Applying While Black: The Collateral Effects of Racial Differences in Work Histories

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Abstract

It is well known that hiring practices that treat job seekers differently by race contribute to racial disparities in employment. Yet hiring practices that treat job seekers equivalently by race may also contribute to racial disparities if there are preexisting racial differences. We focus on the prominent hiring practice of using the prior experience a job seeker lists on her résumé—that is, her work history—to make inferences about her suitability for a given job. Scholars and practitioners alike have long assumed work histories result from job seekers' strategic choices about where to apply and what jobs to accept and are therefore race-neutral. However, Black job seekers face a distinct set of structural constraints—namely, anticipating and experiencing racial discrimination—that restrict the job search strategies and resulting jobs available to them. As a result, they are less likely to construct the related and specialized work histories employers value compared to their White peers. These racial differences in work histories contribute to the racial disparities that Black job seekers experience. We test and find support for this argument using over 490,000 job applications for all 3,683 publicly posted jobs over seven years at two U.S. technology companies. This study uncovers a novel pathway through which race shapes employment, contributing to the literature on racial discrimination and categorization in labor markets.

1 Introduction

More than 65 years after the passage of the Civil Rights Act, racial disparities remain in the workplace. Black Americans earn significantly less than their White counterparts (Leicht, 2008), are less likely to be employed in high-paying or managerial positions (Browne et al., 2001; Zhang, 2021), and are more likely to be unemployed (Holzer et al., 2005). A large and interdisciplinary body of research seeks to understand the extent to which these disparities result from "disparate treatment"—that is, the extent to which employers treat candidates differently due to their race (see Pager et al., 2009; Rivera, 2020 for reviews). While scholars disagree on the source of employer discrimination—i.e., whether it stems from a "taste" for discrimination, statistical discrimination, or implicit bias—they all focus on how racial disparities result from employers treating otherwise identical job seekers from different racial groups differently.

Although this research has given us a rich understanding of how prejudiced and biased employers reproduce racial disparities, it overlooks the fact that disparities in the workplace also emerge when employers treat job seekers equivalently, but their actions have a "disparate impact" due to preexisting racial differences—what is known as structural or institutional discrimination (Ray, 2019; Reskin, 2005; Small & Pager, 2020; Wingfield & Chavez, 2020).[1] For example, when firms downsize by laying off managers with the shortest tenure, they tend to disproportionately lay off members of underrepresented racial groups because members of these groups have only become managers in substantial numbers recently (Kalev, 2014). The literature's predominant focus on differential treatment obscures the ways employers indirectly contribute to racial disparities in employment through practices that lead to disparate outcomes even though they treat job seekers equivalently. By limiting our investigations to the direct effects of the actions of biased individuals, we understate the degree to which organizations contribute to racial disparities.

One of the most prominent and ostensibly race-neutral employer practices is employers' use of the past work experiences a job seeker lists on her résumé —what we refer to as "work histories"—to make inferences about her suitability for a job (Leung, 2014; Pedulla, 2020; Zuckerman et al., 2003). Given the limited information available during the screening process, employers often draw on a job seeker's work history as an informative cue. This widespread practice has received little scrutiny from scholars of racial inequality at least partially because academics and practitioners alike tend to assume that work histories and the cues they contain result from strategic choices (e.g., Barbulescu and Bonet, 2024; Bidwell

[1] Based on Title VII of the Civil Right Act, both disparate treatment and disparate impact can be used as prima facie evidence of discrimination in employment.

and Briscoe, 2010; Merluzzi and Phillips, 2016) and are therefore unaffected by social factors like race.

In this article, we show that work histories are a hidden mechanism of racial inequality in employment. Job seekers "choose" to build work histories within a given set of structural constraints, which may influence the extent to which they build work histories that meet employer expectations. One prominent structural constraint that likely shapes how job seekers build work histories is the experience of racial discrimination. Given that Black Americans face persistent discrimination across industries and at higher levels than any other major racial group in the United States (Kline et al., 2022; Quillian et al., 2017) and are relatively likely to identify discrimination due to their shared history, segregation, and strong racial identity (Davis, 2010; Lamont et al., 2016), we build an argument around Black job seekers' responses to discrimination. We expect that the experience and subsequent anticipation of racial discrimination likely shapes Black job seekers' confidence in their ability and motivation to find jobs in their current work domains, leading them to apply to a broader set of jobs than their White counterparts (Pager & Pedulla, 2015). As a result of this broader job search strategy, Black job seekers likely apply to and accept jobs less related to their prior experience and, over time, become less specialized than otherwise similar White peers who have not had these discriminatory experiences. As such, they are less likely than their peers to build the related and specialized work histories employers value. In this way, even when employers are not prejudiced or biased, because they use work histories as an information cue in the hiring process, racial differences in these work histories may reproduce racial inequality.

Testing these arguments is challenging because it requires detailed data on the work histories of job seekers, the jobs to which they apply, and their employment outcomes. We address this empirical challenge by using hiring data from two high-technology firms based on the U.S. West Coast: BigTechCo (a pseudonym), a large Fortune 500 technology firm, and SmallTechCo (a pseudonym), a smaller private technology firm. The high-technology industry is an advantageous setting for our study because it mostly attracts college-educated job seekers, minimizing the influence of educational, economic, and other structural disadvantages often correlated with race. Our data include the text of the job posting, all the applications for every job posting including résumés, as well as the outcome for each application for each step in the hiring process. This comprised 490,918 applications for 3,683 posted jobs over seven years. To measure the extent to which each job seeker has a work history aligning with employer expectations of related and specialized work histories, we used a novel text analysis technique to analyze the text of the applicant's résumé and the job posting.

Regression estimates, with job-posting fixed effects and individual-level controls, support our theoretical arguments. After controlling for observable measures of experience, education, gender, and networks, we find that Black job seekers are 14.8% less likely to receive a callback than White job seekers. In line with our theorizing, we find that the work histories employers value—specifically, those composed of experience more related to the position in question and more specialized within a single domain of work—partially mediate this racial disadvantage, accounting for 22.9% of the total effect of race on callbacks. This indirect effect is roughly equivalent to the effect of having 3 fewer years of work experience on callbacks. We also conducted robustness checks to rule out alternative explanations such as racial differences in tailoring résumés and rule in our proposed mechanism of applying broadly. Our results are consistent across the two firms, underscoring the potential prevalence of this hidden form of racial inequality.

This study uncovers a novel pathway through which race shapes employment, contributing to the literature on racial inequality in organizations, labor markets, and categorization. By illustrating how a portion of the racial inequality that Black Americans face is embedded in ostensibly race-neutral employer practices, it complements what is already known about how employer practices accentuate differential treatment (Baron & Pfeffer, 1994; Bielby, 2000; Petersen & Saporta, 2004; Reskin, 2000) by showing how employer practices lead to disparate outcomes without differential treatment. Furthermore, it highlights the importance of understanding how the supply and demand sides of the labor market may interact to reproduce inequality (Brands & Fernandez-Mateo, 2017; Correll, 2004). At the same time, it helps to fill a substantial gap in the literature on categorization in labor markets by uncovering a social-structural antecedent of labor market identities and careers, the origins of which are mostly unknown (Barbulescu & Bonet, 2024; Cutolo & Ferriani, 2023; Trapido & Koppman, 2023).

2 Theoretical Background

Hiring has long been considered a critical mechanism of inequality because hiring decisions affect access to jobs, occupations, and income (Bills, 2003). Scholars typically conceive of hiring as a matching process between employers and job seekers. Employers (the demand side of the labor market) look for applicants to fill jobs. Job seekers (the supply side of the labor market) look for jobs that align with their skills and interests.

Theory on the demand side generally focuses on employer decision-making. When employers hire job seekers, their main concern is ascertaining job seekers' productive capacity in the job they need to fill (Bills, 1990; Tilly, 1998). To determine this, employers try to assess a job seeker's underlying, unobservable skill in and commitment to the job in question (Galperin et al., 2020; Leung, 2014). This is difficult, particularly during the initial stage of the hiring process when employers must quickly screen many applications and only have access to limited information about job seekers.

To reduce this uncertainty, employers often rely on observable cues they glean from résumés and assume are correlated with productivity. Some cues are widely viewed as unfair and biased because they rely on ascribed characteristics over which job seekers have no control; for example, employers' use of job seekers' race or gender to make inferences about job seekers' skill or commitment. Other cues are widely viewed as acceptable and unbiased because they are assumed to result from job seekers' strategic choices to invest effort—that is, supply-side behavior. This includes cues like educational credentials (e.g., Becker, 1964; Stiglitz, 1975), endorsements (e.g., Fernandez and Weinberg, 1997; Neckerman and Kirschenman, 1991; Petersen et al., 2000), and work histories (Leung, 2014; Pedulla, 2020; Zuckerman et al., 2003).

Yet sociologists have long called attention to the fact that even cues widely viewed as supply-side choices are shaped by the structural constraints in which job seekers are embedded. For example, although people choose what and how much to study, they generally do not choose where they go to school or how much their parents can support their education (Tomaskovic-Devey et al., 2005). Thus, neighborhood segregation, differences in economic resources, and other structural inequalities contribute to the tendency for students from under-represented racial groups to attain credentials like bachelor's degrees at lower rates than their White counterparts (Bowen & Bok, 1998; Ciocca Eller & DiPrete, 2018). Similarly, even though we choose whom to befriend, well-documented psychological tendencies lead us to gravitate towards people demographically similar to ourselves (McPherson et al., 2001). As a result, job seekers from racial groups that are underrepresented in firms often have fewer contacts, especially influential contacts, at firms than their majority group peers (e.g., Marsden and Gorman, 2001; Petersen et al., 2000; Tassier and Menczer, 2008). Consequently, employers' reliance on seemingly race-neutral criteria like credentials and endorsements can perpetuate racial disparities.

Of the prominent screening criteria mentioned above, only work histories have not yet been linked to racial disparities. As a result, they are still generally viewed by scholars as resulting from job seekers' strategic choices and largely unaffected by structural constraints. For example, Bidwell and Briscoe (2010) describe work histories as reflecting, "the acquisition of career resources, as workers *use* [emphasis our own] one position to acquire the skills, reputation, and relationships necessary to move into a new position requiring those resources" (p.1034). Similarly, O'Mahony and Bechky (2006) describe how job seekers acquire work histories by acting "strategically to assert control over their careers" (p.935). Indeed, Spence's (1973) theory of signaling, on which many of these studies rest, asserts that a signal acquires value because it is something in which the job seeker has chosen to invest (Merluzzi & Phillips, 2016). Employers appear to share this interpretation, viewing a job seeker's work history as an indicator of her choice to invest in and commit to a given career (Leung, 2014; Merluzzi & Phillips, 2016). As a result of this understanding, work histories are widely considered a race-neutral evaluative criterion. For example, a common defense strategy in class action discrimination lawsuits is to show that gender or racial differences in hiring or pay disappear when one statistically accounts for work histories (Bielby, 2000).

Yet job seekers "choose" to accumulate work histories within certain structural constraints. Given that the structural constraints under which job seekers find themselves vary, some job seekers have a more limited set of choices about where and how to apply than others, which likely influences the jobs to which they apply, the offers they accept, and the work histories they build. Indeed, scholars of careers have long noted that a substantial portion of the workforce does not have work histories that look like the ideal career and speculated that the "choice" to pursue one may only be available to the privileged few (Abbott & Hrycak, 1990; Blair-Loy, 1999; Wilensky, 1961). If members of a group find that their ability or motivation to build work histories containing the information cues that employers privilege differs systematically from most job seekers, this difference may lead members of this group to disproportionately build work histories that employers discount and accrue the associated labor market penalties.

How Employers Use Work Histories to Evaluate Job Seekers

Employers use work histories to ascertain job seekers' suitability for a position. To do so, they must first make sense of the complex information of which work histories are composed, typically a list of jobs someone has previously held. One prominent way employers evaluate this information is by using a classificatory schema that organizes this complex information into discrete categories (Douglas, 2003; Zerubavel, 1999), allowing employers to label the prior experiences a job seeker has held as similar or dissimilar to each other and to the position in question. In labor markets, categories are assigned based on the degree to which they require distinctive skills and commitments from one another (Zuckerman et al., 2003). For example, we tend to think experience in human resources requires different skills and commitments than experience in accounting; likewise, we tend to think experience acting in a drama requires different skills and commitments than experience acting in a comedy.

For a job seeker to be considered a viable candidate, an employer must categorize her as similar to the position the employer is trying to fill. Employers tend to dismiss job seekers identified with unrelated categories or whose work histories span so many categories such that they defy categorization because this introduces uncertainty about whether the job seeker is up for the job, a phenomenon known as the "illegitimacy discount" (Zuckerman, 1999; see Zuckerman et al., 2003 and Leung, 2014 for examples in labor markets.)

Employers' evaluation of job seekers vis-à-vis labor market categories primarily unfolds in two main ways. First, because hiring is a matching process, employers assess the relatedness between the category or categories associated with a job seeker's prior experience and those associated with the job for which employers are hiring. As Zuckerman and colleagues put it (2003): "A short answer to the question of what it takes to be recognized as a candidate in a labor-market category is that one must already have experience in that category" (page 1026). Second, employers assess the extent to which job seekers' previous jobs are specialized in a category, as the more experience one has in a category, the greater her expected suitability for a job in that category.

Matching candidates to jobs based on the relatedness between the candidate's prior experience and the job's demands is the most frequently used criterion by which employers evaluate job seekers and is generally regarded as appropriate and unbiased (McDaniel et al., 1988; Moss & Tilly, 2001; Pedulla, 2020; Tilly, 1998). Employers favor job seekers with prior related experience because they assume these job seekers have the skills and commitment needed to be productive immediately. This assumption is grounded in employers' belief that related experience grants job seekers knowledge and commitment that may be applied in a new context (Dokko et al., 2009). By contrast, employers are uncertain about the productivity of job seekers with prior experience unrelated to the job in question and tend to assume that because these job seekers have the skills and commitment for an unrelated job, they do not have those needed for the focal one (Faulkner, 1983; Zuckerman et al., 2003).

Although employers generally prefer job seekers with more related experience over those with less, the former are not always better candidates. Job seekers with more related experience tend to garner higher wages than those with less (Ang et al., 2002; Parent, 2000), but research on the experience-productivity relationship is decidedly mixed: related experience in a prior organization may be positively correlated, negatively correlated, or uncorrelated with success in a new one (e.g., Castilla, 2005; Dokko et al., 2009). This is at least partially because, in addition to category-specific knowledge and commitment, job seekers with related experience bring cognitive and institutional "baggage," that is, deeply ingrained habits and routines that they import and apply inappropriately in their new organizations, which can differ culturally and operationally from their old ones (Dokko et al., 2009). Furthermore, employers who hire based on related experience may miss desirable candidates because it is based on the crude heuristic—that job seekers generally cannot excel across labor market categories (Zuckerman et al., 2003)—which is not always true. For example, when evaluating a job seeker with engineering experience for a customer service role, employers may typecast the engineer as unsuitable because technical and social skills are seen as opposites (Cech, 2013), even if this particular job seeker has the requisite social skills.

Though job seekers with related prior experience are not always better candidates, employers consistently favor them because there is less uncertainty about their skill and commitment compared to job seekers with less related experience. Though this is far from a controversial prediction, it grounds our subsequent theorizing. Therefore, we expect as a baseline:

Hypothesis H0a. *Job seekers with more related work histories are more likely to be called back*

Another prominent way employers use work histories to evaluate candidates is the degree to which the experiences they contain are focused in a single category versus span disparate categories (Ferguson & Hasan, 2013; Leung, 2014; Zuckerman et al., 2003). In other words, holding constant whether a job seeker has prior experience related to the position, it matters whether a job seeker's work history has concentrated within a single labor market category over time (i.e., a specialist) versus has spanned disparate categories (i.e., a generalist).[2] To understand the relationship between these two constructs, we can imagine a job seeker's past jobs as a constellation of points in a multidimensional space defined along axes of distinctive skills. A job seeker's constellation of past jobs may vary in the degree to which it is centered above a specific job posting (the more centered above a specific job, the more related to that job) and in its volume (the more distant the points are from one another, the greater the volume, the less specialized). These constructs may be mechanically related, as the less specialized the previous jobs of a job seeker are to each other, the less related these jobs (as a whole) will be to any given job posting.[3] However, conceptually, these constructs fundamentally differ in that relatedness is a function of the similarity between a job seeker's past experience and a specific job posting while specialization is based on the

[2] In the literature on labor market categorization, it is common to control for the relatedness of prior experience—for example, by restricting the comparison to those within a labor market category, such as applicants for jobs in the same industry or genre (e.g., Merluzzi and Phillips 2016; Ferguson and Hasan 2013; Zuckerman et. al 2003). We theorize these dimensions separately because the relatedness of one's work history, perhaps even more so than the degree to which it is specialized, is taken for granted as a legitimate and race-neutral screening criterion that we believe is, crucially, correlated with race.

[3] We address this mechanical relationship empirically by also using measures of relatedness that are not mechanically correlated with specialization. See Appendix A.5.

internal homogeneity of a job seeker's experience without regard for the job posting to which she has applied.

Employers often favor job seekers with specialized experience because employers believe they have the skills and commitment to be immediately productive, as focused effort suggests greater skill in and commitment to a category (Autor, 2001; Ferguson & Hasan, 2013; Leahey, 2006; Leung, 2014; Pedulla, 2020; Rosen, 1972). By contrast, employers are uncertain about the potential productivity of generalists. Employers do not know if generalists moved around because they are multi-talented "jacks of all trades" or they could not succeed in or were unwilling to commit to any category (Leung, 2014; Pedulla, 2020; Zuckerman et al., 2003). However, when the uncertainty of the employer about productivity is alleviated—for example, when a job seeker is already well-established in their field or has an elite credential—the positive interpretation of generalists as highly motivated and multi-talented "Renaissance men" may be activated (Merluzzi & Phillips, 2016; Zuckerman et al., 2003).

Much like job seekers with more related experiences, job seekers with more specialized experiences are not always better candidates. Compared to specialists, generalists often have a wider range of knowledge to recombine for innovation and problem-solving (Burt, 2004; Hargadon & Sutton, 1997), a better understanding of the work of colleagues and subordinates (Kacperczyk & Younkin, 2017), and greater cognitive breadth and flexibility (Custódio et al., 2013; Won & Bidwell, 2023). As such, they often outperform specialists in settings that require creativity and strategic thinking; for instance, generalist scientists are more highly cited than specialists (Leahey et al., 2017), film professionals who work in a greater number of different roles win more awards than those who span fewer roles (Cattani & Ferriani, 2008), and CEOs with more diverse careers tend lead firms with more strategic distinctiveness and dynamism than those with more focused careers (Crossland et al., 2014).

Yet in a typical labor market, absent other strong cues, the weight of theory suggests that employers are more likely to discount job seekers with generalist as "dilettantes" and "masters-of-none" than reward them as "jack-of-all-trades" because this lack of focus increases uncertainty about their skill and commitment. Therefore, as a second baseline prediction, we expect employers to favor job seekers with specialized work histories over those with less.

Hypothesis H0b. *Job seekers with more specialized work histories are more likely to be called back.*

How Discounted Work Histories Mediate the Relationship between Race and Employment

When making hiring decisions, employers largely favor job seekers with more related and specialized work histories over those with less related and specialized histories. Such preferences are considered appropriate because we assume related and specialized work histories predict success in the job. Such preferences are considered socially acceptable because we assume related and specialized work histories result from job seekers' strategic choices about where and how to search for and accept jobs. Indeed, some scholars go so far as to argue that work histories are only a valuable signal in hiring when they are seen as something in which the job seeker has chosen to invest (Merluzzi & Phillips, 2016; Spence, 1973). As a result of this widespread assumption of how work histories arise, little is known about their social antecedents (Barbulescu & Bonet, 2024; Cutolo & Ferriani, 2023; Trapido & Koppman, 2023).

However calculated these choices may be, they are made within a set of structural constraints, and there are constraints under which the choice to pursue a job outside one's current labor market category may make sense. For example, when job seekers receive feedback that their current category or firm has poor prospects for advancement, they are more motivated to look for jobs in another category (Barbulescu & Bonet, 2024). Similarly, when job seekers are laid off, they are more likely to look for, be offered, and accept jobs in new categories because they do not have the luxury of waiting for the "ideal job" that perfectly matches their experience and goals (Byun & Raffiee, 2023). Such work suggests that job seekers may find themselves ensconced within structural constraints that limit their ability or motivation to craft related and specialized work histories.

These ostensibly strategic choices may contribute to inequality when they stem from structural constraints that members of certain social groups are more likely to face than others. For example, women often face discrimination and hostile workplace climates in male-dominated work domains like engineering and finance, which lowers their motivation to apply to jobs in these domains and inspires them to apply to female-dominated domains in which they are less likely to have these negative experiences (Barbulescu & Bidwell, 2013; Fernandez & Friedrich, 2011). In this way, demand-side practices shape the supply-side choices of female job seekers, turning "constraints into preferences" (Correll, 2004).

We argue that Black Americans' experience with discrimination is another way demand-side practices turn "constraints into preferences." In the United States, Black Americans experience higher levels of discrimination than any other major racial group. A meta-analysis of field experiments put the average employer preferences for Whites over Blacks at 36%

(Quillian et al., 2017). This is true even among Black Americans in the elite middle-class labor market—i.e., the middle and upper portion of the middle-class labor market, in which workers have a college degree or higher (Lacy, 2007). For example, Black lawyers are less likely than their White counterparts to regain employment when their firms dissolve (Rider et al., 2016). For these relatively privileged Black Americans, the main difference between them and their White peers is not occupational status, income, education, cultural capital, or housing, but the racial discrimination they experience as they live out their lives in primarily White workplaces and social settings (Feagin, 1991; Lacy, 2007; Lareau, 2018).

This demand-side action from employers (i.e., discrimination) likely triggers a supply-side reaction from job seekers. Black Americans often perceive discrimination when they are at work and searching for work (Stainback et al., 2018; Wingfield & Chavez, 2020). For example, a survey of a probability sample of residents in four U.S. urban centers found that 46 percent of Black Americans reported discrimination when searching for a job (Goldsmith et al., 2004). We expect Black job seekers' experiences with and anticipation of racial discrimination to shape their belief in their ability and motivation to find jobs in their current labor market categories.

First, Black job seekers' anticipation of discrimination may constrain their ability, or at least their confidence in their ability, to find jobs in their current categories. Job seekers are ostensibly looking for jobs that align with their skills and interests. But Black job seekers are more likely than White job seekers to believe that they do not have the option of conducting a selective search that narrowly targets the "ideal job"—that is, a job that directly builds on their skills and attracts their interest—because they fear that, due to discrimination, this strategy will prolong their job search or leave them without a job. As a consequence, and in line with research on how Black Americans try to ameliorate the effects of discrimination in other settings (Feagin, 1991; Heckman, 1998; Lacy, 2007), Black job seekers likely develop strategies to increase their chance of a short and effective job search.

In response to anticipated discrimination, Black job seekers may employ job search strategies that extend their search outside their current labor market categories. Black job seekers likely expect that some subset of employers will discriminate, but they do not have reliable information about who or when as racial discrimination is widespread across industries and occupations (Kline et al., 2022). As such, they cannot target their searches to positions for which they are less likely to experience discrimination, as suggested by models of self-selection (e.g., Heckman, 1998; Lundberg and Startz, 2007). To increase their hiring chances, Black job seekers apply across a wider range of labor market categories than their White counterparts (Pager & Pedulla, 2015). Black job seekers who employ this strategy may find jobs more quickly and may be more likely to find jobs overall than Black job seekers who apply narrowly, but they are also less likely to ultimately obtain jobs in labor market categories related to their prior experiences.

Second, workplace experiences with discrimination may constrain Black job seekers' motivation to find jobs in their current labor market categories. We know that job seekers consider the status of the labor market category associated with their current job and trade it for other desirable work attributes. For example, job seekers are willing to work for less money in higher-status categories because they expect doing so will be beneficial in the long term (Sabanci & Elvira, 2023). Similarly, job seekers in lower-status categories have a greater incentive to search for jobs outside their current domains than those in higher-status categories (Barbulescu & Bonet, 2024).

Experiences of discrimination at work may, like low status, spur workers to look for a new job outside one's current category. Members of historically marginalized racial groups often question whether they are accepted in settings with a White majority (Allport et al., 1954; Major & O'Brien, 2005) and use situational cues to gauge their comfort (Purdie-Vaughns et al., 2008). Perceptions of discrimination in one's current work domain, such as being overlooked for a promotion or experiencing harassment from a coworker, may be a situational cue that one is not fully accepted. Such experiences may inspire Black Americans to search for jobs in different labor market categories, with the hope that these different domains will be more welcoming.

As such, because of the structural constraints that Black job seekers face, which may constrain their belief in their ability to find jobs in their current categories and enhance their motivation to seek out jobs in different categories, we expect that Black job seekers apply to jobs that are less related to their prior experience than their White peers. Thus, we expect:

Hypothesis H1a. *Black job seekers will have less related work histories than White job seekers.*

Beyond this single hiring event, Black Americans' response to discrimination and resulting job search strategy may have cumulative effects on the specialization of their work histories as the supply- and demand-side forces in the labor market interact over time. The contemporary labor market is marked by workers increasingly moving between firms (Bidwell et al., 2013) and the average employee firm tenure has dropped, with workers holding an average of twelve jobs during their employment lifetime (Bureau of Labor Statistics, 2020). As a result, searching for jobs is an increasingly common occurrence.

To the extent that Black job seekers apply to and subsequently hold jobs that are less related to their prior experience than their White peers, they will likely accumulate work histories composed of jobs less specialized in a labor market category. In other words, if job seekers repeatedly search for jobs less related to their prior experience, they are, over time, more likely to be offered and accept jobs less related to their prior experience than their peers who narrowly focus their searches. As a result, they are likely to build a work history of jobs that are less related to one another, i.e., that are less specialized. In short, owing to the cumulative effects of employing this job search strategy across multiple job searches over time, we expect Black job seekers to have less specialized work histories than White job seekers. Therefore, we expect:

Hypothesis H1b. *Black job seekers will have less specialized work histories than White job seekers.*

Altogether, Black job seekers' anticipation and experiences of discrimination, and their resulting job search strategy, may have collateral effects—that is, negative, unintended consequences—on their future employment. Only a portion of racial disparities in employment can be attributed to biased or prejudiced individuals. Much is entrenched in taken-for-granted organizational systems, processes, and cultures (Ray, 2019). We expect employers' consideration of work histories is one way racial disparities in employment emerge from practices in which employers treat candidates of different races equivalently.

Owing to different choices that are rational responses to constraints they face, we expect Black job seekers to apply to jobs less related to their work histories than their White peers, which over time, leads them to accumulate work histories that are less specialized than their White peers. As employers largely favor job seekers with related and specialized experience, we expect that a portion of the racial disparities Black job seekers experience in employment—in particular, their lower likelihood of being hired by employers—is mediated by their tendency to have less related and specialized work histories than their White counterparts. In summary, we expect that:

Hypothesis H2a. *The lower likelihood of Black job seekers being called back compared to White job seekers is partially mediated by Black job seekers' less related work histories.*

Hypothesis H2b. *The lower likelihood of Black job seekers being called back compared to White job seekers is partially mediated by Black job seekers' less specialized work histories.*

Our hypotheses focus on Black Americans due to the high level and persistence of the racial discrimination they experience. Yet other major racial and/or ethnic groups may also experience discrimination in this setting. To the extent that this is the case, they may also engage in similar supply-side job search responses. We account for these groups in our main analyses.

3 Empirical Setting

We test our proposed theory using hiring data from two high-technology firms based on the U.S. West Coast. The first firm, which we will refer to as BigTechCo (a pseudonym), is a large Fortune 500 technology firm with a valuation in the hundreds of billions. The second firm, which we will refer to as SmallTechCo (a pseudonym), is a smaller private technology firm with a private valuation in the hundred millions. Through a research partnership with an HR analytics firm, we received each firm's automated Applicant Tracking System (ATS) data which tracks all details of all job postings and applications from both firms.

High-technology firms are an ideal setting to test our hypotheses. First, high technology is an industry in which specialization is prized. Although scope conditions for the specialist advantage have been identified (e.g., Byun and Raffiee, 2023; Merluzzi and Phillips, 2016), as a rapidly changing knowledge-intensive industry, we would expect employers to value specialization when hiring in this context (Teodoridis et al., 2019).

Second, Black job seekers who apply to jobs in these firms are generally part of the elite middle class (i.e., typically have at least a college degree). This lessens concerns regarding class-based, economic, and structural alternative explanations for the racial differences we theorize. Black job seekers in the working and lower-middle-class labor market face numerous economic, social, and residential disadvantages in addition to discrimination (e.g., Pattillo, 2013; Wilson, 2012). Yet in the elite middle-class labor market, in-depth ethnographic studies have argued that the main challenge Black Americans experience due to their race is the discrimination they experience as they go about their lives in majority-White workplaces and public spaces (Feagin, 1991; Lacy, 2007; Lareau, 2018). Indeed, when asked how race influences their lives, they primarily describe the strategies they use to avoid discrimination in these spaces, such as wearing a suit to go shopping and highlighting their credentials at work (Feagin, 1991; Lacy, 2007), strategies that parallel the job search strategy we hypothesize.

Finally, as our theorizing focuses on how employers assess job seekers' work histories, we focus on the initial evaluation stage of the hiring process: the decision to call back an applicant conditional on applying to a job posting. We chose this stage because this is the stage in which decisions are primarily based on résumés, while in later stages, interpersonal factors that emerge during interviews such as cultural fit and "passion" move to the fore (Rivera, 2012, 2015). Given the importance of this initial screening and the fact that this is the outcome on which most of the literature on racial discrimination in hiring has focused, we believe it is a critical stage to examine.

3.1 Data

The hiring process at both BigTechCo and SmallTechCo starts with a job posting in their Applicant Tracking System (ATS). The job is then posted on the company website, job boards, and social network sites, such as LinkedIn. When applying for a job, applicants are directed to the company's website to submit an application, which includes their résumés as well as basic information, such as their name, demographics, etc. The ATS keeps detailed records of all the firm's job postings and job applications. For each job posting, we have the text of the job description as well as other details of the role (i.e., location, business division, the hiring manager's name, etc.). These job postings come from 21 different office locations, across 28 business divisions, with 68% of the posted jobs based in the U.S. The dataset also contains all the applications for each job posting, the information contained on submitted résumés, and the employment outcome for each application. In total, the full dataset contains 1.06 million applications across 5,523 job postings posted between 2012 and 2018.

We filter this dataset to only include full-time jobs (i.e., no contract positions), that are based in the U.S. and not actively recruiting at the time of data collection. Because our theoretical predictions focus on the work histories of applicants, we only examine applications from applicants with three or more past jobs in their résumés.[4] The resulting dataset contains 490,918 applications across 3,683 job postings. This includes 444,533 applications across 3,179 job postings from BigTechCo and 46,385 applications across 504 job postings from SmallTechCo.

3.2 Outcome Variable

Our main outcome variable is whether an applicant received a callback conditional on applying to a job posting.[5] Once a set of applications has been received, the hiring manager reviews the applications and chooses a subset of applicants with whom to follow up. This is considered a "callback" and is the first step in the hiring process. The average callback rate is 25% at BigTechCo and 15.2% at SmallTechCo.

[4]We also replicate our analysis with the full sample, and the results are unchanged. See Appendix A.2.

[5]While we also have visibility into the rest of the hiring process—such as which applicants received an interview and a job offer—we do not examine these as our main outcome variables because they are influenced by interpersonal factors beyond the work histories presented on résumés. For completeness, we present analyses on interview and offer outcomes in Appendix A.11. The main results are directionally consistent for interview outcomes, but they attenuate as we progress through the process because later decisions are made based on candidate characteristics that we cannot observe in the data.

3.3 Explanatory Variables

Our main explanatory variables are applicant race, work history relatedness, and work history specialization.

Applicant Race

The ATS dataset we received already had the race of each applicant pre-coded. The majority of applicants self-reported their race in the EEO-1 self-identification form as part of the application process.[6] For the applicants that did not self-report (37%), the HR analytics firm we partnered with predicted the race based on the applicant's name and location. The HR firm reported the overall accuracy of applicant race (including self-reports) to be 92% based on a comparison of the results of the imputed race algorithm with the actual reported race of applicants. To increase confidence in the accuracy of imputed race, we perform sensitivity analysis in Appendix A.4 where we probabilistically assign race using a publicly available race prediction API. Our results remain consistent.

Measures of work history relatedness and specialization

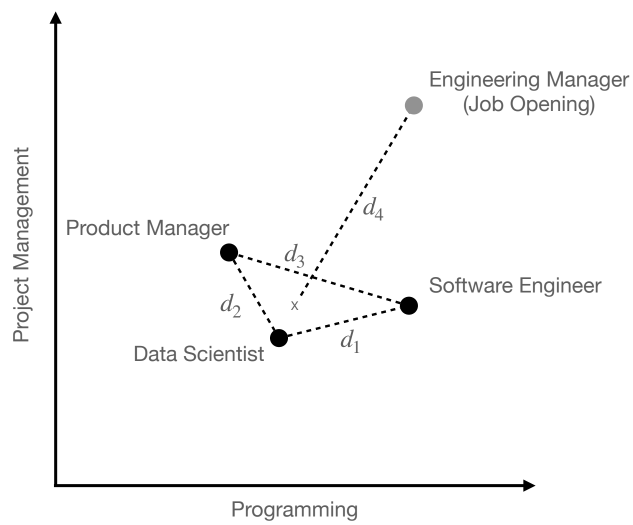
We develop measures of work history relatedness and specialization based on the jobs listed on applicants' résumés. To do so, we begin by conceptualizing a job as a collection of knowledge, skills, and activities (hereafter referred to as core competencies) required to perform that job. For a software engineer, these might include programming, problem-solving, and project management. For a data scientist, these might include programming, data analysis, and statistical modeling. Jobs may be more or less related to each other based on the similarity of their core competencies. From this perspective, a software engineering job may be understood as more related to a data science job than to a marketing job because the former two share more core competencies than the latter two.

Based on this conceptualization of jobs, we use similarity measures between jobs in a latent space of core competencies to develop measures of relatedness and specialization. For an illustration, consider a toy example where only two competencies exist: programming and project management. Consider also an applicant who has previously worked as a software engineer, a data scientist, and a product manager, and is now applying for an engineering management position (i.e., the focal job). Because only two core competencies exist in this example, the individual jobs occupy a two-dimensional space, where each job is located in

[6]The EEO-1 race categories are White, Asian, Black, Hispanic, American Indian/Alaskan Native, and Mixed. Since there were only 313 American Indian/Alaskan Native and Mixed applicants in our dataset, we drop them from our analyses.

this space as a function of how important these two core competencies are weighted for each of these jobs (see Figure 1). For example, in Figure 1, a software engineer job is located farther along the x-axis (which represents the core competency of programming) than a product manager job, suggesting that programming is more important for a software engineer than a product manager. Each job can therefore be identified as a point in this space of core competencies and the distance between the jobs represents how conceptually distant or similar the jobs' core competencies are from one another. In this example, software engineering is less distant/more similar to data science than it is to product management.

Figure 1: Illustration of job distances in a two-dimensional latent space

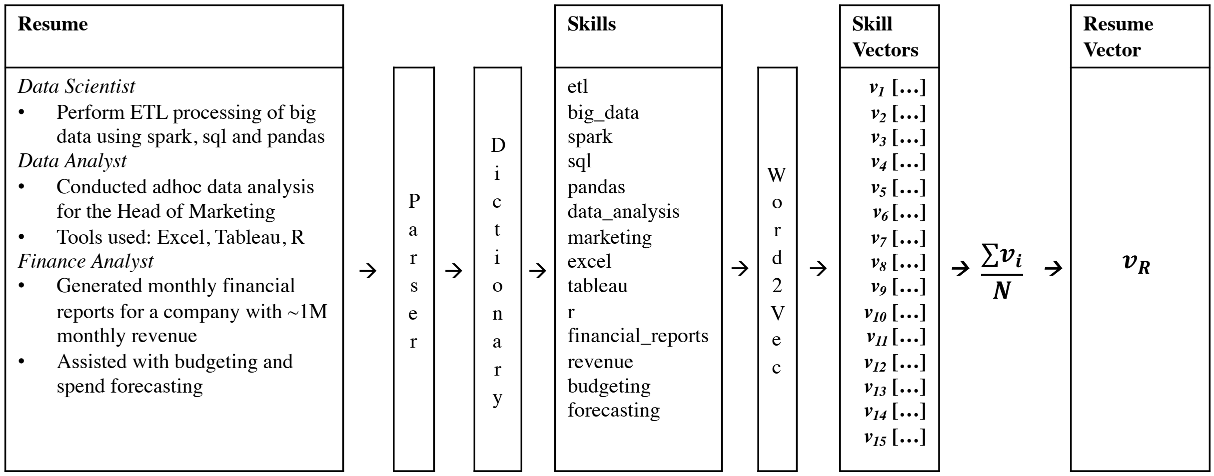


Based on this conceptualization, we measure *relatedness to focal job* using the similarity (i.e., inverse of the distance) between the midpoint of the applicant's past job experiences (represented as 'x') and the focal job opening of engineering manager—i.e., $1 - d_4$ in Figure 1. The closer the midpoint of all jobs in an applicant's past experiences is to the focal job opening, the more related the applicant's work history is to the focal job.

We measure *specialization* using the average pairwise similarity between the applicants's past job experiences — i.e., $\frac{(1-d_1)+(1-d_2)+(1-d_3)}{3}$ in Figure 1. The closer these points are to each other, the more specialized the applicant's work history.

In reality, the similarity between jobs cannot be characterized in only two dimensions. Rather, there are hundreds of dimensions along which jobs can be similar or different from each other. To capture similarities between jobs in this high-dimensional space, we use a Word2Vec model trained on a corpus of résumés. Word2Vec is a neural network model used in natural language processing that learns a vector representation of tokens encountered in the corpus (Mikolov et al., 2013). Similar to the 2-D illustration above, these tokens can

Figure 2: Illustration of creating vector representation for a résumé



be represented as points in a high-dimensional space, and similarity between tokens can be measured using the distance between the points.[7] For example, the similarity score between `data science` and `data engineering` is 0.71, whereas the similarity score between `data science` and `dna sequencing` is 0.17.

To represent jobs in this high-dimensional space, we average the vector representations of core competencies extracted from the relevant text. Specifically, we first parse the relevant document (i.e., résumé, individual job experience, job posting descriptions) into individual tokens. Some of these tokens are relevant knowledge, skills, and activities (i.e., competencies such as `market research`, `financial reporting`, `liaising with engineers`, etc.), while others are not. We extract these relevant tokens using a dictionary of roughly 20,000 competencies created from scraping skills and keywords from public LinkedIn profiles. Each extracted token corresponds to a vector in the Word2Vec model. We then take the average of all the relevant vectors corresponding to each constituent competency term in a description to create a vector representation for (1) the applicant's résumé, (2) each job experience within the résumé, and (3) the description posted of the focal job to which the applicant applied. See Figure 2 for an illustration of this process for a résumé.

Formally, given an applicant's résumé R, consisting of n past job experiences $\{J_1, J_2, \ldots, J_n\}$, and a job posting description J_{focal}, we get vector representations for each of these: $\boldsymbol{v}_R$ for the résumé, $\{\boldsymbol{v}_{J_1} \ldots \boldsymbol{v}_{J_n}\}$ for each of the past job experiences, and $\boldsymbol{v}_{J_{focal}}$ for the focal job

[7] Unlike in the two-dimensional illustration above, where we used euclidian distance, a more common practice is to use cosine distance between the points since there they are normalized between 0 and 2. Cosine distance is defined as $1 - \frac{A \cdot B}{||A||_2||B||_2}$, where A and B are two vectors, and $||A||_2$ is the euclidian norm of A. Cosine similarity is the inverse of cosine distance—i.e., cosine similarity = 1 - cosine distance.

posting description. We then define relatedness to the focal jobs as the cosine similarity[8] between the résumé vector and the focal job vector—higher the cosine similarity, the more related the job seeker's job experiences are to the focal job.

$$\textit{Relatedness to Focal Job} = cos(\boldsymbol{v}_R, \boldsymbol{v}_{J_{focal}}) \tag{1}$$

One potential concern with this measure of relatedness is that it averages across all past jobs in an applicant's résumé. So even if an applicant has all the required competencies for a job opening, having an additional unrelated competency mechanically lowers relatedness to the focal job. To address this, we use two alternate measures of relatedness that use the similarity between the job posting and (1) the most related past job and (2) the most recent job. The results hold regardless of which measure we use (see Appendix A.5). That said, our preferred measure uses the average across all jobs since it is one closest to the experience hiring decision makers have when they evaluate a résumé, as they likely consider an applicant's entire work history.

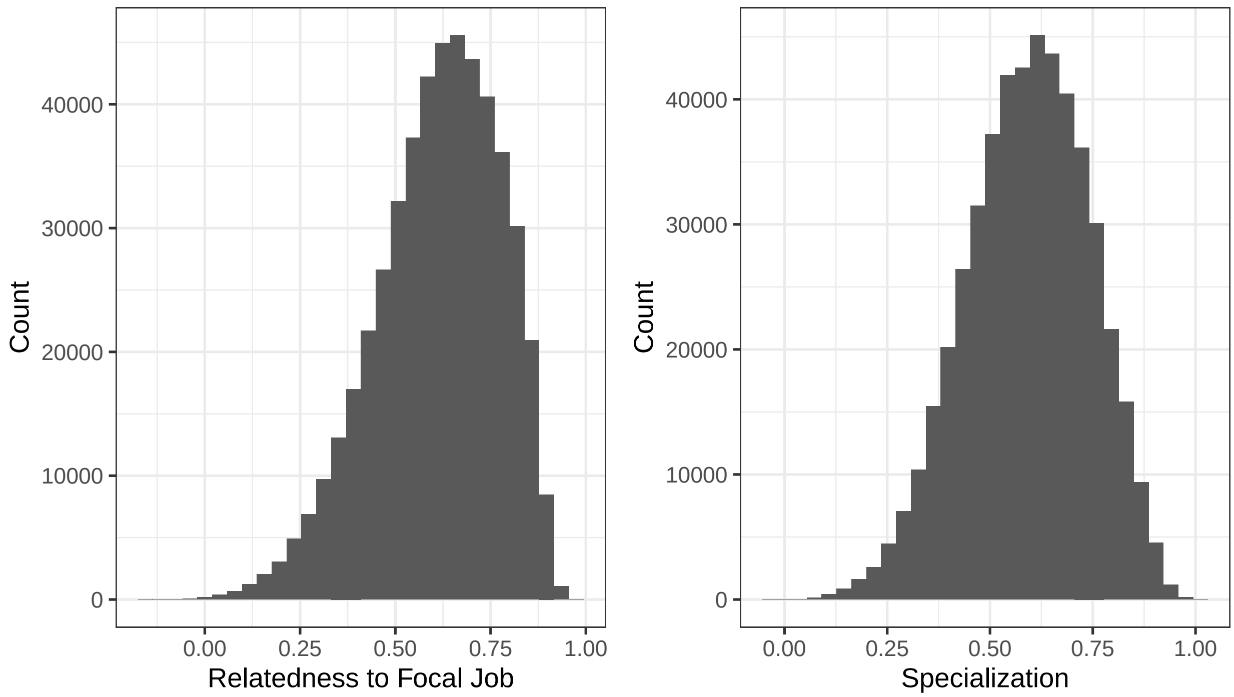
Next, we define work history specialization as the average pairwise cosine similarity between the applicant's past job vectors.

$$\textit{Specialization} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} cos(\boldsymbol{v}_{J_i}, \boldsymbol{v}_{J_j}) \mid i \neq j}{(n^2 - n)/2}, \quad n > 2 \tag{2}$$

We measure relatedness to the focal job and specialization for each application and plot the distribution of these measures in Figure 3. These key mediating variables display ample variation across applications.

[8]Cosine similarity is the inverse of cosine distance—i.e., cosine similarity = 1 - cosine distance

Figure 3: Distribution of work history measures



Our measures of relatedness and specialization are also advancements in the measurement of category-spanning in labor markets, which attempt to measure the extent to which the experiences in one's history are similar to one another and the position. Initial measures relied on the labels associated with labor market categories such as film genres, organizational functions, or job titles, and counted the number of categories with which a product or person was associated; for example, the total number of genres associated with a film (Hsu, 2006). This was extended to account for one's focus one within a category. For example, the number of months a consumer service representative previously worked as a consumer service representative (e.g., Dokko et al., 2009) or using the Herfindahl concentration index to measure the degree to which work experience focused in a function (e.g., Byun and Raffiee, 2023; Ferguson and Hasan, 2013). Another advance was recognizing that the similarity among categories varies due to overlap in the underlying features categories share (e.g., Kovács and Hannan, 2015; Leung, 2014). For example, programming jobs are more similar to website development jobs than to accounts payable jobs because the underlying competencies required to perform them are more similar. Yet these studies proxy for similarity by examining observed overlap and did measure the actual similarities in the features of these categories.

We advance measurement of category-spanning by using machine learning analysis of free-form text in self-reported job descriptions (see Ng and Sherman, 2022). This allows us to more accurately measure the features (i.e., the core competencies) associated with specific category labels (i.e., the job titles) and how much these features differ from one another in a continuous manner. This moves us beyond the use of category labels as a proxy for job similarity and accounts for the underlying differences in features upon which theory rests.

3.4 Control variables

We include a variety of control variables at the job-posting and applicant levels to account for alternative explanations. To account for differences in job postings, we include job-posting fixed effects. At the level of the applicant, we control for the total years of experience, tenure at the current job, educational measures, such as the highest degree they completed (indicators for Doctorate, Masters, Bachelors, Associate, No degree), field of study (STEM, Business, Law, Other), rank of the undergraduate school (according to U.S. News), school region (US, Canada, Europe, Asia, Other, Unknown)[9], their number of past jobs, and an indicator for whether the job seeker has a referral from a current employee. Controlling for whether an applicant was a referral addresses concerns about potential differences in applicants' social networks. We also include the gender of the applicant as a control. Tables 1 and 2 report the summary statistics of all variables, and Table 7 in Appendix A.1 reports the correlation matrix.

As evident from the summary statistics, the main outcome (callback) displays a reasonable amount of variation. Overall, 24% of applicants received a callback. There were, however, differences by race: 24% of White applicants but only 18% of Black applicants received a callback. The average applicant had over 11 years of experience, suggesting that a good proportion of applicants have extensive work histories.

Black applicants appear to contain only slightly less related and specialized work histories than White applicants. These differences here are slight because these are aggregate measures averaging over all job postings; the differences become more pronounced when we compare Black and White applicants within the same job posting (see Table 4). The racial composition of the applicant pool reflects the location (West Coast) and industry (high technology), as White and Asian applicants are the two largest racial groups in our sample. The applicant pool is also highly educated, with the vast majority of applicants having a bachelor's degree or higher. This is aligned with what we would expect in an elite middle-class labor market.

[9] We classify the school region from the education section of the résumé text using the OpenAI gpt-4o-mini API. We use the following prompt: "Based on the education section of the following resume, classify the region of the school. <<resume text>>" and constrain the response to be one of the following options: US, Canada, Europe, Asia, Other, Unknown. Based on a random sample of 200 applicants, the classification accuracy is 90%.

Table 1: Univariate summary statistics

	Mean			Median			SD		
	All	White	Black	All	White	Black	All	White	Black
Callback (1=YES)	0.24	0.24	0.18	0.00	0.00	0.00	0.43	0.43	0.39
Relatedness to Focal Job	0.61	0.62	0.62	0.63	0.64	0.63	0.16	0.16	0.17
Specialization	0.59	0.59	0.58	0.60	0.60	0.58	0.15	0.15	0.16
Yrs of Exp	11.19	11.92	10.99	10.00	10.00	10.00	6.56	6.94	6.28
Tenure at Current Job	2.20	2.39	2.26	1.00	1.00	1.00	3.08	3.37	3.11
Num Jobs Held	5.10	5.17	5.24	5.00	5.00	5.00	2.22	2.29	2.22
Referral	0.02	0.02	0.01	0.00	0.00	0.00	0.14	0.14	0.10

Table 2: Multivariate summary statistics

		N			Percent		
		All	White	Black	All	White	Black
Race	White	259,362			52.8		
	Black	13,509			2.8		
	Asian	166,045			33.8		
	Hispanic	52,002			10.6		
Gender	Male	291,964	151,885	7,128	59.5	58.6	52.8
	Female	198,954	107,477	6,381	40.5	41.4	47.2
Degree	Diploma	11,029	6,949	273	2.2	2.7	2.0
	Bachelors	237,141	139,753	6,930	48.3	53.9	51.3
	Masters	173,740	69,430	4,069	35.4	26.8	30.1
	Doctorate	27,402	16,597	950	5.6	6.4	7.0
	n/a	41,606	26,633	1,287	8.5	10.3	9.5
Field of Study	Technical	176,629	70,887	3,416	36.0	27.3	25.3
	Business	80,300	41,725	3,039	16.4	16.1	22.5
	Law	13,432	9,360	611	2.7	3.6	4.5
	Other	201,593	125,406	5,948	41.1	48.4	44.0
School Rank	Top10	22,071	9,494	478	4.5	3.7	3.5
	11-20	17,815	9,719	346	3.6	3.7	2.6
	21-50	47,570	21,672	743	9.7	8.4	5.5
	51-100	24,731	12,240	390	5.0	4.7	2.9
	101-200	26,499	13,629	545	5.4	5.3	4.0
	Unranked	352,232	192,608	11,007	71.7	74.3	81.5
School Region	US	388,236	208,072	11,764	79.1	80.2	87.1
	Asia	22,285	3,696	65	4.5	1.4	0.5
	Canada	7,071	3,785	155	1.4	1.5	1.1
	Europe	20,195	14,173	404	4.1	5.5	3.0
	Other	26,838	14,225	373	5.5	5.5	2.8
	Unknown	7,302	3,416	253	1.5	1.3	1.9

4 Results

4.1 Applicants with more related and specialized work histories are more likely to receive callbacks

We begin our analysis by testing the baseline hypotheses that applicants whose work histories are more related to the focal job and more specialized are more likely to be called back. We run OLS regressions predicting the likelihood of an applicant receiving a callback (set = 1) and report the results in Table 3.[10] We include relatedness to focal job and specialization as the independent variables of interest, and include applicant attributes and job posting fixed effects as controls.

As hypothesized, both relatedness to focal job and specialization are positively associated with the likelihood of callback. A 0.1 point increase in relatedness corresponds to a 5.19 percentage point (21.62%) increase in the likelihood of callback.[11] Similarly, a 0.1 point increase in specialization, corresponds to a 1.47 percentage point (6.12%) increase in the likelihood of callback.

We plot the predicted probability of callback against the work history measures in Figure 4. The left panel plots the predicted probability of callback against relatedness to focal job, and the right panel plots the predicted probability of callback against specialization. There is a clear positive relationship between both work history measures and the likelihood of callback. These results are directionally consistent across both firms (see Appendix A.3). Taken together, these results corroborate our baseline hypotheses, H0a and H0b.

[10] We report OLS estimates for easier interpretation of coefficients. The coefficients can be interpreted as absolute percentage point changes from the baseline callback rate. The average marginal effects of logit models yield highly similar results. We report logit estimates in A.8.

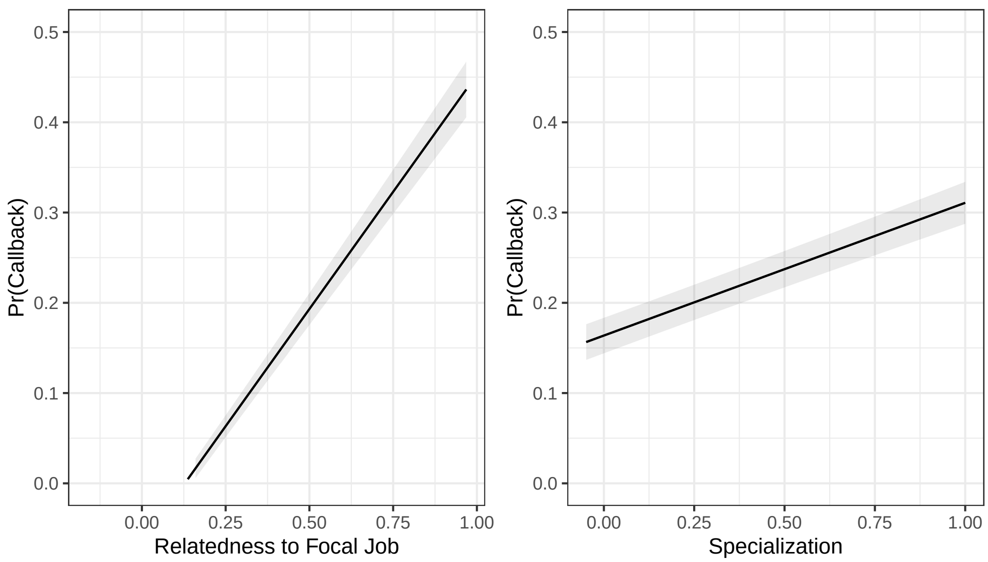
[11] We will use "percentage points" to denote absolute percentage changes, and "%" to denote relative percent changes.

Table 3: OLS regression of callback on work history relatedness and specialization

Dependent Variable:	Callback (1=YES)
Work history measures	
Relatedness to Focal Job	0.519*** (0.005)
Specialization	0.147*** (0.004)
Demographics	
Black	-0.032*** (0.003)
Asian	0.002 (0.001)
Hispanic	0.006** (0.002)
Female	0.011*** (0.001)
Experience	
Yrs of Exp	0.003*** (0.000)
Tenure at Current Job	-0.004*** (0.000)
Num Jobs Held	-0.001** (0.000)
Fixed-effects	
Job Posting	Yes
Degree	Yes
Field of Study	Yes
School Rank	Yes
School Region	Yes
Referral	Yes
Fit statistics	
Observations	468,373
R^2	0.13562

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

Figure 4: Predicted probability of callback vs. relatedness to focal job and specialization



To provide evidence that these relationships stem from employers' reliance on work histories as information signals, as hypothesized, we ran additional analyses in which we included another well-established information signal, referrals, as a moderator. The logic here is that a referral from a current employee would likely offset the illegitimacy discount associated with a less related and specialized work history because it reduces uncertainty about the applicant's suitability by providing more information. In line with our theorizing, we find that referrals attenuate the positive effects of relatedness and specialization (see Appendix A.9 for the regression estimates).

To provide further evidence of the validity of our measurement, we examined the extent to which variance in the competencies included in a job posting moderates the relationship between specialized work histories and callbacks. Logically, the more variation in competencies a job posting exhibits, the more likely the positive relationship between specialization and callbacks will be attenuated because employers seeking to fill jobs requiring greater breadth in competencies will be more likely to prefer applicants who also exhibit similarly generalist work histories. In line with our expectations, and as further support for our measurement, we find that increasing job skill breadth attenuates the positive relationship between specialization and being called back (see Appendix A.10 for the regression estimates).

4.2 Black applicants have less related and specialized work histories

We now turn to testing Hypothesis H1a and Hypothesis H1b—that Black applicants have less related and specialized work histories than White applicants. We test these hypotheses using OLS regressions and report the results in Table 4. Column (1) reports the estimates for relatedness to focal job and Column (2) reports the estimates for specialization.

After controlling for the job-posting and job-seeker characteristics, Black applicants' work histories are 1.25% less related to the focal job than similar White applicants. Similarly, Black applicants' work histories are 1.83% less specialized than similar White applicants. These results are directionally consistent across firms (see Appendix A.3). These results are also consistent if we measure relatedness and specialization based only on the job titles listed on applicants' résumés. Black applicants' job title histories are 4.31% less related to the focal job and 1.8% less specialized than that of similar White applicants (see Section 5.2).

To facilitate interpretation of these differences, we identified job title sequences with differences in magnitude similar to the racial differences we find. For example, the magnitude of the difference in work history relatedness between Black and White applicants is roughly equivalent to the difference between an applicant with prior experience as an Android developer versus prior experience as an iOS developer applying to an Android engineering job. Similarly, the racial difference in specialization is roughly equivalent to the difference in specialization between an applicant who moved from Android developer, to iOS developer, to web developer, versus one who moved from Android developer, to Android developer, to web developer.

Other patterns are also worth noting. Male applicants appear to have less related and specialized work histories than female applicants, in line with previous work showing that women tend to apply more narrowly than men (LinkedIn, 2019; Pager & Pedulla, 2015). Hispanic applicants appear to have less related work histories than White applicants, although they also appear to have slightly more specialized histories. As Hispanics do not experience lower callback rates in this context[12] (see Table 3), these less related work histories are unlikely a response to discrimination, though they may reflect a job search strategy of applying broadly but accepting jobs selectively.

[12] According to meta-analyses, discrimination against applicants of Hispanic/Latin American origin tends be lower than discrimination against Black applicants and has declined over time (Quillian et al., 2017, 2019)

Table 4: OLS regressions of work history relatedness and specialization on applicant race

Dependent Variables: Model:	Relatedness to Focal Job (1)	Specialization (2)
Demographics		
Black	-0.006*** (0.001)	-0.007*** (0.001)
Asian	-0.003*** (0.000)	0.005*** (0.001)
Hispanic	-0.009*** (0.001)	0.001 (0.001)
Female	0.004*** (0.000)	0.007*** (0.000)
Experience		
Yrs of Exp	0.002*** (0.000)	0.002*** (0.000)
Num Jobs Held	0.002*** (0.000)	-0.005*** (0.000)
Tenure at Current Job	-0.001*** (0.000)	-0.001*** (0.000)
Fixed-effects		
Job Posting	Yes	Yes
Degree	Yes	Yes
Field of Study	Yes	Yes
School Rank	Yes	Yes
School Region	Yes	Yes
Referral	Yes	Yes
Fit statistics		
Observations	468,373	468,373
R^2	0.48602	0.14073

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

4.3 Less related and specialized work histories partially mediate the relationship between race and callbacks

Having established that (1) job seekers with more related and specialized work histories are more likely to receive a callback and (2) Black job seekers have less related and less specialized work histories than White job seekers, we next test whether these differences in work history measures partially mediate the callback disadvantage faced by Black job seekers. To do so, we begin by running a series of nested models, where we add measures of work history relatedness and specialization to the model in Table 3. Column (1) is the null model with only race and controls, Column (2) adds relatedness to focal job, Column (3) adds specialization, and Column (4) is the full model with both relatedness and specialization.

As expected, the coefficient for being Black is significant and negative across all models, suggesting that Black applicants are less likely than White applicants to receive a callback, net of the included observable control variables. As shown in Column (1), Black job seekers are 3.6 percentage points less likely to receive a callback compared to White job seekers. Compared to a baseline callback rate of 24% for White job seekers, this is a 14.8% relative difference.[13] Job seekers from other non-White racial groups like Hispanics and Asians do not appear to experience a hiring disadvantage in these firms.

As shown in Columns (1)-(4) in Table 5, the coefficient becomes less negative as we add the measures of relatedness and specialization, suggesting that the effects of race on callback are partially mediated by differences in Black job seekers' work histories. In the null model (1), Black job seekers are 3.6 percentage points less likely to receive a callback compared to White job seekers. In the full model, in contrast, Black job seekers are only 3.2 percentage points less likely to receive a callback.

[13] While this proportional effect is smaller than the average reported across correspondence studies, it is in line with a recent, large-scale field experiment focused on Fortune 500 employers, which found Black job seekers were 2 percentage points (9%) less likely to receive a callback (Kline et al., 2022). This difference may stem from the more formalized human resources processes in larger firms.

Table 5: OLS regression of callback on race and career measures

Dependent Variable:	Callback (1=YES)			
Model:	(1)	(2)	(3)	(4)
Demographics				
Black	-0.036*** (0.003)	-0.033*** (0.003)	-0.034*** (0.003)	-0.032*** (0.003)
Asian	0.001 (0.001)	0.003‡ (0.001)	0.000 (0.001)	0.002 (0.001)
Hispanic	0.002 (0.002)	0.006** (0.002)	0.002 (0.002)	0.006** (0.002)
Female	0.014*** (0.001)	0.012*** (0.001)	0.013*** (0.001)	0.011*** (0.001)
Experience				
Yrs of Exp	0.005*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.003*** (0.000)
Tenure at Current Job	-0.005*** (0.000)	-0.004*** (0.000)	-0.005*** (0.000)	-0.004*** (0.000)
Num Jobs Held	-0.001‡ (0.000)	-0.002*** (0.000)	0.001* (0.000)	-0.001** (0.000)
Work history measures				
Relatedness to Focal Job		0.552*** (0.005)		0.519*** (0.005)
Specialization			0.230*** (0.004)	0.147*** (0.004)
Fixed-effects				
Job Posting	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of Study	Yes	Yes	Yes	Yes
School Rank	Yes	Yes	Yes	Yes
School Region	Yes	Yes	Yes	Yes
Referral	Yes	Yes	Yes	Yes
Fit statistics				
Observations	468,373	468,373	468,373	468,373
R^2	0.11046	0.13340	0.11607	0.13562

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

We formally test the extent to which work history relatedness and specialization mediate the relationship between race and callback with structural equation modeling. We fit a model in which race could have an effect on the likelihood of a callback directly or indirectly through work history relatedness and specialization. We include all the aforementioned controls as dummy variables in the model. Because there are a large number of job postings, controlling for these using dummy variables is not tractable in any SEM software. Instead, to deal with job-posting fixed effects, we fit and estimate a separate model for each job posting separately, and aggregate the results by taking a weighted mean of the coefficients where the weights are the number of observations from each job posting. We report the estimates with bootstrapped standard errors in Table 6. We also estimate a just-identified parsimonious model without any controls and report the results in Table A.6. The results are directionally consistent.

Table 6: Structural equation model with mediation

Subsample:	All
Dep. Var: Callback (1=YES)	
Relatedness to Focal Job	0.451*** (0.011)
Specialization	0.219*** (0.008)
Black (Direct)	-0.034*** (0.005)
Black (via Relatedness to Focal Job)	-0.007*** (0.001)
Black (via Specialization)	-0.003*** (0.001)
Black (Total)	-0.044*** (0.005)
Dep. Var: Career Relevance	
Black	-0.01*** (0.002)
Dep. Var: Career Specialization	
Black	-0.011*** (0.002)

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

As already seen, and in support of Hypothesis H0a and Hypothesis H0b, paths from work history relatedness and specialization to callbacks are positive and significant. The paths from Black to work history relatedness and specialization are negative and significant (H1a and H1b). The direct path from Black to callbacks also remains negative and significant. The indirect path via relatedness to focal job is significant and accounts for 16.3% of the total effects, while the indirect path through specialization is also significant and accounts for 6.5% of the total effects. Together, these indirect effects of work history measures account for 22.9% of the total effects of race on callback. We report the subsample analysis by company in Appendix A.3, and the results are directionally consistent. In summary, our regression analysis and structural equation modeling analyses both support H2a and H2b.

5 Potential drivers of racial differences in work history relatedness and specialization

5.1 Racial differences in breadth of job searches

We argued that one plausible reason for the racial differences in work history measures is that Black job seekers cast a wider net in their job searches than White job seekers to maximize "encounters with less discriminatory opportunities" (Pager & Pedulla, 2015, p.1008). As

Black job seekers, over time, apply to and eventually accept jobs less related to their prior experience, they accumulate work histories that are less specialized.

We provide additional support for our proposed mechanism by examining how much job search breadth varies by race, and the extent to which job search breadth is correlated with work history relatedness and specialization. To measure job search breadth, we take advantage of the fact that our dataset contains multiple applications from the same applicant. The ATS data contains a unique identifier for each applicant, which allows us to track all the applications each applicant submitted over the 7-year period. We find that 41.1% of applicants in our dataset applied to more than one job at one of these two firms. Using this subset of the population, we measure job search breadth in three ways: (1) whether an applicant applied to more than one functional area[14], (2) the number of unique functional areas to which an applicant applied, and (3) the average distance between the jobs to which an applicant applied. For measures (1) and (2), a drawback of using coarse functional areas is that the jobs within an area may be more or less related to each other. To address this, we calculate the average distance between the applied jobs using the same procedure described in Section 3.3 but using published job posting descriptions instead of résumés. This is our preferred measure of job search breadth as it is a more precise continuous measure.

We regress measures of job search breadth on the applicant's race and other characteristics and report the results in Appendix A.7 Table 18. This analysis is at the applicant level on the subset of applicants that applied to more than one job. Regression estimates show that Black applicants apply to a broader range of jobs than White applicants using all three measures. At the extensive margin, Black applicants were 4.5% more likely to apply to more than one functional area than White applicants. At the intensive margin, Blacks applied to 2.5% more unique functional areas than Whites. Finally, the average distance between the jobs Blacks applied to is 3.8% greater than that of Whites. We do not find race differences in the number of jobs to which job seekers apply (see Column 4), although that may be due to the fact that we only have visibility into applications to the two firms for which we have data as opposed to the entire labor market. Taken together, these results suggest that Black job seekers cast a wider net in their job search than White job seekers, consistent with our theory and prior research (Pager & Pedulla, 2015).

Next, we test the relationship between job search breadth and work history measures. To do so, we regress relatedness and specialization on the applicant's search breadth measure (average distance between applied jobs) with applicant and job controls and report the results

[14]The functional areas are: Engineering & Technical, Product & Design, Sales & Marketing, Customer Service & Account Management, Finance & Accounting, HR, Legal & PR, Business Development & Operations, and Other

in Table 19. We find that job search breadth is negatively associated with both work history relatedness and specialization. A 1-point increase in job search breadth corresponds to a -0.3 point change in career relevance and a -0.19 point change in career specialization. These results suggest that broad job search behavior is a plausible mechanism for racial differences in work history relatedness and specialization.

Lastly, to ensure that our main results are not driven by applicants who submitted multiple applications, we re-estimate the main models on the subset of applicants who applied to only one job. The results are consistent.

5.2 Racial differences in résumé crafting

An alternative explanation for racial differences in work history relatedness and specialization is that our measures are capturing differences in how Black and White applicants craft their résumés. If Black applicants are less likely to tailor how they describe their past job experiences on their résumés to fit the focal job description, then we would observe their work histories to be less related and, perhaps, less specialized. To test this, we create an alternate measure of work history relatedness and specialization by only using past job titles rather than the full text used to describe job experiences in résumés. Measuring relatedness and specialization using job titles is less likely to be influenced by résumé crafting because applicants have less freedom to alter previous job titles.

To create these measures, we repeat the same procedure as described in Section 3.3 but using only the job titles instead of the full text used to describe job experiences. SEM estimates, as reported in Table 21, are consistent with our main results. In summary, the racial differences in work history relatedness and specialization are likely not driven by résumé crafting.

6 Discussion and Conclusion

A large body of research seeking to understand the sources of persistent racial inequality in employment emphasizes the extent to which inequality results from employers treating members of different racial groups differently (e.g., Bertrand and Mullainathan, 2004; Kirshenman and Neckerman, 1999; Kline et al., 2022; Pager et al., 2009; Quillian et al., 2017). Organizational scholars have shown how this differential treatment is shaped by organizational practices (Baron & Pfeffer, 1994; Bielby, 2000; Reskin, 2000); for example, how employers' use of formal rubrics or job tests when hiring amplifies or attenuates the extent to which employers discriminate (e.g., Dobbin et al., 2015; Kalev et al., 2006; Reskin, 1999, 2000).

Yet little research considers how employers contribute to racial disparities indirectly through organizational practices that appear race-neutral but inspire disparate outcomes due to pre-existing racial differences. Not only are such practices largely undetected, they are also often deeply institutionalized and therefore unlikely to be seen as open to change (Small & Pager, 2020). Limiting our interest in discrimination to direct differential treatment by employers may dramatically underestimate the degree to which discrimination influences the work lives of Black Americans and members of other underrepresented racial groups.

We develop a novel perspective on how purportedly race-neutral work histories reproduce racial inequality in employment and test our theory by examining all the applications for two high-technology firms based on the U.S. West Coast. We find that Black job seekers are less likely to receive callbacks compared to White job seekers and that information cues from work histories–specifically, the extent to which work histories are composed of related and specialized prior experience—partially mediate this effect. Using a formal test of mediation, we show that the indirect effect of race on callback is partially mediated by less related and specialized work histories, which together account for 22.9% of the total effects of being Black on the likelihood of a callback. In doing so, our findings reveal a hidden mechanism of racial disparities in organizations. Even when employers do not have racial preferences, when they expect job seekers to meet their expectations of how work histories should look, Black job seekers face a disadvantage.

Our article draws attention to the fact that some job seekers, by virtue of their race, are limited in their strategic "choices," and these constraints lead them to build work histories that are less appealing to employers. As such, it extends the conversation on how supply-side and demand-side choices in the labor market interact. Scholars of labor markets typically position their work around supply-side choices or demand-side constraints, but many of the former are induced by the latter (see Brands and Fernandez-Mateo, 2017 for a similar argument). We know this is true of social class and gender. As Bourdieu describes (1984; 175), social class background constrains individual choice through an inculcated "habitus" that turns "necessities into strategies, constraints into preferences." Similarly, gender research shows how demand-side forces, such as anticipated discrimination, cultural beliefs, and socialization shape women's choices to enter and stay in male-dominated occupations (e.g., Bapna et al., 2021; Brands and Fernandez-Mateo, 2017; Correll, 2001, 2004; Storvik and Schøne, 2008).

Our article brings this insight to the study of race and highlights a novel way that the supply-side and demand-side of the labor market interact over time to sustain racial disparities in employment. Seen in this way, what initially looks like a supply-side problem with an easy solution (i.e., tell Black job seekers to apply to more related jobs and over time they will build less "erratic" histories) is actually a more intractable demand-side problem (organizations discriminating against Black Americans while they are at and searching for work). Black job seekers face a Catch-22. If they do not anticipate discrimination by casting a wide net, their job search may drag on and they have a greater risk of not finding a job at all. Yet if they cast a wider net, over time, it will likely become harder to find jobs, let alone jobs matching their skills and interests, because their work histories are less appealing to employers. It may even become a vicious, self-perpetuating cycle, in which even if employers suddenly stopped discriminating, Black job seekers would still have to cast wider nets because they are more likely to have work histories that employers find unappealing. In this way, we expand on the body of research on how the circumstances in which people from marginalized groups find themselves force them to undermine their own career goals, from Willis' 2017 classic study of working-class boys' rejection of the educational system to more recent work on Black Americans' resource-constrained "choices" to voluntarily quit their jobs (Sterling, 2024) and overwork themselves in pursuit of upward mobility in unsustainable and counterproductive ways (Wooten, 2024).

We also redirect the literature on categorization in labor markets by examining the social antecedents to category spanning. Most work in this domain assumes that work histories are the result of individuals strategically constructing careers by choosing job opportunities that develop their skills and affirm their interests (e.g.,Bidwell and Briscoe, 2010; Merluzzi and Phillips, 2016; O'Mahony and Bechky, 2006). As Teodoridis et al. (2019) put it, "The decision of whether to become a specialist or a generalist is a strategic one" (p.896). This has led scholars to largely ignore the antecedents of category-spanning work histories and instead focus on their consequences (e.g., Ferguson and Hasan, 2013; Leung, 2014; Merluzzi and Phillips, 2016; Zuckerman et al., 2003). By highlighting a social antecedent of category-spanning work histories, we provide one new reason why actors "choose" to build discounted work histories and highlight a path to identify many more.

Our study presents many opportunities for future research. Though we use the word "mediation," which implies causality, the relationships we document are correlations. Causal interpretations of SEM models require strong assumptions that are difficult to meet with observational data, such as the presence of no unmeasured confounding variables. Future research can deepen our work by providing more direct causal evidence of this phenomenon—at least for the link between work history relatedness, specialization, and callback. Empirically, we study high-technology companies located in the Bay Area. Future work could examine the extent to which our results generalize beyond this industry and geographic area. For example, scholars could establish how widespread this phenomenon is through a representative national sample. Scholars with data from career networking websites like LinkedIn (e.g., Ng and Sherman, 2022; Ng and Stuart, 2022) could use our methodology to uncover racial differences in work histories that could be correlated with other organizational disadvantages in promotions or salaries. Future studies could also examine whether labor market platforms (e.g., LinkedIn) loosen the supply and demand-side interactions that lead to the hiring disadvantage we uncover here.

At its heart, our study reveals a novel form of structural discrimination. Research on racial inequality in organizations has largely focused on identifying the direct effects of individual prejudice or bias but other features of the labor market contribute to racial inequality, one of which we elucidate here. The fact that employers view job seekers with less related and specialized experience as less suitable candidates is often taken for granted by practitioners and scholars. It also provides employers with a veneer of impartiality in their decision-making process. Yet we find that the relatedness and specialization of work histories splinter along racial lines. By relying on this seemingly race-neutral evaluative schema, employers unknowingly reproduce racial disparities. As such, structural discrimination is a collateral effect of "Applying while Black."

References

Abbott, A., & Hrycak, A. (1990). Measuring Resemblance in Sequence Data: An Optimal Matching Analysis of Musicians' Careers. *American Journal of Sociology*, *96*(1), 144–185.

Allport, G. W., Clark, K., & Pettigrew, T. (1954). The nature of prejudice.

Ang, S., Slaughter, S., & Yee Ng, K. (2002). Human capital and institutional determinants of information technology compensation: Modeling multilevel and cross-level interactions. *Management Science*, *48*(11), 1427–1445.

Autor, D. H. (2001). Why Do Temporary Help Firms Provide Free General Skills Training?*. *The Quarterly Journal of Economics*, *116*(4), 1409–1448.

Bapna, S., Benson, A., & Funk, R. (2021, October). Rejection Communication and Women's Job-Search Persistence.

Barbulescu, R., & Bidwell, M. (2013). Do Women Choose Different Jobs from Men? Mechanisms of Application Segregation in the Market for Managerial Workers. *Organization Science*, *24*(3), 737–756.

Barbulescu, R., & Bonet, R. (2024). Looking for Greener Grass? Prior Status and Exploration-Exploitation Decisions in Job Search. *Organization Science*, *35*(1), 159–176.

Baron, J. N., & Pfeffer, J. (1994). The Social Psychology of Organizations and Inequality. *Social Psychology Quarterly*, *57*(3), 190–209.

Becker, G. S. (1964). Human capita. *New York: National Bureau of Economic R esearch*.

Bertrand, M., & Mullainathan, S. (2004). Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination. *THE AMERICAN ECONOMIC REVIEW*, *94*(4), 79.

Bidwell, M., & Briscoe, F. (2010). The Dynamics of Interorganizational Careers. *Organization Science*, *21*(5), 1034–1053.

Bidwell, M., Briscoe, F., Fernandez-Mateo, I., & Sterling, A. (2013). The employment relationship and inequality: How and why changes in employment practices are reshaping rewards in organizations. *Academy of Management Annals*, *7*(1), 61–121.

Bielby, W. T. (2000). Minimizing workplace gender and racial bias. *Contemporary Sociology*, *29*(1), 120–129.

Bills, D. B. (1990). Employers'use of job history data for making hiring decisions: A fuller specification of job assignment and status attainment. *Sociological Quarterly*, *31*(1), 23–35.

Bills, D. B. (2003). Credentials, signals, and screens: Explaining the relationship between schooling and job assignment. *Review of educational research*, *73*(4), 441–469.

Blair-Loy, M. (1999). Career Patterns of Executive Women in Finance: An Optimal Matching Analysis. *American Journal of Sociology*, *104*(5), 1346–1397.

Bourdieu, P. (1984). *Distinction: A social critique of the judgement of taste*. Harvard University Press.

Bowen, W. G., & Bok, D. (1998). *The shape of the river: Long-term consequences of considering race in college and university admissions*. Princeton University Press.

Brands, R. A., & Fernandez-Mateo, I. (2017). Leaning Out: How Negative Recruitment Experiences Shape Women's Decisions to Compete for Executive Roles. *Administrative Science Quarterly*, *62*(3), 405–442.

Browne, I., Hewitt, C., Tigges, L., & Green, G. (2001). Why Does Job Segregation Lead To Wage Inequality among African Americans? Person, Place, Sector, or Skills? *Social Science Research*, *30*(3), 473–495.

Bureau of Labor Statistics. (2020). *Employee Tenure News Release* (tech. rep.). Beaureau of Labor Statistics.

Burt, R. S. (2004). Structural holes and good ideas. *American journal of sociology*, *110*(2), 349–399.

Byun, H., & Raffiee, J. (2023). Career Specialization, Involuntary Worker–Firm Separations, and Employment Outcomes: Why Generalists Outperform Specialists When Their Jobs Are Displaced. *Administrative Science Quarterly*, *68*(1), 270–316.

Castilla, E. J. (2005). Social networks and employee performance in a call center. *American journal of sociology*, *110*(5), 1243–1283.

Cattani, G., & Ferriani, S. (2008). A core/periphery perspective on individual creative performance: Social networks and cinematic achievements in the hollywood film industry. *Organization science*, *19*(6), 824–844.

Cech, E. A. (2013). Ideological wage inequalities? the technical/social dualism and the gender wage gap in engineering. *Social Forces*, *91*(4), 1147–1182.

Ciocca Eller, C., & DiPrete, T. A. (2018). The paradox of persistence: Explaining the black-white gap in bachelor's degree completion. *American Sociological Review*, *83*(6), 1171–1214.

Correll, S. J. (2001). Gender and the career choice process: The role of biased self-assessments. *American journal of Sociology*, *106*(6), 1691–1730.

Correll, S. J. (2004). Constraints into preferences: Gender, status, and emerging career aspirations. *American sociological review*, *69*(1), 93–113.

Crossland, C., Zyung, J., Hiller, N. J., & Hambrick, D. C. (2014). Ceo career variety: Effects on firm-level strategic and social novelty. *Academy of Management Journal*, *57*(3), 652–674.

Custódio, C., Ferreira, M. A., & Matos, P. (2013). Generalists versus specialists: Lifetime work experience and chief executive officer pay. *Journal of Financial Economics*, *108*(2), 471–492.

Cutolo, D., & Ferriani, S. (2023). Now It Makes More Sense: How Narratives Can Help Atypical Actors Increase Market Appeal. *Journal of Management*, 01492063231151637.

Davis, F. J. (2010). *Who is black?: One nation's definition*. Penn State Press.

Dobbin, F., Schrage, D., & Kalev, A. (2015). Rage against the iron cage: The varied effects of bureaucratic personnel reforms on diversity. *American Sociological Review*, *80*(5), 1014–1044.

Dokko, G., Wilk, S. L., & Rothbard, N. P. (2009). Unpacking prior experience: How career history affects job performance. *Organization science*, *20*(1), 51–68.

Douglas, M. (2003). *Purity and danger: An analysis of concepts of pollution and taboo*. Routledge.

Faulkner, R. R. (1983). *Music on Demand*. Transaction Publishers.

Feagin, J. R. (1991). The Continuing Significance of Race: Antiblack Discrimination in Public Places. *American Sociological Review*, *56*(1), 101–116.

Ferguson, J.-P., & Hasan, S. (2013). Specialization and Career Dynamics: Evidence from the Indian Administrative Service. *Administrative Science Quarterly*, *58*(2), 233–256.

Fernandez, R. M., & Friedrich, C. (2011). Gender Sorting at the Application Interface. *Industrial Relations: A Journal of Economy and Society*, *50*(4), 591–609.
Fernandez, R. M., & Weinberg, N. (1997). Sifting and Sorting: Personal Contacts and Hiring in a Retail Bank. *American Sociological Review*, *62*(6), 883–902.
Galperin, R. V., Hahl, O., Sterling, A. D., & Guo, J. (2020). Too Good to Hire? Capability and Inferences about Commitment in Labor Markets. *Administrative Science Quarterly*, *65*(2), 275–313.
Goldsmith, A. H., Sedo, S., Darity, W., & Hamilton, D. (2004). The labor supply consequences of perceptions of employer discrimination during search and on-the-job: Integrating neoclassical theory and cognitive dissonance. *Journal of Economic Psychology*, *25*(1), 15–39.
Hargadon, A., & Sutton, R. I. (1997). Technology brokering and innovation in a product development firm. *Administrative science quarterly*, 716–749.
Heckman, J. J. (1998). Detecting Discrimination. *Journal of Economic Perspectives*, *12*(2), 101–116.
Holzer, H. J., Offner, P., & Sorensen, E. (2005). Declining employment among young black less-educated men: The role of incarceration and child support. *Journal of Policy Analysis and Management*, *24*(2), 329–350.
Hsu, G. (2006). Jacks of all trades and masters of none: Audiences' reactions to spanning genres in feature film production. *Administrative science quarterly*, *51*(3), 420–450.
Kacperczyk, A., & Younkin, P. (2017). The paradox of breadth: The tension between experience and legitimacy in the transition to entrepreneurship. *Administrative Science Quarterly*, *62*(4), 731–764.
Kalev, A. (2014). How you downsize is who you downsize: Biased formalization, accountability, and managerial diversity. *American Sociological Review*, *79*(1), 109–135.
Kalev, A., Dobbin, F., & Kelly, E. (2006). Best practices or best guesses? assessing the efficacy of corporate affirmative action and diversity policies. *American sociological review*, *71*(4), 589–617.
Kirshenman, J., & Neckerman, K. (1999). We'd Love to Hire Them, But... The Meaning of Race for Employers. In *Race And Ethnic Conflict*. Routledge.
Kline, P., Rose, E. K., & Walters, C. R. (2022). Systemic Discrimination Among Large U.S. Employers*. *The Quarterly Journal of Economics*, *137*(4), 1963–2036.
Kovács, B., & Hannan, M. T. (2015). Conceptual spaces and the consequences of category spanning. *Sociological science*, *2*, 252–286.
Lacy, K. R. (2007, July). *Blue-Chip Black: Race, Class, and Status in the New Black Middle Class*. University of California Press.
Lamont, M., Moraes Silva, G., Mizrachi, N., Guetzkow, J., & Welburn, J. (2016). Getting respect: Responding to stigma and discrimination in the united states, brazil, and israel.
Lareau, A. (2018). Unequal Childhoods: Class, Race, and Family Life. In *Inequality in the 21st Century*. Routledge.
Leahey, E. (2006). Gender Differences in Productivity: Research Specialization as a Missing Link. *Gender & Society*, *20*(6), 754–780.

Leahey, E., Beckman, C. M., & Stanko, T. L. (2017). Prominent but less productive: The impact of interdisciplinarity on scientists' research. *Administrative Science Quarterly*, *62*(1), 105–139.

Leicht, K. T. (2008). Broken Down by Race and Gender? Sociological Explanations of New Sources of Earnings Inequality. *Annual Review of Sociology*, *34*(Volume 34, 2008), 237–255.

Leung, M. D. (2014). Dilettante or Renaissance Person? How the Order of Job Experiences Affects Hiring in an External Labor Market <sup/>. *American Sociological Review*, *79*(1), 136–158.

LinkedIn. (2019). *Gender Insights Report - How women find jobs differently* (tech. rep.).

Lundberg, S., & Startz, R. (2007). Information and racial exclusion. *Journal of Population Economics*, *20*(3), 621–642.

Major, B., & O'Brien, L. T. (2005). The Social Psychology of Stigma. *Annual Review of Psychology*, *56*(1), 393–421.

Marsden, P. V., & Gorman, E. H. (2001). Social networks, job changes, and recruitment. *Sourcebook of labor markets: Evolving structures and processes*, 467–502.

McDaniel, M. A., Schmidt, F. L., & Hunter, J. E. (1988). Job experience correlates of job performance. *Journal of applied psychology*, *73*(2), 327.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual review of sociology*, *27*(1), 415–444.

Merluzzi, J., & Phillips, D. J. (2016). The Specialist Discount: Negative Returns for MBAs with Focused Profiles in Investment Banking. *Administrative Science Quarterly*, *61*(1), 87–124.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed Representations of Words and Phrases and their Compositionality. In C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, & K. Q. Weinberger (Eds.), *Advances in Neural Information Processing Systems 26* (pp. 3111–3119). Curran Associates, Inc.

Moss, P., & Tilly, C. (2001). *Stories employers tell: Race, skill, and hiring in america*. Russell Sage Foundation.

Neckerman, K., & Kirschenman, J. (1991). Hiring strategies, racial bias, and inner-city workers. *Social problems*, *38*(4), 433–447.

Ng, W., & Sherman, E. L. (2022). In Search of Inspiration: External Mobility and the Emergence of Technology Intrapreneurs. *Organization Science*, *33*(6), 2300–2321.

Ng, W., & Stuart, T. E. (2022). Acquired employees versus hired employees: Retained or turned over? *Strategic Management Journal*, *43*(5), 1025–1045.

O'Mahony, S., & Bechky, B. A. (2006). Stretchwork: Managing the Career Progression Paradox in External Labor Markets. *Academy of Management Journal*, *49*(5), 918–941.

Pager, D., Bonikowski, B., & Western, B. (2009). Discrimination in a Low-Wage Labor Market: A Field Experiment. *American Sociological Review*, *74*(5), 777–799.

Pager, D., & Pedulla, D. (2015). Race, Self-Selection, and the Job Search Process. *American Journal of Sociology*, *120*(4), 1005–1054.

Parent, D. (2000). Industry-specific capital and the wage profile: Evidence from the national longitudinal survey of youth and the panel study of income dynamics. *Journal of Labor Economics*, *18*(2), 306–323.

Pattillo, M. (2013). *Black picket fences: Privilege & peril among the black middle class.* University of Chicago Press.

Pedulla, D. (2020, April). *Making the Cut: Hiring Decisions, Bias, and the Consequences of Nonstandard, Mismatched, and Precarious Employment*. Princeton University Press.

Petersen, T., & Saporta, I. (2004). The Opportunity Structure for Discrimination. *American Journal of Sociology*, *109*(4), 852–901.

Petersen, T., Saporta, I., & Seidel, M.-D. L. (2000). Offering a job: Meritocracy and social networks. *American Journal of Sociology*, *106*(3), 763–816.

Purdie-Vaughns, V., Steele, C. M., Davies, P. G., Ditlmann, R., & Crosby, J. R. (2008). Social identity contingencies: How diversity cues signal threat or safety for African Americans in mainstream institutions. *Journal of Personality and Social Psychology*, *94*(4), 615–630.

Quillian, L., Heath, A., Pager, D., Midtbøen, A. H., Fleischmann, F., & Hexel, O. (2019). Do some countries discriminate more than others? evidence from 97 field experiments of racial discrimination in hiring. *Sociological Science*, *6*, 467–496.

Quillian, L., Pager, D., Hexel, O., & Midtbøen, A. H. (2017). Meta-analysis of field experiments shows no change in racial discrimination in hiring over time. *Proceedings of the National Academy of Sciences*, *114*(41), 10870–10875.

Ray, V. (2019). A Theory of Racialized Organizations. *American Sociological Review*, *84*(1), 26–53.

Reskin, B. (1999). Occupational segregation by race and ethnicity among women workers. *Latinas and African American women at work: Race, gender, and economic inequality*, 183–206.

Reskin, B. (2000). The proximate causes of employment discrimination. *Contemporary sociology*, *29*(2), 319–328.

Reskin, B. (2005). Including Mechanisms in our Models of Ascriptive Inequality. In L. B. Nielsen & R. L. Nelson (Eds.), *Handbook of Employment Discrimination Research: Rights and Realities* (pp. 75–97). Springer Netherlands.

Rider, C. I., Sterling, A. D., & Tan, D. (2016). Career mobility and racial diversity in law firms. *Diversity in practice: Race, gender, and class in legal and professional careers*, 357–82.

Rivera, L. A. (2012). Hiring as Cultural Matching: The Case of Elite Professional Service Firms. *American Sociological Review*, *77*(6), 999–1022.

Rivera, L. A. (2015). Go with Your Gut: Emotion and Evaluation in Job Interviews. *American Journal of Sociology*, *120*(5), 1339–1389.

Rivera, L. A. (2020). Employer Decision Making. *Annual Review of Sociology*, *46*(1), 215–232.

Rosen, S. (1972). Learning and Experience in the Labor Market. *The Journal of Human Resources*, *7*(3), 326–342.

Sabanci, H., & Elvira, M. M. (2023). The Outcomes of Cross-Category Career Moves: How Cross-Industry Mobility and Industry Prestige Jointly Impact Executive Compensation. *Academy of Management Journal*, amj.2020.1423.

Small, M. L., & Pager, D. (2020). Sociological Perspectives on Racial Discrimination. *Journal of Economic Perspectives*, *34*(2), 49–67.

Spence, M. (1973). Job Market Signaling. *The Quarterly Journal of Economics*, *87*(3), 355.

Stainback, K., Jason, K., & Walter, C. (2018). Organizational context and the well-being of black workers: Does racial composition affect psychological distress? In *Race, identity and work* (pp. 137–164). Emerald Publishing Limited.
Sterling, A. D. (2024). This is why i leave: Race and voluntary departure. *Administrative Science Quarterly*, *69*(4), 926–961.
Stiglitz, J. E. (1975). The theory of" screening," education, and the distribution of income. *The American economic review*, *65*(3), 283–300.
Storvik, A. E., & Schøne, P. (2008). In search of the glass ceiling: Gender and recruitment to management in Norway's state bureaucracy1. *The British Journal of Sociology*, *59*(4), 729–755.
Tassier, T., & Menczer, F. (2008). Social network structure, segregation, and equality in a labor market with referral hiring. *Journal of Economic Behavior & Organization*, *66*(3-4), 514–528.
Teodoridis, F., Bikard, M., & Vakili, K. (2019). Creativity at the Knowledge Frontier: The Impact of Specialization in Fast- and Slow-paced Domains. *Administrative Science Quarterly*, *64*(4), 894–927.
Tilly, C. (1998). *Durable inequality*. University of California Press.
Tomaskovic-Devey, D., Thomas, M., & Johnson, K. (2005). Race and the accumulation of human capital across the career: A theoretical model and fixed-effects application. *American Journal of Sociology*, *111*(1), 58–89.
Trapido, D., & Koppman, S. (2023). Creativity as privilege. *Research in Organizational Behavior*, *43*, 100193.
Wilensky, H. L. (1961). Orderly Careers and Social Participation: The Impact of Work History on Social Integration in the Middle Mass. *American Sociological Review*, *26*(4), 521–539.
Willis, P. (2017). *Learning to labour: How working class kids get working class jobs*. Routledge.
Wilson, W. J. (2012). *The truly disadvantaged: The inner city, the underclass, and public policy*. University of Chicago Press.
Wingfield, A. H., & Chavez, K. (2020). Getting In, Getting Hired, Getting Sideways Looks: Organizational Hierarchy and Perceptions of Racial Discrimination. *American Sociological Review*.
Won, S., & Bidwell, M. (2023). Finding the right path to the top: How past interorganizational moves impact executive selection outcomes. *Strategic Management Journal*, *44*(10), 2341–2376.
Wooten, T. (2024). Effort traps: Socially structured striving and the reproduction of disadvantage. *American Journal of Sociology*, *130*(2), 344–383.
Zerubavel, E. (1999). *Social mindscapes: An invitation to cognitive sociology*. Harvard University Press.
Zhang, L. (2021). Shaking Things Up: Disruptive Events and Inequality. *American Journal of Sociology*, *127*(2), 376–440.
Zuckerman, E. W. (1999). The categorical imperative: Securities analysts and the illegitimacy discount. *American journal of sociology*, *104*(5), 1398–1438.

Zuckerman, E. W., Kim, T.-Y., Ukanwa, K., & von Rittmann, J. (2003). Robust Identities or Nonentities? Typecasting in the Feature-Film Labor Market. *American Journal of Sociology*, *108*(5), 1018–1073.

A Appendix

A.1 Correlation matrix of key variables

Table 7: Correlation matrix

	Callback	Relatedness to Focal Job	Specialization	Yrs of Exp	Tenure at Current Job	Num Jobs Held	Referral
Callback	1	.	.	.	.	.	.
Relatedness to Focal Job	.13	1	.	.	.	.	.
Specialization	.10	.22	1	.	.	.	.
Yrs of Exp	.08	.15	.13	1	.	.	.
Tenure at Current Job	.00	.02	.03	.42	1	.	.
Num Jobs Held	.05	.09	.00	.37	-.04	1	.
Referral	.17	.04	.02	.03	.01	.01	1

A.2 Comparison to the full sample

This section reports the comparison of descriptive statistics between the filtered sample (applicants with more than 2 previous jobs) and the full sample (all applicants). There are no significant differences in the demographic distributions of the applicants between the two samples.

Table 10 reports the mediation analysis with the full sample, and the results are consistent with the main analysis.

Table 8: Comparison of univariate statistics between the filtered and full samples

Sample:	Applicants with > 2 jobs			All applicants		
	Mean	Median	SD	Mean	Median	SD
Callback (1=YES)	0.24	0.00	0.43	0.22	0.00	0.42
Yrs of Exp	11.19	10.00	6.56	10.50	9.00	6.58
Tenure at Current Job	2.20	1.00	3.08	2.45	1.00	3.39
Num Jobs Held	5.10	5.00	2.22	4.32	4.00	2.49
Referral	0.02	0.00	0.14	0.02	0.00	0.14

Table 9: Comparison of multivariate statistics between the filtered and full samples

Sample:		Applicants with > 2 jobs		All applicants	
		N	Percent	N	Percent
Race	White	259,362	52.83	328,032	52.61
	Black	13,509	2.75	16,613	2.66
	Asian	166,045	33.82	210,163	33.71
	Hispanic	52,002	10.59	68,720	11.02
Gender	Male	291,964	59.47	372,546	59.75
	Female	198,954	40.53	250,982	40.25
Degree	Diploma	11,029	2.25	16,171	2.59
	Bachelor	237,141	48.31	301,633	48.38
	Master	173,740	35.39	215,709	34.59
	Doctorate	27,402	5.58	32,752	5.25
	N/A	41,606	8.48	57,263	9.18
Field of Study	Technical	176,629	35.98	225,261	36.13
	Business	80,300	16.36	94,520	15.16
	Law	13,432	2.74	15,503	2.49
	Other	201,593	41.06	261,556	41.95
School Rank	Top10	22,071	4.5	26,211	4.2
	11-20	17,815	3.63	21,553	3.46
	21-50	47,570	9.69	57,656	9.25
	51-100	24,731	5.04	30,552	4.9
	101-200	26,499	5.4	33,880	5.43
	Unranked	352,232	71.75	453,676	72.76
School Region	US	388,236	79.08	487,816	78.23
	Asia	22,285	4.54	27,847	4.47
	Canada	7,071	1.44	8,821	1.41
	Europe	20,195	4.11	26,333	4.22
	Other	26,838	5.47	36,142	5.8
	Unknown	7,302	1.49	9,836	1.58

Table 10: Structural equation model with mediation (full sample)

Subsample:	All
Dep. Var: Callback (1=YES)	
Relatedness to Focal Job	0.453*** (0.009)
Specialization	0.189*** (0.007)
Black (Direct)	-0.036*** (0.005)
Black (via Relatedness to Focal Job)	-0.007*** (0.001)
Black (via Specialization)	-0.003*** (0.001)
Black (Total)	-0.047*** (0.005)
Dep. Var: Career Relevance	
Black	-0.012*** (0.002)
Dep. Var: Career Specialization	
Black	-0.013*** (0.002)

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

A.3 Sub-sample analysis by company

This section reports the regression estimates for each company separately.

Table 11: OLS reegression of callback on work history measures and applicant race

Dependent Variable:	Callback (1=YES)	
Company Subset:	BigTechCo	SmallTechCo
Model:	(1)	(2)
Work history measures		
Relatedness to Focal Job	0.531*** (0.005)	0.339*** (0.015)
Specialization	0.161*** (0.004)	0.026* (0.011)
Demographics		
Black	-0.033*** (0.003)	-0.013 (0.013)
Asian	0.003‡ (0.002)	-0.006 (0.004)
Hispanic	0.007** (0.002)	-0.008 (0.008)
Female	0.012*** (0.001)	0.002 (0.003)
Experience		
Yrs of Exp	0.004*** (0.000)	-0.003*** (0.000)
Num Jobs Held	-0.001*** (0.000)	0.004*** (0.001)
Tenure at Current Job	-0.004*** (0.000)	-0.002** (0.001)
Fixed-effects		
Job Posting	Yes	Yes
Degree	Yes	Yes
Field of Study	Yes	Yes
School Rank	Yes	Yes
School Region	Yes	Yes
Referral	Yes	Yes
Fit statistics		
Observations	423,249	45,124
R^2	0.13289	0.13356

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

Table 12: OLS regressions of work history measures on applicant race

Dependent Variables:	Relatedness to Focal Job		Specialization	
Company Subset:	BigTechCo	SmallTechCo	BigTechCo	SmallTechCo
Model:	(1)	(2)	(3)	(4)
Demographics				
Black	-0.005*** (0.001)	-0.017*** (0.005)	-0.007*** (0.001)	-0.016** (0.006)
Asian	-0.003*** (0.000)	0.002‡ (0.001)	0.004*** (0.001)	0.007*** (0.002)
Hispanic	-0.009*** (0.001)	-0.010*** (0.003)	0.001 (0.001)	-0.007* (0.003)
Female	0.004*** (0.000)	0.000 (0.001)	0.008*** (0.000)	0.000 (0.001)
Experience				
Num Jobs Held	0.002*** (0.000)	0.002*** (0.000)	-0.005*** (0.000)	-0.007*** (0.000)
Yrs of Exp	0.002*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Tenure at Current Job	-0.001*** (0.000)	-0.003*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Fixed-effects				
Job Posting	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of Study	Yes	Yes	Yes	Yes
School Rank	Yes	Yes	Yes	Yes
School Region	Yes	Yes	Yes	Yes
Referral	Yes	Yes	Yes	Yes
Fit statistics				
Observations	423,249	45,124	423,249	45,124
R^2	0.47696	0.57482	0.13516	0.19200

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

Table 13: SEM with mediation

Subsample:	BigTechCo	SmallTechCo
Dep. Var: Callback (1=YES)		
Relatedness to Focal Job	0.447*** (0.011)	0.382*** (0.037)
Specialization	0.221*** (0.009)	0.098*** (0.021)
Black (Direct)	-0.033*** (0.005)	0.02 (0.021)
Black (via Relatedness to Focal Job)	-0.007*** (0.001)	-0.004‡ (0.002)
Black (via Specialization)	-0.003*** (0.001)	-0.002* (0.001)
Black (Total)	-0.043*** (0.006)	0.015 (0.021)
Dep. Var: Career Relevance		
Black	-0.01*** (0.002)	-0.009‡ (0.006)
Dep. Var: Career Specialization		
Black	-0.01*** (0.002)	-0.018* (0.008)

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

A.4 Sensitivity analysis of race imputation

In the ATS data, 67% of the applicants self-reported their race. For the applicants that did not self-report (37%), the HR analytics firm predicted the race based on the applicant's name and location. The HR firm reports the overall accuracy of race (including self-reports) to be 92%. One concern is that our reported estimates are biased because of the imputation of race.

To increase confidence in the accuracy of imputed race, we perform sensitivity analysis using a bootstrap approach where we probabilistically assign race using a publicly available race prediction API[15]. The bootstrap procedure is as follows:

1. For each applicant in the dataset, get the predicted race probabilities using the race prediction API. For example, for an applicant named "John Rioz", the predicted race proabilities are: `"White": 0.204, "Asian": 0.011, "Black": 0.009, "Hispanic": 0.776`.

[15] API used: https://ethnicolr.readthedocs.io/

2. Randomly sample 37% of the applicants in the dataset.

3. For each applicant in this sample, randomly sample a race based on the predicted probabilities—e.g., probabilitically assign the race "Hispanic" to the above applicant with probability 77.6%, "White" with probability 20.4%, and so on.

4. For the remaining 63% of the applicants, keep their race as observed in the data.

5. Estimate a SEM with this new sample and save the results.

6. Repeat steps 2-5 100 times and calculate the bootstrapped mean and standard error estimates.

Table 14 reports the results of this analysis. As we would expect, the individual estimates are attenuated due to the induced error in race. However, the results remain significant and the overall patterns of results are the same as those in the main analysis. The indirect effects of career relevance and specialization on callback account for 22.7% of the total effect of race on callback.

Table 14: SEM with probabilistic race assignment

Subsample:	All
Dep. Var: Callback (1=YES)	
Relatedness to Focal Job	0.45*** (0.01)
Specialization	0.193*** (0.008)
Black (Direct)	-0.018*** (0.004)
Black (via Relatedness to Focal Job)	-0.004*** (0.001)
Black (via Specialization)	-0.001* (0.0)
Black (Total)	-0.022*** (0.004)
Dep. Var: Career Relevance	
Black	-0.006*** (0.001)
Dep. Var: Career Specialization	
Black	-0.003‡ (0.001)

Bootstrapped heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

A.5 Alternate measures of relatedness to focal job

One potential concern with our measure of relatedness is that it averages across all past jobs in an applicant's résumé. So even if an applicant has all the required skills for a job opening, having an additional unrelated job on their resume mechanically lowers their relatedness to the focal job. To address this, we use two alternate measures of relatedness: (1) the maximum cosine similarity between the applicant's past jobs and the focal job opening vector and (2) the cosine similarity between the most recent job and the focal job opening vector. Formally, given a set of job histories $\{J_1, J_2 ... J_n\}$, where n is the most recent job, the measures are defined as:

$$\textit{Relatedness to Focal Job (most related)} = max\left[\{cos(\boldsymbol{v}_{J_1}, \boldsymbol{v}_{J_{focal}}), ...cos(\boldsymbol{v}_{J_n}, \boldsymbol{v}_{J_{focal}})\}\right] \tag{3}$$

$$\textit{Relatedness to Focal Job (most recent)} = cos(\boldsymbol{v}_{J_n}, \boldsymbol{v}_{J_{focal}}) \tag{4}$$

Table 15 and Table 16 report the results of the SEM model using the most related job and the most recent job as the measure of relatedness, respectively.

Table 15: SEM using the most related job for relatedness

Subsample:	All
Dep. Var: Callback (1=YES)	
Relatedness to Focal Job (most similar job)	0.462*** (0.012)
Specialization	0.218*** (0.009)
Black (Direct)	-0.034*** (0.005)
Black (via Relatedness to Focal Job)	-0.006*** (0.001)
Black (via Specialization)	-0.003*** (0.001)
Black (Total)	-0.043*** (0.005)
Dep. Var: Career Relevance	
Black	-0.009*** (0.002)
Dep. Var: Career Specialization	
Black	-0.011*** (0.002)

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

Table 16: SEM using the most recent job for relatedness

Subsample:	All
Dep. Var: Callback (1=YES)	
Relatedness to Focal Job (most recent job)	0.315*** (0.008)
Specialization	0.196*** (0.009)
Black (Direct)	-0.035*** (0.005)
Black (via Relatedness to Focal Job)	-0.006*** (0.001)
Black (via Specialization)	-0.003*** (0.001)
Black (Total)	-0.044*** (0.005)
Dep. Var: Career Relevance	
Black	-0.016*** (0.002)
Dep. Var: Career Specialization	
Black	-0.011*** (0.002)

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

A.6 SEM without controls

This section reports the structural equation model estimates using a parsimonious just-identified model without any controls.

Table 17: SEM without controls

Subsample:	All
Dep. Var: Callback (1=YES)	
Relatedness to Focal Job	0.338*** (0.005)
Specialization	0.209*** (0.005)
Black (Direct)	-0.051*** (0.003)
Black (via Relatedness to Focal Job)	-0.003*** (0.001)
Black (via Specialization)	-0.003*** (0.0)
Black (Total)	-0.056*** (0.003)
Dep. Var: Career Relevance	
Black	-0.008*** (0.001)
Dep. Var: Career Specialization	
Black	-0.013*** (0.001)

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

A.7 Regression tables for the analysis of plausible mechanisms

This section reports the regression tables for Section 5.

Table 18: OLS regressions of job search breadth on applicant race

Dependent Variables: Model:	N Job Cat. Applied > 1 (1)	N Job Cat. Applied (2)	Avg. Dist. b/w Applied Jobs (3)	N Jobs Applied (4)
Demographics				
Black	0.022* (0.011)	0.043‡ (0.022)	0.011*** (0.003)	0.028 (0.060)
Asian	-0.061*** (0.004)	-0.116*** (0.008)	0.001 (0.001)	-0.014 (0.020)
Hispanic	0.031*** (0.006)	0.073*** (0.012)	0.008*** (0.002)	0.039 (0.030)
Female	0.040*** (0.004)	0.075*** (0.007)	0.002* (0.001)	-0.137*** (0.018)
Experience				
Num Jobs Held	0.004*** (0.001)	0.007*** (0.002)	-0.001** (0.000)	0.055*** (0.006)
Yrs of Exp	-0.001*** (0.000)	-0.004*** (0.001)	0.000*** (0.000)	-0.004** (0.002)
Tenure at Current Job	-0.001 (0.001)	0.000 (0.001)	0.000* (0.000)	-0.014*** (0.004)
Fixed-effects				
Degree	Yes	Yes	Yes	Yes
Field of Study	Yes	Yes	Yes	Yes
School Rank	Yes	Yes	Yes	Yes
School Region	Yes	Yes	Yes	Yes
Referral	Yes	Yes	Yes	Yes
Fit statistics				
Observations	80,287	80,287	77,059	194,819
R^2	0.05318	0.04808	0.01196	0.00316

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

Table 19: OLS regressions of work history relatedness and specialization on job search breadth

Dependent Variables:	Relatedness to Focal Job	Specialization
Model:	(1)	(2)
Job search breadth		
Avg. Dist. b/w Applied Jobs	-0.304*** (0.002)	-0.185*** (0.002)
Demographics		
Black	-0.002‡ (0.001)	-0.006*** (0.001)
Asian	-0.003*** (0.000)	0.004*** (0.001)
Hispanic	-0.007*** (0.001)	0.001 (0.001)
Female	0.004*** (0.000)	0.007*** (0.000)
Experience		
Yrs of Exp	0.002*** (0.000)	0.002*** (0.000)
Num Jobs Held	0.002*** (0.000)	-0.005*** (0.000)
Tenure at Current Job	-0.001*** (0.000)	-0.001*** (0.000)
Fixed-effects		
Job Posting	Yes	Yes
Degree	Yes	Yes
Field of Study	Yes	Yes
School Rank	Yes	Yes
School Region	Yes	Yes
Referral	Yes	Yes
Fit statistics		
Observations	379,743	379,743
R^2	0.50358	0.14442

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

Table 20: SEM using unique applications

Subsample:	Unique Applications
Dep. Var: Callback (1=YES)	
Relatedness to Focal Job	0.339*** (0.024)
Specialization	0.067*** (0.019)
Black (Direct)	-0.012 (0.012)
Black (via Relatedness to Focal Job)	-0.006* (0.002)
Black (via Specialization)	-0.004** (0.001)
Black (Total)	-0.022‡ (0.012)
Dep. Var: Career Relevance	
Black	-0.013** (0.005)
Dep. Var: Career Specialization	
Black	-0.019** (0.006)

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

Table 21: SEM with mediation using job titles for career relevance and specialization

Subsample:	All
Dep. Var: Callback (1=YES)	
Relatedness to Focal Job	0.263*** (0.011)
Specialization	0.145*** (0.011)
Black (Direct)	-0.033*** (0.008)
Black (via Relatedness to Focal Job)	-0.006*** (0.001)
Black (via Specialization)	-0.001 (0.001)
Black (Total)	-0.04*** (0.008)
Dep. Var: Career Relevance	
Black	-0.021*** (0.003)
Dep. Var: Career Specialization	
Black	-0.007‡ (0.004)

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

A.8 Logit models

This section reports the logit regression estimates for the likelihood of receiving a callback.

Table 22: Logit regressions of callback on race and work history measures

Dependent Variable:	Callback (1=YES)			
Model:	(1)	(2)	(3)	(4)
Demographics				
Black	-0.242*** (0.025)	-0.229*** (0.025)	-0.235*** (0.024)	-0.227*** (0.025)
Asian	0.007 (0.009)	0.018‡ (0.009)	0.002 (0.009)	0.015 (0.009)
Hispanic	0.012 (0.013)	0.042** (0.013)	0.011 (0.013)	0.039** (0.013)
Female	0.089*** (0.008)	0.078*** (0.008)	0.080*** (0.008)	0.073*** (0.008)
Experience				
Yrs of Exp	0.027*** (0.001)	0.021*** (0.001)	0.025*** (0.001)	0.020*** (0.001)
Num Jobs Held	-0.003‡ (0.002)	-0.009*** (0.002)	0.005** (0.002)	-0.003 (0.002)
Tenure at Current Job	-0.029*** (0.001)	-0.025*** (0.001)	-0.028*** (0.001)	-0.024*** (0.001)
Work history measures				
Relatedness to Focal Job		3.933*** (0.039)		3.724*** (0.039)
Specialization			1.484*** (0.026)	1.012*** (0.028)
Fixed-effects				
Job Posting	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of Study	Yes	Yes	Yes	Yes
School Rank	Yes	Yes	Yes	Yes
School Region	Yes	Yes	Yes	Yes
Referral	Yes	Yes	Yes	Yes
Fit statistics				
Observations	466,832	466,832	466,832	466,832

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

A.9 Referral as a moderator

This section reports the OLS regression estimates with referral as a moderator for work history measures.

Table 23: Regression of callback on work history measures with referral interaction

Dependent Variable:	Callback (1=YES)
Work history measures	
Relatedness to Focal Job	0.521*** (0.005)
Relatedness to Focal Job × Referral	-0.102*** (0.029)
Specialization	0.148*** (0.004)
Specialization × Referral	-0.076* (0.034)
Referral	0.554*** (0.026)
Demographics	
Black	-0.032*** (0.003)
Asian	0.002 (0.001)
Hispanic	0.006** (0.002)
Female	0.011*** (0.001)
Experience	
Yrs of Exp	0.003*** (0.000)
Tenure at Current Job	-0.004*** (0.000)
Num Jobs Held	-0.001** (0.000)
Fixed-effects	
Job Posting	Yes
Degree	Yes
Field of Study	Yes
School Rank	Yes
School Region	Yes
Fit statistics	
Observations	468,373
R^2	0.13566

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

A.10 Job skill variance as a moderator

This section reports the OLS regression estimates with job skill variance as a moderator. Job skill variance measure is defined as the mean pairwise distance of skills in a job posting description.

Table 24: Regression of callback on career measures with interaction of job skill variance

Dependent Variable:	Callback (1=YES)
Model:	(1)
Work history measures	
Specialization	0.331*** (0.047)
Specialization × Skill Variance in Focal Job	-0.191** (0.060)
Relatedness to Focal Job	-0.236*** (0.044)
Relatedness to Focal Job × Skill Variance in Focal Job	0.752*** (0.058)
Skill Variance in Focal Job	-0.281*** (0.042)
Demographics	
Black	-0.034*** (0.003)
Asian	0.004** (0.001)
Hispanic	0.002 (0.002)
Female	0.007*** (0.001)
Experience	
Yrs of Exp	0.003*** (0.000)
Num Jobs Held	0.000 (0.000)
Tenure at Current Job	-0.004*** (0.000)
Fixed-effects	
Business Unit	Yes
Degree	Yes
Field of Study	Yes
Referral	Yes
School Rank	Yes
School Region	Yes
Fit statistics	
Observations	468,373
R^2	0.08648

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*

A.11 Interview and offer outcomes

This section reports the OLS regression estimates with interview and offer as outcome variables.

Table 25: Regression of interview and offer on career measures

Dependent Variables:	Interview	Offer
Model:	(1)	(2)
Work history measures		
Relatedness to Focal Job	0.117*** (0.002)	0.022*** (0.001)
Specialization	0.010*** (0.002)	0.000 (0.001)
Demographics		
Black	-0.016*** (0.001)	-0.003*** (0.001)
Asian	-0.011*** (0.001)	-0.002*** (0.000)
Hispanic	-0.007*** (0.001)	-0.003*** (0.000)
Female	0.007*** (0.001)	0.003*** (0.000)
Experience		
Yrs of Exp	0.000*** (0.000)	0.000*** (0.000)
Num Jobs Held	0.000‡ (0.000)	0.000* (0.000)
Tenure at Current Job	-0.001*** (0.000)	0.000 (0.000)
Fixed-effects		
Job Posting	Yes	Yes
Degree	Yes	Yes
Field of Study	Yes	Yes
School Rank	Yes	Yes
School Region	Yes	Yes
Referral	Yes	Yes
Fit statistics		
Observations	468,373	468,373
R^2	0.06738	0.06857

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ‡: 0.1*