robust standard errors clustered at the participant level, as the unit of analysis is an individual selection decision. Accordingly, participants in the isolated choice and simulated collective choice conditions contribute one observation each to the model, while participants in the collective choice condition contribute five observations each. The model includes two indicator variables, one each for the collective choice condition ($Collective_{ij}$) and the simulated collective choice condition ($Simulated_{ij}$). The isolated choice condition is used as the reference group for these indicator variables. The model is as follows:

$$BlackApplicantSelected_{ij} = \beta_0 + \beta_1 \text{Collective}_{ij} + \beta_2 \text{Simulated}_{ij} + \epsilon_{ij} \tag{6}$$

The previously described model is also fit using binomial logistic regression, rather than ordinary least squares regression, as a robustness check. The model is shown below:

$$logit(P(BlackApplicantSelected_{ij} = 1)) = \beta_0 + \beta_1 \text{Collective}_{ij} + \beta_2 \text{Simulated}_{ij} \tag{7}$$

Subsequent modeling includes indicator variables for participants' race, ethnicity, gender, political affiliation, and educational attainment. These additional indicator variables are represented in the following model as a vector variable ($ParticipantCharacteristics_i$):

$$\begin{aligned} BlackApplicantSelected_{ij} = \beta_0 + \beta_1 \text{Collective}_{ij} + \beta_2 \text{Simulated}_{ij} \\ + \beta_3 \text{ParticipantCharacteristics}_i + \epsilon_{ij} \end{aligned} \tag{8}$$

As an exploratory analysis, I additionally ran the previous model with interaction terms to test for treatment effect heterogeneity. The model with interaction terms is shown below:

$$\begin{aligned} BlackApplicantSelected_{ij} = \beta_0 &+ \beta_1 \text{Collective}_{ij} + \beta_2 \text{Simulated}_{ij} \\ &+ \beta_3 \text{ParticipantCharacteristics}_i \\ &+ \beta_4 (\text{Collective}_{ij} \times \text{ParticipantCharacteristics}_i) \\ &+ \beta_5 (\text{Simulated}_{ij} \times \text{ParticipantCharacteristics}_i) + \epsilon_{ij} \end{aligned} \tag{9}$$

After fitting a model with participant characteristics, I estimated a model to examine the association between the experience level of the selected applicant and the likelihood that the selected applicant is Black. Due to the data limitation of only observing the race and experience of the selected candidates, and not the race and experience of the other two candidates presented for a position, I was not able to model how experience affects the likelihood of selecting a Black applicant. Without these data, I also could not model candidate experience at the candidate level, which would have allowed me to test the effect of candidates' years of experience on the probability of being hired with interaction terms between candidate race and candidate experience. This modeling approach would have allowed me to test whether experience differentially affects the likelihood of selecting a candidate depending on candidate race. Recognizing these limitations for interpretation, I ran an ordinary least squares regression model with robust standard errors clustered at the participant level with whether a Black applicant was selected to be interviewed as the outcome. The indicator variables were for study condition and candidate experience. The fitted model was as follows, with subsequent modeling including interaction terms between study condition and experience:

$$\begin{aligned} BlackApplicantSelected_{ij} = \beta_0 &+ \beta_1 \text{Collective}_{ij} + \beta_2 \text{Simulated}_{ij} \\ &+ \beta_3 \text{MediumExperience}_{ij} + \beta_4 \text{HighExperience}_{ij} + \epsilon_{ij} \end{aligned} \tag{10}$$

Lastly, I examined whether the probability that the selected applicant was Black varied by participants' self-reported consideration of company diversity. Participants were categorized as "considered diversity" (those who somewhat or strongly agreed with the statement "In selecting who to interview, I considered how my choices impacted the overall diversity of the company"), "did not consider diversity" (those who somewhat or strongly disagreed), or "neutral" (neither agreed nor disagreed), with the neutral category serving as the reference group. For this analysis, I estimated the following model, which I then extended with interaction terms between the study condition and participant stance on considering diversity:

$$BlackApplicantSelected_{ij} = \beta_0 + \beta_1 \text{Collective}_{ij} + \beta_2 \text{Simulated}_{ij} + \beta_3 \text{ConsideredDiversity}_i + \beta_4 \text{DidNotConsiderDiversity}_i + \epsilon_{ij} \quad (11)$$

3.5 Results

3.5.1 Racial Composition of Selected Applicants

1,265 participants (580 in the isolated condition, 116 in the collective condition, and 569 in the simulated collective condition) completed 1,729 decisions about who to interview for each of the job postings. Black applicants were selected in 39.48% of the decisions in the isolated choice condition, which presented participants with three candidates for a job and asked participants to choose one to interview. In the collective choice condition, in which participants were asked to choose one job candidate out of three for five different positions, Black applicants were selected in 36.55% of all decisions. Lastly, in the simulated collective choice condition, in which participants were asked to choose one out of three job applicants to interview after being provided with information about the last two employees hired by the company, Black applicants were selected in 43.76% of all interview decisions. Black applicants were selected 7.42% less often (or 2.93 percentage points) in the collective choice condition compared to the isolated choice condition, yet 10.84% more often (or 4.28 percentage points) in the simulated collective choice condition compared to the isolated

choice condition. All of these selection rates are high considering that Black applicants comprised 33% of the applicant pool and that information about applicant quality was randomly assigned.

To examine differences in the racial composition of selected job applicants across selection conditions, I first fit an ordinary least squares regression model with robust standard errors clustered at the participant level, as mentioned in **3.4.4 Statistical Methods**. For this model, the outcome is whether a Black applicant was selected by participants to be interviewed. The model incorporates robust standard errors clustered by participant, as the unit of analysis is an individual selection decision (with participants in the collective choice condition contributing five observations each). **Model 1** includes two indicator variables, one each for the collective choice condition and the simulated collective choice condition. The isolated choice condition is used as the reference group for these indicator variables. **Model 2** is similar, but swaps the indicator for the simulated collective choice condition for an indicator for the isolated choice condition, making the simulated collective choice condition the reference group here. The results of these regression models can be seen in **Table 7**.

To test the study's hypotheses, I first turned to **Model 1** in **Table 7**. Looking at the first hypothesis (the probability of selecting a Black job candidate will be higher in the simulated collective choice condition than in the isolated choice condition), there is insufficient evidence that, in the simulated collective choice condition, the probability of workers with hiring experience selecting Black applicants to interview for a job opening is significantly different than in the isolated choice context ($t(1146.6) = 1.471$, $p = 0.142$). Similarly, I fail to reject the null hypothesis for the second hypothesis (the probability of selecting a Black job candidate will be higher in the collective choice condition than in the isolated choice condition), and found insufficient evidence that the effect of being in the collective choice context on the probability of workers with hiring experience selecting Black candidates to interview for a job opening is significantly different than in the isolated choice context ($t(383.8) = -1.125$, $p = 0.261$).

Turning to **Model 2** in **Table 7**, I found that the collective choice condition significantly decreases ($\beta_{Collective} = -0.072$, $t(387.4) = -2.727$, $p < 0.01$) the probability of workers with

Table 7. Relationship between Black Applicant Selection and Hiring Condition

	Model 1	Model 2
Intercept	0.395***	0.438***
	(0.020)	(0.021)
Collective Choice	-0.029	-0.072**
	(0.026)	(0.026)
Simulated Collective Choice	0.043	
	(0.029)	
Isolated Choice		-0.043
		(0.029)
Num.Obs.	1729	1729
R2	0.004	0.004
R2 Adj.	0.002	0.002
AIC	2439.6	2439.6
BIC	2461.4	2461.4
RMSE	0.49	0.49
Std.Errors	by: ProlificID	by: ProlificID

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Linear probability models are shown with cluster-robust standard errors in parentheses.

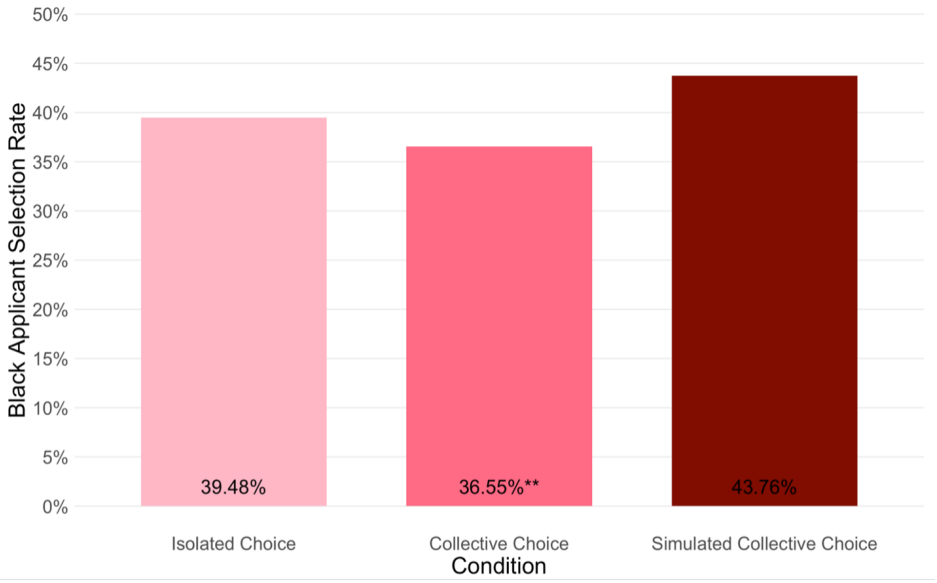


Figure 11. Black Applicant Selection Rate, Disaggregated by Condition
Note: + $p < 0.1$ ∗ $p < .05$; ∗∗ $p < .01$; ∗ ∗ ∗ $p < .001$. Symbols indicate the level of significance of the differences in Black applicant selection rate in the isolated and collective choice conditions compared to the simulated collective choice condition. Symbols for level of significance are based on **Model 2** in **Table 7**.

hiring experience selecting Black applicants to interview for a job opening when compared to the simulated collective choice condition. In other words, the data did not support the third hypothesis (the probability of selecting a Black job candidate in the simulated collective choice condition will not be statistically different than in the collective choice condition). Black applicants were selected 19.73% more often (or 7.21 percentage points) in the simulated collective choice condition than in the collective choice condition. The findings from **Model 2** in **Table 7** are visualized in **Figure 11**. As a robustness check, I estimated the previously described models using binomial logistic regression, and found that none of the previously described results change in statistical significance. The results of these binomial logistic regression models can be seen in **Table 8**.

3.5.2 Accounting for Participant Characteristics

To determine whether participants' characteristics accounted for variation in the probability of a Black applicant being selected, I ran **Model 1** in **Table 9**. I found that Black / African American participants with hiring experience were significantly more likely to select Black applicants to

Table 8. Binomial Logistic Regression Results for Relationship between Black Applicant Selection and Hiring Condition

	Logit Model 1	Logit Model 2
Intercept	-0.427***	-0.251**
	(0.085)	(0.085)
Collective Choice	-0.124	-0.301**
	(0.110)	(0.110)
Simulated Collective Choice	0.176	
	(0.120)	
Isolated Choice		-0.176
		(0.120)
Num.Obs.	1729	1729
AIC	2325.7	2325.7
BIC	2342.1	2342.1
Log.Lik.	-1159.843	-1159.843
RMSE	0.49	0.49
Std.Errors	Custom	Custom

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Cluster-robust standard errors are in parentheses.

interview for a job opening compared to White participants ($\beta_{Black} = 0.082$, $t(186.72) = 2.701$, $p < 0.01$). Put into context, holding other participant characteristics constant, Black participants selected Black applicants for an interview 23.99% more often (or 8.23 percentage points) than White participants. I also found the that Asian / Asian American participants with hiring experience were somewhat less likely (marginally statistically significant) to select Black applicants to interview for a job opening compared to White participants ($\beta_{Asian/AsianAmerican} = -0.077$, $t(47.88) = -1.731$, $p = 0.090$). Additionally, I found that participants with hiring experience who self-identified as Democrats or as leaning toward being a Democrat were significantly more likely to select Black applicants to interview for a job opening compared to participants who self-identified as Republican or as leaning toward being a Republican ($\beta_{Democrat} = 0.065$, $t(486.22) = 2.472$, $p < 0.05$). In other words, maintaining other participant characteristics the same, Democrats selected Black applicants for an interview 19.08% more often (or 6.54 percentage points) than Republicans. As for other participant demographic characteristics, there is insufficient evidence to suggest a significant difference in the probability of selecting Black applicants to interview for a job opening (see **Model 1** in **Table 9**).

Lastly, as an exploratory (and not pre-registered) analysis, I checked for treatment effect heterogeneity by adding interaction terms between the selection condition and participant characteristics. The results of this analysis can be seen in **Model 2** of **Table 9**. In **Model 2**, the coefficient for Asian / Asian American ($\beta_{Asian/AsianAmerican} = -0.165$, $t(44.275) = -2.174$, $p < 0.05$) represents the difference in the probability of selecting a Black applicant between Asian / Asian American participants and White participants in the isolated choice condition. This means that Asian / Asian American participants in the isolated choice condition were significantly less likely to select a Black applicant compared to White participants. However, looking at the interaction terms between Asian / Asian American and other study conditions, which are positive but not significant, there is insufficient evidence that the selection behavior of Asian / Asian American participants differs significantly from the selection behavior of White participants in the collective choice condition and the simulated collective choice condition. These interaction terms test whether the difference between Asian /

Table 9. Relationship between Black Applicant Selection and Hiring Condition, with Controls for Participant Characteristics

	Model 1	Model 2
Intercept	0.343*** (0.033)	0.403*** (0.054)
Collective Choice	-0.030 (0.026)	-0.077 (0.068)
Simulated Collective Choice	0.042 (0.029)	-0.087 (0.075)
Black / African American	0.082** (0.030)	0.042 (0.057)
Asian / Asian American	-0.077+ (0.044)	-0.165* (0.076)
Hispanic, Latino, or Spanish origin	-0.009 (0.031)	0.003 (0.063)
Woman	0.007 (0.022)	-0.029 (0.042)
Democrat or Lean Democrat	0.065* (0.026)	0.053 (0.049)
Independent	0.030 (0.030)	0.001 (0.056)
Graduate degree (for example: MA, MS, MD, JD, PhD)	-0.007 (0.029)	-0.021 (0.054)
Bachelor's degree (for example: BA, BS)	0.015 (0.026)	-0.014 (0.048)
Collective * Black / African American		0.036 (0.073)
Simulated * Black / African American		0.083 (0.084)
Collective * Asian / Asian American		0.155 (0.095)
Simulated * Asian / Asian American		0.119 (0.134)
Collective * Hispanic, Latino, or Spanish origin		-0.048 (0.076)
Simulated * Hispanic, Latino, or Spanish origin		0.006 (0.091)
Collective * Woman		0.047 (0.055)
Simulated * Woman		0.059 (0.059)
Collective * Democrat or Lean Democrat		0.004 (0.064)
Simulated * Democrat or Lean Democrat		0.041 (0.069)
Collective * Independent		0.015 (0.073)
Simulated * Independent		0.068 (0.080)
Collective * Graduate degree		0.013 (0.069)
Simulated * Graduate degree		0.021 (0.078)
Collective * Bachelor's degree		0.002 (0.062)
Simulated * Bachelor's degree		0.083 (0.067)
Num.Obs.	1729	1729
R2	0.014	0.022
R2 Adj.	0.007	0.003
AIC	2443.2	2468.6
BIC	2525.1	2659.5
RMSE	0.49	0.48
Std.Errors	by: ProlificID	by: ProlificID

Note: + $p < 0.1$ * $p < .05$; ** $p < .01$; *** $p < .001$. Linear probability models are shown with cluster-robust standard errors in parentheses.

Asian American and White participants in selecting Black applicants differs significantly across selection conditions. The lack of statistical significance suggests that the gap between these groups observed in the isolated choice condition does not significantly widen or narrow in the collective or simulated collective choice conditions. For all other interactions, I found insufficient evidence to suggest a statistically significant difference in the effect of selection conditions varying across different subgroups in the population of workers with hiring experience. It is important to note, however, that **Model 2** is statistically underpowered due to small sample size of racial minorities, so results should be interpreted with caution.

3.5.3 The Role of Candidate Experience

Across all selection decisions, the candidate with the most experience was selected 58.24% of the time. For selection decisions made in an isolated context, the candidate with the most experience was selected 58.45% of the time. The job applicant with the most experience out of the three was chosen for an interview 61.21% of the time in the collective choice condition and in 55.01% of simulated collective choice condition selection decisions. However, it is important to note that decisions on who to interview based on perceived applicant quality are informed by more than just applicants' years of experience. In other words, information about candidates' quality and suitability for a position can also be gained by looking at information about what candidates accomplished in previous roles. This information was also provided on job applicants' résumés. Therefore, years of experience is a crude measure for candidate experience and, more generally, candidate quality.

To examine the association between the experience level of the selected applicant and the likelihood that the selected applicant is Black, the variable for years of experience was constructed in relation to all of the candidates in a candidate pool (for each job posting, there were three job applicants). Experience was randomly assigned so that one candidate always had the lowest amount of experience, one candidate always had a medium amount of experience, and one candidate always had the most or highest amount of experience. Candidates' years of experience have clear ordering based on this relational construction of the variable. However, some values for years of experience

are only present for some of the job positions (e.g., candidates for the accountant position always had 2, 4, or 5 years of experience) and, furthermore, these job positions did not have even representation of Black applicants in their candidate pools (e.g., out of three applicants for each position, the design had no Black applicants for the Marketing Coordinator position, two Black applicants for the District Manager position, and 1 Black applicant for each of the other three positions). Therefore, candidate experience is best thought of as an ordinal variable.

To examine whether selected Black applicants tend to have medium or high experience more often than low experience, I ran **Model 1** in **Table 10**, which includes indicator variables for whether the selected applicant had a medium or high level of experience. Candidates with the lowest amount of experience serve as the reference group. **Model 2** in **Table 10** treats candidate experience as a continuous variable. Model 1 is preferred, given that experience levels were constructed relationally within each decision set. Importantly, these models should be interpreted with care: I only observe the race and experience of the selected applicant, not of all applicants shown to participants. As such, the analysis captures the association between the experience level of the selected applicant and the probability that the selected applicant is Black, rather than the effect of experience on the selection of Black applicants more broadly. In other words, these results help me examine the racial composition of selected candidates at different experience levels, not how experience affects the probability that a Black applicant is selected from the full applicant pool.

In **Model 1**, I find a marginally statistically significant association indicating that selected applicants with medium experience were more likely to be Black than selected applicants with low experience ($\beta_{MediumExperience} = 0.064$, $t(404.7) = 1.787$, $p = 0.075$). However, there is insufficient evidence that selected applicants with high experience were more or less likely to be Black than those with low experience ($t(333.0) = -0.237$, $p = 0.813$). In **Model 2**, I treat experience as a continuous variable. I did not find enough evidence for a statistically significant association between years of experience and whether the selected applicant is Black.

To assess whether the association between candidate experience and the likelihood of selecting a Black applicant varies by selection context, I added interaction terms in **Model 3** in

Table 10. Relationship between Black Applicant Selection and Hiring Condition, with Controls for Candidate Experience

	Model 1	Model 2	Model 3
Intercept	0.385***	0.428***	0.336***
	(0.031)	(0.043)	(0.044)
Collective Choice	-0.030	-0.029	0.059
	(0.026)	(0.026)	(0.064)
Simulated Collective Choice	0.039	0.043	0.108
	(0.029)	(0.029)	(0.067)
Medium Experience	0.064+		0.128*
	(0.036)		(0.063)
High Experience	-0.007		0.053
	(0.031)		(0.051)
Years of Experience		-0.007	
		(0.009)	
Collective * Medium Experience			-0.128
			(0.086)
Simulated * Medium Experience			-0.075
			(0.090)
Collective * High Experience			-0.102
			(0.074)
Simulated * High Experience			-0.092
			(0.077)
Num.Obs.	1729	1729	1729
R2	0.007	0.004	0.009
R2 Adj.	0.005	0.002	0.004
AIC	2437.1	2440.9	2442.3
BIC	2469.8	2468.1	2496.8
RMSE	0.49	0.49	0.49
Std.Errors	by: ProlificID	by: ProlificID	by: ProlificID

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Linear probability models are shown with cluster-robust standard errors in parentheses.

Table 10. In **Model 3**, the positive and statistically significant coefficient for $MediumExperience$ ($\beta_{MediumExperience} = 0.128$, $t(237.7) = 2.034$, $p < 0.05$) indicates that, in the isolated choice condition (the reference group), selected applicants with medium experience were more likely to be Black than selected applicants with low experience. Stated differently, the coefficient for $MediumExperience$ reflects the estimated difference in the probability that a selected applicant is Black when comparing medium experience applicants to low experience applicants within the isolated choice condition. The interaction terms between medium experience and the collective and simulated collective choice conditions indicate how the association between medium experience and selecting a Black applicant differs from the isolated choice condition. They represent the additional difference (relative to the isolated choice condition) in the association between medium experience and selection of a Black applicant within the collective or simulated collective conditions. Since they are not statistically significant, there is insufficient evidence that the strength or direction of this association differs in the collective or simulated collective conditions. Linear probability models with study conditions, participant characteristics, candidate experience, and interaction terms are shown in **Table 11**.

3.5.4 Did Participants Consider Company Diversity?

After completing their decisions on who to interview, participants were asked to indicate how they made their decisions: (1) "In selecting who to interview, I considered how my choices impacted the overall success of the company," (2) "In selecting who to interview, I considered how my choices impacted the overall diversity of the company," and (3) "In selecting who to interview, I chose the most qualified candidate." When asked if they considered how their choices impacted the overall success of the company, 96.59% of participants indicated that they strongly or somewhat agreed. Similarly, when asked if they chose the most qualified candidate, 94.91% of participants indicated that they strongly or somewhat agreed. However, participants varied when asked if they considered how their choices impacted the overall diversity of the company: 40.02% of participants

Table 11. Relationship between Black Applicant Selection and Hiring Condition, with Controls for Participant Characteristics and Candidate Experience

	Model 1	Model 2
Intercept	0.334*** (0.041)	0.351*** (0.065)
Collective Choice	-0.031 (0.026)	0.007 (0.088)
Simulated Collective Choice	0.039 (0.029)	-0.035 (0.096)
Black / African American	0.079** (0.030)	0.037 (0.058)
Asian / Asian American	-0.070 (0.045)	-0.162* (0.076)
Hispanic, Latino, or Spanish origin	-0.007 (0.031)	0.011 (0.063)
Woman	0.007 (0.022)	-0.030 (0.042)
Democrat or Lean Democrat	0.062* (0.026)	0.052 (0.049)
Independent	0.027 (0.030)	-0.009 (0.057)
Graduate degree (for example: MA, MS, MD, JD, PhD)	-0.005 (0.029)	-0.021 (0.054)
Bachelor's degree (for example: BA, BS)	0.017 (0.026)	-0.019 (0.048)
Medium Experience	0.059+ (0.036)	0.118+ (0.065)
High Experience	-0.005 (0.031)	0.055 (0.053)
Collective * Black / African American		0.038 (0.073)
Simulated * Black / African American		0.084 (0.084)
Collective * Asian / Asian American		0.156 (0.096)
Simulated * Asian / Asian American		0.131 (0.133)
Collective * Hispanic, Latino, or Spanish origin		-0.052 (0.076)
Simulated * Hispanic, Latino, or Spanish origin		-0.006 (0.091)
Collective * Woman		0.044 (0.055)
Simulated * Woman		0.059 (0.059)
Collective * Democrat or Lean Democrat		0.006 (0.064)
Simulated * Democrat or Lean Democrat		0.039 (0.069)
Collective * Independent		0.025 (0.073)
Simulated * Independent		0.079 (0.080)
Collective * Graduate degree		0.015 (0.069)
Simulated * Graduate degree		0.021 (0.078)
Collective * Bachelor's degree		0.007 (0.062)
Simulated * Bachelor's degree		0.090 (0.067)
Collective * Medium Experience		-0.127 (0.089)
Simulated * Medium Experience		-0.060 (0.091)
Collective * High Experience		-0.103 (0.075)
Simulated * High Experience		-0.084 (0.078)
Num.Obs.	1729	1729
R2	0.017	0.027
R2 Adj.	0.009	0.004
AIC	2442.0	2472.7
BIC	2534.7	2696.4
RMSE	0.49	0.48
Std.Errors	by: ProlificID	by: ProlificID

Note: Linear probability models are shown with cluster-robust standard errors in parentheses.

indicated that they strongly or somewhat agreed, 39.39% of participants indicated that they strongly or somewhat disagreed, and 20.39% of participants neither agreed nor disagreed.

In an exploratory analysis, I ran **Models 1 - 3** in **Table 12**. In this series of models, I estimated how participants who indicated that they considered how their choices impacted company diversity (operationalized as those who either strongly or somewhat agreed with the prompt "In selecting who to interview, I considered how my choices impacted the overall diversity of the company") and participants who indicated that they did not consider how their choices impacted company diversity (operationalized as those who either strongly or somewhat disagreed with the prompt "In selecting who to interview, I considered how my choices impacted the overall diversity of the company") differed from those who neither agreed or disagreed with the statement. In **Model 1**, I found statistically significant and positive associations (not causal as measurement of diversity consideration came after candidate selection) between the selection of Black applicants and both participants who considered company diversity ($\beta_{ConsideredCompanyDiversity} = 0.179$, $t(324.6) = 6.007$, $p < 0.001$) and (surprisingly) participants who did not consider company diversity ($\beta_{DidNotConsiderCompanyDiversity} = 0.061$, $t(325.2) = 2.124$, $p < 0.05$) in comparison to participants who were neutral on whether they considered how their choices would impact company diversity. These statistically significant associations ($\beta_{ConsideredCompanyDiversity} = 0.181$, $t(310.4) = 6.056$, $p < 0.001$; $\beta_{DidNotConsiderCompanyDiversity} = 0.064$, $t(307.7) = 2.183$, $p < 0.05$) were still present when I added indicator variables for the study conditions (collective choice condition and simulated collective choice condition, with the isolated choice condition as the reference group once again) in **Model 2**.

In the preferred model, **Model 3**, I examined how participants' self-reported diversity considerations (measured after participants made their decision about whom to interview) are associated with their likelihood of selecting a Black applicant and how this differs depending on participants' study condition (i.e., isolated choice condition, collective choice condition, and simulated collective choice condition). This is the preferred model as I would expect the different study conditions to differentially motivate participants to consider how their choices would impact

Table 12. Relationship between Black Applicant Selection and Hiring Condition, with Controls for Consideration of Company Diversity

	Model 1	Model 2	Model 3
Intercept	0.303***	0.301***	0.336***
	(0.023)	(0.029)	(0.041)
Collective Choice		-0.035	-0.012
		(0.027)	(0.056)
Simulated Collective Choice		0.039	-0.086
		(0.029)	(0.057)
Considered Company Diversity	0.179***	0.181***	0.113*
	(0.030)	(0.030)	(0.053)
Did Not Consider Company Diversity	0.061*	0.064*	0.040
	(0.029)	(0.029)	(0.053)
Collective * Considered Company Diversity			-0.058
			(0.071)
Collective * Did Not Consider Company Diversity			0.007
			(0.069)
Simulated * Considered Company Diversity			0.257***
			(0.074)
Simulated * Did Not Consider Company Diversity			0.054
			(0.073)
Num.Obs.	1729	1729	1729
R2	0.022	0.025	0.040
R2 Adj.	0.020	0.023	0.036
AIC	2408.2	2405.7	2386.5
BIC	2430.1	2438.4	2441.0
RMSE	0.48	0.48	0.48
Std.Errors	by: ProlificID	by: ProlificID	by: ProlificID

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Linear probability models are shown with cluster-robust standard errors in parentheses. The controls for consideration of company diversity are in reference to those who were neutral about its consideration.

company diversity. The coefficient for $ConsideredCompanyDiversity$ indicates that, within the isolated choice condition (the reference group), participants who later reported considering how their choices impacted company diversity were more likely to have selected a Black applicant than participants who were neutral about diversity considerations ($\beta_{ConsideredCompanyDiversity} = 0.113$, $t(272.53) = 2.116, p < 0.05$). This association was even stronger among participants in the simulated collective choice condition, as indicated by a positive and statistically significant interaction term ($\beta_{Simulated*ConsideredCompanyDiversity} = 0.257$, $t(509.1) = 3.493$, $p < 0.001$), suggesting that the relationship between reported diversity considerations and the selection of Black applicants was more pronounced in that condition. However, the interaction between $ConsideredCompanyDiversity$ and the collective choice condition was not statistically significant, providing no evidence that this association differed from the isolated choice condition. Lastly, there is insufficient evidence ($t(271.65) = 0.766, p = 0.444$) to support the previously significant (in **Model 1** and **Model 2**) association between not considering how choices impacted company diversity and the selection of Black applicants, relative to participants who were neutral about diversity considerations.

3.5.5 Sensitivity Analyses

3.5.5.1 Focusing Only on Decisions with Black Applicants

As mentioned in **Section 3.4.3 Survey Instrument and Data Collection Procedure**, participants were assigned to select job applicants to interview across five different positions: marketing coordinator, district manager, accountant, software engineer, and data scientist. However, in an attempt to make the objectives of the study less obvious, not all five job positions included Black job applicants. The marketing coordinator position always included three White job applicants across all three study conditions (i.e., isolated choice condition, collective choice condition, and simulated collective choice condition). As a sensitivity analysis, I reran pertinent models only for decisions with Black applicants (i.e., district manager, accountant, software engineer, and data scientist). **Table 13** shows the ordinary least squares regression models with robust standard errors

Table 13. Relationship between Black Applicant Selection and Hiring Condition, Focusing Only on Decisions with Black Applicants

	Model 1	Model 2	Model 3	Model 4
Intercept	0.492***	0.438***	0.469***	0.412***
	(0.023)	(0.038)	(0.036)	(0.048)
Collective Choice	-0.036	-0.036	-0.037	-0.038
	(0.031)	(0.031)	(0.031)	(0.031)
Simulated Collective Choice	0.051	0.051	0.046	0.046
	(0.033)	(0.033)	(0.033)	(0.033)
Black / African American		0.097**		0.093**
		(0.034)		(0.034)
Asian / Asian American		-0.091+		-0.083
		(0.053)		(0.053)
Hispanic, Latino, or Spanish origin		0.003		0.005
		(0.036)		(0.036)
Woman		0.004		0.005
		(0.026)		(0.026)
Democrat or Lean Democrat		0.058+		0.055+
		(0.031)		(0.031)
Independent		0.020		0.017
		(0.035)		(0.035)
Graduate degree (for example: MA, MS, MD, JD, PhD)		0.008		0.012
		(0.034)		(0.034)
Bachelor's degree (for example: BA, BS)		0.019		0.022
		(0.030)		(0.030)
Medium Experience			0.087*	0.086*
			(0.040)	(0.041)
High Experience			0.007	0.013
			(0.036)	(0.036)
Num.Obs.	1387	1387	1387	1387
R2	0.005	0.017	0.010	0.021
R2 Adj.	0.004	0.008	0.007	0.010
AIC	2014.3	2019.6	2011.5	2017.7
BIC	2035.2	2098.1	2042.9	2106.6
RMSE	0.50	0.50	0.50	0.49
Std.Errors	by: ProlificID	by: ProlificID	by: ProlificID	by: ProlificID

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Linear probability models are shown with cluster-robust standard errors in parentheses.

clustered at the participant level. It is important to note that the district manager position had two Black applicants (instead of just one like the other three job positions) across all three study conditions, so baseline selection rates of Black applicants are expected to be higher. As shown in **Table 13**, the previously described results withstand regardless of whether or not I include decisions with only White job applicants in my analyses.

3.5.5.2 Differences Across Job Positions

Considering that participants made selection decisions for different job positions, it is possible that selection rates of Black applicants for interviews were different across different positions and, furthermore, that the study conditions (i.e., isolated choice conditions, collective choice condition, and simulated collective choice condition) heterogeneously impacted the selection of Black applicants depending on the job position(s) shown to study participants. **Table 14** shows an exploratory sensitivity analysis to examine this possibility. In checking for differences across positions job candidates applied for (i.e., marketing coordinator, accountant, district manager, software engineer, and data scientist), I limited the check to positions that had the same number (one per position) of Black job applicants (instead of 0 in the marketing coordinator position or 2 in the district manager position). These models should be interpreted with caution, however, as the collective choice condition now only includes three of the five decisions participants in the collective choice condition made and that some of their choices that would lead to more diverse groups are now excluded from the analysis.

Looking at **Model 1**, there is a negative and statistically significant difference in the probability of selecting a Black applicant for interview for a software engineer position compared to an accountant position ($\beta_{SoftwareEngineer} = -0.095$, $t(518.9) = -2.580$, $p < 0.05$), indicating that participants were more likely to select Black applicants for an interview for an accountant position than a software engineer position. There was insufficient evidence, however, that participants' selection of Black applicants for a data scientist position significantly differed from the selection of Black applicants for an accountant position. In **Model 2**, I added indicator variables for the study conditions, and

Table 14. Variation in Relationship between Black Applicant Selection and Hiring Condition Across Job Positions

	Model 1	Model 2	Model 3
Intercept	0.458***	0.441***	0.470***
	(0.027)	(0.034)	(0.046)
Collective Choice		-0.016	-0.074
		(0.036)	(0.065)
Simulated Collective Choice		0.068+	0.039
		(0.038)	(0.066)
Data Scientist Position	-0.016	-0.016	-0.087
	(0.039)	(0.039)	(0.065)
Software Engineer Position	-0.095*	-0.095**	-0.111+
	(0.037)	(0.037)	(0.064)
Collective * Data Scientist Position			0.139
			(0.096)
Collective * Software Engineer Position			0.034
			(0.089)
Simulated * Data Scientist Position			0.074
			(0.093)
Simulated * Software Engineer Position			0.015
			(0.092)
Num.Obs.	1040	1040	1040
R2	0.007	0.013	0.015
R2 Adj.	0.005	0.009	0.007
AIC	1484.1	1482.3	1487.8
BIC	1503.8	1512.0	1537.3
RMSE	0.49	0.49	0.49
Std.Errors	by: ProlificID	by: ProlificID	by: ProlificID

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Linear probability models are shown with cluster-robust standard errors in parentheses.

found similar results for differences in selection rates across job positions and that, compared to the isolated choice condition, participants in the simulated collective choice condition (for the three job positions in these models) were somewhat more likely (marginal statistical significance) to select Black applicants for an interview ($\beta_{SimulatedCollectiveChoice} = 0.068$, $t(688.9) = 1.811$, $p = 0.071$). Lastly, in **Model 3**, I find insufficient evidence that the differences in Black applicant selection rates based on job position significantly vary by study condition.

3.6 Discussion

3.6.1 Summary of Key Findings

I found insufficient evidence that either the simulated collective choice or collective choice conditions increased the probability of workers with hiring experience selecting Black applicants to interview compared to the isolated choice condition. Surprisingly, the simulated collective choice condition significantly increased the probability of workers with hiring experience selecting Black applicants to interview compared to the collective choice condition, with Black applicants being chosen approximately 20% more often in the simulated collective choice condition than in the collective choice condition. Looking at participant characteristics, I found that Black participants with hiring experience were significantly more likely to select Black applicants (about 24% more often) than White participants, while Asian participants were somewhat less likely (marginal statistical significance) to do so. Additionally, Democrats were significantly more likely (by approximately 19%) than Republicans to select Black applicants.

In examining the association between the experience level of the selected applicant and the likelihood that the selected applicant is Black, I found a marginally statistically significant association indicating that selected applicants with medium experience were more likely to be Black than selected applicants with low experience. However, there is insufficient evidence that selected applicants with high experience were more or less likely to be Black than those with low experience. I additionally found that nearly all participants reported considering company success (96.59%)

and candidate qualifications (94.91%) when making their selection decisions, but fewer than half (40.02%) reported considering how their choices would impact company diversity. In exploratory analyses, I found that those who self-reported considering diversity were significantly more likely to have selected Black applicants than participants neutral about diversity, with this association being strongest in the simulated collective choice condition.

3.6.2 Comparisons to Prior Research

The main findings from this study differ from the research conducted by Chang et al. (2020) and Luo et al. (2022), which established the isolated (and collective) choice effect. **Table 15** details the key differences in study designs as well as the varying selection rates documented in each of the studies, including this study. I argue that the changes made to the design for this study (i.e., experience randomly assigned independently from applicant race, applicant information that more closely resembles real world application materials, and a sample of workers who have experience making hiring decisions) are important for increasing external validity. Findings from prior research are therefore possibly contingent on design choices of making Black applicants always have moderate experience, a hiring scenario with very little to no information about an applicant, and participants that do not have experience making hiring decisions.

It is possible that using a sample of individuals with hiring experience worked to decrease the size of the gap of selection rates between different experimental conditions. It is also likely that not limiting underrepresented candidates to having a moderate amount of experience increased baseline selection rates of the social category under study. In other words, while Black men were selected in 14.8% of the decisions in the isolated choice condition in Study 1A in Luo et al.'s (2022) work, I found that this group had a selection rate of 39.5% in the same condition. Increasing the amount of information about job applicants presented to participants also likely made it more difficult for participants to gauge which candidate was the most qualified. Ultimately, the use of a sample with hiring experience and the design choice of randomly assigning experience likely played the largest role in the differences in results between this study and prior research. These differences in the

documented effects suggest that real-world testing with workplaces and organizations (e.g., field experiments) is needed.

One final difference relates to the timing of data collection in this study relative to prior research. Data for this study were collected in October 2024, a period marked by heightened public discourse and polarization surrounding issues of (in)equality and diversity. The potential influence of this context on participant responses is unclear: for some, it may have increased support for organizational racial diversity, while for others, it may have led to decreased support.

3.6.3 Limitations

Though the present study makes methodological advances toward external validity, it is not without its limitations. Three main limitations are the inclusion of photos, the unidimensional representation of diversity, and the lack of clarity in the mechanism behind the simulated collective choice condition. Firstly, the inclusion of photos is a limitation for two reasons despite photos being used by prior researchers: (1) it is likely some participants have seen these photos before due to their popularity in survey research and (2) in most cases in the United States, those making decisions about which candidates to advance from the application to the interview stage would not see photos of job applicants or know what they look like.

Secondly, this study operationalizes diversity as unidimensional by focusing only on racial diversity. Selection decisions rarely occur with diversity along only one social position (i.e., woman vs. man or Black vs. White), rather job applicants have multiple identities that intersect. Therefore, hiring decision-makers often make selection decisions that require mentally juggling diversity across multiple social categories. Furthermore, even within racial diversity, there is more diversity than what was included in this study (i.e., Black and White job applicants) for reasons of statistical power. Examining several characteristics (e.g., gender and race) in one study would be important because different status positions can combine in ways that are sometimes counterintuitive (Pedulla, 2018). As an example, in the job application process, Pedulla (2014) found that White men are penalized for being gay, whereas Black straight men receive less favorable evaluations than their

Table 15. Comparing Designs and Results Across Studies

Design Components and Results	**Study 1 of "The Isolated Choice Effect and Its Implications for Gender Diversity in Organizations" (Chang et al., 2020)**	**Study 1A of "The Isolated Choice Effect: An Underlying Psychological Mechanism Influencing Racial Diversity in Organizations" (Luo et al., 2022)**	**"Simulating Collective Choices: Can the Benefits of Collective Choices be Replicated for Isolated Choices?" (Garcia Fernandez, 2025)**
Social Category	Gender: men and women	Race: Black and White	Race: Black and White
Sample	500 participants obtained through Amazon Mechanical Turk	565 participants obtained through Amazon Mechanical Turk	1,265 participants with **hiring experience** obtained through Prolific
Job Applicant Information	(1) Candidate picture taken from the Chicago Face Database, (2) most recent job, and (3) number of years of experience	(1) Candidate picture ("virtual human faces taken from generated photos"), (2) years of experience, and (3) candidate ages	(1) Candidate picture taken from the Chicago Face Database, (2) candidate name tested by Gaddis (2017b), (3) candidate education information (including university, name of degree, and when degree was completed), (4) years of experience, (5) name of most recent job, and (6) information about what candidate accomplished in most recent position
Underrepresented Candidate Experience	Applicants signaled to be women always had more years of experience than one of the men, yet fewer years of experience than the other	Applicants signaled to be Black men always had fewer years of experience and were younger than one of the White men, yet had more years of experience and were older than the other	Applicants were randomly assigned experience based on a pool of three previously prepared experience profiles (i.e., years of experience, degree, name of most recent job, and description of what candidate accomplished in most recent position)
Selection Rates of Women (Chang et al.) or Black Men (Luo et al. and Garcia Fernandez)	Isolated Choice Condition: 7.4%	Isolated Choice Condition: 14.8%	Isolated Choice Condition: 39.5%
	Collective Choice Condition: 18.0%	Collective Choice Condition: 25.9%	Collective Choice Condition: 36.6%
	Simulated Collective Choice Condition: NA	Simulated Collective Choice Condition: NA	Simulated Collective Choice Condition: 43.8%
Decision	Choose 1 applicant to hire	Choose 1 applicant to hire	Choose 1 applicant to interview

Black gay counterparts. This understanding that multiple social categories can combine in shaping (dis)advantage, a framework known as intersectionality (Crenshaw, 1991; McCall, 2005), suggests that this study's approach to modeling workplace diversity can be seen as reductive.

Thirdly, the mechanism underlying the simulated collective choice condition remains unclear. If an employee already knows an organization's demographic composition, does that create the environment of the simulated collective condition? Or is the mechanism of the simulated collective choice condition the reminder to the employee about the organization's demographic composition right before the employee makes a selection decision? It is also possible that the collective and simulated collective choice conditions trigger different types of thinking for participants. On the one hand, the simulated collective choice condition in this study provided participants with information that the two previous hires were White. If participants have a preference to factor race in their decision-making process, their decision is made easier by this information. On the other hand, in the collective choice condition, participants are more likely to gain an understanding of the racial composition of the applicant pool than the participants in the isolated choice condition (as a result of seeing an applicant pool that is five times larger), and may therefore attempt to select a pool of candidates that more closely resembles the racial composition of the applicant pool. Future work should distinguish between these different mechanisms as this knowledge has important implications for researchers and practitioners. For example, the simulated collective choice condition as constructed in this study could be particularly useful for a strongly homogeneous organization interested in beginning to diversify.

3.6.4 Implications

This study provides a better understanding of whether the benefits of collective choices can be simulated in scenarios where choices are made in isolation. This is important knowledge for researchers and practitioners alike, as solutions to address workplace inequalities are of theoretical and practical importance. Simulated collective decisions might do a better job of presenting decision-makers with an organization's current context. They can also potentially apply to all sorts

of selection decisions, unlike prior researchers' operationalization of collective choices, which most organizations would find hard to implement because many organizations might struggle to coordinate selection decisions across departments.

Simulated collective choices might also organically occur in various scenarios. For example, if individuals making selection decisions are involved in the selection of all employees, they therefore might have a better sense of an organization's demographic composition. Practically, providing employees making hiring decisions information about the current composition of an organization is an easily implementable intervention. Collective choices too already occur within departments of an organization (as opposed to across departments as conceptualized in prior studies). As an example, in academia, departments often engage in cluster hires, through which multiple individuals are hired at once rather than recruiting candidates individually. Therefore, organizations may benefit from deviating from how collective choices have been defined in the past and thinking creatively about how isolated and individual hires contributes more generally to the collective organization's many goals.

Future work should endeavor to implement different designs to test and extend isolated, collective, and simulated collective choice contexts. First, field experiments are needed to test how different selection contexts impact the diversity of selected groups in real world hiring and selection processes. While some selection contexts may fairly select individuals for an organization, other selection contexts may advantage some groups over others. Therefore, field experiments could be extremely useful. Future research should also seek to leverage natural experiments to assess the impact of collective or simulated collective choice contexts on organizational diversity, particularly within organizations undergoing or preparing for changes in their selection processes. Lastly, an alternative operationalization of the collective choice condition worth examining is hiring multiple individuals for the same position, as opposed to hiring one individual for each of several distinct positions. While organizations are more commonly faced with filling multiple roles across different departments rather than multiple openings for a single position, findings may nonetheless be sensitive to these differing operationalizations.

The findings from this study put into question the isolated choice effect (and the collective choice effect) and shed light on the importance of testing these interventions with real-world organizations. Furthermore, this work poses questions about ensuring the legality of any potential changes to selection processes as well as questions of how contemporary movements against diversity and inclusion might frame these efforts.

4 Gender Inequality in Employee Reward Allocation: Can Increasing Clarity in Reward Allocation Criteria Decrease Inequality?

Abstract: This study examines how gender inequality emerges in seemingly meritocratic systems and whether increasing clarity in performance-based reward allocation criteria can mitigate such disparities. Drawing on a survey experiment with 1,626 participants with management experience, who collectively made 8,130 bonus allocation decisions and 1,626 promotion decisions, I test whether clarifying reward allocation criteria affects gendered patterns in workplace rewards. I find evidence that overall bonus allocations to employees signaled to be women do not differ significantly between clear and ambiguous reward allocation conditions. However, participant gender plays an important role, with women allocating higher bonuses to employees signaled to be women, particularly in the ambiguous condition. Within the ambiguous condition, women allocated significantly higher bonuses, by 7.69% on average, to employees signaled to be women than to employees signaled to be men. In contrast, there is little evidence of gender-based differences in allocations when the reward allocation criteria are clear. Promotion decisions reveal a similar pattern. Although there is no overall difference in promotion rates for employees signaled to be women across conditions, women were more likely than men to select a woman for promotion, especially in the ambiguous condition. In the ambiguous condition, women were 5.6 percentage points more likely than men to promote a woman, which is a difference equivalent to 28% of the expected baseline rate. Additionally, an exploratory analysis of racial differences in outcomes for employees signaled to be men reveals that women allocate significantly lower bonuses to White and Asian American men, relative to White women, under the ambiguous condition. Men did not exhibit the same pattern. These findings illustrate how ambiguity in reward allocation criteria allows for inequality in the rewards that are ultimately allocated, particularly through the differential behavior of different groups of decision-makers.

Clarifying reward allocation criteria decreases this inequality. This study contributes to research on gender inequality in organizations and highlights the importance of increasing clarity in reward allocation criteria to decrease inequality in the workplace.

4.1 Introduction

How are rewards allocated in workplaces? Workplaces strive to implement meritocratic reward allocation processes. Meritocracy consists of allocating rewards and opportunities based on individuals' abilities, efforts, accomplishments, and merits as opposed to individuals' demographic characteristics such as gender (Castilla, 2008, 2015; Castilla & Benard, 2010). For a system to be meritocratic, individuals need to be rewarded equally, regardless of identities unrelated to merit, if they perform equally as well as one another (Castilla & Benard, 2010). Meritocratic reward allocation processes are hard to implement. First, agents within an organization can disagree on definitions of merit and how to measure it. Second, evaluations of merit can be influenced by factors other than individuals' accomplishments and efforts. Third, it can be unclear how organizations are to assign rewards based on these evaluations of individuals' merits. A growing body of research suggests that seemingly meritocratic reward allocation processes do not always function as intended (Heilman, Caleo, & Manzi, 2024; Castilla, 2008, 2015; Correll, Weisshaar, Wynn, et al., 2020), particularly in the allocation of rewards such as promotions, salaries, and professional recognition. This paper examines how gender disparities emerge within ostensibly meritocratic reward allocation systems.

In the workplace, one way to allocate rewards to employees in a meritocratic manner is through performance evaluations. Performance evaluations consist of setting standards for employees, measuring employee performance using these standards, and allocating rewards such as compensation and promotions based on employees' performance (Correll, Weisshaar, Wynn, et al., 2020). Formal performance evaluations are widespread and are used by approximately 90% of corporations (Human Resource Management, 2014). However, these formalized bureaucratic procedures may fail to allocate rewards in a truly meritocratic manner. For example, Castilla documented performance-

reward bias, in which women (and minorities) with equal performance evaluation ratings received lower compensation than white men (2008). Furthermore, Joshi, Son, and Roh found evidence that sex disparities in rewards (e.g., salaries, bonuses, and promotions) were significantly greater than gender differences in performance evaluations, with the former being 14 times larger. Moreover, the observed differences in rewards between men and women could not be accounted for by variations in performance evaluations (Joshi, Son, & Roh, 2015). As a last example, Correll et al. identified how gender stereotypes influence performance reviews through the Viewing and Valuing Social Cognitive Processing Model, which proposes that managers both observe employee traits and behaviors at different frequencies based on employee gender and assign differential values (i.e., ratings) to these behaviors depending on whether the employee is a man or a woman (Correll, Weisshaar, Wynn, et al., 2020).

There is evidence, however, that organizations can play a role in how well performance evaluations are linked to meritocratic reward allocation processes. Ambiguity in reward allocation processes contributes to gender inequality by creating opportunities for gender bias and discrimination, as stereotypes may fill gaps in unclear evaluation criteria (Correll, 2017). This issue is particularly pronounced when managers lack clear guidelines on how to weigh and integrate performance information, leading to differential treatment of men and women (Heilman, Caleo, & Manzi, 2024). In promotion decisions, for example, managers must navigate multiple performance ratings and data points, but often do so with considerable flexibility and ambiguity (Heilman, Caleo, & Manzi, 2024). Reducing ambiguity in reward allocation presents an opportunity to mitigate gender disparities.

This paper examines gender inequality in reward allocation using data collected from a survey experiment that manipulates reward allocation criteria based on performance evaluations. 1,626 participants with management experience made 8,130 bonus allocation decisions and 1,626 promotion decisions. By testing an intervention aimed to address ambiguity in reward allocation processes, this study adds to the literature on how interventions that increase clarity in evaluation and reward allocation contexts can address gender inequality (Correll, Weisshaar, Wynn, et al., 2020; Heilman, Caleo, & Manzi, 2024). More broadly, this study adds to the literature on how

organizational practices can shape workplace inequality (Rivera & Tilcsik, 2019; Small & Pager, 2020).

4.2 Theoretical Background

4.2.1 Gender in the Workplace

Inequality based on the effects of status differences, including differences in respect and regard (Ridgeway, 2014), provides a lens through which to understand the construction and maintenance of gender inequality in the workplace. Macro level beliefs about a group's status impacts micro-level interactions by shaping which individuals are more likely to receive resources (such as salaries and bonuses) and/or positions of power (such as promotions) (Ridgeway, 2014). Extensive research has shown that the beliefs about gendered characteristics of the ideal worker and the devaluation of women's work (i.e., workplaces with more women than men and work that is gender-typed as work done by women) are deeply embedded in the practices, policies, and procedures of workplaces (Acker, 1990; England, 2010; Ridgeway, 2014). This can be seen in (1) gender stereotypes and (2) gender typing and gender segregation of workplaces.

Gender stereotypes, "the widely shared conceptions about the attributes of men and women ... [that] include personality, cognitive, and physical attributes as well as attributes related to interests and abilities" (Heilman, Caleo, & Manzi, 2024), are key to the psychological pathways that inform gender bias and gender discrimination. Gender bias and gender discrimination, in turn, can help maintain gender inequality in the workplace through the unequal allocation of employee rewards, such as bonuses, financial compensation, and promotions (Heilman, Caleo, & Manzi, 2024; Joshi, Son, & Roh, 2015). Gender stereotypes about what women are like (i.e., descriptive stereotypes) and expectations about how women should behave (i.e., prescriptive stereotypes) can result in women's performances being devalued, successes not being rewarded, and punishments for competence (Heilman, 2001; Brewer, Osborne, Mueller, et al., 2020; Wynn & Carian, 2023; Benson, Li, & Shue, 2023). Over the decades, researchers have mapped gender stereotypes onto two

main categories: agency and communion (Bakan, 1966; Broverman, Vogel, Broverman, et al., 1972). Gender stereotypes depict men, and not women, as having agency: men are believed to be "bold, dominant, assertive, independent, self-confident, competitive, and ambitious" (Heilman, Caleo, & Manzi, 2024). Gender stereotypes about women, and not men, depict women as being communal (e.g., affectionate, nurturing, sensitive, sympathetic, helpful, relationship-oriented, and sociable) (Heilman, Caleo, & Manzi, 2024). Most studies on gender stereotypes and their significance use this validated, two-dimensional model of masculine and feminine attributes (Heilman, Caleo, & Manzi, 2024).

Gender typing and gender segregation of workplaces (called sex-typing and sex-segregation by some researchers[8]) also shapes inequality. Research has found that, in jobs that are numerically overrepresented by men, women are evaluated more negatively because these positions are associated with men (Heilman, Caleo, & Manzi, 2024). Compared to gender-neutral or female gender-typed fields, women tend to be evaluated and rewarded less favorably than men in male gender-typed fields, including upper-level management, STEM fields, and entrepreneurship (Heilman, Caleo, & Manzi, 2024). Researchers have conducted meta-analyses and found that women are favored in hiring for women-dominant occupations (which have lower average salaries than men-dominant occupations), while men are favored in hiring for men-dominant occupations (Galos & Coppock, 2023). A recent meta-analysis focusing on studies in the United States reproduced these findings: the likelihood of a female job applicant receiving a callback increases as the number of female workers in an occupation rises (Park & Oh, 2025). However, in the context of the United States, this advantage of females receiving more callbacks than males in female-dominated jobs applies only to White female job applicants and not to Black female job applicants (Park & Oh, 2025). Furthermore, evidence suggests that women, as a result of both between and within firm sorting, are sorted into lower-paying firms and into lower-paying jobs within those firms (Han & Tomaskovic-Devey, 2025).

[8]The terms gender and sex are not interchangeable. I make an attempt to use whatever term was used in the research being cited in order to match the original researchers' language and/or method for capturing sex/gender in the original studies.

4.2.2 Performance Evaluations

Formal performance evaluations are widely used, with about 90% of corporations adopting their use to review employee performance (Human Resource Management, 2014). Performance evaluations involve establishing standards for employees and assessing their performance against these standards (Correll, Weisshaar, Wynn, et al., 2020). The standards captured in performance evaluations need to accurately capture job duties to build buy-in from employees for the use of performance evaluations in assessing performance. Performance evaluations differ from workplace to workplace, but often include both qualitative (in the form of written comments) and quantitative (such as ratings on different criteria) components. Researchers have found that written comments in performance evaluations often differ in significant ways depending on the gender of the employee being evaluated, with employee traits and behaviors being observed (i.e., commented upon) at different frequencies based on employee gender (Biernat, Tocci, & Williams, 2011; Correll, Weisshaar, Wynn, et al., 2020). Researchers have also documented that traits and behaviors are assigned different values (in the form of ratings) depending on the gender of the employee (Biernat, Tocci, & Williams, 2011; Correll, Weisshaar, Wynn, et al., 2020). Correll et al. (2020) call this the Viewing and Valuing Social Cognitive Processing Model, which proposes that managers can both observe employee traits/behaviors at different frequencies based on employee gender and assign differential values (i.e., ratings) to these behaviors depending on whether the employee is a man or a woman (Correll, Weisshaar, Wynn, et al., 2020). For example, managers can view men as more agentic or be more likely to comment on the agentic behavior of employees that are men. Managers can then also value men's agentic behavior more highly than women's agentic behavior. This results in gender differences in both the viewing and valuing of agentic behavior (Correll, Weisshaar, Wynn, et al., 2020). Not every behavior has to have gender differences in both viewing and valuing: behaviors can have gender differences in just how frequently they are observed, in just the value assigned to the behavior, or neither of the two (Correll, Weisshaar, Wynn, et al., 2020).

Performance evaluations are often seen as an organizational practice that is meritocratic and impervious to bias. However, like many other organizational practices, performance evaluations can produce inequality by advantaging some groups while simultaneously disadvantaging others. This can occur regardless of the intent in the development/enforcement of the performance evaluation, or the biases/prejudices of the individuals involved in the process (Small & Pager, 2020). In the case of performance evaluations, managers' biases might influence the ratings and comments they make when reviewing employees. Additionally, the way an evaluation is designed can influence the amount of bias that is reflected on the performance ratings (Rivera & Tilcsik, 2019). It is important to note that the evaluation design does not eliminate the bias itself, but rather influences how the bias is reflected in the evaluation (Rivera & Tilcsik, 2019). Performance evaluations can also provide a false sense of fairness to employees and managers (Dobbin & Kalev, 2022a) and thus work to obfuscate gender inequality.

4.2.3 From Performance Evaluations to Reward Allocations

Workplace rewards, such as financial compensation (e.g., salary, raises, and bonuses) and promotions, are often allocated based on performance evaluations. However, how or to what extent performance evaluations are used to allocate rewards can vary. Research shows there can be large differences in rewards, even when performance evaluations are taken into account. In a meta-analysis spanning over 30 years and including studies from various industries, Joshi, Son, and Roh (2015) found that the gender gap in rewards (e.g., bonuses, salary, and promotions) (d = .56) was 14 times greater than the gap in performance evaluations (d = .04). Furthermore, differences in performance evaluations did not account for the observed disparities in rewards between men and women (Joshi, Son, & Roh, 2015).

The way in which a reward allocation system is designed based on performance evaluations can affect gender inequality. As an example, Castilla analyzed longitudinal data from a single workplace with 8,898 employees and found evidence of a phenomenon he named "performance-reward bias," where women (and minorities) were compensated less than White men despite having equal

performance evaluation ratings (2008). Castilla (2008) found that salary growth is slower for women than men, and slower for African Americans and Latinos when compared to White employees. This was the case even after accounting for years of experience, education, and performance evaluations. This is significant because, even in seemingly merit-based organizations, bias influences salary increases, leading to different pay raises for employees with identical performance scores, roles, and qualifications (2008). In a follow-up study (2015), Castilla looked at the differences in performance-based reward decisions before and after top-level management introduced procedures to increase accountability and transparency about its performance-based reward decisions. The changes made included the creation of a performance-reward committee, which had the resources and the power to make changes to reward decisions. Additionally, senior managers and HR members, on a yearly basis, were given information about pay decisions made the previous year. These data were aggregated by performance levels and key employee demographics as well. Castilla's findings suggest that, in doing so, the company was able to reduce pay gaps (2015). Castilla's research provides a key example of how modifications to such reward allocation systems based on performance evaluations can help reduce gender disparities (2008, 2015). This not only shows how rewards are allocated based on evaluations, but how the amount of inequality can be decreased based on how performance evaluations are used to allocate rewards.

4.2.4 Potential Lever: Clarity in Reward Allocation Criteria

A relevant factor in gender inequality in reward allocation is the ambiguity of processes that are used to allocate rewards. Ambiguous evaluation instructions and/or reward allocation criteria allow for more opportunities for gender bias and discrimination because gender stereotypes can be used to fill gaps in knowledge (Correll, 2017). As a result, men and women are rated and rewarded differently, especially in contexts rife with ambiguity. This issue of ambiguity can compound when managers do not have clear instruction on how to weigh and integrate information (Heilman, Caleo, & Manzi, 2024). When making promotion decisions, managers have a myriad of performance

ratings and information at their disposal to complete the decision-making process, but are left with ambiguity and flexibility regarding what to do with the data (Heilman, Caleo, & Manzi, 2024).

Reducing ambiguity in reward allocation processes is therefore an opportunity to decrease gender inequality in the workplace as it minimizes the reliance on gender stereotypes about ideal workers and beliefs about gender-typed work to fill gaps in knowledge. A process for allocating rewards that is ambiguous in its instructions allows for managers to rely on their personal criteria and beliefs for making decisions on how to assign rewards. These criteria can be informed by gender stereotypes of workers, and ideas of certain occupations based on how that occupation is gender-typed. Therefore, even when a performance evaluation has accurately captured employee performance and minimized or even eliminated manager bias in the actual performance evaluation, bias in the allocation of rewards can be introduced if there is ambiguity in reward allocation criteria. This could theoretically create a reward allocation environment with larger gender inequality even when bias and inequality in evaluations has been addressed. A process for allocating rewards with clear criteria eliminates the reliance of gender stereotypes and beliefs about gender-typed occupations in making decisions on how to assign rewards. This is the case if the clear criteria are based specifically on employees' merit. **Figure 12** depicts the hypothesized process through which gender inequality in reward allocation is influenced by clarity in reward allocation criteria. However, this process is yet to be empirically tested.

4.2.5 Addressing Gaps in the Literature

This study adds to the literature in two main areas. First, the study of employer decision making has focused predominantly on early stages of employer decision making (i.e., hiring stages), creating a need for a stronger understanding of employer decision making in later stages, such as compensation and promotion decisions (Rivera, 2020). In addressing bonus allocations and promotions, this study builds on literature on how employers allocate rewards, and of interventions to decrease gender inequality in how rewards are allocated. Second, this study addresses a current question posed by the existing literature on gender stereotypes and gender typed work, performance

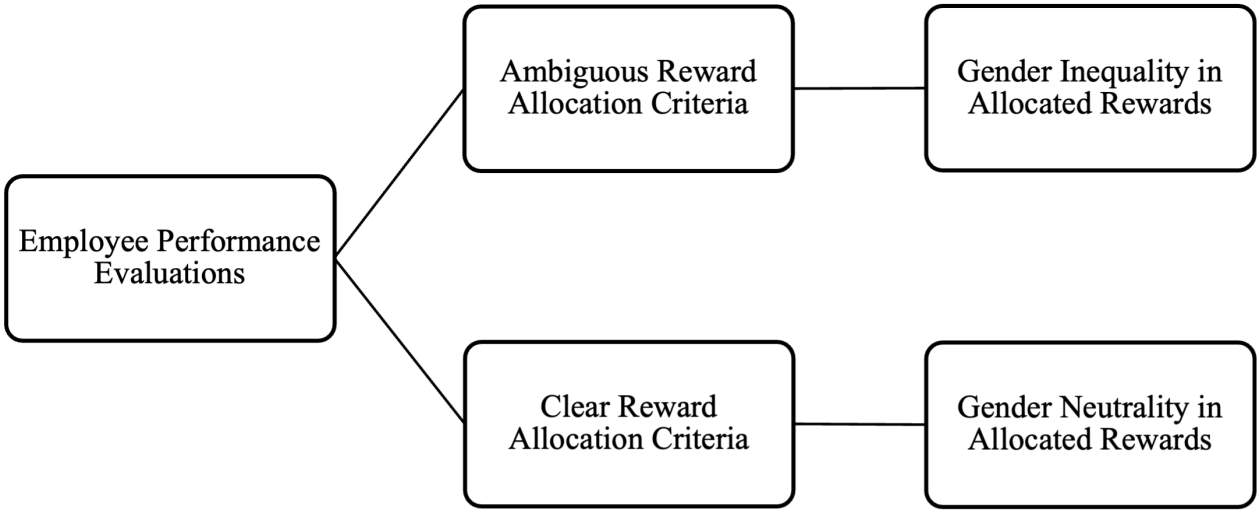


Figure 12. Ambiguous vs. Clear Reward Allocation Criteria
Note: This figure illustrates the hypothesized process through which gender inequality in reward allocation is influenced by clarity in reward allocation criteria.

evaluations, and reward allocations: can increasing clarity in reward allocation criteria reduce gender inequality? Given prior research showing that gender disparities in rewards far exceed those in performance evaluations (Joshi, Son, & Roh, 2015), this study presents an opportunity to extend research on gender inequality in the workplace with meaningful implications for theory and practice.

4.3 Research Question and Hypotheses

4.3.1 Research Question

How does gender inequality in the allocation of workplace rewards, such as bonuses and promotions, differ between conditions with clear criteria and ambiguous criteria for reward allocation?

4.3.2 Hypotheses

1. Looking at bonus allocations:

   (a) The average amount in bonuses allocated to women will be higher in the clear condition than in the ambiguous condition.

(b) In the ambiguous condition, the average amount in bonuses allocated to women will be lower than the average amount allocated to men.

(c) In the clear condition, the average amount in bonuses allocated to women will not be statistically different than the average amount allocated to men.

2. Looking at promotions:

(a) The probability of selecting a woman for promotion will be higher in the clear condition than in the ambiguous condition.

(b) In the ambiguous condition, the proportion of women selected for promotion will be less than the proportion of employees signaled to be women.

(c) In the clear condition, the proportion of women selected for promotion will not be statistically different than the proportion of employees signaled to be women.

4.4 Data and Methods

4.4.1 Design

This study utilizes a between-subjects experimental design to investigate gender inequality in reward allocation as a result of the clarity of reward allocation criteria. The main independent variables in the study include: (1) the reward allocation criteria condition that the participant is assigned to and (2) the signals for the gender and race of the employee whose performance evaluation is being viewed.

The first main manipulated variable is the reward allocation criteria condition that the participant was assigned to. In the **ambiguous condition**, participants were asked to review the performance evaluations of different employees. These performance evaluations consisted of ratings on various job-related categories along with written comments for each rating. Written comments in performance evaluations often differ in significant ways depending on the gender of the employee being evaluated, and the language is often valued differently depending on the gender of the employee

(Biernat, Tocci, & Williams, 2011; Correll, Weisshaar, Wynn, et al., 2020). To account for this, written comments were created to match the quantitative ratings and were randomly assigned to an employee name. After the participant was done reviewing the performance evaluations for five employees, the participant was asked to allocate $23,000[9] in bonuses. They were also asked to choose one employee to promote. No further instructions were provided. In the **clear condition**, participants reviewed performance evaluations for five employees. The participant was then asked to review the recommended bonus allocation for each employee. These recommended bonus allocations were based on the averages of the ratings across the categories on the performance evaluations. The average rating for each employee was provided to participants as well in this condition. After reviewing these recommendations, participants allocated $23,000 in bonuses. Participants were also asked to choose an employee to promote after being presented with a promotion recommendation, which was based on the employee with the highest average rating across the categories on the performance evaluations.

The second manipulated variable in this survey experiment are the signals for gender and race of the job candidate. Though gender is the primary focus of the study, both White and Asian American racial identities are signaled in the study, with two of the names (of men) signaling Asian American identity to more closely resemble the demographic composition of the software engineer occupation. According to the U.S. Bureau of Labor Statistics, women made up 19.4% of software developers in 2020 (Labor Statistics, 2022b). Furthermore, the U.S. Census Bureau's 2011 American Community Survey reported that 30.1% of software developers were Asian and 59.1% were non-Hispanic White (Landivar, 2013). In an attempt to mirror the occupation's demographic composition, the race and gender signals for the employees shown to survey participants were as follows: two White men, two Asian American men, and 1 White woman. As done by previous researchers (Pedulla, 2016; Quadlin, 2018), job candidates were signaled to be either a man or a woman using their names. The names were selected using pretested names that were validated for

[9]Indeed.com reports that the average yearly bonus for a software engineer as of February 2025 is $5,000 (Indeed.com, 2025). $23,000 was selected as a reasonable amount that five employees, combined, would receive.

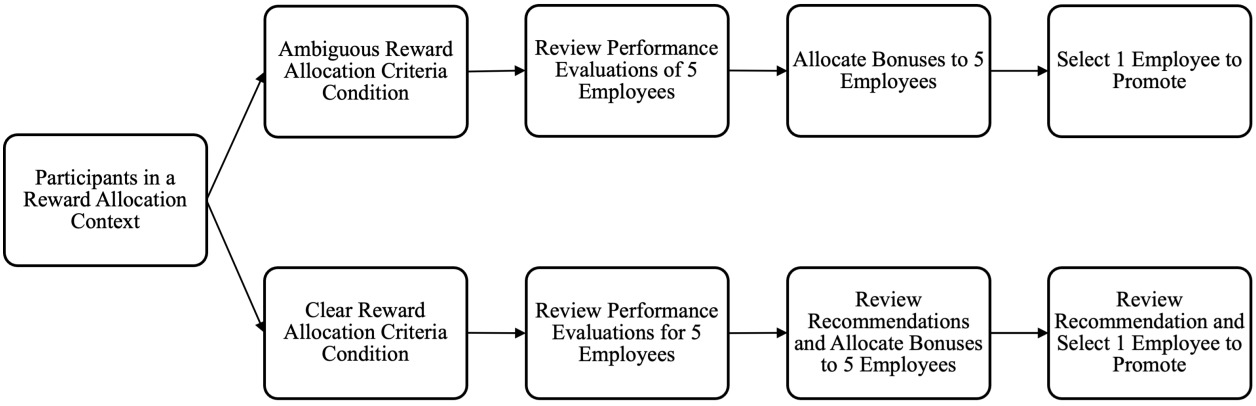


Figure 13. Experimental Design Comparing the Effects of Clear vs. Ambiguous Reward Allocation Criteria on Gender Inequality in a Workplace Context
Note: This figure illustrates the study's experimental design and outlines the data collection process from participants' perspective based on their treatment assignment.

their ability to signal the intended ethnicity (Crabtree, Kim, Gaddis, et al., 2023). It is worth noting that names additionally signal citizenship and socioeconomic status (i.e., income and education) (Crabtree, Kim, Gaddis, et al., 2023), so I carefully selected names (from Crabtree et al.'s validated names) for this study that minimized variation in perceived citizenship and socioeconomic status.

There are two main dependent variables of interest in the survey experiment. The first outcome is who is selected for promotion: either an employee signaled to be a woman is selected or an employee signaled to be a man is selected. The second outcome of interest is the amount of money that is allocated (as a bonus) to employees signaled to be men and the amount of money that is allocated (as a bonus) to employees signaled to be women. The design of this study is shown in **Figure 13**.

4.4.2 Reward Allocation Context: Software Engineers

Gender (and race) are social constructs that are context-specific (Park & Oh, 2025). Social scientists have documented how stereotypes and bias affect employees of different genders (and racial groups) differently depending on the context of the workplace. Therefore, I carefully selected

a context (i.e., an occupation) for reward allocation. Participants engaged in employee reward allocation for employees who work as software engineers. More generally, research has shown that the U.S. technology sector tends to hire and retain White and Asian men at disproportionately high rates, while women and other racial minorities remain underrepresented and significantly segregated within the tech workforce (Han & Tomaskovic-Devey, 2025). This makes the technology sector an area of research focus for sociologists interested in the study of gender and racial discrimination, inequality, and power (Han & Tomaskovic-Devey, 2025).

The occupation of software engineers was chosen for this study due to its gender segregation, with software engineer positions being predominantly held by men. Data from the U.S. Bureau of Labor Statistics indicates that 19.4% of software developers[10] in 2020 were women (Labor Statistics, 2022b). Researchers have found evidence for a preference for male applicants in occupations with more men than women (Park & Oh, 2025). Not only are women less likely to be hired, but researchers have also found evidence that, in jobs that are numerically overrepresented by men, women are evaluated and rewarded more negatively because these positions are associated with men (Heilman, Caleo, & Manzi, 2024).

The employees evaluated in the survey experiment were software engineers, and survey participants were asked to choose an employee to promote to the position of senior software engineer. This promotion to a leadership role was expected to activate gender bias as upper-level management roles are male gender-typed (Heilman, Caleo, & Manzi, 2024). Furthermore, research has indicated that high-achieving women in STEM fields, where they are underrepresented and often stereotyped as low-performing, are more likely to face penalties in hiring (Quadlin, 2018).

Software engineer was selected as the position for several reasons beyond the occupation's gender segregation and it being a male gender-typed occupation: it is lucrative (and thus presents an area with potentially large economic differences), it is an occupation with a growing number of opportunities (therefore it will have continued relevance), and it is an occupation with many

[10]The U.S. Bureau of Labor Statistics reports data for software developers, which is a title used interchangeably with software engineers on most occasions, with some slight differences between different organizations.

employees (and thus findings speak directly to a large group of employees). According to data from the U.S. Bureau of Labor Statistics, software developers in the United States had a median annual wage of $132,270 in 2023 (Employment Projections Program, 2024). Additionally, in 2023, there were over 1.692 million software developers (Employment Projections Program, 2024). In terms of job outlook, the U.S. Bureau of Labor Statistics predicts 17.9% growth from 2023 to 2033 for this occupation, which is much faster than the average job growth (Employment Projections Program, 2024). These indicators suggest that findings can have immediate ramifications for a large workforce, with further research needing to be done in other jobs and industries to test generalizability.

4.4.3 Participants

The sample for this study was recruited through Prolific ("Prolific", 2014). Existing research indicates that participants sourced from Prolific and CloudResearch (in comparison to those from MTurk, Qualtrics, or undergraduate student pools) demonstrate higher rates of attention check compliance, provide more thoughtful responses, adhere more closely to instructions, recall previously presented information more accurately, possess unique IP addresses and geolocations more frequently, and engage more carefully with survey materials (Douglas, Ewell, & Brauer, 2023). Moreover, the evidence suggests that the cost per high-quality respondent, defined as those meeting established data quality criteria, is lower on Prolific than on CloudResearch, MTurk, and Qualtrics (Douglas, Ewell, & Brauer, 2023). Prolific is particularly well-suited for online data collection as it enables researchers to filter participants based on their prior study participation, thereby mitigating concerns related to non-naivete by excluding individuals who have completed an extensive number of surveys (Prolific, 2024).

The target population for this study consisted of individuals who were at least 25 years old at the time of survey completion, resided in the United States, and (critically for the study's external validity) had prior management experience. To qualify, participants must have answered "Yes" to the following question: "Do you have any experience being in a management position?" To ensure data quality, eligible participants must have previously completed a minimum of 10 but no more than 200

surveys, maintained a prior submission approval rating of at least 95%, and not complete the survey using a mobile device or tablet. Additionally, following Prolific's protocol, survey submissions from participants who completed the study exceptionally quickly, defined as three standard deviations below the mean completion time, were excluded. This exclusion criterion was applied separately for each study condition (i.e., clear condition or ambiguous condition), resulting in the removal of 0 participants. Finally, participants were required to correctly answer two attention check questions to be included in the study. In accordance with Prolific's guidelines, participants were given two opportunities to respond correctly to each attention check question; those who failed both attempts were excluded from the sample.

Data collection occurred in February of 2025 with a sample of participants with management experience. **Table 16** shows participants' demographic characteristics. The demographic characteristics are presented first for the entire sample, and they are then disaggregated based on the condition to which participants were assigned. A total of 1,626 participants completed the study (810 in the ambiguous condition and 816 in the clear condition), resulting in 1,626 promotion decisions and 8,130 bonus allocations. Respondents' median time to complete the survey was nine minutes and 18 seconds (25th percentile: six minutes and 21.25 seconds; 75th percentile: 13 minutes and 23 seconds). In the ambiguous condition, the median completion time was nine minutes and nine seconds, while in the clear condition, the median time was nine minutes and 26.5 seconds. For the entire sample, the mean age was 42.80.

In terms of education completed, 39.42% of participants indicated having a bachelor's degree, 31.80% a graduate degree, 13.41% had some college credit with no degree, 9.35% had an associate's degree, 5.90% had a high school diploma or equivalent, and 0.12% had less than a high school diploma. When asked about political affiliation, 21.65% of participants identified as Democrats (with an additional 11.87% indicating leaning toward the Democratic Party), 21.34% identified as Independents, and 33.52% identified as Republicans (along with an additional 10.15% indicating leaning toward the Republican Party). 55.23% of participants identified as women, while 44.22% identified as men. In response to the question, "Are you of Hispanic, Latino, or Spanish origin?",

Table 16. Participant Demographic Characteristics

Descriptive Statistic	All Participants	Ambiguous Condition	Clear Condition
Sample Size	1626	810	816
Mean Age	42.80	42.77	42.83
Educational Attainment			
Less than high school diploma or equivalent	0.12%	0.00%	0.25%
High school diploma or equivalent	5.90%	6.30%	5.51%
Some college credit, no degree	13.41%	13.83%	12.99%
Associate's degree	9.35%	10.49%	8.21%
Bachelor's degree	39.42%	38.27%	40.56%
Graduate degree	31.80%	31.11%	32.48%
Political Affiliation			
Republican	33.52%	32.35%	34.68%
Lean Republican	10.15%	11.48%	8.82%
Independent	21.34%	21.23%	21.45%
Lean Democrat	11.87%	11.48%	12.25%
Democrat	21.65%	21.85%	21.45%
A political affiliation not listed	1.48%	1.60%	1.35%
Gender			
Man	44.22%	45.56%	42.89%
Woman	55.23%	53.83%	56.62%
A gender identity not listed	0.55%	0.62%	0.49%
Hispanic, Latino, or Spanish			
Hispanic, Latino, or Spanish	12.30%	13.83%	10.78%
Not Hispanic, Latino, or Spanish	87.70%	86.17%	89.22%
Race			
White	72.57%	72.35%	72.79%
Black or African American	16.61%	16.30%	16.91%
Asian or Asian American	4.43%	3.83%	5.02%
American Indian or Alaska Native	1.23%	1.85%	0.61%
Native Hawaiian or Other Pacific Islander	0.31%	0.49%	0.12%
Middle Eastern, Arab American, or North African	0.37%	0.37%	0.37%
Multiracial	3.63%	3.83%	3.43%
A race not listed	0.86%	0.99%	0.74%

Note: To assess the success of random assignment, I tested for differences in participant demographic characteristics across experimental conditions (i.e., ambiguous and clear conditions). I conducted an ANOVA for age and chi-squared tests for categorical variables including education, political affiliation, gender, ethnicity, and race. In addition, I ran logistic regressions with robust standard errors for each binary demographic variable (e.g., White as the outcome and the clear condition as the independent variable). None of the tests yielded statistically significant differences at the $p < .05$ level, suggesting successful random assignment.

87.70% of respondents answered no, while 12.30% answered yes. Regarding racial identity, the majority of respondents self-identified as White (72.57%), followed by Black or African American (16.61%) and then Asian or Asian American (4.43%). The remaining demographic characteristics of participants, disaggregated by study condition, are presented in **Table 16**.

4.4.4 Survey Instrument and Data Collection Procedure

The survey was designed and administered using Qualtrics' survey design software ("Qualtrics", 2005) and distributed to participants recruited through Prolific. From the participants' perspective, data collection for this survey experiment followed a structured sequence of steps. First, participants provided informed consent before proceeding with the study. They then completed initial screening questions to confirm their eligibility for participation. Once their eligibility was verified, participants were informed that they would be reviewing performance evaluations of software engineers and making decisions about reward allocations for these employees. Participants were also given a brief job description for a software engineer. At this stage, they also completed attention checks to ensure data quality. Participants were then randomly assigned to one of two reward allocation conditions: the ambiguous condition or the clear condition.

In the ambiguous condition, participants reviewed the performance evaluations of five software engineers. These evaluations included numerical ratings from one (the lowest rating) to five (the highest rating) for five different categories along with written comments for each rating. The five different categories were quality of work, quantity of work, job skills, communication and teamwork, and leadership. The evaluations also displayed the employees' names. Among the five employees, one was signaled to be a White woman, while the remaining four were signaled to be men (two White and two Asian American). After reviewing the evaluations, participants were instructed to allocate a total of $23,000 in bonuses among the employees and to select one employee for promotion. No additional guidance was provided regarding how to make these decisions.

In the clear condition, participants also reviewed performance evaluations for five employees. However, in this condition, they were additionally presented with a recommended bonus allocation

for each employee, calculated based on employees' average ratings across the performance evaluation categories. The average rating for each employee was also explicitly provided. Participants were informed that employees with higher average ratings were recommended to receive larger bonuses. Similarly, when selecting an employee for promotion, participants were shown a promotion recommendation, which was based on the employee with the highest average rating across all evaluation categories.

After making reward allocation decisions, participants answered a series of demographic questions, including questions on race and ethnicity, gender, political affiliation, and educational attainment. The full survey instrument, including all questions and materials presented to participants, is available in **Appendix E: Survey Instrument for Gender Inequality in Employee Reward Allocation Study**.

4.4.5 Statistical Methods

4.4.5.1 Gender Differences

Both the study design and data analysis plan were pre-registered with the Open Science Foundation. All data cleaning, statistical analyses, model estimations, and data visualizations were conducted using R statistical software (Team, 2024). For analyses involving a binary outcome variable, statistical models employed linear regression as prior research (Gomila, 2021) has demonstrated that, in many cases, linear regression provides a more effective approach than logistic regression for estimating causal effects of treatments on dichotomous outcomes. This is because, as Gomila (2021) argues, linear regression offers interpretable coefficients in terms of probability changes (e.g., $\beta_1 = 0.02$ can be interpreted as the treatment causing a 2 percentage point increase in the probability of observing $Y_i = 1$) and yields unbiased estimates of treatment effects when applied to binary dependent variables.

To examine gender differences in bonus allocations, a variety of models were employed to address each of the study's hypotheses. The first estimated model is an ordinary least squares

regression model with heteroskedasticity-robust standard errors with the amount in bonuses allocated to employees signaled to be women as the outcome variable. The model included an indicator variable for the clear condition, with the ambiguous condition serving as the reference category. The model is then extended to include additional indicator variables for participants' race, gender, educational attainment, and political affiliation. These additional indicator variables are represented in the model as a vector variable ($ParticipantCharacteristics_i$). The full first model incorporated interaction terms between participants' demographic characteristics and the clear condition indicator variable to assess potential heterogeneity in reward allocation decisions based on participant characteristics. This model is shown below:

$$\begin{aligned} BonusesforWomen_i = \beta_0 + \beta_1 \text{Clear}_i + \beta_2 \text{ParticipantCharacteristics}_i \\ + \beta_3 (\text{Clear}_i \times \text{ParticipantCharacteristics}_i) + \epsilon_i \end{aligned} \tag{12}$$

The second model is an ordinary least squares regression model with cluster-robust standard errors (robust standard errors clustered by participant) and the amount allocated as a bonus (regardless of the employee's gender) as the outcome. The unit of analysis is a single bonus allocation (with each participant making five bonus allocations, so each participant is included in the model five times). An indicator variable for whether the employee was signaled to be a woman was included (with men as the reference group). An indicator variable for the clear condition, with the ambiguous condition serving as the reference category, is also included. Lastly, an interaction term between whether the employee was signaled to be a woman and the study condition was included. This model was first fitted for all participants, then only women, and lastly only men. The second model is as follows:

$$\begin{aligned} BonusAllocation_{ij} = \beta_0 + \beta_1 \text{WomanEmployee}_{ij} + \beta_2 \text{Clear}_j \\ + \beta_3 (\text{WomanEmployee}_{ij} \times \text{Clear}_j) + \epsilon_{ij} \end{aligned} \tag{13}$$

To examine gender differences in promotions, an ordinary least squares regression model with heteroskedasticity-robust standard errors was estimated to examine whether a woman was selected

for promotion, which was a variable measured at the participant level since each participant made only one promotion decision. The model included an indicator variable for the clear condition, with the ambiguous condition serving as the reference group. The model was then extended to include additional indicator variables for participants' race, gender, educational attainment, and political affiliation (these additional indicator variables are once again represented as a vector variable, $ParticipantCharacteristics_i$). The full model incorporated interaction terms between participants' demographic characteristics and the clear condition indicator variable to explore potential heterogeneity in promotion decisions. As a robustness check, a logistic regression model was also estimated with promotion decisions as the outcome variable. These two models are shown below:

$$\begin{aligned} WomanPromoted_i = \beta_0 + \beta_1 \text{Clear}_i + \beta_2 \text{ParticipantCharacteristics}_i \\ + \beta_3(\text{Clear}_i \times \text{ParticipantCharacteristics}_i) + \epsilon_i \end{aligned} \tag{14}$$

$$\begin{aligned} \text{logit}(P(WomanPromoted_i = 1)) = \beta_0 + \beta_1 \text{Clear}_i + \beta_2 \text{ParticipantCharacteristics}_i \\ + \beta_3(\text{Clear}_i \times \text{ParticipantCharacteristics}_i) \end{aligned} \tag{15}$$

To further test gender differences in promotions, I used a one-tailed, one-sample proportion test to compare the observed proportion of women selected for promotion in the **ambiguous condition** to the expected proportion of 0.2 (since only one of the five candidates was signaled to be a woman). The test statistic for a one-sample proportion test is as follows:

$$Z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}} \tag{16}$$

where $\hat{p}$ is the observed proportion of women selected, p_0 (which equals 0.2) is the expected proportion under the null hypothesis, and n is the total number of promotion decisions made in the ambiguous condition. Lastly, I used a two-tailed one-sample proportion test to compare the observed

proportion of women selected for promotion in the **clear condition** to the expected proportion of 0.2 (since only one of the five candidates was signaled to be a woman in the clear condition as well). The test-statistic is the same as above; however, this last test differs in that it is two-tailed (so, the p-value is multiplied by two to account for both tails of the distribution) and for participants in the clear condition.

4.4.5.2 Racial Differences

The last set of statistical methods used for this study test for racial differences in men's outcomes. To examine differences in bonus allocations to men based on different types of reward allocation criteria, I began with an ordinary least squares regression model using heteroskedasticity-robust standard errors, where the outcome variable is the amount in bonuses allocated to employees signaled to be White men. The key predictor is an indicator variable for the clear condition, with the ambiguous condition as the reference category. I then extend the model by incorporating additional indicator variables for participants' race, gender, educational attainment, and political affiliation, represented as a vector variable ($ParticipantCharacteristics_i$) in the model below. To examine potential heterogeneity in reward allocation decisions based on the interaction between participant characteristics and the study condition, I also included interaction terms between participants' demographic characteristics and the clear condition indicator variable. The model is presented below:

$$\begin{aligned} BonusesforWhiteMen_i = \beta_0 + \beta_1 \text{Clear}_i + \beta_2 \text{ParticipantCharacteristics}_i \\ + \beta_3 (\text{Clear}_i \times \text{ParticipantCharacteristics}_i) + \epsilon_i \end{aligned} \tag{17}$$

As shown below, this same modeling approach was used for employees signaled to be Asian American men:

$$\begin{aligned} Bonuses for Asian American Men_i = \beta_0 + \beta_1 \text{Clear}_i + \beta_2 \text{ParticipantCharacteristics}_i \\ + \beta_3 (\text{Clear}_i \times \text{ParticipantCharacteristics}_i) + \epsilon_i \end{aligned} \tag{18}$$

I then looked at whether, on average, bonus allocations to employees signaled to be Asian American men or White men differed from bonus allocations to employees signaled to be (White) women. To do this, I estimated an ordinary least squares regression model with cluster-robust standard errors (robust standard errors clustered by participant) and the amount allocated as a bonus as the outcome. The unit of analysis is a single bonus allocation (participants each made five bonus allocations). An indicator variable for whether the employee was signaled to be a White man and another indicator variable for whether the employee was signaled to be an Asian American man were included (with White women as the reference group). An indicator variable for the clear condition, with the ambiguous condition serving as the reference category, is also included. Lastly, interaction terms between employee characteristics and study condition were included. This model was first fitted for all participants, then only women, and lastly only men. This model is as follows:

$$\begin{aligned} Bonus Allocation_{ij} = \beta_0 + \beta_1 \text{WhiteManEmployee}_{ij} + \beta_2 \text{AsianAmericanManEmployee}_{ij} \\ + \beta_3 \text{Clear}_j + \beta_4 (\text{WhiteManEmployee}_{ij} \times \text{Clear}_j) \\ + \beta_5 (\text{AsianAmericanManEmployee}_{ij} \times \text{Clear}_j) + \epsilon_{ij} \end{aligned} \tag{19}$$

To examine racial differences in promotions, I followed a similar approach as done for examining gender differences in promotions. I first estimated an ordinary least squares regression model with heteroskedasticity-robust standard errors with whether a White man was selected for promotion as the outcome. Since each participant made only one promotion decision, this outcome was measured at the participant level. The model included an indicator variable for the clear condition, with the ambiguous condition as the reference group. I then extended the model

by adding indicator variables for participants' race, gender, educational attainment, and political affiliation, represented collectively as a vector variable ($ParticipantCharacteristics_i$). The full model also incorporated interaction terms between participants' demographic characteristics and the clear condition indicator to examine potential heterogeneity in promotion decisions. As a robustness check, I estimated a logistic regression model with promotion decisions as the outcome variable. Both models are presented below:

$$\begin{aligned} WhiteManPromoted_i = \beta_0 + \beta_1 \text{Clear}_i + \beta_2 \text{ParticipantCharacteristics}_i \\ + \beta_3(\text{Clear}_i \times \text{ParticipantCharacteristics}_i) + \epsilon_i \end{aligned} \tag{20}$$

$$\begin{aligned} \text{logit}(P(WhiteManPromoted_i = 1)) = \beta_0 + \beta_1 \text{Clear}_i + \beta_2 \text{ParticipantCharacteristics}_i \\ + \beta_3(\text{Clear}_i \times \text{ParticipantCharacteristics}_i) \end{aligned} \tag{21}$$

I then repeated the modeling process for employees signaled to be Asian American men:

$$\begin{aligned} AsianAmericanManPromoted_i = \beta_0 + \beta_1 \text{Clear}_i + \beta_2 \text{ParticipantCharacteristics}_i \\ + \beta_3(\text{Clear}_i \times \text{ParticipantCharacteristics}_i) + \epsilon_i \end{aligned} \tag{22}$$

$$\begin{aligned} \text{logit}(P(AsianAmericanManPromoted_i = 1)) = \beta_0 + \beta_1 \text{Clear}_i + \beta_2 \text{ParticipantCharacteristics}_i \\ + \beta_3(\text{Clear}_i \times \text{ParticipantCharacteristics}_i) \end{aligned} \tag{23}$$

To assess whether promotion rates for employees signaled to be men differed by race from the expected rate of 0.4, I conducted two-tailed, one-sample proportion tests. First, I compared the observed proportion of White men or Asian American men selected for promotion in the **ambiguous condition** to the expected proportion of 0.4, given that two of the five candidates fell into these

Table 17. Differences in Reward Allocations

Employee Signal	Clear Condition Bonus	Ambiguous Condition Bonus	Clear Condition Promotion Rate	Ambiguous Condition Promotion Rate
Women	$4634.82	$4760.07	22.06%	22.22%
All Men	$4591.29	$4559.98	77.94%	77.78%
White Men	$4579.54	$4520.71	40.44%	39.26%
Asian American Men	$4603.05	$4599.25	37.50%	38.52%

Note: Observed average bonus allocations and promotion rates, disaggregated by study condition and employee signal.

categories. The test statistic for a one-sample proportion test is:

$$Z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}} \tag{24}$$

where $\hat{p}$ is the observed proportion of White men or Asian American men selected, p_0 (which equals 0.4) is the expected proportion under the null hypothesis, and n is the total number of promotion decisions in the ambiguous condition. I lastly repeated this analysis for the clear condition.

4.5 Results

4.5.1 Describing Differences in Reward Allocations

Table 17 shows the average bonus amount allocated to women and men in the clear condition versus the ambiguous condition. Bonus allocations to men are first shown for all men and then disaggregated into White men and Asian American men. If gender (and race) does not play a role in bonus allocations, we would expect the average bonus allocation to be $4,600 (or, more precisely, not statistically different from $4,600) across employee signals and conditions. We can see in **Table 17** that, after 8,130 bonus allocation decisions, bonus allocations were more similar in the clear condition than in the ambiguous condition, with tests for statistical significance to follow in **Section 4.5.2**. **Table 17** also shows that, across 1,626 promotion decisions, women were promoted at higher rates than expected (20% due to one in five employees signaled to be women) in both the clear

condition and the ambiguous condition, with tests for statistical significance to follow in **Section 4.5.3**.

4.5.2 Bonus Allocations

To test hypothesis 1a (the average amount in bonuses allocated to women will be higher in the clear condition than in the ambiguous condition), I first used **Model 1** in **Table 18**, which is an ordinary least squares regression model with heteroskedasticity-robust standard errors and the amount in bonuses allocated to employees signaled to be women as the outcome variable. I found insufficient evidence that the effect of clear reward allocation criteria on the average amount in bonuses allocated to women by people with management experience differs significantly from the effect of ambiguous reward allocation criteria ($t(1624) = -1.223$, $p = 0.221$). In other words, there is insufficient evidence that the average amount in bonuses allocated to women is significantly different with clear reward allocation criteria compared to ambiguous reward allocation criteria.

Models 2 and **3** in **Table 18** allowed me to then examine how bonus amounts allocated to employees signaled to be women in the ambiguous condition differ from bonus amounts allocated to employees signaled to be women in the clear condition after accounting for participant characteristics. **Model 2** adds participants' race, ethnicity, gender, educational attainment, and political affiliation, and suggests that (holding other variables constant) women, compared to men, allocate somewhat higher bonuses (marginal statistical significance) to employees signaled to be women ($\beta_{Woman} = 180.509$, $t(1613) = 1.773$, $p = 0.077$). This \$180.51 difference is equal to 3.924% of the average bonus amount for all employees (\$4,600).

Model 3 in **Table 18** adds interaction terms between participants' demographic characteristics and the clear condition indicator variable (of which only the interaction term for clear criteria and women is shown in **Table 18**; all other interaction terms are not statistically significant) to assess potential heterogeneity in reward allocation decisions in different conditions based on participant characteristics. It shows that this difference (of women, compared to men, allocating somewhat higher bonuses to employees signaled to be women) can be attributed specifically to the ambiguous

Table 18. Relationship between Bonuses Allocated to Women and Study Condition, with Controls for Participant Characteristics

	Model 1	Model 2	Model 3
Intercept	4760.071***	4612.349***	4512.301***
	(89.954)	(168.749)	(269.136)
Clear Condition	-125.249	-121.002	66.474
	(102.392)	(100.843)	(298.909)
Black / African American		112.647	278.119
		(137.876)	(254.148)
Asian / Asian American		-193.322	-127.077
		(193.594)	(389.668)
Hispanic, Latino, or Spanish origin		-74.194	72.194
		(168.264)	(269.365)
Woman		180.509+	313.432+
		(101.840)	(177.169)
Democrat or Lean Democrat		11.209	-64.495
		(110.410)	(190.208)
Independent		-34.717	-12.473
		(145.183)	(260.526)
Graduate degree (for example: MA, MS, MD, JD, PhD)		102.685	26.745
		(141.179)	(249.878)
Bachelor's degree (for example: BA, BS)		-57.135	-91.750
		(131.378)	(234.780)
Clear Condition * Woman			-250.460
			(202.539)
Num.Obs.	1626	1626	1626
R2	0.001	0.013	0.024
R2 Adj.	0.000	0.006	0.010
Log.Lik.	-14714.542	-14704.756	-14695.778
RMSE	2060.28	2047.91	2036.64
Std.Errors	Custom	Custom	Custom

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Ordinary least squares regression models with heteroskedasticity-robust standard errors in parentheses. Not all interaction terms in the model are shown on the table.

Table 19. Relationship between Bonus Allocations and Study Condition, Accounting for Employee Gender Signal

	All Participants	Women	Men
Intercept	4559.982***	4529.215***	4607.142***
	(22.487)	(30.722)	(30.923)
Is Employee Signaled to be a Woman?	200.089+	353.927*	-35.711
	(112.434)	(153.612)	(154.615)
Clear Condition	31.312	55.072	-6.768
	(25.602)	(35.052)	(35.674)
Is Employee Signaled to be a Woman in the Clear Condition?	-156.561	-275.359	33.840
	(128.009)	(175.258)	(178.370)
Num.Obs.	8130	4490	3595
R2	0.001	0.003	0.000
R2 Adj.	0.001	0.002	-0.001
AIC	145953.4	80604.5	64452.2
BIC	145988.4	80636.5	64483.2
RMSE	1913.46	1912.09	1889.03
Std.Errors	by: ProlificID	by: ProlificID	by: ProlificID

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Ordinary least squares regression models with cluster-robust standard errors in parentheses.

condition: women in the ambiguous reward allocation criteria condition, compared to men in the ambiguous reward allocation criteria condition, allocate somewhat higher bonuses (marginal statistical significance) to employees signaled to be women (β_{Woman} = 313.432, $t(1602) = 1.769$, $p = 0.077$). This $313.43 difference is equal to 6.824% of the average bonus amount for all employees ($4,600).

To test hypothesis 1b (in the ambiguous condition, the average amount in bonuses allocated to women will be lower than the average amount in bonuses allocated to men), I first estimated the

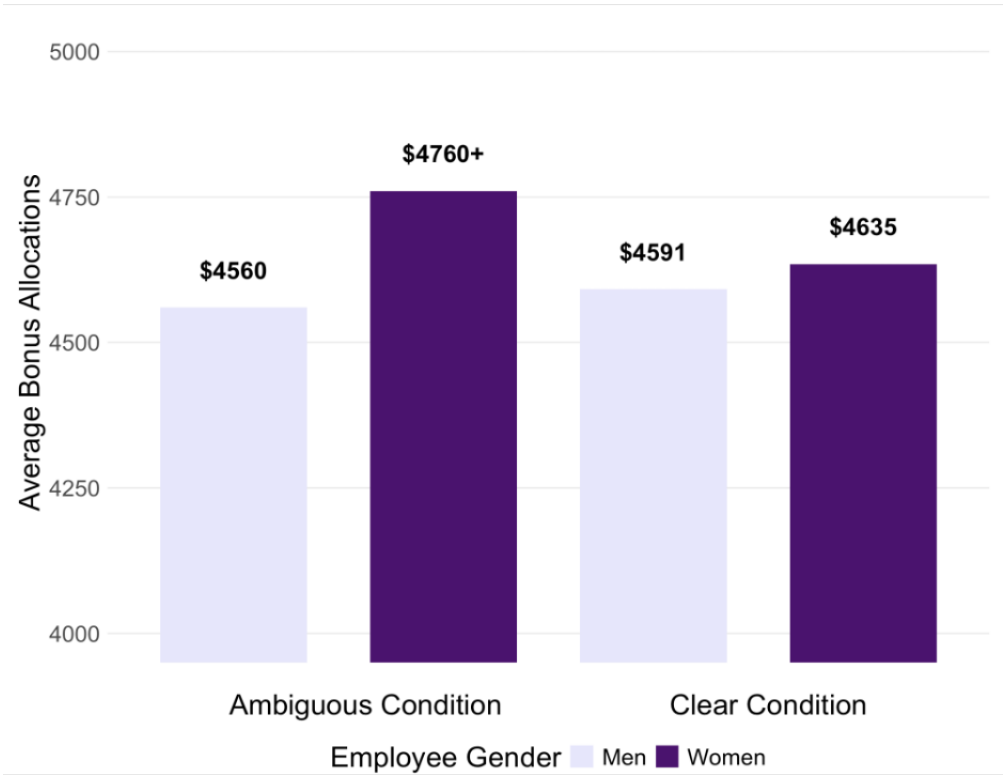


Figure 14. Bonus Allocations Disaggregated by Employee Gender and Condition
Note: $+\ p < 0.1 * p < .05$; $** p < .01$; $*** p < .001$. Symbols indicate the level of significance of the differences in the average bonus allocations based on the **All Participants** model in **Table 19**.

model named **All Participants** in **Table 19**. This model is an ordinary least squares regression model with cluster-robust standard errors (clustered by participant) and the amount allocated as a bonus (regardless of the employee's gender) as the outcome. The unit of analysis is a single bonus allocation (with each participant making five bonus allocations and included in the model five times). The model includes an indicator variable for whether the employee was signaled to be a woman (with men as the reference group) and an indicator variable for the clear condition, with the ambiguous condition serving as the reference category. Lastly, an interaction term between whether the employee was signaled to be a woman and the study condition was included.

Looking at the coefficient and statistical significance for whether the employee is signaled to be a woman in the **All Participants** model in **Table 19**, there is not enough evidence that, in the ambiguous condition, the average amount in bonuses allocated to women is lower than the average amount in bonuses allocated to men. In fact, there is some evidence for the opposite:

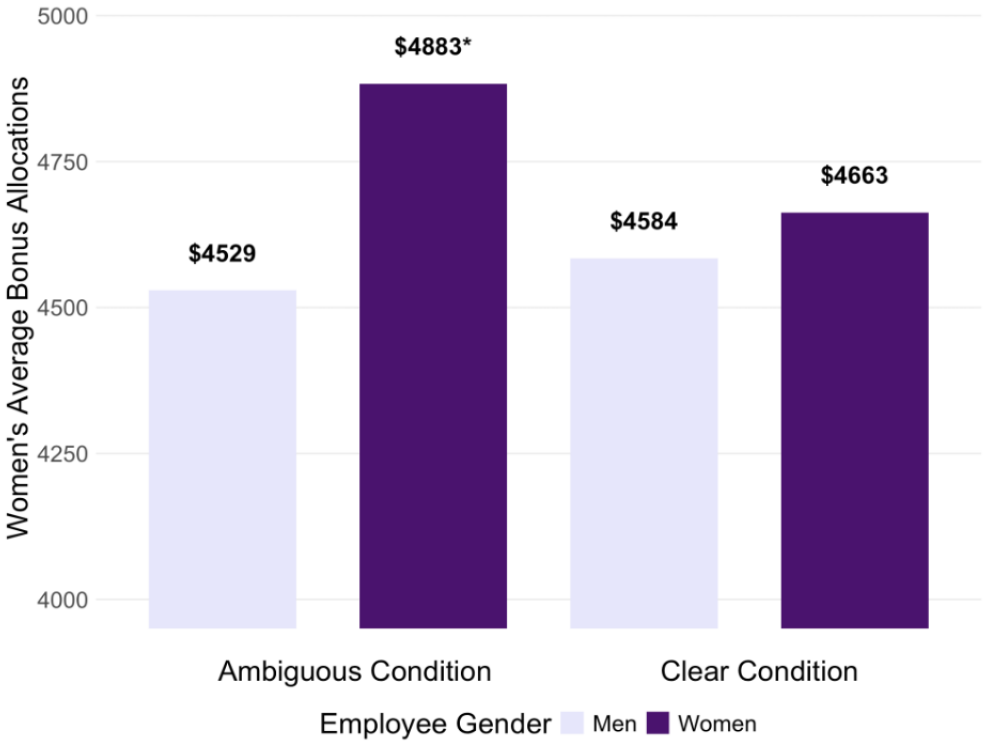


Figure 15. Women's Bonus Allocations Disaggregated by Employee Gender and Condition
Note: $+\ p < 0.1 * p < .05; ** p < .01; *** p < .001$. Symbols indicate the level of significance of the differences in women's average bonus allocation based on the **Women** model in **Table 19**.

in the ambiguous condition, the average amount in bonuses allocated to women is somewhat higher (marginal statistical significance) than the average amount in bonuses allocated to men ($\beta_{IsEmployeeSignaledtobeaWoman?} = 200.089, t(807) = 1.780, p = 0.076$). This $200.09 difference in the bonus allocation between employees signaled to be men and employees signaled to be women in the ambiguous condition is equal to 4.350% of the average bonus amount for all employees ($4,600) and is shown in **Figure 14**.

I additionally estimated the same model separately for women and men, as shown by the models called **Women** and **Men** in **Table 19**. In doing so, I was able to determine that the finding that, in the ambiguous condition, the average amount in bonuses allocated to employees signaled to be women is somewhat higher (marginal statistical significance) than the average amount in bonuses allocated to employees signaled to be men is attributable to women allocating employees signaled to be women significantly higher bonuses than to employees signaled to be men (for

the model named **Women**, $\beta_{IsEmployeeSignaledtobeaWoman?} = 353.927$, $t(433) = 2.304$, $p = 0.022$). This $353.93 difference in women's bonus allocations between employees signaled to be men and employees signaled to be women in the ambiguous condition is equal to 7.694% of the average bonus amount for all employees ($4,600) and is shown in **Figure 15**. When looking at men in the ambiguous condition (for the model named **Men**, $\beta_{IsEmployeeSignaledtobeaWoman?} = -35.711$, $t(368) = -0.2310$, $p = 0.818$), there is insufficient evidence that the average amount in bonuses allocated to employees signaled to be women is significantly different than the average amount in bonuses allocated to employees signaled to be men.

To test hypothesis 1c (in the clear condition, the average amount in bonuses allocated to women will not be statistically different than the average amount allocated to men), I fit two ordinary least squares regression models with cluster-robust standard errors (clustered by participant as each participant makes five bonus allocations) and the amount allocated as a bonus (regardless of the employee's gender) as the outcome. The models include an indicator variable for whether the employee was signaled to be a woman (with men as the reference group). The first model is for the subsection of participants in the ambiguous condition and the second model is for participants in the clear condition. Looking at the model named **Participants in Clear Condition** in **Table 20**, the findings support hypothesis 1c: in the clear condition, the average amount in bonuses allocated to employees signaled to be women by participants with management experience is not statistically different than the average amount allocated to men (for the model named **Participants in Clear Condition**, $\beta_{IsEmployeeSignaledtobeaWoman?} = 43.528$, $t(815) = 0.7115$, $p = 0.477$).

4.5.3 Promotions

To test hypothesis 2a (the probability of selecting a woman for promotion will be higher in the clear condition than in the ambiguous condition), I first ran **LPM/OLS Model 1** in **Table 21**, which is an ordinary least squares regression model for the following outcome: whether a woman was selected for promotion. This model includes an indicator variable for the clear condition (with the ambiguous condition serving as the reference group). I found insufficient evidence that the effect

Table 20. Relationship between Bonus Allocations and Employee Gender Signal, Disaggregated by Study Condition

	Participants in Ambiguous Condition	Participants in Clear Condition
Intercept	4559.982***	4591.294***
	(22.487)	(12.235)
Is Employee Signaled to be a Woman?	200.089+	43.528
	(112.434)	(61.177)
Num.Obs.	4050	4080
R2	0.001	0.000
R2 Adj.	0.001	0.000
AIC	74178.9	70920.9
BIC	74197.8	70939.9
RMSE	2294.36	1438.88
Std.Errors	by: ProlificID	by: ProlificID

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Ordinary least squares regression models with cluster-robust standard errors in parentheses.

Table 21. Relationship between Promotion of Women and Study Condition, with Controls for Participant Characteristics

	LPM/OLS Model 1	LPM/OLS Model 2	LPM/OLS Model 3
Intercept	0.222***	0.199***	0.173***
	(0.015)	(0.028)	(0.037)
Clear Condition	-0.002	-0.004	0.048
	(0.021)	(0.021)	(0.053)
Black / African American		-0.026	0.018
		(0.027)	(0.041)
Asian / Asian American		-0.053	0.031
		(0.047)	(0.080)
Hispanic, Latino, or Spanish origin		-0.030	-0.002
		(0.031)	(0.044)
Woman		0.044*	0.056+
		(0.021)	(0.029)
Democrat or Lean Democrat		0.017	0.034
		(0.024)	(0.034)
Independent		0.005	0.033
		(0.028)	(0.041)
Graduate degree (for example: MA, MS, MD, JD, PhD)		0.031	0.017
		(0.028)	(0.039)
Bachelor's degree (for example: BA, BS)		-0.009	-0.021
		(0.025)	(0.036)
Clear Condition * Woman			-0.025
			(0.041)
Num.Obs.	1626	1626	1626
R2	0.000	0.010	0.016
R2 Adj.	-0.001	0.003	0.002
AIC	1761.8	1767.1	1779.8
BIC	1778.0	1842.6	1914.6
RMSE	0.42	0.41	0.41

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Linear probability models with heteroskedasticity-robust standard errors in parentheses. All of the interaction terms in the model are not shown on the table.

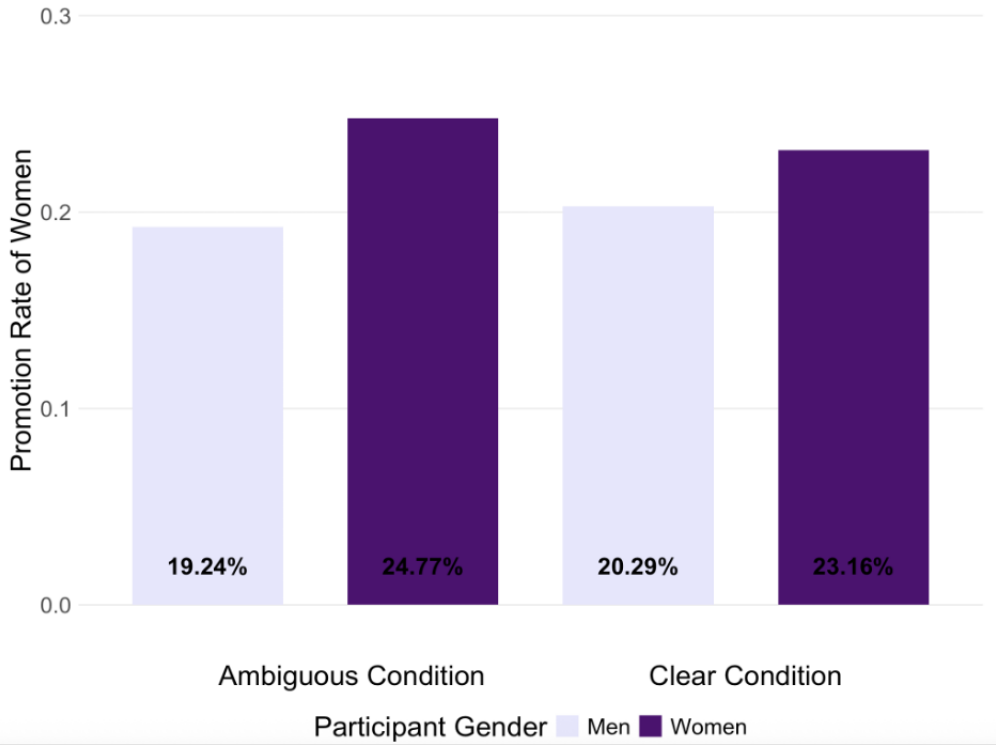


Figure 16. Promotion Rate of Women in Each Condition, Disaggregated by Participant Gender
Note: The observed promotion rates are shown. Since these observed promotion rates are disaggregated only by study condition and participant gender, they do not exactly match the predicted values of any of the models in **Table 21**.

of clear reward allocation criteria on the probability of selecting a woman for promotion by people with management experience is significantly different than the effect of ambiguous reward allocation criteria ($t(1624) = -0.079$, $p = 0.937$). In other words, there is insufficient evidence that people with management experience making decisions with clear reward allocation criteria have a higher probability of selecting a woman for promotion than people with management experience making decisions with ambiguous reward allocation criteria.

To extend the prior analysis, **LPM/OLS Model 2** and **LPM/OLS Model 3** in **Table 21** allowed me to examine how the probability of selecting a woman for promotion in the ambiguous condition differs from the probability of selecting a woman for promotion in the clear condition after accounting for participant characteristics. **LPM/OLS Model 2** adds participants' race, ethnicity, gender, educational attainment, and political affiliation. Similar to findings for bonus allocations, this model suggests that women (holding other characteristics constant) select employees signaled

to be women for promotion at a higher probability than men ($\beta_{Woman} = 0.044$, $t(1613) = 2.120$, $p = 0.034$). This 4.4 percentage point difference in the probability of women, compared to men, selecting a woman for promotion is substantively large, as it is equal to 22% of the expected probability of 20% (since one in five candidates is signaled to be a woman).

LPM/OLS Model 3 in **Table 21** adds interaction terms between participants' demographic characteristics and the clear condition indicator variable (of which only the interaction term for the clear condition and women is shown in **Table 21**; all other interaction terms are not statistically significant and are not shown on the table despite being in the model) to assess potential heterogeneity in reward allocation decisions in different conditions based on participant characteristics. The model suggests that this difference (of women selecting employees signaled to be women for promotion at a higher probability than men) can be attributed specifically to the ambiguous condition: women in the ambiguous reward allocation criteria condition, compared to men in the ambiguous reward allocation criteria condition, select employees signaled to be women for promotion at a somewhat higher probability ($\beta_{Woman} = 0.056$, $t(1602) = 1.923$, $p = 0.055$). This 5.6 percentage point difference in the probability of women selecting a woman for promotion in the ambiguous condition is substantively large, as it is equal to 28% of the expected probability of 20% (since one in five candidates is signaled to be a woman). As a visual aid to help understand these findings, the observed promotion rates of women in each condition, disaggregated by participant gender are shown in **Figure 16**. Since these observed promotion rates are disaggregated only by study condition and participant gender, they do not exactly match the predicted values of any of the models in **Table 21**. Finally, as a robustness check, I reran LPM/OLS Model 3 in **Table 21** as a logistic regression model (the findings are shown in **Table 22**). None of the previously described results change in statistical significance.

To evaluate hypothesis 2b (in the ambiguous condition, the proportion of women selected for promotion will be less than the proportion of employees signaled to be women), I conducted a one-tailed one-sample proportion test and found insufficient evidence that the observed proportion of women selected for promotion in the ambiguous condition ($\hat{p} = 0.222$) is less than the expected

Table 22. Binomial Logistic Regression Results for Relationship between Promotion of Women and Study Condition with Controls for Participant Characteristics

	Logistic Regression Model
Intercept	-1.550***
	(0.226)
Clear Condition	0.273
	(0.325)
Black / African American	0.105
	(0.234)
Asian / Asian American	0.173
	(0.430)
Hispanic, Latino, or Spanish origin	-0.013
	(0.257)
Woman	0.329+
	(0.174)
Democrat or Lean Democrat	0.197
	(0.198)
Independent	0.192
	(0.230)
Graduate degree (for example: MA, MS, MD, JD, PhD)	0.095
	(0.221)
Bachelor's degree (for example: BA, BS)	-0.124
	(0.212)
Clear Condition * Woman	-0.150
	(0.247)
Num.Obs.	1626
AIC	1738.0
BIC	1867.5
Log.Lik.	-845.019
F	0.952
RMSE	0.41
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001	

Note: Robust standard errors in parentheses.

proportion ($p_0 = 0.200$, since one of the five candidates is signaled to be a woman) in the ambiguous condition, $z = 1.581$, $p = 0.943$. In other words, there is no strong evidence that participants in the ambiguous condition were less likely to select the employee signaled to be a woman for promotion than expected to by chance. Indeed, the observed proportion of women selected for promotion in the ambiguous condition ($\hat{p} = 0.222$) is somewhat higher (marginal statistical significance) than the expected proportion in the ambiguous condition ($p_0 = 0.200$), $z = 1.581$, $p = 0.057$.

Finally, to test hypothesis 2c (in the clear condition, the proportion of women selected for promotion will not be statistically different than the proportion of employees signaled to be women), I conducted a two-tailed one-sample proportion test and found insufficient evidence that the observed proportion of women selected for promotion in the clear condition ($\hat{p} = 0.221$) is statistically different than the expected proportion ($p_0 = 0.200$) of women selected for promotion in the clear condition, $z = 1.470$, $p = 0.141$. Therefore, the findings support the hypothesis that in the clear condition, the proportion of women selected for promotion is not statistically different than the proportion of employees signaled to be women. However, like in the ambiguous condition, if I instead test whether the selected proportion of women is higher, I find that the observed proportion of women selected for promotion in the clear condition ($\hat{p} = 0.221$) is somewhat higher (marginal statistical significance) than the expected proportion in the clear condition ($p_0 = 0.200$), $z = 1.470$, $p = 0.071$.

4.5.4 Racial Differences in Men's Outcomes

4.5.4.1 Bonus Allocations for White and Asian American Men

As an exploratory analysis, I tested for differences in the outcomes of employees signaled to be White men versus employees signaled to be Asian American men. Beginning with bonus allocations, this analysis followed the same process utilized to examine for differences in reward allocations based on reward allocation criteria and employee gender. I first estimated an ordinary least squares regression model with heteroskedasticity-robust standard errors, where the outcome

Table 23. Relationship between Bonuses Allocated to White Men and Study Condition, with Controls for Participant Characteristics

	White Model 1	White Model 2	White Model 3
Intercept	4520.714***	4527.544***	4526.661***
	(48.501)	(86.586)	(126.384)
Clear Condition	58.825	55.135	78.843
	(58.103)	(58.280)	(156.808)
Black / African American		85.064	145.602
		(83.411)	(143.407)
Asian / Asian American		56.639	-223.857
		(129.785)	(225.354)
Hispanic, Latino, or Spanish origin		74.412	65.894
		(95.041)	(149.959)
Woman		-28.533	-33.097
		(58.549)	(96.849)
Democrat or Lean Democrat		-85.203	-71.688
		(62.410)	(106.133)
Independent		-98.130	-173.125
		(85.554)	(142.529)
Graduate degree (for example: MA, MS, MD, JD, PhD)		73.917	88.868
		(78.094)	(126.054)
Bachelor's degree (for example: BA, BS)		61.506	154.627
		(73.235)	(121.111)
Clear Condition * Asian / Asian American			475.137+
			(268.968)
Num.Obs.	1626	1626	1626
R2	0.001	0.007	0.017
R2 Adj.	0.000	-0.001	0.003
AIC	27594.3	27606.6	27611.6
BIC	27610.5	27682.1	27746.4
RMSE	1169.77	1166.27	1160.18

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Ordinary least squares regression models with heteroskedasticity-robust standard errors in parentheses.

variable was the amount in bonuses allocated to employees signaled to be White men (see **Table 23** for model results). The key predictor is an indicator variable for the clear condition, with the ambiguous condition as the reference category. I then extended the model by including participant characteristics and interaction terms between participant characteristics and the clear condition. I repeated this modeling process with the amount in bonuses allocated to employees signaled to be Asian American men (see **Table 24** for model results). These models allowed me to compare the bonus allocations to White or Asian American men in the ambiguous condition to bonus allocations to White or Asian American men in the clear condition. These models do not provide immediate comparisons between bonus allocations to White women (only one employee was signaled to be a woman, and this employee was also signaled to be White) versus bonus allocations to White or Asian American men.

Focusing first on employees signaled to be White men, **Model 1** in **Table 23** shows that there is insufficient evidence that the effect of clear reward allocation criteria on the average amount in bonuses allocated to White men by people with management experience is significantly different than the effect of ambiguous reward allocation criteria ($\beta_{ClearCondition} = 58.825$, $t(1624) = 1.012$, $p = 0.312$). In other words, there is no strong evidence to conclude that bonus allocations to employees signaled to be White men differ between the clear and ambiguous conditions. Looking at **Model 2** and **Model 3** in **Table 23**, the marginally significant and positive interaction term between the clear condition and the indicator variable for Asian / Asian American participants ($\beta_{ClearCondition*Asian/AsianAmerican} = 475.137$, $t(1602) = 1.767$, $p = 0.077$) suggests that Asian / Asian American participants are somewhat more influenced by clear reward allocation criteria than White participants. In other words, in the clear reward allocation condition, Asian American participants are more likely to allocate larger bonuses to employees signaled as White men than they would in the ambiguous condition, in contrast to White participants, for whom there is insufficient evidence of a significant change in bonus allocations between the two conditions. However, this marginally significant difference should be considered with caution due to low representation of

Asian / Asian American participants in the study (31 Asian / Asian American participants in the ambiguous condition and 41 in clear condition).

Next, focusing on employees signaled to be Asian American men, I estimated the models in **Table 24**. I found insufficient evidence (**Model 1**) to conclude that bonus allocations to employees signaled to be Asian American men differ between the clear and ambiguous conditions ($\beta_{ClearCondition} = 3.799$, $t(1624) = 0.066$, $p = 0.947$). After adding participant characteristics in **Model 2**, the model provided evidence that, holding all other factors constant, Black / African American participants allocate somewhat lower amounts (marginal statistical significance) in bonuses to employees signaled to be Asian American men compared to White participants ($\beta_{Black/AfricanAmerican} = -141.388$, $t(1613) = -1.748$, $p = 0.081$). Lastly, in (**Model 3**), which adds interaction terms between participant characteristics and the clear condition, I find evidence that in the ambiguous condition, Black / African American participants allocate significantly lower bonuses to employees signaled to be Asian American men compared to White participants ($\beta_{Black/AfricanAmerican} = -284.662$, $t(1602) = -2.116$, $p = 0.034$). Furthermore, the marginally significant and positive interaction term between the clear condition and Black / African American participants ($\beta_{ClearCondition*Black/AfricanAmerican} = 269.437$, $t(1602) = 1.652$, $p = 0.099$) indicates that the gap in bonus allocations between Black and White participants is smaller in the clear condition than in the ambiguous condition. Some caution should once again be taken in interpreting these results due to there being 132 Black / African American participants in the ambiguous condition and 138 in the clear condition.

I then looked at whether, on average, bonus allocations to employees signaled to be Asian American men or White men differed from bonus allocation to employees signaled to be (White) women. First, I visualized the observed average bonus allocations disaggregated by employee gender, employee race, and study condition in **Figure 17**. Next, I estimated an OLS regression model with cluster-robust standard errors (clustered by participant) to examine bonus allocations. The unit of analysis is a single bonus allocation, with each participant making five allocations. The model includes indicators for whether the employee was signaled to be a White man or an Asian American

Table 24. Relationship between Bonuses Allocated to Asian American Men and Study Condition, with Controls for Participant Characteristics

	Asian Model 1	Asian Model 2	Asian Model 3
Intercept	4599.250***	4666.282***	4717.189***
	(48.631)	(87.846)	(133.590)
Clear Condition	3.799	5.366	-112.080
	(57.219)	(56.980)	(155.306)
Black / African American		-141.388+	-284.662*
		(80.878)	(134.525)
Asian / Asian American		40.022	287.395
		(160.133)	(331.515)
Hispanic, Latino, or Spanish origin		-37.315	-101.991
		(96.961)	(156.438)
Woman		-61.721	-123.619
		(57.606)	(97.191)
Democrat or Lean Democrat		79.598	103.935
		(62.127)	(107.541)
Independent		115.489	179.362
		(82.073)	(140.282)
Graduate degree (for example: MA, MS, MD, JD, PhD)		-125.260	-102.240
		(77.091)	(128.434)
Bachelor's degree (for example: BA, BS)		-32.938	-108.751
		(71.933)	(124.694)
Clear Condition * Black / African American			269.437+
			(163.127)
Num.Obs.	1626	1626	1626
R2	0.000	0.008	0.015
R2 Adj.	-0.001	0.001	0.001
AIC	27543.9	27552.3	27563.1
BIC	27560.1	27627.8	27698.0
RMSE	1151.76	1146.94	1143.02

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Ordinary least squares regression models with heteroskedasticity-robust standard errors in parentheses.



Figure 17. Average Bonus Allocations Disaggregated by Employee Gender, Employee Race, and Study Condition

Note: + $p < 0.1$ ∗ $p < .05$; ∗∗ $p < .01$; ∗ ∗ ∗ $p < .001$. Symbols indicate the level of significance of the differences in the average bonus allocations based on the **All Participants** model in **Table 26**.

man (with White woman as the reference category), an indicator for the clear condition (with the ambiguous condition as the reference category), and interaction terms between employee identity and study condition. This model was estimated for all participants, then separately for women and men. Results are shown in **Table 25**.[11] Looking first at the **All Participants** model in **Table 25**, the negative and statistically significant coefficient for the variable indicating whether the employee is signaled to be a White man suggests that, on average in the ambiguous condition, employees signaled to be White men receive significantly lower bonus allocations from people with management experience compared to White women ($\beta_{WhiteManEmployee} = -239.357$, $t(807) = -1.990$, $p = 0.047$). This $239.357 difference represents 5.203% of the average bonus amount for all employees ($4,600).

Focusing in on differences by participant gender, I next visualized women's observed average bonus allocations disaggregated by employee characteristics and study condition (shown in **Figure 18**). Turning to the statistical models, the model named **Women** in **Table 25** uses the same model mentioned in the previous paragraph, but focuses on the subset of participants that are women. This model provides evidence that women with management experience allocated lower bonuses to both White men ($\beta_{WhiteManEmployee} = -384.645$, $t(433) = -2.319$, $p = 0.021$) and Asian American men ($\beta_{AsianAmericanManEmployee} = -323.210$, $t(433) = -1.988$, $p = 0.047$) compared to the amount in bonuses allocated to White women in the ambiguous condition. Women in the ambiguous condition allocated employees signaled to be White men, on average, $384.65 less in bonuses than to employees signaled to be White women, a difference equal to 8.36% of the average bonus amount for all employees ($4,600). For employees signaled to be Asian American men, women in the ambiguous condition allocated $323.21 less in bonuses than to employees signaled to be White women, which is equivalent to 7.03% of the average bonus amount for all employees. In estimating the same model for men (model named **Men** in **Table 25**), I found insufficient evidence for men allocating significantly different bonuses to employees signaled to be White or Asian American men compared to employees signaled to be White women.

[11] As a supplementary analysis, I also ran these models separately for different racial groups, included in **Appendix F: Additional Models for Racial Differences in Men's Outcomes**.

Table 25. Relationship between Bonus Allocations and Study Condition, Accounting for Employee Characteristics

	All Participants	Women	Men
Intercept	4760.071***	4883.142***	4571.431***
	(89.947)	(122.890)	(123.692)
Is Employee Signaled to be a White Man?	-239.357*	-384.645*	-10.634
	(120.279)	(165.836)	(165.404)
Is Employee Signaled to be an Asian American Man?	-160.822	-323.210*	82.057
	(120.527)	(162.571)	(169.976)
Clear Condition	-125.249	-220.287	27.072
	(102.407)	(140.206)	(142.696)
Is Employee Signaled to be a White Man in the Clear Condition?	184.075	291.696	0.726
	(138.887)	(190.523)	(195.457)
Is Employee Signaled to be an Asian American Man in the Clear Condition?	129.048	259.021	-68.405
	(137.188)	(186.015)	(194.771)
Num.Obs.	8130	4490	3595
R2	0.001	0.003	0.000
R2 Adj.	0.000	0.002	-0.001
AIC	145955.9	80607.9	64455.3
BIC	146004.9	80652.8	64498.6
RMSE	1913.29	1911.97	1888.78
Std.Errors	by: ProlificID	by: ProlificID	by: ProlificID

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Ordinary least squares regression models with cluster-robust standard errors in parentheses.

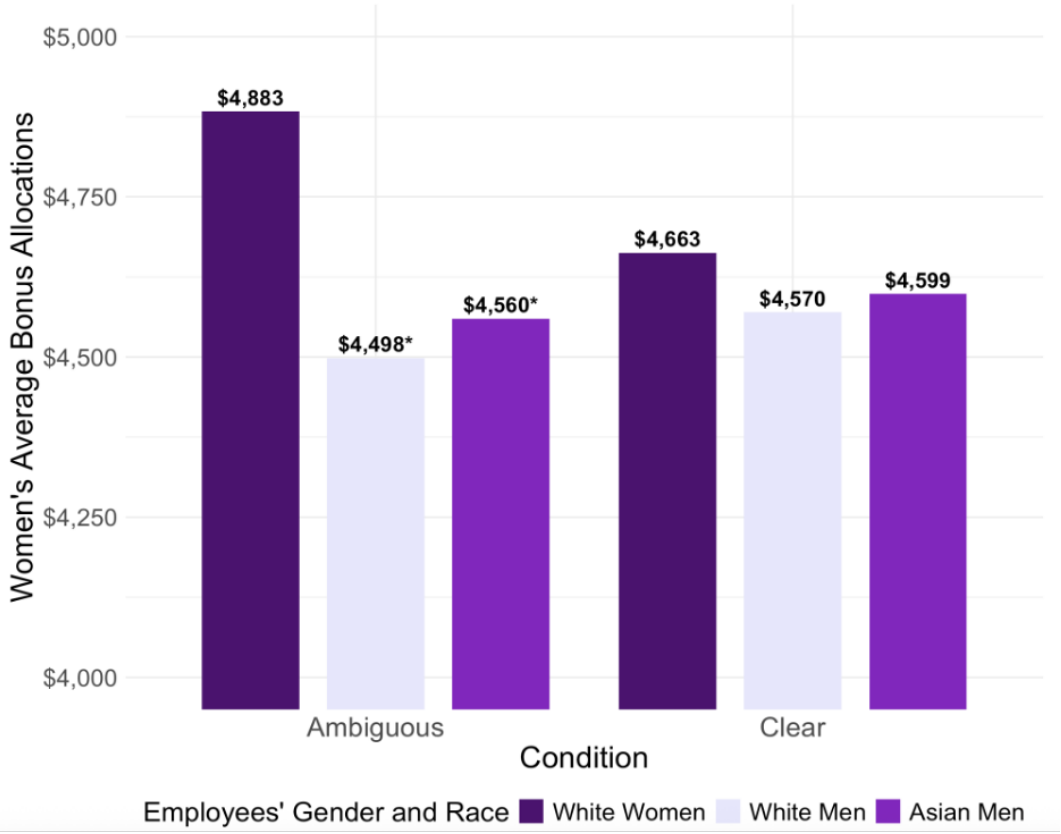


Figure 18. Women's Average Bonus Allocations Disaggregated by Employee Gender, Employee Race, and Study Condition

Note: $+\ p < 0.1 * p < .05$; $** p < .01$; $*** p < .001$. Symbols indicate the level of significance of the differences in women's average bonus allocations based on the **Women** model in **Table 25**.

4.5.4.2 Promotions for White and Asian American Men

Using a similar analytical process as used when examining differences in promotions based on reward allocation criteria and employee gender, I tested for differences in promotion rates of employees signaled to be White men and employees signaled to be Asian American men. The model results can be found in **Table 26**. I first estimated an OLS regression model with heteroskedasticity-robust standard errors, where the outcome was whether a White man was selected for promotion. The model (**White Model 1** in **Table 26**) included an indicator variable for the clear condition, with the ambiguous condition as the reference category. The model findings suggest that there is insufficient evidence that people with management experience in the clear condition selected White men for promotion at a different rate than in the ambiguous condition ($\beta_{ClearCondition} = 0.012$, $t(1624) = 0.4868$, $p = 0.626$).

After adding participant characteristics to the model (**White Model 2** in **Table 26**), I found evidence that participants who identified as Hispanic, Latino, or Spanish origin were somewhat more likely (marginal statistical significance) than participants who identified as non-Hispanic, Latino, or Spanish origin to select a White man for promotion ($\beta_{Hispanic} = 0.071$, $t(1613) = 1.826$, $p = 0.068$). This 7.1 percentage point difference in the probability of Hispanics selecting a White man for promotion is substantively meaningful, as it is equal to 17.75% of the expected probability of 40% (since two in five employees are signaled to be White men). Additionally, I found evidence that participants who identified as Independents were less likely than participants who identified as Republicans (or leaning Republican) to select a White man for promotion ($\beta_{Independent} = -0.070$, $t(1613) = -2.165$, $p = 0.031$). This 7.0 percentage point difference in the probability of Independents selecting a White man for promotion is substantively meaningful, as it is equal to 17.5% of the expected probability of 40%.

In the last model for the promotion of White men (**White Model 3** in **Table 26**), I added interaction terms between study condition and participant characteristics (for the purpose of fitting the figure in one page, statistically insignificant interactions are not shown on the table but are included in the model), and found evidence for a statistically significant and positive interaction term between

Table 26. Relationship between Promotion of White or Asian American Men and Study Condition, with Controls for Participant Characteristics

	White Model 1	White Model 2	White Model 3	Asian Model 1	Asian Model 2	Asian Model 3
Intercept	0.393***	0.416***	0.451***	0.385***	0.385***	0.375***
	(0.017)	(0.034)	(0.044)	(0.017)	(0.034)	(0.045)
Clear Condition	0.012	0.013	-0.052	-0.010	-0.009	0.005
	(0.024)	(0.024)	(0.064)	(0.024)	(0.024)	(0.064)
Black / African American		0.006	-0.016		0.020	-0.001
		(0.033)	(0.048)		(0.033)	(0.047)
Asian / Asian American		0.021	-0.080		0.032	0.049
		(0.060)	(0.086)		(0.060)	(0.092)
Hispanic, Latino, or Spanish origin		0.071+	0.003		-0.041	-0.001
		(0.039)	(0.052)		(0.037)	(0.051)
Woman		-0.040	-0.030		-0.004	-0.026
		(0.025)	(0.035)		(0.024)	(0.034)
Democrat or Lean Democrat		-0.029	-0.060		0.012	0.026
		(0.028)	(0.040)		(0.028)	(0.040)
Independent		-0.070*	-0.051		0.065*	0.018
		(0.032)	(0.046)		(0.033)	(0.046)
Graduate degree (for example: MA, MS, MD, JD, PhD)		0.025	-0.008		-0.056+	-0.009
		(0.032)	(0.045)		(0.032)	(0.045)
Bachelor's degree (for example: BA, BS)		0.022	0.027		-0.014	-0.006
		(0.030)	(0.042)		(0.030)	(0.042)
Clear Condition * Hispanic, Latino, or Spanish origin			0.155*			-0.088
			(0.078)			(0.073)
Num.Obs.	1626	1626	1626	1626	1626	1626
R2	0.000	0.009	0.020	0.000	0.011	0.020
R2 Adj.	0.000	0.002	0.006	-0.001	0.004	0.006
AIC	2297.6	2305.1	2308.7	2269.8	2273.6	2281.1
BIC	2313.8	2380.6	2443.6	2285.9	2349.1	2415.9
RMSE	0.49	0.49	0.48	0.49	0.48	0.48

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Linear probability models with heteroskedasticity-robust standard errors in parentheses. All of the interaction terms in the model are not shown on the table.

the clear condition and Hispanic participants ($\beta_{ClearCondition*Hispanic} = 0.155$, $t(1602) = 1.982$, $p = 0.048$), indicating that the gap in promotions between Hispanic, Latino, or Spanish origin and non-Hispanic, Latino, or Spanish origin participants is larger in the clear condition than in the ambiguous condition. Some caution should be taken in interpreting these results due to there only being 112 Hispanic, Latino, or Spanish origin participants in the ambiguous condition and 88 in the clear condition.

Turning to the promotions of employees signaled to be Asian American men, I first estimated **Asian Model 1**, which is the same as **White Model 1**, but with the promotion of employees signaled to be Asian American men as the outcome (in **Table 26**). The findings from this model suggest that there is insufficient evidence that people with management experience in the clear condition selected Asian American men for promotion at a different rate than in the ambiguous condition ($\beta_{ClearCondition} = -0.010$, $t(1624) = -0.423$, $p = 0.672$).

After incorporating participant characteristics into the model (**Asian Model 2** in **Table 26**), I found that participants identifying as Independents were significantly more likely than those identifying as Republicans (or leaning Republican) to select an Asian American man for promotion ($\beta_{Independent} = 0.065$, $t(1613) = 1.971$, $p = 0.0489$). This 6.5 percentage point difference in the likelihood of Independents selecting an Asian American man for promotion is notable, as it represents 16.25% of the expected probability of 40% (given that two out of five employees were signaled to be Asian American men). Additionally, participants with a graduate degree were somewhat less likely (marginal statistical significance) than those with less than a bachelor's degree to select an Asian American man for promotion ($\beta_{GraduateDegree} = -0.056$, $t(1613) = -1.768$, $p = 0.077$). This 5.6 percentage point difference is also meaningful, as it constitutes 14% of the expected probability of 40%.

In the last model for the promotion of Asian American men (**Asian Model 3** in **Table 26**), I added interaction terms between study condition and participant characteristics (for the purpose of fitting the figure in one page, statistically insignificant interactions are not shown on the table but are

included in the model), and found insufficient evidence that the effect of the clear condition differs based on participants' demographic traits.

Lastly, to assess whether promotion rates for employees signaled to be White or Asian American men differed from the expected rate of 0.4, I conducted two-tailed, one-sample proportion tests. First, I found insufficient evidence that the observed proportion of White men selected for promotion in the ambiguous condition ($\hat{p} = 0.393$) is statistically different than the expected proportion ($p_0 = 0.400$) of White men selected for promotion in the ambiguous condition, $z = -0.430$, $p = 0.667$. Second, looking at the promotion rate for Asian American men in the ambiguous condition, I once again found not enough evidence that the observed proportion of Asian American men selected for promotion in the ambiguous condition ($\hat{p} = 0.385$) is statistically different than the expected proportion ($p_0 = 0.400$) of Asian American men selected for promotion in the ambiguous condition, $z = -0.861$, $p = 0.389$. Third, I once again found a lack of strong evidence that the observed proportion of White men selected for promotion in the clear condition ($\hat{p} = 0.404$) is statistically different than the expected proportion ($p_0 = 0.400$) of White men selected for promotion in the clear condition, $z = 0.257$, $p = 0.797$. Fourth, I found a lack of evidence that that the observed proportion of Asian American men selected for promotion in the clear condition ($\hat{p} = 0.375$) is statistically different than the expected proportion ($p_0 = 0.400$) of Asian American men selected for promotion in the clear condition, $z = -1.458$, $p = 0.145$. Therefore, the findings suggest that, in both the ambiguous condition and the clear condition, the proportions of White men and Asian American men selected for promotion were not statistically different than the proportions of employees signaled to be White men and Asian American men respectively.

4.6 Discussion

4.6.1 Summary of Key Findings

I found that bonus allocations to employees signaled to be women do not significantly differ between the clear and ambiguous reward allocation conditions. However, when accounting for

participant characteristics, women, compared to men, allocate somewhat higher bonuses (marginal statistical significance) to employees signaled to be women by an amount equal to approximately 3.92% of the average bonus amount of $4,600 ($p = 0.077$). This tendency is more pronounced in the ambiguous condition, where women, compared to men, allocate somewhat higher bonuses (marginal statistical significance) to employees signaled to be women by an amount representing 6.82% of the average bonus amount ($p = 0.077$). Moreover, within the ambiguous condition, bonus allocations to employees signaled to be women are modestly higher than those to employees signaled to be men ($p = 0.076$), with the effect driven predominantly by women, who on average allocate higher bonuses to employees signaled to be women versus employees signaled to be men in the ambiguous condition. This difference in bonus allocation amounts is equal to 7.69% ($p = 0.022$) of the average bonus amount for all employees. Conversely, in the clear condition, there is little evidence to suggest any meaningful difference in bonus allocations based on employee or participant gender.

Regarding promotion decisions, I found insufficient evidence to suggest that the probability of selecting a woman for promotion differs between the ambiguous and clear conditions ($p = 0.937$). However, after accounting for participant characteristics, I found evidence that women are more likely than men to select an employee signaled to be a woman for promotion ($p = 0.034$) with a 4.4 percentage point higher probability, which is substantively large and equal to 22% of the expected probability. This difference appears to be driven specifically by differences in the ambiguous condition, in which women, compared to men, exhibit a somewhat higher probability (marginal statistical significance), by 5.6 percentage points ($p = 0.055$), of selecting a woman for promotion. This difference amounts to 28% of the expected probability. Furthermore, looking at the proportion of women selected for promotion within the ambiguous condition, the observed rate of 22.2% is not significantly lower than the expected 20% ($p = 0.943$). In fact, it is somewhat higher (marginal statistical significance; $p = 0.057$). In the clear condition, the observed proportion of 22.1% is not significantly different from the expected proportion ($p = 0.141$), although a one-tailed test suggests a somewhat higher (marginal statistical significance) than expected promotion rate ($p = 0.071$).

In exploratory analyses of racial differences in the outcomes for employees signaled to be men, I found that bonus allocations to employees signaled to be White men ($p = 0.312$) or Asian American men ($p = 0.947$) do not significantly differ between the ambiguous and clear reward allocation conditions. However, employees signaled to be White men, on average in the ambiguous condition, receive significantly lower bonuses than those signaled to be (White) women ($p = 0.047$) by a difference representing 5.20% of the average bonus amount for all employees. This pattern in the ambiguous condition is driven predominantly by women, who allocate significantly lower bonuses to both White men (by an amount equal to 8.362% of the average bonus amount; $p = 0.021$) and Asian American men (by an amount equal to 7.026% of the average bonus amount; $p = 0.047$) relative to the bonuses they allocate to White women. I found insufficient evidence that men allocate different bonus amounts to employees signaled to be White or Asian American men in comparison to White women.

Finally, regarding promotion decisions for employees signaled to be White or Asian American men, I found insufficient evidence of different promotion rates between the ambiguous and clear conditions for either group ($p = 0.626$ for employees signaled to be White men; $p = 0.672$ for employees signaled to be Asian American men). One-sample proportion tests suggested that the observed promotion rates for both White and Asian American men in both conditions do not significantly differ from the expected 40%.

4.6.2 Challenges and Considerations

This study used performance evaluations as the basis from which to reward allocations, which requires making sure that performance evaluations both accurately capture job duties and minimize evaluator bias. In order for this choice to be justifiable, performance evaluations need to accurately set job standards and assess employees against them, typically using both written comments and numerical ratings. Research shows that written feedback and ratings often differ based on employee gender, with certain traits and behaviors being observed and valued differently for men and women (Correll, Weisshaar, Wynn, et al., 2020). In coupling performance evaluations to reward allocations,

it is important to consider whether the same employees are making both decisions (i.e., performance evaluations and reward allocations), or whether different employees are making these decisions as this too has implications for fair distribution of workplace rewards. The current study presents a way, but not necessarily the only way, to increase clarity in reward allocation based on performance evaluations. Organizations need to decide which metrics are most important to organizational success and then allocate rewards such as bonuses and promotions accordingly.

While basing bonus allocation decisions on performance evaluations for employees' current position is logical, promotion decisions based on performance evaluations for employees' current position may not be. This is because the best performing employee may not be the best candidate for a management position. As one example, researchers analyzed sales worker performance data from 214 firms and found evidence for the Peter Principle, which suggests that promotions are based more on current job performance than on traits that predict managerial success (Benson, Li, & Shue, 2023). They found evidence that this practice leads to costly inefficiencies, implying that firms may either be making suboptimal promotion decisions or accepting these costs in exchange for the motivational benefits of promotion-based incentives (Benson, Li, & Shue, 2023).

An interesting challenge that needs further testing by researchers and practitioners is presented by recent research findings that people systematically prefer options that perform better on a dimension that has been quantified (Chang, Kirgios, Mullainathan, et al., 2024). More specifically, researchers have found evidence for quantification fixation, in which people making tradeoff decisions involving both qualitative and quantitative attributes tend to prioritize quantitative information. This bias influences choices across various domains, leading individuals to favor the option that performs better on numerically expressed criteria (Chang, Kirgios, Mullainathan, et al., 2024). This has ramifications for how performance evaluations are constructed, as the information that is quantified is likely to more strongly influence the reward allocation process than qualitative information included in a performance evaluation. To the extent that clear reward allocation criteria can reduce gender inequality requires careful choices about what is and is not quantified in the performance evaluation.

While clarity in criteria for bonus allocations can be easily constructed by a workplace, clarity in promotion decision criteria can be more difficult. There are at least two major reasons why this is the case: timing and the pool of individuals under consideration. While bonus allocations occur on a regular (and usually predetermined) basis, promotions often occur infrequently (e.g., an employee leaves an organization, an organization decides to expand the number of positions at a certain level, etc.). Therefore, while the most recent performance evaluations may influence a bonus allocation, an accumulation of many performance evaluations may influence a promotion decision. Secondly, while bonus allocations consider all of the current employees in a current position, promotions may consider employees from different departments and individuals from outside of the organization. Therefore, uniform evaluation materials may not be available across all candidates being considered for promotion.

Lastly, it is important to note how findings in this study are not generalizable to the reward allocations of all women, but rather only White women. Findings do not necessarily reflect how women of different racial groups (as well as the intersection of women with other social positions) are rewarded under ambiguous versus clear reward allocation contexts. This is an important caveat, as research suggests that findings from experiments on gender bias primarily generalize to White women, while the experiences of Black women (Park & Oh, 2025) and women of other racial groups may follow different patterns.

4.6.3 Implications

What effects do clear reward allocation criteria have on gender inequality? In this study, I found evidence that clarity in reward allocation criteria reduces gender inequality in a surprising manner: the clear condition changes the bonus allocation behavior of women to be more meritocratic compared to the bonus allocation behavior of women in the ambiguous condition. Though I found evidence in the ambiguous condition that women, compared to men, on average allocate higher bonuses to employees signaled to be women compared to employees signaled to be men, I found insufficient evidence to suggest meaningful differences in bonus allocations from either men or

women based on employee gender in the clear condition. Similarly, I found evidence that women are more likely than men to select an employee signaled to be a woman for promotion. This effect is more prominent in the ambiguous condition. In examining racial differences in the outcomes of employees signaled to be men, I found evidence that, in the ambiguous condition, employees signaled to be White men receive lower bonuses than those signaled to be White women. This pattern in the ambiguous condition (and, importantly, not in the clear condition) is primarily driven by women, who allocate lower bonuses to both White and Asian American men compared to the amount in bonuses they allocated to White women. These findings suggest that clarity in criteria can decrease inequality in workplace reward allocations.

Additional research (including field experiments) needs to be conducted to document the contours of this phenomenon, as inequality in reward allocation is likely to look different depending on the occupation. However, the evidence here suggests that winners and losers in reward allocation processes are, at least in part, molded by the clarity of the instructions. This avenue of research is important as differences in reward allocations, even small ones, can have cumulative economic effects in yearly income and wealth accumulation.

5 Conclusion

Social scientists have thoroughly documented a variety of inequalities in the workplace. Though progress has been made in reducing gender and racial inequalities, inequalities in hiring, pay, evaluation, promotion, and termination persist. Though these inequalities are caused by individuals, organizations, and broader social trends and forces, the papers in this dissertation focused on the role of organizations. The studies in this dissertation employed experimental and survey methods to examine some of the ways workplaces can address these inequalities by focusing on how organizations attract, select, and reward employees. These findings contribute to the growing sociological literature on the role of organizations in creating and mitigating workplace inequality.

The findings from the three papers in this dissertation provide several implications. First, the findings highlight how the context in which employers make decisions can significantly influence differences in outcomes for different groups. This implication is most salient in papers two and three, in which I examined isolated versus collective/simulated collective selection contexts and ambiguous versus clear reward allocation criteria. The findings from these papers reinforce that inequality is not just a function of supply side differences (due to experimental manipulation of employee characteristics) or of demand side bias of decision-makers, but also of the decision-making structures organizations use as well. This has implications for the interventions used to reduce workplace inequality, as structural and informational changes to organizational practices have the potential to influence outcomes in hiring and reward allocation.

Second, the findings from these studies highlight how organizational efforts will not have the same effect on everyone. In other words, heterogeneity is to be expected based on the intervention. This was highlighted in each paper, but it was most salient in papers one (in which Black participants and Democrats were more attracted to workplaces with inclusion efforts than White participants and Republicans respectively) and three (in which clarity in reward allocation criteria has an effect on women's reward allocation behavior). This has implications for organizations regarding implementation, as initiatives should not be expected to have the same effects or to be received the

same by all employees. Rather, policies and practices need rigorous testing across demographic subgroups to ensure that they do not inadvertently reproduce, create, or worsen inequality. This needs to be a part of any implementation strategy.

A third implication is the tension between a need for testing in real-world, natural settings and the potential legal and political difficulty that may result from this testing. Put differently, there are tradeoffs to be considered between needing evidence-based practices with the capacity to reduce inequality and the real-world feasibility of gathering this evidence and/or implementing these practices.

Beyond these implications, there are many questions that need to be examined by researchers in the future. First, there are remaining questions about each specific paper in this dissertation: different designs for collective choices need to be tested, the effect of clarity in reward allocation criteria in decreasing inequality needs to be rigorously tested for robustness across industries and operationalizations, and a better understanding is needed about how different types of inclusion efforts affect organizational attraction. Second, future research designs should better build-in understandings of how responses to and effects of organizational practices vary by gender, race, political affiliation, and other characteristics. Research designs that are constructed with this understanding will be better able to document differences in benefits across groups, and whether the different gaps between groups are addressed by the intervention. Lastly, researchers should further wrestle with the legal and ethical considerations involved in changing organizational practices.

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Appendix A: Survey Instrument for Diversity at Work Study

CONSENT FORM PAGE

- If participant provided consent, the study continued to the next page.
- If participant did not provide consent, the following message appeared as per protocol for Prolific: "As you have indicated that you do not consent to participate in this study, please return this submission on Prolific by selecting the "stop without completing" button."

[Next Page]

PROLIFIC ID PAGE

1. What is your Prolific ID? *Please note that this response should auto-fill with the correct ID.*

EXPERIMENTAL TREATMENT PAGE

[Not shown to participants]

- Information Conditions randomly shown without replacement (i.e., if one company is assigned the Diversity Information Condition, the other company cannot be assigned the same condition and is instead assigned the General Information Condition) in the designated areas of workplace information:
    - Diversity Information Condition: We embrace diversity to foster fairness, inclusion, and innovation. Our commitment ensures equal opportunities, values all perspectives, and strengthens our organizational performance. We support employees through employee resource groups, mentorship programs, and a dedicated diversity task force.
    - General Information Condition: We value transparency and open communication, fostering an environment where feedback is encouraged and addressed. Our leadership is committed to providing clear goals and guidance to support success. Hard work and dedication are recognized through rewards and career progression.
- Company Information randomly shown without replacement (if participant is first shown Company Information One, they are shown Company Information Two next).
    - Company Information One: Our company provides top-notch services while maintaining excellence. We foster a fast-paced, collaborative environment where employees think creatively and work together to achieve success. Our employees continuously grow through training and development opportunities.
    - Company Information Two: At our company, we deliver exceptional outcomes by working together as a cohesive team. Employees are empowered to take ownership and contribute innovative solutions. We support growth through professional development and advancement opportunities.

[Questions below were shown to participants]

1. Carefully read this company description. You will review two descriptions in total.

   [Diversity Information Condition or General Information Condition]. [Company Information One or Company Information Two].

   Which of the following best describes a key value emphasized in this workplace? *Please re-read the company description above if you are not sure. You will have two opportunities to get this question correct.* [*Options below shown in random order. Options are designed to match either the* Diversity Information Condition *or the* General Information Condition*. The options provided below are for the* Diversity Information Condition].

   a. Promoting fairness, inclusion, and innovation through diversity initiatives
   b. Encouraging transparency, open communication, and feedback
   c. Recognizing hard work through rewards and bonuses
   d. Maintaining a work from home and flexible culture

2. [Skipped if participant correctly answered the question on the first try.] *You did not answer the question correctly. Please re-read the company description below if you are not sure. This is your last opportunity to get this question correct.*

   [Diversity Information Condition or General Information Condition]. [Company Information One or Company Information Two].

   Which of the following best describes a key value emphasized in this workplace? [*Options below shown in random order. Options are designed to match either the* Diversity Information Condition *or the* General Information Condition*. The options provided below are for the* Diversity Information Condition].

   a. Promoting fairness, inclusion, and innovation through diversity initiatives
   b. Encouraging transparency, open communication, and feedback
   c. Recognizing hard work through rewards and bonuses
   d. Maintaining a work from home and flexible culture

3. **When you think about this company, how much do you agree with the following statements?** *[1 = Strongly Disagree to 7 = Strongly Agree]* If needed, you can read the company description again below.

   [Diversity Information Condition or General Information Condition]. [Company Information One or Company Information Two].

a. I would feel accepted at this company.
b. This company's values align well with my personal values.
c. This company would offer great financial compensation.
d. This company would offer many career opportunities.

[Next Page]

4. This is one of two company descriptions you will read. Please review it carefully.

   [Diversity Information Condition or General Information Condition]. [Company Information One or Company Information Two].

   Which of the following best describes a key value emphasized in this workplace? *Please re-read the company description above if you are not sure. You will have two opportunities to get this question correct.* [*Options below shown in random order. Options are designed to match either the* Diversity Information Condition *or the* General Information Condition*. The options provided below are for the* General Information Condition].

   a. Encouraging transparency, open communication, and feedback
   b. Promoting fairness, inclusion, and innovation through diversity initiatives
   c. Supporting employees through diversity task force
   d. Prioritizing diverse perspectives

5. [Skipped if participant correctly answered the question on the first try.] *You did not answer the question correctly. Please re-read the company description below if you are not sure. This is your last opportunity to get this question correct.*

   [Diversity Information Condition or General Information Condition]. [Company Information One or Company Information Two].

   Which of the following best describes a key value emphasized in this workplace? [*Options below shown in random order. Options are designed to match either the* Diversity Information Condition *or the* General Information Condition*. The options provided below are for the* General Information Condition].

   a. Encouraging transparency, open communication, and feedback
   b. Promoting fairness, inclusion, and innovation through diversity initiatives
   c. Supporting employees through diversity task force
   d. Prioritizing diverse perspectives

6. **When you think about this company, how much do you agree with the following statements?** *[1 = Strongly Disagree to 7 = Strongly Agree]* If needed, you can read the company description again below.

[Diversity Information Condition or General Information Condition]. [Company Information One or Company Information Two].

a. I would feel accepted at this company.
b. This company's values align well with my personal values.
c. This company would offer great financial compensation.
d. This company would offer many career opportunities.

[Next Page]

7. Which of these two companies would you rather work for as an employee? [*Forced choice between two options below which are shown in random order.*]
    a. [Diversity Information Condition or General Information Condition]. [Company Information One or Company Information Two].
    b. [Diversity Information Condition or General Information Condition]. [Company Information One or Company Information Two].

[Next Page]

DEMOGRAPHIC INFORMATION PAGE

[Questions below shown in random order.]

1. Are you of Hispanic, Latino, or Spanish origin?
    a. No
    b. Yes

2. What is your race? Please select one.
    a. American Indian or Alaska Native
    b. Asian or Asian American
    c. Black or African American
    d. Middle Eastern, Arab American, or North African
    e. Native Hawaiian or Other Pacific Islander
    f. White
    g. Multiracial
    h. A race not listed (please specify below)

3. What is your gender identity? Please select one.
    a. Man
    b. Woman
    c. A gender identity not listed (please specify below)

4. In politics today, how do you consider yourself?
    a. Republican
    b. Lean Republican
    c. Independent

d. Lean Democrat
e. Democrat
f. A political affiliation not listed (please specify below)

5. What is the highest degree or level of school you have completed?
    a. Less than high school diploma or equivalent
    b. High school diploma or equivalent (for example: General Educational Development/GED or similar credential)
    c. Some college credit, no degree
    d. Associate's degree (for example: AA, AS)
    e. Bachelor's degree (for example: BA, BS)
    f. Graduate degree (for example: MA, MS, MD, JD, PhD)

[Next Page]

SURVEY COMPLETION PAGE

Thank you for your time and help.

Who to contact with questions:

Jennifer L. Jennings
Email: jlj@princeton.edu

Alejandro J. Garcia Fernandez
Email: alejandro.garciafernandez@princeton.edu

If you have questions regarding your rights as a research subject, or if problems arise which you do not feel you can discuss with the Investigator, please contact the Institutional Review Board at:

Phone: (609) 258-8543
Email: irb@princeton.edu

Appendix B: Logistic Regression Models for Nationally Representative Sample

Logistic Regression Models with Ascribed Statuses for Nationally Representative Sample

	Logit Model 1	Logit Model 2	Logit Model 3	Logit Model 4
Intercept	-0.519***	-0.293**	-0.440***	-0.630***
	(0.113)	(0.099)	(0.131)	(0.152)
Black / African American	0.989***			0.989***
	(0.279)			(0.280)
Asian / Asian American	0.067			0.034
	(0.360)			(0.362)
Hispanic, Latino, or Spanish origin		-0.031		-0.170
		(0.246)		(0.264)
Woman			0.275	0.264
			(0.181)	(0.185)
Num.Obs.	500	500	500	500
AIC	673.8	686.1	683.9	675.3
BIC	690.7	694.6	692.3	700.6
Log.Lik.	-332.903	-341.070	-339.930	-331.648
F	5.317	0.015	2.289	3.640
RMSE	0.49	0.49	0.49	0.49

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Logistic Regression Models with Achieved Statuses for Nationally Representative Sample

	Logit Model 1	Logit Model 2	Logit Model 3
Intercept	-1.061***	-0.317*	-1.071***
	(0.193)	(0.136)	(0.222)
Democrat	1.472***		1.493***
	(0.256)		(0.258)
Independent	0.718**		0.752**
	(0.238)		(0.241)
Graduate degree		0.317	0.300
		(0.240)	(0.252)
Bachelor's degree		-0.137	-0.210
		(0.206)	(0.214)
Num.Obs.	500	500	500
AIC	652.4	684.9	652.6
BIC	665.1	697.5	673.7
Log.Lik.	-323.206	-339.433	-321.313
F	16.728	1.643	9.094
RMSE	0.48	0.49	0.48

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Logistic Regression Models with All Participant Characteristics for Nationally Representative Sample

	All Characteristics Logit Model	Interaction Logit Model
Intercept	-1.436***	-1.685***
	(0.264)	(0.295)
Black / African American	1.054***	1.943***
	(0.293)	(0.488)
Asian / Asian American	0.165	0.167
	(0.382)	(0.389)
Hispanic, Latino, or Spanish origin	-0.147	-0.159
	(0.276)	(0.280)
Woman	0.325+	0.600*
	(0.194)	(0.261)
Democrat	1.529***	2.076***
	(0.265)	(0.369)
Independent	0.751**	0.785**
	(0.246)	(0.252)
Graduate degree	0.274	0.321
	(0.259)	(0.263)
Bachelor's degree	-0.273	-0.293
	(0.221)	(0.225)
Black / African American * Woman		-0.795
		(0.669)
Black / African American * Democrat		-2.439**
		(0.902)
Democrat * Woman		-0.581
		(0.446)
Black / African American * Woman * Democrat		1.080
		(1.243)
Num.Obs.	500	500
AIC	643.4	640.1
BIC	685.6	699.1
Log.Lik.	-311.722	-306.042
F	5.638	4.621
RMSE	0.47	0.46

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix C: Linear Probability Models for Quota Sample

Linear Probability Models with Ascribed Statuses for Quota Sample

	Model 1	Model 2	Model 3	Model 4
Intercept	0.503***	0.541***	0.523***	0.494***
	(0.029)	(0.021)	(0.029)	(0.036)
Black / African American	0.067			0.066
	(0.041)			(0.041)
Hispanic, Latino, or Spanish origin		-0.041		-0.037
		(0.068)		(0.068)
Woman			0.027	0.027
			(0.041)	(0.041)
Num.Obs.	598	598	598	598
R2	0.004	0.001	0.001	0.006
R2 Adj.	0.003	-0.001	-0.001	0.001
AIC	868.1	870.4	870.4	871.4
BIC	881.3	883.6	883.5	893.4
RMSE	0.50	0.50	0.50	0.50

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Linear Probability Models with Achieved Statuses for Quota Sample

	Model 1	Model 2	Model 3
Intercept	0.483***	0.485***	0.406***
	(0.029)	(0.039)	(0.046)
Democrat	0.107**		0.123**
	(0.041)		(0.041)
Graduate degree (for example: MA, MS, MD, JD, PhD)		0.091+	0.116*
		(0.054)	(0.054)
Bachelor's degree (for example: BA, BS)		0.059	0.083+
		(0.050)	(0.050)
Num.Obs.	598	598	598
R2	0.012	0.005	0.020
R2 Adj.	0.010	0.002	0.015
AIC	863.8	869.9	863.0
BIC	877.0	887.5	885.0
RMSE	0.50	0.50	0.49

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Linear Probability Models with All Participant Characteristics for Quota Sample

	All Characteristics Model	Interaction Model
Intercept	0.358***	0.324***
	(0.054)	(0.064)
Black / African American	0.065	0.162*
	(0.040)	(0.080)
Hispanic, Latino, or Spanish origin	-0.044	-0.045
	(0.067)	(0.066)
Woman	0.035	0.048
	(0.040)	(0.079)
Democrat	0.123**	0.188*
	(0.041)	(0.079)
Graduate degree (for example: MA, MS, MD, JD, PhD)	0.122*	0.104+
	(0.054)	(0.054)
Bachelor's degree (for example: BA, BS)	0.086+	0.077
	(0.049)	(0.049)
Black / African American * Woman		-0.046
		(0.113)
Black / African American * Democrat		-0.150
		(0.114)
Democrat * Woman		0.016
		(0.113)
Black / African American * Woman * Democrat		0.004
		(0.160)
Num.Obs.	598	598
R2	0.026	0.032
R2 Adj.	0.016	0.015
AIC	865.1	869.5
BIC	900.3	922.2
RMSE	0.49	0.49

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix D: Survey Instrument for Simulating Collective Choices Study

CONSENT FORM PAGE

[Please reference separate document titled "Consent Form – Simulated Collective Choice Effects Study"]

- If participant provides consent, the study will continue to the next page.
- If participant does not provide consent, the following message will appear as per protocol for Prolific: "As you have indicated that you do not consent to participate in this study, please return this submission on Prolific by selecting the "stop without completing" button."

SCREENER VALIDATION PAGE

1. What is your current age in years? [*Looking for participants who are over 24 years of age*]
    a. Under 18 years
    b. 18-24 years
    c. 25-34 years
    d. 35-44 years
    e. 45-54 years
    f. 55-64 years
    g. 65-74 years
    h. 75-84 years
    i. 85-94 years
    j. 95 years or over

2. In what country do you currently reside? [*Looking for participants whose country of residence is in the United States of America]*
    a. Dropdown menu

3. Do you have any experience in making hiring decisions (i.e., have you been responsible for hiring job candidates)? [*Looking for participants with experience in making hiring decisions]*
    a. Yes
    b. No
    c. Rather not say

- If participant passes the screening questions, the participant will be moved on to the next page.

- If a participant's response does not match their prescreening answers, I will redirect them to a separate end of survey page that reads, as per Prolific protocol: "You are ineligible for this study as you have provided information which is inconsistent with your Prolific prescreening responses. Please return your submission on Prolific by selecting the "stop without completing" button."

PRE-TREATMENT ATTENTION CHECKS

1. **Instructions**
   Your Task: Review job applications and select who the company should interview.
   Company: Electronics retail company that sells items such as computers and cell phones. The company operates a chain of in-person stores and an online store.
   Positions Available: The company wants to hire a total of five people, one for each of the five different positions available, including a Marketing Coordinator, Accountant, District Manager, Software Engineer, and Data Scientist.

   What will you do in this survey? *Please re-read the study instructions above if you are not sure. You will have two opportunities to get this question correct.*
   a. Choose which job you would like to apply for out of five options
   b. Review job applications for an electronics retail company and select who to interview
   c. Review products sold by an electronics retail company
   d. Offer product suggestions to an electronics retail company

2. How many job applicants is the company hiring in total? *Please re-read the study instructions below if you are not sure. You will have two opportunities to get this question correct.*

   Instructions
   Your Task: Review job applications and select who the company should interview.
   Company: Electronics retail company that sells items such as computers and cell phones. The company operates a chain of in-person stores and an online store.
   Positions Available: The company wants to hire a total of five people, one for each of the five different positions available, including a Marketing Coordinator, Accountant, District Manager, Software Engineer, and Data Scientist.
   a. Zero
   b. One
   c. Two
   d. Three
   e. Four
   f. Five
   g. Six

- If participant answers both comprehension check questions correctly, they will move on to the next page.
- If a participant fails a comprehension check twice, they will then be immediately asked to return their submission by closing the survey and clicking "Stop Without Completing" on

Prolific, as per Prolific protocol. They will see the following message: "You failed this comprehension check twice. Please return your submission by closing the survey and selecting the "stop without completing" button."

- Prolific does not allow for the rejection of participants based on failed comprehension checks. They are instead asked to return their submission (if they do not respond to this request in 7 days, I will contact the researcher support team and they can make the returns for me).

[If participant passes the comprehension check questions, the participant is randomly assigned to one of the following: the isolated choice condition, the collective choice condition, or the simulated collective choice condition. To balance the number of hiring decisions made by participants, five times as many participants will be randomly assigned to the isolated choice condition and the simulated collective choice condition than to the collective choice condition.]

[Next Page]

COLLECTIVE CHOICE CONDITION

There are 3 applicants for each position. Your task is to select 1 job applicant to interview for each of the 5 positions. It is your goal to interview the candidates you believe will help make the company the most successful. Below are the job descriptions for the positions available.

Marketing Coordinator: Develops marketing strategies to promote products both online and in-store. Manages social media to drive brand engagement and boosts sales through campaigns.

District Manager: Leads and guides store managers across multiple locations. Focuses on increasing sales, managing budgets, and fostering high standards.

Software Engineer: Designs, develops, and maintains software to improve customer experience and company operations. Works within teams to enhance digital platforms.

Data Scientist: Analyzes company data to find insights and forecast trends. Uses advanced statistical techniques to make data-driven decisions and improve efficiency.

Accountant: Manages financial transactions, prepares financial reports, and ensures compliance with accounting principles and regulations. Analyzes financial data and helps with company decisions.

1. Whom would you like to interview for the Marketing Coordinator position? *[Candidates will be randomly ordered.]*
    a. Hunter Nielsen *[Candidate matched by random assignment to one of the three Experience Options listed below].*
    b. Zachary Becker *[Candidate matched by random assignment to one of the three Experience Options listed below].*
    c. Jake Walsh *[Candidate matched by random assignment to one of the three Experience Options listed below].*

Experience Option 1:
EDUCATION
Oregon State University
Bachelor of Arts in Marketing (2018-2022)

WORK EXPERIENCE
Years of Experience: 2
Marketing Communications Coordinator (2022-Present)

- Assisted in the development and execution of multi-channel marketing campaigns to increase brand visibility and customer engagement.
- Conducted market research to identify trends, customer needs, and provide insights to inform strategy.
- Managed social media accounts, resulting in a 25% increase in followers and engagement through targeted content and promotional campaigns.

Experience Option 2:
EDUCATION
Louisiana State University
Bachelor of Arts in Marketing (2016-2020)

WORK EXPERIENCE
Years of Experience: 4
Marketing Administrator (2020-Present)

- Collaborated with the design team to create promotional materials, including brochures, email newsletters, and online advertisements.
- Analyzed marketing data using tools such as Google Analytics to provide performance reports and actionable insights to improve campaign effectiveness.
- Monitored and reported on KPIs to optimize campaigns to improve click-through rates and conversion rates by 33%.

Experience Option 3:
EDUCATION
Kansas State University
Bachelor of Arts in Marketing (2014-2018)

WORK EXPERIENCE
Years of Experience: 6
Marketing Associate (2018-Present)

- Supported the coordination of events and product launches, ensuring seamless execution and alignment with marketing goals.
- Assisted in the management of marketing budgets, tracking expenditures, and ensuring campaigns stayed within budget limits.
- Worked closely with sales teams to align marketing efforts with lead generation goals, contributing to a 40% increase in sales leads.

2. Whom would you like to interview for the Accountant position? *[Candidates will be randomly ordered.]*
    a. Darius Banks *[Candidate matched by random assignment to one of the three Experience Options listed below].*
    b. Seth McGrath *[Candidate matched by random assignment to one of the three Experience Options listed below].*
    c. Todd Stein *[Candidate matched by random assignment to one of the three Experience Options listed below].*

Experience Option 1:
EDUCATION
University of Arkansas
Bachelor of Science in Business Administration (2018-2022)

WORK EXPERIENCE
Years of Experience: 2
Financial Accountant (2022-Present)

- Managed and maintained accurate financial records, including accounts payable/receivable, payroll, and general ledger transactions.
- Prepared and analyzed monthly, quarterly, and annual financial statements, ensuring compliance with accounting standards and regulations (GAAP/IFRS).
- Conducted reconciliations of bank accounts, credit card statements, and other financial accounts to ensure accuracy and resolve discrepancies.

Experience Option 2:
EDUCATION
University of Rhode Island
Bachelor of Science in Business Administration (2016-2020)

WORK EXPERIENCE
Years of Experience: 4
Management Accountant (2020-Present)

- Assisted in budgeting and forecasting processes to provide financial insights and recommendations to support business decision-making.
- Processed and filed tax returns to ensure compliance with local, state, and federal regulations, while identifying potential tax savings.
- Managed month-end and year-end close processes, including journal entries, accruals, and balance sheet reconciliations.

Experience Option 3:
EDUCATION
Georgia State University
Bachelor of Science in Business Administration (2015-2019)

WORK EXPERIENCE
Years of Experience: 5
Auditor (2019-Present)

- Collaborated with external auditors during financial audits to prepare necessary documentation and address any audit inquiries.
- Monitored and ensured compliance with internal controls to help reduce risk and prevent fraud.
- Utilized accounting software such as QuickBooks, SAP, and Oracle to streamline financial reporting and data management.

3. Whom would you like to interview for the District Manager position? *[Candidates will be randomly ordered.]*
    a. Tremayne Booker *[Candidate matched by random assignment to one of the three Experience Options listed below].*
    b. Jamal Washington *[Candidate matched by random assignment to one of the three Experience Options listed below].*
    c. Logan Meyer *[Candidate matched by random assignment to one of the three Experience Options listed below].*

Experience Option 1:
EDUCATION
University of Oklahoma
Bachelor of Business Administration (2018-2022)

WORK EXPERIENCE
Years of Experience: 2
Store Manager (2022-Present)

- Managed daily operations of the store, ensuring smooth execution of all processes, from opening to closing, while maintaining high standards of service.
- Led a team of 20 employees, overseeing hiring, training, scheduling, and performance management to ensure a productive work environment.
- Increased store revenue by 5% through the implementation of effective sales strategies, merchandising, and promotional activities.

Experience Option 2:
EDUCATION
Ohio University
Bachelor of Business Administration (2016-2020)

WORK EXPERIENCE
Years of Experience: 4
Area Manager (2020-Present)

- Oversaw operations for 3 stores within a designated area, ensuring alignment with corporate goals and driving performance improvements across all locations.
- Led, coached, and developed 3 store managers, providing guidance on operational efficiency, sales strategies, and leadership development.

- Increased regional revenue by 4% through targeted sales initiatives, process optimization, and consistent execution of promotional campaigns.

Experience Option 3:
EDUCATION
University of Alabama
Bachelor of Business Administration (2014-2018)

WORK EXPERIENCE
Years of Experience: 6
District Manager (2018-Present)
- Coordinated successful rollouts of new products and promotions across all stores, driving 5% increase in sales.
- Oversaw district budget and expenses, achieving a 6% reduction in operational costs through efficient resource allocation and vendor negotiations.
- Tracked store performance using data analytics, generating actionable insights, and presenting regular reports to regional leadership.

4. Whom would you like to interview for the Software Engineer position? *[Candidates will be randomly ordered.]*
    a. Denzel Jefferson *[Candidate matched by random assignment to one of the three Experience Options listed below].*
    b. Matthew Decker *[Candidate matched by random assignment to one of the three Experience Options listed below].*
    c. Ryan Andersen *[Candidate matched by random assignment to one of the three Experience Options listed below].*

Experience Option 1:
EDUCATION
University of Nebraska-Lincoln
Bachelor of Science in Computer Science (2018-2022)

WORK EXPERIENCE
Years of Experience: 2
Software Developer (2022-Present)
- Collaborated with cross-functional teams, including product managers and designers, to gather requirements and deliver user-centric software solutions within project timelines.
- Wrote clean, efficient, and well-documented code that improved system functionality and reduced bugs by 10%.
- Led the implementation of new online customer interface, increasing application efficiency by 15% and enhancing user experience.

Experience Option 2:
EDUCATION
University of Utah
Bachelor of Science in Computer Science (2017-2021)

WORK EXPERIENCE
Years of Experience: 3
Programmer (2021-Present)

- Performed unit testing, debugging, and optimization of software, resulting in a 12% reduction in system downtime and faster application response times.
- Participated in code reviews and provided mentorship to junior developers, ensuring adherence to best practices and coding standards.
- Developed and integrated RESTful APIs, enhancing system interoperability and enabling data exchange between 4 systems.

Experience Option 3:
EDUCATION
Colorado State University
Bachelor of Science in Computer Science (2015-2019)

WORK EXPERIENCE
Years of Experience: 5
Software Analyst (2019-Present)

- Utilized version control systems such as Git to track changes, manage releases, and maintain codebase integrity across multiple projects.
- Improved software security by implementing encryption, authentication, and other security protocols, leading to 15% reduction in vulnerabilities.
- Refactored legacy code, improving system performance and maintainability while reducing technical debt by 8%.

5. Whom would you like to interview for the Data Scientist position? *[Candidates will be randomly ordered.]*
    a. Tyrone Jackson *[Candidate matched by random assignment to one of the three Experience Options listed below].*
    b. Scott Larsen *[Candidate matched by random assignment to one of the three Experience Options listed below].*
    c. Dustin Hartman *[Candidate matched by random assignment to one of the three Experience Options listed below].*

Experience Option 1:
EDUCATION
University of Mississippi
Bachelor of Science in Data Science (2017-2021)

WORK EXPERIENCE
Years of Experience: 3
Data Analyst (2021-Present)

- Collected, cleaned, and analyzed large datasets using tools such as Excel, SQL, and Python, providing actionable insights that drove a 10% improvement in decision-making.

- Developed and maintained interactive dashboards and reports using tools like Tableau, and Google Data Studio, enabling stakeholders to track key performance metrics in real-time.
- Conducted in-depth data analysis to identify trends, patterns, and correlations, leading to a 10% increase in sales growth.

Experience Option 2:
EDUCATION
University of Idaho
Bachelor of Science in Data Science (2016-2020)

WORK EXPERIENCE
Years of Experience: 4
Data Scientist (2020-Present)

- Utilized SQL to query and extract data from databases, optimizing queries to reduce processing time by 15%.
- Collaborated with cross-functional teams to define data needs and KPIs, delivering insights that guided business strategy and improved marketing campaign performance by 18%.
- Presented findings and visualizations to management and stakeholders, communicating complex data insights in a clear and actionable manner.

Experience Option 3:
EDUCATION
University of Kentucky
Bachelor of Science in Data Science (2015-2019)

WORK EXPERIENCE
Years of Experience: 5
Data Engineer (2019-Present)

- Performed A/B testing and statistical analysis to evaluate the impact of product or process changes, resulting in a 20% improvement in user engagement.
- Automated data collection and reporting processes using Python and Excel macros, reducing manual data processing time by 15 hours per week.
- Conducted market research and competitor analysis, providing insights that influenced product development and pricing strategies.

ISOLATED CHOICE CONDITION

[Similar to the Collective Choice Condition; however, participants in this condition will make only one decision about which applicant to interview for one of the five positions. Participants will be randomly assigned to make an interview decision for one of the five positions. Below is an example of what this looks like.]

1. There are 3 applicants for the Marketing Coordinator position. Your task is to select 1 job applicant to interview for the Marketing Coordinator position. It is your goal to interview the

candidate you believe will help make the company the most successful. Below is the job description for the position available.

Marketing Coordinator: Develops marketing strategies to promote products both online and in-store. Manages social media to drive brand engagement and boosts sales through campaigns.

Whom would you like to interview for the Marketing Coordinator position?

a. Hunter Nielsen *[Candidate matched by random assignment to one of the three Experience Options listed below].*
b. Zachary Becker *[Candidate matched by random assignment to one of the three Experience Options listed below].*
c. Jake Walsh *[Candidate matched by random assignment to one of the three Experience Options listed below].*

Experience Option 1:
EDUCATION
Oregon State University
Bachelor of Arts in Marketing (2018-2022)

WORK EXPERIENCE
Years of Experience: 2
Marketing Communications Coordinator (2022-Present)

- Assisted in the development and execution of multi-channel marketing campaigns to increase brand visibility and customer engagement.
- Conducted market research to identify trends, customer needs, and provide insights to inform strategy.
- Managed social media accounts, resulting in a 25% increase in followers and engagement through targeted content and promotional campaigns.

Experience Option 2:
EDUCATION
Louisiana State University
Bachelor of Arts in Marketing (2016-2020)

WORK EXPERIENCE
Years of Experience: 4
Marketing Administrator (2020-Present)

- Collaborated with the design team to create promotional materials, including brochures, email newsletters, and online advertisements.
- Analyzed marketing data using tools such as Google Analytics to provide performance reports and actionable insights to improve campaign effectiveness.
- Monitored and reported on KPIs to optimize campaigns to improve click-through rates and conversion rates by 33%.

Experience Option 3:
EDUCATION
Kansas State University
Bachelor of Arts in Marketing (2014-2018)

WORK EXPERIENCE
Years of Experience: 6
Marketing Associate (2018-Present)

- Supported the coordination of events and product launches, ensuring seamless execution and alignment with marketing goals.
- Assisted in the management of marketing budgets, tracking expenditures, and ensuring campaigns stayed within budget limits.
- Worked closely with sales teams to align marketing efforts with lead generation goals, contributing to a 40% increase in sales leads.

SIMULATED COLLECTIVE CHOICE CONDITION

[Participants in this condition will make only one decision about which applicant to interview for one of the five positions. Participants will therefore be shown only one of the five questions below.]

1. There are 3 applicants for the Marketing Coordinator position. Your task is to select 1 job applicant to interview for the Marketing Coordinator position. The last 2 employees the company hired to fill the position are shown below along with the 3 applicants. It is your goal to interview the candidate you believe will help make the company the most successful. Below is the job description for the position available.

Marketing Coordinator: Develops marketing strategies to promote products both online and in-store. Manages social media to drive brand engagement and boosts sales through campaigns.

Previous Employee 1:
Todd Stein

EDUCATION
University of Idaho
Bachelor of Arts in Marketing (2017-2021)

WORK EXPERIENCE
Years of Experience: 3
Marketing Coordinator (2021-Present)
- Managed social media accounts across multiple platforms, growing audience reach by 20% over six months.
- Assisted in the development of marketing materials, including brochures, presentations, and web content.
- Conducted market research and analyzed competitor activities to support strategic decision-making.

Previous Employee 2:
Seth McGrath

EDUCATION
University of Kentucky
Bachelor of Arts in Marketing (2015-2019)

WORK EXPERIENCE
Years of Experience: 5
Marketing Associate (2019-Present)
- Coordinated promotional events, product demos, and webinars, contributing to a 15% increase in lead generation.
- Monitored and reported on key performance indicators (KPIs) such as website traffic, social media engagement, and email open rates.
- Collaborated with design and content teams to develop marketing assets that aligned with brand messaging.

Whom would you like to interview for the Marketing Coordinator position?
[The same candidate profiles used for the Collective Choice Condition will be used for this condition.]

2. There are 3 applicants for the Accountant position. Your task is to select 1 job applicant to interview for the Accountant position. The last 2 employees the company hired to fill the position are shown below along with the 3 applicants. It is your goal to interview the candidate you believe will help make the company the most successful. Below is the job description for the position available.

Accountant: Manages financial transactions, prepares financial reports, and ensures compliance with accounting principles and regulations. Analyzes financial data and helps with company decisions.

Previous Employee 1:
Jake Walsh

EDUCATION
Oregon State University
Bachelor of Science in Business Administration (2017-2021)

WORK EXPERIENCE
Years of Experience: 3
Auditor (2021-Present)
- Evaluated internal controls and identified areas for improvement, resulting in enhanced operational efficiency.

- Prepared detailed audit reports with findings, risk assessments, and actionable recommendations for senior management.
- Collaborated with cross-functional teams to ensure accurate financial reporting and adherence to company policies.

Previous Employee 2:
Logan Meyer

EDUCATION
Louisiana State University
Bachelor of Science in Business Administration (2015-2019)

WORK EXPERIENCE
Years of Experience: 5
Accountant (2019-Present)
- Reviewed and analyzed financial data to ensure proper allocation of costs and accurate reporting of financial performance.
- Collaborated with external auditors during year-end audits, providing documentation and ensuring smooth audit processes.
- Monitored cash flow, managed accounts, and prepared financial projections to support strategic planning.

Whom would you like to interview for the Accountant position?

[The same candidate profiles used for the Collective Choice Condition will be used for this condition.]

3. There are 3 applicants for the District Manager position. Your task is to select 1 job applicant to interview for the District Manager position. The last 2 employees the company hired to fill the position are shown below along with the 3 applicants. It is your goal to interview the candidate you believe will help make the company the most successful. Below is the job description for the position available.

District Manager: Leads and guides store managers across multiple locations. Focuses on increasing sales, managing budgets, and fostering high standards.

Previous Employee 1:
Ryan Andersen

EDUCATION
University of Rhode Island
Bachelor of Business Administration (2017-2021)

WORK EXPERIENCE
Years of Experience: 3
Area Manager (2021-Present)
- Managed operations across 4 locations within the area, driving consistent performance and meeting corporate objectives.
- Led, trained, and developed a team of store managers, increasing overall area sales by 18% within one year.
- Ensured compliance with company policies, safety regulations, and customer service standards across all area locations.

Previous Employee 2:
Matthew Decker

EDUCATION
Georgia State University
Bachelor of Business Administration (2015-2019)

WORK EXPERIENCE
Years of Experience: 5
District Manager (2019-Present)
- Managed and coached store managers, improving team performance and achieving a 20% increase in overall sales within the district.
- Developed and implemented district-wide strategies for maximizing profitability, reducing expenses by 15% year-over-year.
- Analyzed sales reports and key performance indicators (KPIs) to identify areas for improvement and drive growth across all stores.

Whom would you like to interview for the District Manager position?

[The same candidate profiles used for the Collective Choice Condition will be used for this condition.]

4. There are 3 applicants for the Software Engineer position. Your task is to select 1 job applicant to interview for the Software Engineer position. The last 2 employees the company hired to fill the position are shown below along with the 3 applicants. It is your goal to interview the candidate you believe will help make the company the most successful. Below is the job description for the position available.

Software Engineer: Designs, develops, and maintains software to improve customer experience and company operations. Works within teams to enhance digital platforms.

Previous Employee 1:
Scott Larsen

EDUCATION
University of Alabama
Bachelor of Science in Computer Science (2017-2021)

WORK EXPERIENCE
Years of Experience: 3
Software Developer (2021-Present)
- Designed, developed, and maintained scalable web and mobile applications using programming languages such as Java, Python, and JavaScript.
- Collaborated with cross-functional teams (designers, product managers, and QA) to deliver software solutions that met business requirements and user needs.
- Wrote efficient, reusable, and maintainable code, improving system performance by 20%.

Previous Employee 2:
Dustin Hartman

EDUCATION
University of Oklahoma
Bachelor of Science in Computer Science (2015-2019)

WORK EXPERIENCE
Years of Experience: 5
Software Engineer (2019-Present)
- Led the development of a key feature for a web application, resulting in a 15% increase in user engagement.
- Integrated APIs and third-party services, enhancing functionality and expanding the capabilities of applications.
- Conducted code reviews and provided mentorship to junior developers, promoting best coding practices and improving overall code quality.

Whom would you like to interview for the Software Engineer position?

[The same candidate profiles used for the Collective Choice Condition will be used for this condition.]

5. There are 3 applicants for the Data Scientist position. Your task is to select 1 job applicant to interview for the Data Scientist position. The last 2 employees the company hired to fill the position are shown below along with the 3 applicants. It is your goal to interview the candidate you believe will help make the company the most successful. Below is the job description for the position available.

Data Scientist: Analyzes company data to find insights and forecast trends. Uses advanced statistical techniques to make data-driven decisions and improve efficiency.

Previous Employee 1:
Hunter Nielsen

EDUCATION
Colorado State University
Bachelor of Science in Data Science (2017-2021)

WORK EXPERIENCE
Years of Experience: 3
Data Analyst (2021-Present)
- Collected, cleaned, and analyzed large datasets to support data-driven decision-making, improving operational efficiency by 15%.
- Created interactive dashboards and visualizations using tools like Tableau and Power BI, providing actionable insights for senior management.
- Developed and maintained SQL queries to extract, manipulate, and analyze data from relational databases, reducing data processing time by 20%.

Previous Employee 2:
Zachary Becker
EDUCATION
University of Utah
Bachelor of Science in Data Science (2015-2019)

WORK EXPERIENCE
Years of Experience: 5
Data Scientist (2019-Present)
- Performed A/B testing and analyzed results to optimize product features, leading to a 12% increase in user engagement.
- Generated detailed reports on market trends, customer behavior, and business performance, facilitating better decision-making.
- Identified patterns and anomalies in data, providing recommendations that contributed to a 25% reduction in costs.

Whom would you like to interview for the Data Scientist position?

[The same candidate profiles used for the Collective Choice Condition will be used for this condition.]

MECHANISMS QUESTIONS PAGE

[Questions below shown in random order.]

1. In selecting who to interview, I considered how my choices impacted the **overall success of the company**.
    a. Strongly Disagree
    b. Somewhat Disagree

c. Neither Agree nor Disagree
d. Somewhat Agree
e. Strongly Agree

2. In selecting who to interview, I considered how my choices impacted the **overall diversity of the company**.
    a. Strongly Disagree
    b. Somewhat Disagree
    c. Neither Agree nor Disagree
    d. Somewhat Agree
    e. Strongly Agree
3. In selecting who to interview, I chose the **most qualified candidate**.
    a. Strongly Disagree
    b. Somewhat Disagree
    c. Neither Agree nor Disagree
    d. Somewhat Agree
    e. Strongly Agree

DEMOGRAPHIC INFORMATION PAGE

1. Are you of Hispanic, Latino, or Spanish origin?
    a. No
    b. Yes

2. What is your race? Please select one.
    a. American Indian or Alaska Native
    b. Asian or Asian American
    c. Black or African American
    d. Middle Eastern, Arab American, or North African
    e. Native Hawaiian or Other Pacific Islander
    f. White
    g. Multiracial
    h. A race not listed (please specify below)

3. What is your gender identity? Please select one.
    a. Man
    b. Woman
    c. A gender identity not listed (please specify below)

4. In politics today, how do you consider yourself?
    a. Republican
    b. Lean Republican
    c. Independent
    d. Lean Democrat
    e. Democrat
    f. A political affiliation not listed (please specify below)

5. What is the highest degree or level of school you have completed?
    a. Less than high school diploma or equivalent
    b. High school diploma or equivalent (for example: General Educational Development/GED or similar credential)
    c. Some college credit, no degree
    d. Associate's degree (for example: AA, AS)
    e. Bachelor's degree (for example: BA, BS)
    f. Graduate degree (for example: MA, MS, MD, JD, PhD)

SURVEY COMPLETION PAGE

Thank you for your time and help with providing hiring recommendations.

Who to contact with questions:

Jennifer L. Jennings
Email: jlj@princeton.edu

Alejandro J. Garcia Fernandez
Email: alejandro.garciafernandez@princeton.edu

If you have questions regarding your rights as a research subject, or if problems arise which you do not feel you can discuss with the Investigator, please contact the Institutional Review Board at:

Phone: (609) 258-8543
Email: irb@princeton.edu

Appendix E: Survey Instrument for Gender Inequality in Employee Reward Allocation Study

CONSENT FORM PAGE

- If participant provided consent, the study continued to the next page.
- If participant did not provide consent, the following message appeared as per protocol for Prolific: "As you have indicated that you do not consent to participate in this study, please return this submission on Prolific by selecting the "stop without completing" button."

[Next Page]

SCREENER VALIDATION PAGE

1. What is your current age in years? [*Looking for participants who are over 24 years of age*]
    a. Under 18 years
    b. 18-24 years
    c. 25-34 years
    d. 35-44 years
    e. 45-54 years
    f. 55-64 years
    g. 65-74 years
    h. 75-84 years
    i. 85-94 years
    j. 95 years or over

2. In what country do you currently reside? [*Looking for participants whose country of residence is in the United States of America]*
    a. Dropdown menu

3. Do you have any experience being in a management position? [*Looking for participants with management experience]*
    a. Yes
    b. No
    c. Rather not say

- If participant passed the screening questions, the participant was moved on to the next page.
- If a participant's responses did not match their prescreening answers, I redirected them to a separate end of survey page that read, as per Prolific protocol: "You are ineligible for this study as you have provided information which is inconsistent with your Prolific

prescreening responses. Please return your submission on Prolific by selecting the "stop without completing" button."

[Next Page]

PRE-TREATMENT ATTENTION CHECKS

1.

Instructions

Your Tasks: Review the performance evaluations for five software engineers. These performance evaluations consist of ratings from 1 (the lowest rating) to 5 (the highest rating) for five different categories along with written comments on employee performance. Your tasks are to (1) assign $23,000 in bonuses and (2) select one software engineer for promotion to the position of senior software engineer.

Software Engineer Job Description: Designs, develops, and maintains software to improve company operations. Works within teams to enhance digital platforms.

What will you do in this survey? *Please re-read the study instructions above if you are not sure. You will have two opportunities to get this question correct.*

a. Provide ratings to software engineers for their performance evaluations.
b. Assign bonuses and select one software engineer for promotion.
c. Hire software engineers for a technology company.
d. Review the code of software engineers who work at a technology company.

2. What is the highest rating a software engineer can receive on their performance evaluation? *Please re-read the study instructions below if you are not sure. You will have two opportunities to get this question correct.*

Instructions

Your Tasks: Review the performance evaluations for five software engineers. These performance evaluations consist of ratings from 1 (the lowest rating) to 5 (the highest rating) for five different categories along with written comments on employee performance. Your tasks are to (1) assign $23,000 in bonuses and (2) select one software engineer for promotion to the position of senior software engineer.

Software Engineer Job Description: Designs, develops, and maintains software to improve company operations. Works within teams to enhance digital platforms.

a. 1
b. 2
c. 3
d. 4
e. 5

- If participant answered both comprehension check questions correctly, they were moved on to the next page.
- If a participant failed a comprehension check twice, they were then immediately asked to return their submission by closing the survey and clicking "Stop Without Completing" on Prolific, as per Prolific protocol. They will see the following message: "You failed this comprehension check twice. Please return your submission by closing the survey and selecting the "stop without completing" button."
    - Prolific does not allow for the rejection of participants based on failed comprehension checks. They are instead asked to return their submission.

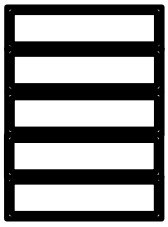
[If participant passed the comprehension check questions, the participant was randomly assigned to one of the following: the ambiguous reward allocation condition or the clear reward allocation condition.]

[Next Page]

AMBIGUOUS CONDITION

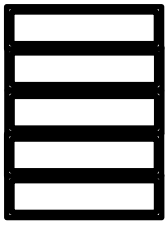
1. As a reminder, a **software engineer** designs, develops, and maintains software to improve company operations. Software engineers work within teams to enhance digital platforms. Below are the performance evaluations of five software engineers. Choose how to give out $23,000 in bonuses to the software engineers by entering an amount (from $0 to $23,000) in the box next to the employee. **You will not be able to advance to the next page unless the total sum adds up to $23,000**.

    a. Name and Performance Evaluation
    b. Name and Performance Evaluation
    c. Name and Performance Evaluation
    d. Name and Performance Evaluation
    e. Name and Performance Evaluation



2. Below are the performance evaluations of the same five software engineers. Now choose one software engineer to promote to the position of **senior software engineer**. A senior software engineer leads the design, development, and maintenance of software to enhance company operations. The senior software engineer serves as a technical expert, mentors teams, and drives innovation to improve digital platforms.

    a. Name and Performance Evaluation
    b. Name and Performance Evaluation
    c. Name and Performance Evaluation
    d. Name and Performance Evaluation
    e. Name and Performance Evaluation



Name Bank: each of the name options below will be shown in a random order.
Michael Wagner
Richard Hoffman

Alan Wang
Peter Li
Mary Snyder (signal for woman)

Bank of Performance Evaluations: each of the options below will be randomly matched with one of the names above.

Option 1
Leadership (4) – Initiative and the ability to guide others are evident in daily work, as demonstrated when assisting junior developers with troubleshooting complex issues. Taking on additional leadership responsibilities will further showcase potential in this area.
Job Skills (4) – Strong technical skills and a solid understanding of the work. Learning continuously and staying updated with industry trends will further strengthen expertise.
Quality of Work (4) – Work is consistently high quality, demonstrating strong attention to detail and accuracy. Successfully debugged critical application issues, preventing additional interrupted workflow.
Quantity of Work (3) – Productivity remains steady, though improvements in time management would help meet deadlines more consistently. More effective task prioritization can enhance overall output, such as ensuring key feature development is completed before lower-priority tasks.
Communication and Teamwork (3) – Collaboration with others is effective, though clarity and responsiveness in communication could be improved. More proactive engagement with team members will enhance overall teamwork, such as responding more promptly to pull request feedback.

Option 2
Leadership (5) – Exhibits strong leadership by taking initiative, guiding junior software engineers effectively, and fostering a positive team environment. A proactive approach to mentoring and decision-making has significantly influenced project direction and team success.
Job Skills (4) – Possesses solid technical expertise and a strong understanding of the work, contributing effectively to projects. Working on expanding knowledge in emerging technologies and refining problem-solving approaches will further strengthen overall performance.
Quality of Work (4) – Delivers high-quality work regularly, with a solid focus on accuracy and thoroughness. A more structured approach to complex tasks, like clear documentation for newly developed features, can enhance overall efficiency and elevate the quality even further.
Quantity of Work (5) – Maintains an outstanding level of productivity, effectively managing a high workload without compromising quality. Exceptional time management skills contribute significantly to project success, as seen in the ability to consistently juggle multiple high-priority tasks without delays.
Communication and Teamwork (4) – Works well with colleagues and communicates effectively to support collaboration. Strengthening proactive engagement in discussions and providing clearer updates on project progress will further enhance teamwork and coordination.

Option 3
Leadership (3) – Demonstrates some leadership potential but could benefit from taking more initiative in guiding and supporting team members. Additional opportunities to lead projects or

mentor others will help strengthen leadership abilities, such as volunteering to review and improve team coding standards.
Job Skills (4) – Technical skills and understanding of the work are solid, allowing for effective contributions. Continuing to expand expertise and refine problem-solving approaches will enhance overall performance, as seen in efforts to adopt best practices for database optimization.
Quality of Work (5) – Work is consistently of the highest quality, demonstrating accuracy, thoroughness, and competence. A strong focus on excellence in all tasks contributes significantly to overall success, as reflected in the well-documented and error-free code contributions.
Quantity of Work (4) – Productivity is generally strong, with tasks completed on time and with good efficiency. Further improvements in managing workload could help achieve even greater consistency in meeting deadlines.
Communication and Teamwork (4) – Collaboration is effective, with good communication and positive interaction with team members. Fostering more proactive engagement and clarity in communication could improve team dynamics, such as providing more detailed status updates in stand-up meetings.

Option 4
Leadership (2) – Limited leadership engagement has been observed, and more initiative is needed to guide others effectively. Taking on small leadership tasks or seeking opportunities to mentor colleagues will help build essential leadership skills, such as by offering to assist newer team members with onboarding.
Job Skills (3) – Technical skills and understanding are sufficient but require further development to tackle more complex tasks confidently. Seeking additional training or mentorship will help in strengthening these key competencies, such as becoming more proficient in performance optimization techniques.
Quality of Work (3) – Work is generally accurate but occasionally lacks consistency in meeting the expected level of detail and thoroughness. Focusing on improving the quality control process will help achieve more reliable results and reduce the number of revisions needed before deployment.
Quantity of Work (4) – Productivity is solid, with tasks completed within reasonable timelines. To improve further, focusing on time management and minimizing distractions can enhance efficiency and output, particularly in handling last-minute requests.
Communication and Teamwork (3) – Collaboration with the team is functional, but communication could benefit from greater clarity and consistency. Enhancing active listening skills and contributing more proactively to discussions will improve teamwork, particularly in cross-team projects.

Option 5
Leadership (5) – Demonstrates outstanding leadership by taking initiative and guiding others effectively. A proactive approach to mentoring and decision-making has positively influenced team dynamics and project direction.
Job Skills (5) – Technical expertise is outstanding, demonstrating a deep understanding of the work and its complexities. Advanced skills make a strong impact on project execution and problem-solving, such as implementing optimized algorithms that improve system performance on a regular basis.

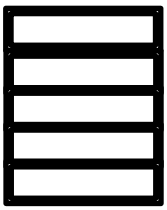
Quality of Work (4) – Work is reliably accurate, thorough, and well-executed. Continued attention to streamlining processes can further enhance efficiency and effectiveness, as seen in the recent effort to automate repetitive deployment tasks.
Quantity of Work (4) – Productivity is strong, with tasks completed in a timely and efficient manner. A continued focus on balancing workload across multiple priorities will help maintain consistency in meeting deadlines.
Communication and Teamwork (5) – Collaboration with colleagues is seamless, with clear and effective communication. Positive approach to teamwork strengthens the work environment and enhances project outcomes, as shown by facilitating productive cross-team discussions to resolve workflow issues.

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CLEAR CONDITION

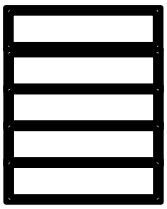
3. As a reminder, a **software engineer** designs, develops, and maintains software to improve company operations. Software engineers work within teams to enhance digital platforms. Below are the performance evaluations of five software engineers along with their **recommended bonuses**. The recommended bonuses are based on employees' average ratings, with higher-rated employees being recommended to receive larger bonuses. After reviewing the performance evaluations and bonus recommendations for each employee, enter an amount (from $0 to $23,000) in the box next to the employee's name. **You will not be able to advance to the next page unless the total sum adds up to $23,000**.

    a. Name and Performance Evaluation with Recommendation
    b. Name and Performance Evaluation with Recommendation
    c. Name and Performance Evaluation with Recommendation
    d. Name and Performance Evaluation with Recommendation
    e. Name and Performance Evaluation with Recommendation



4. Review the promotion recommendation below, which is **based on the employee with the highest average rating.** After reviewing the promotion recommendation, choose one software engineer to promote to the position of **senior software engineer**. A senior software engineer leads the design, development, and maintenance of software to enhance company operations. The senior software engineer serves as a technical expert, mentors teams, and drives innovation to improve digital platforms.

    a. Name and Performance Evaluation with Recommendation
    b. Name and Performance Evaluation with Recommendation
    c. Name and Performance Evaluation with Recommendation
    d. Name and Performance Evaluation with Recommendation
    e. Name and Performance Evaluation with Recommendation



Name Bank: the same as the ambiguous condition

Bank of Performance Evaluations with Recommendations: each of the options was randomly matched with one of the names above.

Option 1:
NOT Recommended for Promotion
Recommended Bonus: $4,150
Average Rating: 3.6

Leadership (4) – Initiative and the ability to guide others are evident in daily work, as demonstrated when assisting junior developers with troubleshooting complex issues. Taking on additional leadership responsibilities will further showcase potential in this area.
Job Skills (4) – Strong technical skills and a solid understanding of the work. Learning continuously and staying updated with industry trends will further strengthen expertise.
Quality of Work (4) – Work is consistently high quality, demonstrating strong attention to detail and accuracy. Successfully debugged critical application issues, preventing additional interrupted workflow.
Quantity of Work (3) – Productivity remains steady, though improvements in time management would help meet deadlines more consistently. More effective task prioritization can enhance overall output, such as ensuring key feature development is completed before lower-priority tasks.
Communication and Teamwork (3) – Collaboration with others is effective, though clarity and responsiveness in communication could be improved. More proactive engagement with team members will enhance overall teamwork, such as responding more promptly to pull request feedback.

Option 2:
RECOMMENDED FOR PROMOTION
Recommended Bonus: $5,700
Average Rating: 4.6

Leadership (5) – Demonstrates outstanding leadership by taking initiative and guiding others effectively. A proactive approach to mentoring and decision-making has positively influenced team dynamics and project direction.
Job Skills (5) – Technical expertise is outstanding, demonstrating a deep understanding of the work and its complexities. Advanced skills make a strong impact on project execution and problem-solving, such as implementing optimized algorithms that improve system performance on a regular basis.
Quality of Work (4) – Work is reliably accurate, thorough, and well-executed. Continued attention to streamlining processes can further enhance efficiency and effectiveness, as seen in the recent effort to automate repetitive deployment tasks.
Quantity of Work (4) – Productivity is strong, with tasks completed in a timely and efficient manner. A continued focus on balancing workload across multiple priorities will help maintain consistency in meeting deadlines.
Communication and Teamwork (5) – Collaboration with colleagues is seamless, with clear and effective communication. Positive approach to teamwork strengthens the work environment and

enhances project outcomes, as shown by facilitating productive cross-team discussions to resolve workflow issues.

Option 3:
NOT Recommended for Promotion
Recommended Bonus: $4,600
Average Rating: 4

Leadership (3) – Demonstrates some leadership potential but could benefit from taking more initiative in guiding and supporting team members. Additional opportunities to lead projects or mentor others will help strengthen leadership abilities, such as volunteering to review and improve team coding standards.
Job Skills (4) – Technical skills and understanding of the work are solid, allowing for effective contributions. Continuing to expand expertise and refine problem-solving approaches will enhance overall performance, as seen in efforts to adopt best practices for database optimization.
Quality of Work (5) – Work is consistently of the highest quality, demonstrating accuracy, thoroughness, and competence. A strong focus on excellence in all tasks contributes significantly to overall success, as reflected in the well-documented and error-free code contributions.
Quantity of Work (4) – Productivity is generally strong, with tasks completed on time and with good efficiency. Further improvements in managing workload could help achieve even greater consistency in meeting deadlines.
Communication and Teamwork (4) – Collaboration is effective, with good communication and positive interaction with team members. Fostering more proactive engagement and clarity in communication could improve team dynamics, such as providing more detailed status updates in stand-up meetings.

Option 4:
NOT Recommended for Promotion
Recommended Bonus: $3,450
Average Rating: 3.0

Leadership (2) – Limited leadership engagement has been observed, and more initiative is needed to guide others effectively. Taking on small leadership tasks or seeking opportunities to mentor colleagues will help build essential leadership skills, such as by offering to assist newer team members with onboarding.
Job Skills (3) – Technical skills and understanding are sufficient but require further development to tackle more complex tasks confidently. Seeking additional training or mentorship will help in strengthening these key competencies, such as becoming more proficient in performance optimization techniques.
Quality of Work (3) – Work is generally accurate but occasionally lacks consistency in meeting the expected level of detail and thoroughness. Focusing on improving the quality control process will help achieve more reliable results and reduce the number of revisions needed before deployment.
Quantity of Work (4) – Productivity is solid, with tasks completed within reasonable timelines. To improve further, focusing on time management and minimizing distractions can enhance efficiency and output, particularly in handling last-minute requests.

Communication and Teamwork (3) – Collaboration with the team is functional, but communication could benefit from greater clarity and consistency. Enhancing active listening skills and contributing more proactively to discussions will improve teamwork, particularly in cross-team projects.

Option 5:
NOT Recommended for Promotion
Recommended Bonus: $5,100
Average Rating: 4.4

Leadership (5) – Exhibits strong leadership by taking initiative, guiding junior software engineers effectively, and fostering a positive team environment. A proactive approach to mentoring and decision-making has significantly influenced project direction and team success.
Job Skills (4) – Possesses solid technical expertise and a strong understanding of the work, contributing effectively to projects. Working on expanding knowledge in emerging technologies and refining problem-solving approaches will further strengthen overall performance.
Quality of Work (4) – Delivers high-quality work regularly, with a solid focus on accuracy and thoroughness. A more structured approach to complex tasks, like clear documentation for newly developed features, can enhance overall efficiency and elevate the quality even further.
Quantity of Work (5) – Maintains an outstanding level of productivity, effectively managing a high workload without compromising quality. Exceptional time management skills contribute significantly to project success, as seen in the ability to consistently juggle multiple high-priority tasks without delays.
Communication and Teamwork (4) – Works well with colleagues and communicates effectively to support collaboration. Strengthening proactive engagement in discussions and providing clearer updates on project progress will further enhance teamwork and coordination.

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POST-TREATMENT PAGE

1. What do you think this study is about? Do not provide information that may identify you, either directly or indirectly. *[Open-ended question.]*

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DEMOGRAPHIC INFORMATION PAGE

1. Are you of Hispanic, Latino, or Spanish origin?
    a. No
    b. Yes

2. What is your race? Please select one.
    a. American Indian or Alaska Native
    b. Asian or Asian American
    c. Black or African American

d. Middle Eastern, Arab American, or North African
e. Native Hawaiian or Other Pacific Islander
f. White
g. Multiracial
h. A race not listed (please specify below)

3. What is your gender identity? Please select one.
    a. Man
    b. Woman
    c. A gender identity not listed (please specify below)

4. In politics today, how do you consider yourself?
    a. Republican
    b. Lean Republican
    c. Independent
    d. Lean Democrat
    e. Democrat
    f. A political affiliation not listed (please specify below)

5. What is the highest degree or level of school you have completed?
    a. Less than high school diploma or equivalent
    b. High school diploma or equivalent (for example: General Educational Development/GED or similar credential)
    c. Some college credit, no degree
    d. Associate's degree (for example: AA, AS)
    e. Bachelor's degree (for example: BA, BS)
    f. Graduate degree (for example: MA, MS, MD, JD, PhD)

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SURVEY COMPLETION PAGE

Thank you for your time and help with providing recommendations for promotions and employee bonuses.

Who to contact with questions:

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If you have questions regarding your rights as a research subject, or if problems arise which you do not feel you can discuss with the Investigator, please contact the Institutional Review Board at:

Phone: (609) 258-8543
Email: irb@princeton.edu

Appendix F: Additional Models for Racial Differences in Men's Outcomes

	White Participants	Black Participants	Asian American Participants
Intercept	4691.824***	4903.023***	4510.323***
	(99.410)	(227.580)	(376.689)
Is Employee Signaled to be a White Man?	-165.217	-211.889	-166.452
	(135.470)	(314.302)	(383.827)
Is Employee Signaled to be an Asian American Man?	-64.343	-545.669+	390.645
	(132.458)	(295.943)	(653.129)
Clear Condition	-35.216	-274.038	-109.347
	(115.493)	(251.601)	(408.700)
Is Employee Signaled to be a White Man in the Clear Condition?	61.352	158.194	555.964
	(158.662)	(348.503)	(466.938)
Is Employee Signaled to be an Asian American Man in the Clear Condition?	26.688	526.901	-282.596
	(153.374)	(337.544)	(682.743)
Num.Obs.	5900	1350	360
R2	0.001	0.006	0.014
R2 Adj.	0.000	0.002	0.000
AIC	105722.2	24323.9	6405.4
BIC	105768.9	24360.4	6432.6
RMSE	1880.67	1967.92	1733.73
Std.Errors	by: ProlificID	by: ProlificID	by: ProlificID

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001