Interviews*

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Abstract

Interviews allow employers to learn about workers, but do they also enable workers to learn about firms? Studying 500,000 interview reports from Glassdoor, we find candidates for high-paying jobs are 9 percent more likely to reject a job offer if they believe the interview was easy. Easy interviews appear to convey poor "fit" as those who accept offers after easy interviews are one-half of a standard deviation less satisfied with their jobs and 14 percent less likely to remain with their employer for at least one year. Analysis of interview narratives using a large language model reveals difficult interviews signal colleague ability whereas easy interviews convey a nonselective process. Complementary evidence from a randomized field experiment suggests difficult interview assessments may induce applicants with less human capital to self-select out of the process. Interviews offer workers a preview of match quality, highlighting a channel through which labor markets may become less efficient if firms automate hiring with AI.

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"I don't want to belong to any club that will accept me as a member." - Groucho Marx

1 Introduction

It is hard to imagine a more ubiquitous feature of the labor market than the job interview. Almost every worker, regardless of age or experience, has had many interviews, not just for the job they currently have but also for roles where they did not get an offer, or for roles for which they received an offer but subsequently turned it down. Notwithstanding their prevalence and relevance, the *worker's* perspective on interviews remains largely unexplored, especially in economics. Can the job interview itself determine whether a candidate will decide to accept or reject an offer?

Despite the simplicity of the question, the answer is not well known. This lack of clarity is likely not for lack of want, but rather lack of data. Answering this question requires observing, for many workers, each one's job offers, each one's perceptions of the interviews that preceded those offers, and each one's decisions to accept or reject those offers. With the advent of online job boards, specifically Glassdoor, such data now exist. We observe the summaries of job interviews for many workers interviewing for many vacancies at many firms, all of whom received a job offer, not all of whom accepted it.

Through the lens of personnel economics (Oyer and Schaefer, 2011), interviews allow firms to distinguish between and screen workers during the recruitment process. Less attention, however, has been given to the worker's information problem: choosing among firms that appear similar but differ in hard-to-observe ways. Such differences could reflect, for instance, corporate culture, work-life balance, interpersonal relations, or high-performance work systems, such as on-the-job training.[1] If workers care about these externally opaque non-wage aspects of jobs (e.g., Wiswall and Zafar, 2017; Sockin, 2022; Maestas *et al.*, 2023), then processes that provide prospective job seekers with information on these aspects should affect labor supply decisions. Interviews may plausibly serve this function, offering workers a revealing glimpse into candidate firms. Given the rising use of algorithms and artificial intelligence in firms' hiring processes, understanding what, if any, critical information workers gauge from the traditional interview process—and would reasonably miss out on if the process were fully automated—is ever more pressing.

Whether interviews offer workers a meaningful glimpse into the workplaces they may join, to the best of our knowledge, has not been empirically established.[2] Studying half a

[1] Since such attributes typically cannot be assessed before joining the firm, jobs are intrinsically more akin to experience goods rather than inspection goods (Nelson, 1970; Menzio and Shi, 2011).

[2] While Coffman *et al.* (2017) studies applicants' offer acceptance decisions, their analysis pertains to the effects of an informational nudge in the offer letter.

million interview reports from Glassdoor, we fill this gap in the literature and establish a link between workers' interview experiences and their labor market outcomes. For each interview reported, we observe whether the worker received a job offer and whether they accepted the position or turned it down. We also observe how difficult each worker perceived their interview process to be—a key metric that we will show conveys valuable information to the job seeker. Further, workers provide a free-response description characterizing the interview process, which we analyze using a large language model (LLM) to explore the mechanisms behind our results. Altogether, these data shed new light on whether—and how—interview impressions steer workers toward or away from employers.

We focus our empirical analysis on high-wage occupations for practical, conceptual, and methodological reasons. First, Glassdoor over-samples high-skilled workers from high-paying industries and occupations (Karabarbounis and Pinto, 2018; Liu *et al.*, 2022), resulting in a rich collection of interview reports with wide coverage of workers and employers across management, finance, technology, healthcare, and law. Second, match quality carries heightened stakes for workers in high-skilled settings, as beneficial matches can improve long-term career trajectories and skill accumulation vis-à-vis peer effects and on-the-job learning (Reagans *et al.*, 2005; Mas and Moretti, 2009; Jarosch *et al.*, 2021; Atkin *et al.*, 2022). Third, workers in these roles exhibit strong preferences for non-wage job attributes (e.g., Sockin, 2022; Colonnelli *et al.*, 2023; Cullen *et al.*, 2025), which may be signaled during the interview process. Together, these features position high-paying occupations as a salient context for examining whether interviews influence labor market outcomes.

We begin by considering acceptance and rejection decisions. Even for the same vacancy—the same firm, job title, local labor market, and time period—candidates who thought the interview was easy are 9 percent more likely to reject the job offer. Notably, interviews that are conducted remotely, involve technical exercises, or highlight the role's responsibilities experience outsize declines in offer acceptance rates if they were considered easy—suggesting a role for perceptions of skill development and non-wage amenities traditionally gauged through onsite visits. When a worker has more than one offer in the same quarter, they are 13–25 percentage points more likely to reject the offer from the firm whose interview they perceived as easier. We estimate, based on the sample of workers who report multiple offers, the decline in the probability of offer acceptance associated with an easy interview to be equivalent to that associated with a marked 43 log points (35 percentage points) lower wage.

We might anticipate interview impressions—as an ex ante precursor—to track realized match quality. Since many workers upload their resumes to Glassdoor when creating a profile, we can link, for those who accepted an offer, their interview with the corresponding job on their resume. Comparing workers who list on their resumes the same job title at the

same firm, those who considered the interview easy exit 18 percent earlier, translating into a 14 percent lower likelihood of remaining with the firm for at least one year. Thus, we can conclude that perceptions of the interview process predict not just immediate outcomes (e.g., offer acceptance) but also longer-run outcomes (e.g., retention).

Do these shorter spells reflect workers who perceive the interview as easy being more likely to be laid off due to poor performance, or do they reflect such workers more often voluntarily quitting to pursue better matches? Evidence from other data on Glassdoor strongly hints at the latter. Using Glassdoor employer reviews, where candidates rate their employers along various dimensions, we find that job spells starting with easy interviews have lower satisfaction than jobs with a not-easy interview (0.64 stars out of 5, about one-half of a standard deviation). For context, this penalty is larger than the effect of learning your employer engaged in corporate misconduct (Gadgil and Sockin, 2020) or received an Accounting and Auditing Enforcement Release from the U.S. Securities and Exchange Commission (Zhou and Makridis, 2021). Given the established link between job satisfaction and voluntary turnover (Freeman, 1978; Akerlof *et al.*, 1988; Card *et al.*, 2012), along with the observations that this result holds even after accounting for individual ability, and that workers are somewhat more likely to allude to voluntarily quitting in their employer reviews if the interview was easy, we interpret the higher rate of turnover as likely reflecting poor match quality from the perspective of the worker, rather than that of the firm.

To better understand the information workers accrue through interviews, we turn to free-response descriptions workers write about the interview process. We employ an LLM to determine whether a description indicates: (i) prospective colleagues being of high ability[3], (ii) prospective colleagues being pleasant[4], (iii) the interview experience being engaging, and (iv) the worker believing the firm "would hire anyone."[5] Turning first to prospective colleagues, we find job seekers are *two-to-three times* more likely to characterize the firm as employing high-ability colleagues if they believe the interview was not easy. They are no more likely though to believe the firm employs pleasant colleagues—distinguishing opportunities for human capital growth from social amicability. By contrast, after an easy interview, job seekers are *four-to-five times* more likely to believe the firm would hire anyone and 15–20

[3]High-ability peers facilitate knowledge spillovers and productivity gains (Herbst and Mas, 2015; Ashraf and Bandiera, 2018; Jarosch *et al.*, 2021), especially through face-to-face interactions (Atkin *et al.*, 2022).

[4]Positive relations with coworkers may improve job satisfaction (Sockin, 2022) and retention (Jäger *et al.*, 2024), especially when the job entails frequent interactions with coworkers (Krueger and Schkade, 2008).

[5]We also consider whether the interview offered a "realistic job preview." The U.S. Office of Personnel Management writes that a realistic job preview can "provide candidates a richer description of the agency and the job (e.g., work environment, duties, expectations) to help them decide if they are a good match." Although realistic job previews generally raise offer acceptance rates, the increase is shallower for interviews that were considered easy. See Wanous (1973) for an early discussion of realistic job previews.

percent less likely to consider the interview process engaging.

Importantly, these interview-based reported perceptions of colleagues are not inaccurate. Establishments with greater worker skill—proxied for by the average worker fixed effect from an Abowd *et al.* (1999), or AKM, regression of log wages using Glassdoor pay reports—more often evoke the belief among job seekers of high-ability peers. Inversely, establishments with lower worker skill more often convey the firm would accept anybody. By credibly signaling the ability of prospective peers, interviews provide a unique channel through which high-ability workers can discern which workplaces are comprised of other high-ability workers—thereby facilitating sorting and potentially augmenting income inequality (Song *et al.*, 2019).

To complement this observational evidence, we conduct a randomized field experiment to mitigate two key identification challenges, specifically reverse causality, in which workers first reject offers and consider interviews as easy retrospectively when reflecting on their difficulty, and endogenous attrition, in that we only observe acceptance and rejection decisions for those who completed the interview process and not for those who may have self-selected out. In the context of recruiting a university data scientist, we randomly vary the difficulty of a technical assessment that we administer to active job seekers as a first-round interview. While the experimental setting differs from our observational data—notably, no offers are extended during the study period and applicants do not interact with any employees of the hiring firm—the results provide suggestive evidence on two fronts.

First, regarding reverse causality, we find candidates who perceive the interview assessment as easy exhibit lower behavioral engagement with the hiring process. Engagement is measured *before* any offers are made, meaning that the subjective interview experience itself, rather than some correlated factors potentially related to the receipt and rejection of an offer, drives candidate interest. Second, the experiment sheds light on selection dynamics. Relative to the easier assessment, the more difficult one induces candidates with less human capital to self-select out and not finish the assessment. Whether such selection benefits employers depends critically on context; it may improve the quality of new hires when applicants are plentiful, but could prove costly if it exacerbates hiring difficulties in tight labor markets. While the experiment cannot definitively establish all mechanisms at play in our observational setting, it does provide controlled evidence that interview difficulty causally affects candidate behavior, lending support to our preferred interpretation that workers use the interview process as a lens to gauge match quality.

The evidence we document, both observational and experimental, is consistent with learning about opportunities for human capital development and acting on career concerns. However, such a result also accords with the theory of "effort justification" from cognitive psychology. According to this theory, individuals who undergo challenging or unpleasant

experiences to achieve a goal subsequently value that goal more highly, as they seek to justify their investment of effort (Aronson and Mills, 1959; Gerard and Mathewson, 1966). Through this lens, effort adds value (Inzlicht *et al.*, 2018). Although we cannot rule out this behavioral mechanism, the observed pattern emerges among job seekers interviewing for the same position—which in principle should elicit similar effort among candidates. Moreover, our findings relate to high-stakes decisions about accepting and remaining in a job, which stands in contrast to the lower-stakes contexts examined within this literature (e.g., Kruger *et al.*, 2004; Norton *et al.*, 2012).

This work contributes to three strands of the literature. The first is the empirical literature on the implications of interviews for workers and firms. Interviews have been predominantly studied in fields such as organizational science, sociology, and psychology, with methods ranging from lab experiments to qualitative surveys (e.g., Highhouse, 2008; Dana *et al.*, 2013; Rivera, 2012, 2015).[6] In summarizing the human resources literature, Judge *et al.* (2000) remark that recruiters "probably do not have a large impact on actual job choices," though Barber (1998) notes that applicants have favorable reactions when recruiters exude warmth, informativeness, and competence—however, the evidence is scant and mixed. In economics, Shukla (2025) demonstrates subjective interviews can be a channel for discrimination by social class in elite multinationals, while Jabarian and Henkel (2025) show AI-led interviews can improve hiring outcomes for low-wage service work. Notably, whereas Jabarian and Henkel (2025) focus on low-paying jobs, our work centers on high-paying ones, for which labor is less substitutable. To our knowledge, no prior study has considered the worker's perception of the interview experience, in particular its difficulty, and shown its effect on labor market sorting as well as firm tenure and job satisfaction thereafter.

The second strand of literature pertains to how workers respond to the revelation of information about employers when engaged in job search. Benson *et al.* (2019), for instance, show that highly-rated employers receive increased labor supply in online labor markets, Sockin and Sojourner (2023) that improved Glassdoor ratings increase applications to small firms, Bryan *et al.* (2022) that workers, especially high-quality ones, sort towards startups with better quality science and business models when such information is available, and Ward (2022) that job seekers sort away from companies with below-average levels of employee happiness when such information is revealed. Our work demonstrates that job interviews are another information-revelation mechanism by which workers will sort, as workers can

[6] While there is indirect evidence in economics on job acceptance or rejection—for instance, by gender for recent college graduates (Cortes *et al.*, 2024)—there is little direct evidence.

learn about peer ability and opportunities for skill development.[7] Our findings thus relate to the broader literature on search-and-matching frictions in the labor market (e.g., Diamond, 1982; Mortensen and Pissarides, 1994) by highlighting the *two-sided* nature of the interview process.[8] We demonstrate that perceived interview difficulty can reduce uncertainty around match quality, much as workers in classic job-matching models learn about the quality of an employer (Jovanovic, 1979). That interviews help explain which matches form in the short run and endure in the long run suggests jobs are not entirely experience goods (Nelson, 1970; Menzio and Shi, 2011), as interviews may render them quasi-inspection goods.

Third, the paper makes a contribution in terms of measurement, building on the growing literature in text algorithms for economics (Gentzkow *et al.*, 2019; Ash and Hansen, 2023). The use of aligned LLMs to label text datasets (in our case, interview descriptions) is a relatively new approach that offers a scalable, reproducible alternative to human annotation (Ash *et al.*, 2024; Ludwig *et al.*, 2025). Our fine-tuned RoBERTa models—which we employ to scale up the annotations produced by an LLM—illustrate the usefulness of deep learning for text classification in economics (Dell, 2024). Further, we add to other recent work using text analysis to measure non-wage dimensions of work (Sockin, 2022; Lagos, 2024; Arold *et al.*, 2025). Our approach uncovers previously inaccessible, qualitative impressions of jobs—such as beliefs about peer ability—and makes them amenable to quantitative study. These measurement approaches open new avenues for understanding how non-wage attributes, worker attitudes, and cultural dimensions influence labor market outcomes.

2 Data

This section sets the stage with background information on Glassdoor and detail on how we compile our dataset of interview reports.

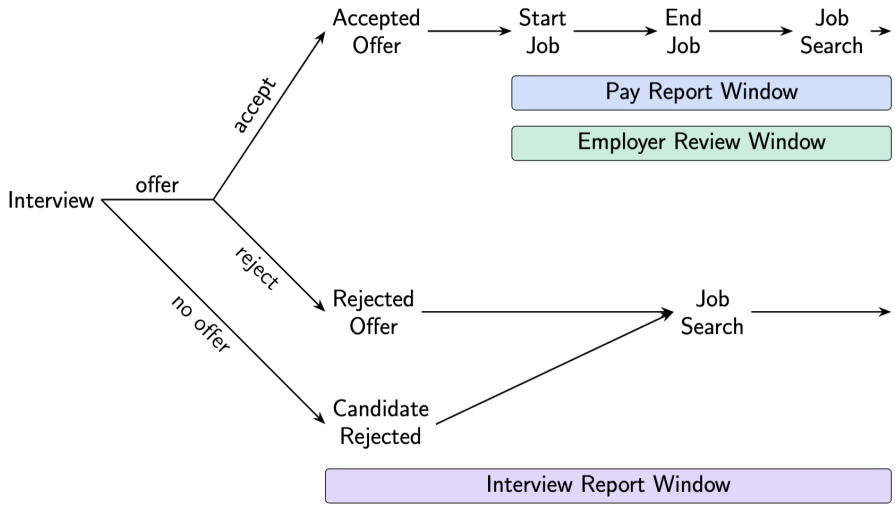
Platform Overview. Our data come from the website Glassdoor, an online labor market platform where workers can anonymously share information about pay, job satisfaction, and their interview experiences. Visitors to Glassdoor are incentivized to contribute through a "give-to-get" mechanism, whereby they gain access to the information others have provided once they themselves contribute.[9] Workers can satisfy the give-to-get requirement by

[7] Workers may also use the interview to learn whether the firm is willing to bargain over wages (Caldwell *et al.*, 2025); however, in many knowledge-worker settings, wages are relatively transparent, which reduces the need to discover pay during interviews (Hall and Krueger, 2012).

[8] Relatedly, Friedrich *et al.* (2024) find that the introduction of subjective interviews reduced attrition from medical school programs by improving match quality.

[9] This give-to-get mechanism has been found to reduce selection bias in accumulating extreme responses when it comes to job satisfaction (Marinescu *et al.*, 2021).

Figure 1: Timeline of Glassdoor Reports



Notes: Figure 1 illustrates the timing of the data generation process for Glassdoor interview reports, employer reviews, and pay reports.

submitting one of four surveys: a pay report, an employer review, a benefits rating, or an interview report. Workers are assigned unique identifiers, allowing us to link individuals across surveys. Access expires after one year, which can be refreshed with an additional contribution. Although we do incorporate pay reports and employer reviews in the analysis, our primary focus is the interview reports. A timeline of the data generating process is presented in Figure 1.

Interview Reports. When disclosing an interview experience, each respondent is asked for their employer and job title. They can also provide the location in which the interview took place, but this is not required. Since this survey is a summary of their interview experience, workers are asked: whether they had a positive, neutral, or negative experience overall, for a free-response description of the interview process, and to recall any particular interview questions they were asked. Workers are also asked the difficulty level of the interview, to which they can respond very easy, easy, average, difficult, or very difficult. We translate this measure of difficulty into a 1-5 integer scale, which is increasing in difficulty, and we create an indicator for "the interview was easy," equaling one for very easy and easy responses and zero otherwise. Next, respondents state whether they received an offer for the job in question, and if they did, whether they accepted or rejected it. Respondents also have the option to disclose a number of additional aspects of the interview process, including how

they received the interview (e.g., an employee referral[10]), how many days the process took, when the interview occurred, the form(s) the interview took (e.g., a phone discussion), and any testing that occurred (e.g., personality test, drug test). Appendix Figures A1 and A2 provide snapshots from a sample Glassdoor submission form.

The data on offers and acceptances are self-reported, and we cannot externally verify these actions. That said, we have good reason to believe that Glassdoor participants report offer and acceptance decisions truthfully. In principle, given that Glassdoor is anonymous, giving truthful reports is incentive-compatible. In the data, what we observe is consistent with truthful reporting. First, among workers who report accepting an offer, we can pinpoint the hiring firm on 34.0 percent of resumes after the interview date (Appendix Figure A7). Among those who report rejecting the offer, the share is 2.1 percent; among those who did not receive an offer in the first place, 1.2 percent. Second, there are objective differences between offers and non-offers. Interviews that resulted in an offer are reported as taking on average 17 percent longer (Appendix Table A16) and workers who receive an offer have on average nearly one-fifth of a standard deviation greater ability (as proxied for by worker fixed effects in an AKM model on log total pay, Appendix Table A17) than those who report not receiving an offer. Third, among those who report receiving offers, the differences in interview duration and worker ability between rejected and accepted offers are small in comparison. All of these data points are consistent with truthful reporting.

Main Sample. Our analysis focuses only on *high-paying occupations*, identified by their Standard Occupational Classification (SOC) codes.[11] This restriction offers both practical and conceptual advantages. First, Glassdoor considerably over-samples from these occupations such that we have particularly rich coverage of these jobs.[12] Second, high-wage workers have strong preferences for non-wage amenities (e.g., Sockin, 2022; Colonnelli *et al.*, 2023; Maestas *et al.*, 2023; Cullen *et al.*, 2025) and since these occupations feature relatively transparent base pay (Hall and Krueger, 2012), interview experiences may be especially relevant in shaping perceptions over amenities. Third, workers in these occupations tend to have career concerns and benefit from human capital accumulation through peer effects and on-the-job learning (e.g., Jarosch *et al.*, 2021) such that a poor worker-firm match can be quite costly.

[10]Workers who are referred to a vacancy may enter with different expectations about the firm and its employees and amenities. For instance, Hampole *et al.* (2023) find that female MBA students are more likely to learn about female-friendly firms when their social network comprises more females.

[11]Specifically, we include SOC codes 11 (Management), 13 (Business and Financial Operations), 15 (Computer and Mathematical), 17 (Architecture and Engineering), 23 (Legal), and 29 (Healthcare Practitioners and Technical)—all occupational groups that typically command higher wages.

[12]While these occupations represent 32 percent of full-time employment in the representative American Community Survey, they represent 57 percent of the Glassdoor interviews database (Appendix Figure A13).

And fourth, these occupations have high marginal products, so firms will tend to expend more resources screening for them.[13]

We take a number of additional steps to arrive at our ultimate dataset. The iterative procedure, along with the number of observations discarded at each step, is detailed in Appendix Table A2. We first restrict the sample to interviews from 2008 through 2024. Then, since we are interested in the decision to accept or reject an offer, we exclude the 38 percent of interview reports where the worker was not offered the job. We then exclude interviews for which either perceived difficulty or the industry of the firm are unavailable. Next, we restrict the sample to the six high-paying occupations of interest, which reduces the sample by about two-thirds. Next, to focus on matches that do not have a definite end date determined ex ante, we exclude interviews that correspond to internships—though, for internships as well, job seekers increasingly reject offers after easy interviews (Appendix E). Finally, to reduce measurement error in the recollection of past interview experiences, of the remaining interview reports, we exclude the 15 percent that are submitted to Glassdoor more than two years after the interview date. The final sample includes 508,000 interview reports. Summary statistics for characteristics of the interviews are available in panel A of Table A3. In our sample, 20 percent of offers are rejected and 80 percent accepted.

Imputing Wages. Since workers are not asked to disclose the wages they were offered when submitting their interview reports, we impute offered wages using Glassdoor pay reports. For each firm–job title pair, we calculate the mean base pay from these reports and merge these averages with our interviews data. Through this process, we are able to impute a wage for 297,000 interviews. We believe these imputed averages are valid proxies for posted wages for three reasons. One, job titles explain more than 90 percent of the variance in posted wage ranges (Marinescu and Wolthoff, 2020). Two, Glassdoor wages align well with representative data across industries (Karabarbounis and Pinto, 2018), occupations (Gibson, 2021), and universities (Martellini *et al.*, 2024). And three, for a subset of workers, we can assign them their actual wage since they submitted a Glassdoor pay report for the same firm, job title, and year of the interview after accepting the offer. For this subset of 27,000 workers, we estimate an elasticity of imputed wages to actual wages close to one, and imputed wages explain about 88 percent of the variation in actual wages (Appendix Table A10). Further, the distribution of imputed wages in our interviews sample closely tracks the distribution of wages for these occupations in the American Community Survey (ACS), particularly for higher wages (Appendix Figure A14).

[13]Looking at the full database of Glassdoor interviews, the median length of the interview process that results in a job offer is twice as long for these occupations as it is for all other occupations.

Selection Concerns. Given the self-reported nature of Glassdoor interviews, it would be reassuring to find other data sets with which to externally validate the Glassdoor sample. Unfortunately, given the novelty of studying job seekers' decisions to accept or reject job offers, few such comparisons exist. With regard to interview difficulty, on the website Onsites.fyi (referred to herein as Onsites), individuals can also disclose interview experiences, primarily for jobs in software engineering. When we compare the reported level of difficulty between this website and Glassdoor, we find considerable overlap (more on this below). Meanwhile, in the context of Teach for America positions, Coffman *et al.* (2017) find that 16 percent of offers are rejected. Our baseline rejection rate is comparable.

A separate potential concern is that Glassdoor interview reports are differentially selected from the rest of the Glassdoor database. For instance, workers who disclose interview reports may be positively or negatively selected on ability. To check this concern, we take the database of Glassdoor pay reports and estimate a regression with worker and firm fixed effects in the style of Abowd *et al.* (1999). Taking these worker fixed effects as proxies for ability, we plot the distribution for workers in the interviews sample and those in the database overall. The two distributions are nearly identical (Appendix Figure A15). Further, workers who disclose interview reports may be less satisfied with their jobs, as many of them are searching for new jobs. However, when we compare job satisfaction ratings from our interview sample to the broader sample, again the distributions look alike (Appendix Figure A16). Thus, our interviews sample does not appear differently selected on ability or sentiment.

Demographic Observables. When creating a profile on the website, users are asked to provide their gender and age. We observe gender for 204,000 interviews and age for 108,000. For workers who uploaded a resume to Glassdoor, we additionally observe their educational background. This includes, if listed, their university of study[14], major of study[15], undergraduate grade point average (GPA), and any post-Bachelor's degree. In summary, we observe educational histories for 182,000 interviews, for which we observe college graduate quality for 157,000, major of study for 135,000, and GPA for 23,000. Summary statistics for these demographics are available in panel B of Table A3.

Interview Difficulty. Our primary barometer for the interview process is the perceived difficulty of the interview reported by the job seeker. Respondents report difficulty on a

[14]We can ascertain whether the worker attended university outside the United States and the college graduate quality, as measured by Martellini *et al.* (2024), of their undergraduate alma mater.

[15]We partition into STEM (biological or physical sciences, engineering, technology) and non-STEM (arts and humanities, business, communication, education, health or social service, social sciences) majors.

five-point scale, ranging from "very easy" to "very difficult." The distribution of interview difficulty is plotted in Appendix Figure A3.[16] For ease of exposition, and to avoid concerns regarding heterogeneous interpretations of the five-point scale across sub-samples[17], we create an easy-interview indicator, which equals one if respondents record easy or very easy and zero otherwise. Roughly 35% of respondents believe their interview was easy.

Given the import of this measure, we take steps to internally and externally validate reported interview difficulty. First, we extract whether the job seeker mentions the term "easy" in their free-response descriptions of the interview process. We observe that the fraction of interviews that mention "easy" monotonically decreases with interview difficulty (Appendix Figure A6); about 22 percent of interviews deemed "very easy" mention it compared with only about 8 percent for those rated "average" and 4 percent for those rated "difficult." Next, we evaluate which employers offer the most difficult interviews. Intuitively, we find that difficult interviews are experienced with elite employers in management consulting, finance, and technology. This includes prestigious consulting firms (Weinstein, 2022) such as McKinsey and Bain & Company, as well as "superstar" firms (Autor *et al.*, 2020) such as Amazon and Google (Appendix Table A4). By comparison, firms in our sample with the least difficult interviews come from retail, food services, and insurance (Appendix Table A5).

For external validation, we turn to a different website, Onsites, that also collects summary information with regards to interview experiences. Onsites caters primarily to jobs in software engineering for technology firms; as such, we caveat that comparison with Onsites cannot necessarily speak to the validity of interview difficulty for other occupations and industries on Glassdoor. For this website as well, respondents are asked to record the difficulty level of their interview on a five-point scale. For each firm and job title pair we observe on Onsites, of which there are about 500, we calculate the average perceived difficulty level. Then, in Appendix D, we compare Onsites' averages with those for the same firm-job title pairs in Glassdoor. A one-level increase in difficulty on Glassdoor corresponds to a statistically significant increase of 0.5–1.1 levels in Onsites. Glassdoor interview difficulty thus appears to capture latent differences in difficulty between interviews.

Since we are interested in how perceptions of the interview process affect acceptance decisions, understanding whether and where there is variation in interview difficulty is necessary; if all job seekers thought interviews were easy, there would be no variation off of which to identify differences. Appendix Table A8 summarizes the variation in our easy indicator be-

[16]The average difficulty rating is 2.67 (Appendix Table A3). Also plotted is the distribution for interviews that did not culminate in an offer, which are excluded from our sample but may reasonably exhibit a different distribution across difficulty levels (e.g., rejected candidates finding the interview more cumbersome).

[17]The concern is that rather than identifying latent differences related to interview difficulty, we capture differences in reporting functions for the five-point scale (Oswald, 2008; Bond and Lang, 2019).

tween firms and workers. First, the length of the interview process is strongly correlated with difficulty, alone explaining 5 percent of the variation.[18] Incorporating firm fixed effects increases the explained variation to above 20 percent, demonstrating that knowing the hiring firm alone is not a perfect predictor of difficulty.Knowing the job seeker and hiring firm can explain 80 percent of the variation, suggesting about one-fifth of interview difficulty is match-specific, e.g., which managers are involved or even possibly what the weather was.[19]

3 Methods

This section details the procedure used for analyzing the text narratives of Glassdoor interview reports with a large language model (LLM), as well as the estimation strategies used for studying interview difficulty and worker outcomes.

3.1 Text Analysis of Interview Narratives

We first clean the dataset to focus on observations with interpretable text[20], and then use a stratified sampling approach to select a sub-sample to annotate with the LLM. For each unique combination of two-digit NAICS industry and Glassdoor interview difficulty (very easy, easy, average, difficult, and very difficult), we randomly select 500 observations. If there are fewer than 500 observations in the sample for any given combination, we use all such observations. This produces a dataset of 33,752 interview narratives.

Next, we use an aligned LLM to analyze the content of the interview descriptions in the sub-sample and annotate them across nine dimensions of interest. They are: colleague ability, colleague pleasantness, whether "they'd accept anybody," direct assessment, compensation, hours and scheduling, workplace amenities, interview engagement, and realistic job preview. The LLM used is GPT-4o-mini and the prompt for each is available in Appendix A.

To ensure the quality of the LLM's annotations, we hired two freelancers with experience of text annotation from the online freelancing platform Upwork. We provided the annotators with 100 interview descriptions, randomly sampled from this dataset of 33,752 narratives, and asked them the same prompts that we had used to train the LLM. Comparing the two annotators' responses with those of the LLM, we observe an agreement score between human annotations and those of the LLM of over 75 percent (Appendix Table A1). The

[18] This is observed across the entire wage distribution (Appendix Figure A4).

[19] We find little evidence of learning-by-doing when it comes to interview difficulty. Although interviews appear to get progressively harder over time for workers, this largely reflects the different firms and job titles workers interview with as their careers progress (Appendix Table A13).

[20] We exclude observations where the text contains fewer than eight words of at least three letters or more, is a duplicate of another observation, or contains phrases that may have indicated they were not written by a job seeker. This trims the dataset by about 1 percent to 2,477,000 observations.

agreement rate of the LLM with the annotators is almost identical to agreement between the two annotators, indicating that we are close to the upper bound in terms of accuracy, given the subjective nature of these measurable concepts. We interpret the high agreement score as indicative of the LLM producing reliable interpretations for each prompt.

Last, for each prompt, we use the GPT-generated annotations to fine-tune a RoBERTa model on a binary classification task. We interpret labels of "Definitely Yes" and "Probably Yes" as the positive class, and the rest as the negative class. Each model is fine-tuned by optimizing hyper-parameters (i.e., learning rate, training batch size, and the number of training epochs). We then use the trained models to scale up the binary annotations for each prompt to all Glassdoor interview reports, not just those that received offers.

3.2 Estimation Strategy

To test for a statistical relation between interview difficulty and worker outcomes, we estimate

$$Y_{i,k,t} = \beta \times 1(\text{Easy interview})_{i,k,t} + \lambda + \mathbf{X}'_{i,k,t}\gamma + \varepsilon_{i,k,t} \tag{1}$$

where $Y_{i,k,t}$ is an outcome of interest for worker i interviewing at firm k during calendar quarter t, for example an indicator equaling one if the worker accepts a job offer. The term λ represents a set of fixed effects (FE), i.e., indicators for group membership by observation. Every specification includes fixed effects for firm industry interacted with the vacancy's occupation, flexibly absorbing variation in acceptance rates and interview difficulty by industry $\times$ occupation. We also include fixed effects for the vacancy's metro area interacted with the calendar quarter, adjusting for city-level seasonal variation. Further, each specification includes calendar quarter of the interview, interacted with calendar quarter of the Glassdoor submission, flexibly absorbing variation across time both in terms of when interviews occurred and when the user disclosed the associated data.[21] Additional fixed effects are included in follow-up specifications, including firm FE, firm $\times$ job $\times$ metro $\times$ time FE, worker FE, and even worker $\times$ time FE, as detailed below. $\mathbf{X}_{i,k,t}$ can include other worker or firm covariates, for example the imputed wage, also as indicated below.

We can think of our treatment as the impact of a firm characteristic – interview difficulty – on workers. For each interview report, we measure the perceived difficulty of the associated firm. The very rich fixed effects described above adjust for many confounding sources, but

[21] About one-half of interview reports are written in the same calendar quarter the interview process began, while the other half are submitted later. Individuals may have rosier or murkier memories if an interview happened in the past. For example, for workers who accepted the offer, the interview experience may be clouded by experiences on the job since then. Indeed, there are perceptible differences for those who submit reviews after more time has passed (Appendix Figure A19). Those who accepted the offer are significantly more likely to write the interview was easy, those who rejected the offer that it was difficult.

they do not adjust for a particularly important source – coming from the specific worker × firm match. In particular, the worker has an individualized experience with a firm that is correlated with that worker's specific difficulty perception, which is also correlated with worker outcomes such as offer acceptance.

To adjust for this source of confounding, we construct a firm-level measure of interview difficulty that purges the experience of worker i. Specifically, we construct a leave-one-out "ease" index—the share of *other* applicants at the same firm who rated the interview as easy—which acts as a proxy for the interview's objective difficulty.[22] With this instrumental variable (IV) strategy, we estimate the effect of a firm's interview difficulty on a worker's decision, netting out the worker's endogenous contribution to the measure of firm difficulty. In particular, this leave-one-out instrument is robust to social desirability bias, where workers might selectively annotate interviews as easy or not due to concerns over self-image.

Formally, let L_k be the set of workers interviewing at firm k. Define the instrument as

$$Z_{i,k,t} = \frac{1}{|L_k| - 1} \sum_{i' \in L_k, i' \neq i} 1(\text{Easy interview})_{i',k,t} \tag{2}$$

the average of 1(Easy interview) across all other workers that interview with the same firm, as desired. Naturally, we restrict the sample to firms with at least two applicants such that this index is defined. In the first stage, worker i's interview perception is instrumented with other workers' interview perceptions:

$$1(\text{Easy interview})_{i,k,t} = \phi Z_{i,k,t} + \lambda^{Z}_{i,k,t} + \mathbf{X}'_{i,k,t}\gamma_Z + \varepsilon^{Z}_{i,k,t}, \tag{3}$$

where the other independent variables are the same as in equation (1). The two-equation system is estimated using two-stage least-squares, with clustered standard errors and robust F-statistics are reported to test the relevance of the instrument.

4 Interview Difficulty and Offer Acceptance

This section presents the main evidence on how workers respond to variation in the intensity of the interview process. Our main regressions estimate the relationship between perceived interview difficulty and the probability of rejecting offers, conditional on receiving an offer. In our preferred "leave-one-out" specification, we instrument for an individual's perceived interview difficulty at a firm using the average perceived difficulty among other candidates in

[22] This variable is constructed in the spirit of a leave-one-out Bartik (shift-share) instrument for employment or economic growth (Bartik, 1991).

that firm. The regressions include rich fixed effects and we report comprehensive robustness checks. To summarize, we find that easy interviews increase the probability of rejected offers.

We are interested in variation across workers and firms in the offer rejection rate. A primary factor is the offered wage, where one would expect that, for a given interview and all else equal, rejection rates would decrease with higher wages.[23] In Figure 2, we plot the offer rejection rate for different wage levels, with separate plots for easy interviews and not-easy interviews.[24] Consistent with high-wage workers getting more offers, we see higher rejection rates at higher wages. Further, we see systematic differences in the rejection rate between easy (red) and not-easy (blue) interviews. Across the wage distribution, at each wage level above the very bottom, rejection rates are higher after easy interviews. For the highest-paying jobs, we witness rejections rates upwards of 35 percent after easy interviews but below 25 percent after not-easy interviews. This would suggest that the interview process itself is a valuable input into the decision to accept or reject an offer—in particular that an easy interview is less favorable to a difficult interview. Indeed, job seekers on average report greater dissatisfaction (i.e., a "thumbs-down" experience overall) with easy interviews than not-easy interviews (Appendix Figure A8).

The main OLS and IV estimates for equation (1), with offer acceptance as the outcome, are reported in Table 1. The first column introduces the baseline specification. The coefficient β is an economically and statistically significant -0.06, indicating that easy interviews are rejected 6 percentage points more often than not easy interviews.[25] Given a baseline rejection rate of 16.7 percent for not-easy interviews, this wedge equates to a roughly one-third increase in offer rejection rate. Column 2 gives the associated IV specification, showing a statistically significant and larger coefficient (-0.18) for the local average treatment effect. In column (3), we tighten the comparison to workers interviewing for the same vacancy—effectively pins down the skill requirements, compensation, and responsibilities of the job—by incorporating firm $\times$ job title $\times$ metropolitan area $\times$ calendar quarter fixed effects. Though this considerably thins the sample, we find a similar coefficient: easy interviews are rejected 7.0 percentage points more often.

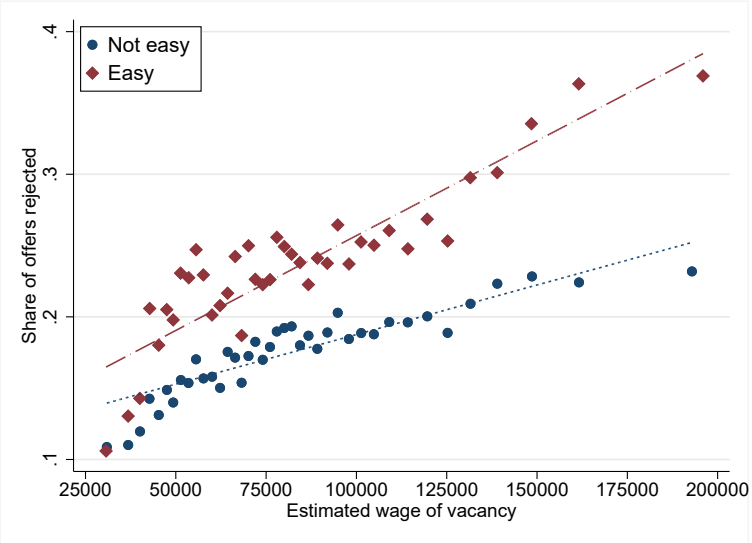
One source of confounding that we would like to address is due to differential selection of which job seekers accept an offer and disclose the decision on Glassdoor. To address

[23] Job seekers increasingly apply to vacancies that advertise greater wages (Marinescu and Wolthoff, 2020; Belot *et al.*, 2022). In the cross section, however, higher-wage workers might get more offers, leading to higher rejection rates overall at higher wages.

[24] We observe the same pattern if, in lieu of the estimate wage of the vacancy, we partitioned interviews according to other proxies of match productivity, e.g., the worker's AKM-derived fixed effect or the college graduate quality of the job seeker's alma mater (Appendix Figure A20).

[25] Estimating Equation 1 separately by occupation reveals this effect is driven by management, business and finance, computer and mathematical, and architecture and engineering jobs (Appendix Table A9).

Figure 2: Probability of Rejecting a Job Offer by Wage and Interview Difficulty



Notes: Figure 2 displays a binscatter of the fraction of offers that are rejected against the imputed wage of the vacancy and the worker's perceived interview difficulty. The imputed wage reflects the average pay reported on Glassdoor for the given firm and job title. 'Easy' corresponds to difficulty levels "very easy" and "easy" whereas 'Not Easy' corresponds to difficulty levels "average," "difficult," and "very difficult."

Table 1: Probability of Accepting a Job Offer by Perception of Interview Difficulty

	1(Accepts job offer)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1(Easy interview)	-0.057***	-0.186***	-0.070***	-0.203***	-0.632***	-0.131**	-0.163***
	(0.002)	(0.020)	(0.008)	(0.023)	(0.181)	(0.055)	(0.037)
Imputed log wage of vacancy							0.324***
							(0.081)
Specification	OLS	IV	OLS	OLS	IV	OLS	OLS
Cragg-Donald F statistic		2770.32			40.43		
Mean DV for not easy	0.816	0.817	0.818	0.560	0.557	0.620	0.546
Observations	500,258	466,052	35,628	5,680	5,323	1,833	2,475
Workers	483,891	450,918	35,187	2,657	2,490	877	1,169
R^2	0.06	-0.02	0.51	0.59	-0.11	0.84	0.60
Metro-Quarter FE	✓	✓		✓	✓		
Firm-Job title-Metro-Quarter FE			✓				
Worker-Quarter FE				✓	✓	✓	✓
Firm FE						✓	

Notes: Table 1 summarizes the relation between the probability an offer is accepted and the workers' perceived difficulty level of the interview process with the iterated addition of fixed effects for the location, firm, job title, and worker. Each specification includes industry-occupation and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

this and other worker-level confounds, Table 1 Columns 4 through 7 look at within-worker across-interview variation by including worker × calendar-quarter fixed effects. Interacting worker and time FE further accounts for differences in labor market conditions, preferences, or human capital that may evolve over time for the same worker. In this specification, identification of β stems from workers who experience both an easy interview and a not-easy interview; in other words, what is required is within-worker variation in perceived difficulty—which assuages concerns that what we identify in the cross-section is differences in reporting functions rather than realized interview experiences (Bond and Lang, 2019). This specification limits the sample significantly as we require workers to report multiple job offers around the same time (about 5,500 interviews).

First, the OLS estimates are reported in column (4). With worker×time FE included, candidates are 20 percentage points more likely to reject easy interviews. That is much larger than the cross-sectional OLS estimate and close to the cross-sectional IV estimate. In turn, the IV spec including worker×time FE (column 5) gives a larger LATE estimate. Finally, when we take a step further and include firm FE in OLS (column 6) —as some firms may have a reputation for more difficult interviews than others—this within-worker estimate remains large at 13 percentage points.

To gauge whether workers would accept lower pay to have a more difficult interview, in column (7) we incorporate the imputed wage for each vacancy into our within-worker model. When we narrow in on the same worker's choice set, greater wages are associated with increased acceptance rates. That confirms that the greater rejection rate for higher-paying jobs observed in Figure 2 is cross-sectional. Next, with a coefficient of 0.324 on the logarithm of the imputed wage and a -0.163 easy-interview coefficient, we can calibrate the effect size of an easy interview. That is, an easy interview reduces the probability of acceptance by the same amount as a 50 log points (40 percentage points) reduction in the wage.[26]

Sensitivity and Heterogeneity. We next demonstrate the ubiquity of this result that easy interviews increasingly produce rejected offers by re-estimating Equation (1) for various sub-samples of interviews. The resulting estimates are available in Appendix Figure A17.

We first recognize that Glassdoor skews toward young, college-educated workers in high-paying industries (Liu *et al.*, 2022). To show the composition of our sample does not drive our results, we take representative weights from the American Community Survey (ACS) such

[26]Offer acceptance is positively correlated with pay and negatively correlated with interview difficulty. One identification question is that interview difficulty is a proxy for (bargaining over) pay. We can check for this using other data from Glassdoor on pay reports for the same jobs we observe interviews. Using this subset that we can match, we find that the difference in total pay between easy and not-easy interviews is the same (Appendix Table A11). Easy interviews thus do not appear to signal or reflect differences in the realization of pay for the vacancy.

that re-weighting would match U.S. employment by industry, occupation, sex, metropolitan area, and pay. Even after re-weighting, the coefficient remains negative and statistically significant, albeit somewhat attenuated.

We also recognize that there may be recall bias in perceptions of difficulty or the interview process more broadly for those who disclose their interviews to Glassdoor with a delay. Indeed, when we restrict the sample to only interview reports that are submitted within one month of the interview process ending, easy interviews are rejected 14 percentage points more often—a marked 18 percent lower than the acceptance rate for not-easy interviews. As measurement error induced by delayed reporting biases our estimates toward zero, our benchmark estimate is likely a conservative lower bound. There is also the concern that, for those who accepted the offer and submitted their interview report with a delay, that their experiences on the job muddied their memory of the interview and its difficulty. Reassuringly though, if we were to restrict the sample to only rejected offers and accepted offers where the interview report was submitted to Glassdoor before the worker began the job spell (which we can observe from their resume), still easy interviews are rejected more often (Appendix Table A14). Respondents also need not disclose the date when the interview occurred. When we restrict the sample to only such interview reports, which comprise about two-fifths of the sample, the estimate is similar to that under the benchmark.

We next consider demographics. Although we observe across the wage distribution that men are more likely to reject offers than women (Appendix Figure A9, panel a) and younger workers more than older workers (panel b), both men and women are similarly more likely to reject easy interviews, as are workers across the age spectrum. Younger workers are somewhat more responsive to easy interviews than older workers, suggesting interview difficulty may be an especially meaningful signal for workers early in their careers.

Turning to educational background, we consider workers with different majors, universities, grades, and degrees. Workers with STEM degrees as well as those with non-STEM degrees exhibit comparable negative responses to easy interviews. Though the coefficient is negative for both, graduates from universities with above-average college graduate quality (as defined in Martellini *et al.* (2024)) exhibit a slightly stronger decrease in offer acceptance rates after an easy interview than graduates from universities with below-average college graduate quality. For workers with above-average and below-average grade point averages, the estimates are significantly negative and not dissimilar. Perhaps somewhat surprisingly, the largest estimate we observe for any sub-sample is graduates from a university outside the United States. Such job seekers are more than 10 percentage points more likely to reject an offer after an easy interview; relative to an acceptance rate of 81.5 percent for not-easy interviews, this represents a 13 percent drop. Last, we consider workers with a post-Bachelor's

degree and again find a sharp negative response to easy interviews.

We next consider each job seeker's prior work experience. Whether it is workers with little experience, i.e., were recruited through their university, or workers with relevant experience, i.e., a previous job on their resume was for the same occupation as the vacancy, both increasingly reject easy interviews. Whether workers are searching on-the-job, i.e., conduct the interview while employed, or searching off-the-job, i.e., conduct the interview while unemployed, both increasingly reject easy interviews.[27] We also consider whether the worker would likely be receiving an above-average pay raise or a below-average pay raise (based on the most recent firm and job title on their resume before the interview) if they were to accept the offer; again, for both, we observe reduced acceptance rates following easy interviews—though the effect is considerably stronger for the former.

Next, we narrow in on competition for the job. We first merge in monthly metropolitan area unemployment rates from the Bureau of Labor Statistics and partition labor markets into above-average (looser) and below-average (tighter) labor markets. Although we observe negative reactions to easy interviews in looser and tighter markets, the decline in acceptance rates is twice the magnitude among the latter—consistent with workers exhibiting more bargaining power and rejecting offers when available labor is scarce. We next partition interviews by whether the vacancy attracts a relatively high or low amount of job seeker interest.[28] For vacancies that are highly sought after by job seekers ex ante as well those that are less sought after, we observe similarly negative coefficients. Last, we consider whether the vacancy is a competitive interview process, in that it is relatively challenging to receive a job offer. For this exercise, we incorporate interviews that did not result in an offer, and for each firm and job title pair, we calculate the fraction of interviews that result in offers.[29] Again, both sets—vacancies that are relatively competitive for ultimately receiving an offer and those that are not so competitive—witness greater rejection rates after easy interviews; however, we do observe a more negative response to an easy interview among the latter—a mechanism we return to in Section 5.

Last, we consider whether we observe the same pattern across interviews of varying characteristics. To identify each of the following aspects, we look whether they are explicitly mentioned in the free-response descriptions respondents provide in their reports. When the interview involves human resources or includes management, easy interviews are increasingly

[27] We determine whether a worker is searching on-the-job or off-the-job by examining whether the interview occurred during a job, or between two jobs, on their resume.

[28] To determine this partition, we use data on job seeker application rates from Sockin and Sojourner (2023), which enable us to gauge for each firm and job title pair, the ratio of applications to impressions.

[29] Appendix Figure A5 relates imputed wages to interview outcomes, showing high-paying jobs have lower offer rates, consistent with more selective hiring at higher wages (Mueller *et al.*, 2023; Bassier *et al.*, 2023).

rejected for both. And, if the interview involved a video component conducted remotely over Zoom, included a coding exercise, or highlighted the responsibilities that would be required, we observe particularly negative effects of 8–10 percentage points—suggesting that interviews may be especially important barometers when workplace attributes are more opaque and when skill development is relayed.

5 Interviews as Learning Opportunities

Having established workers extract meaningful content from their interview experiences, we now examine several specific channels through which this learning might occur. In this section, we explore a signaling channel. That is, during the interview process, workers learn about firm characteristics and about the potential quality of a match. To explore this mechanism, first we show that our effects are largest for small firms with less-established reputations. Second, we explore mechanisms using text analysis of interview narratives.

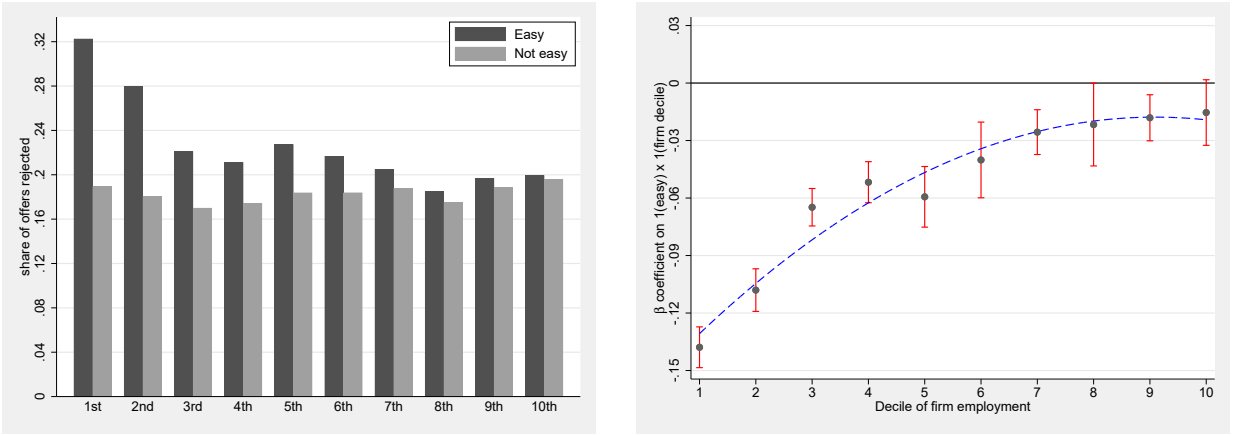
5.1 Heterogeneity by Employer Reputation

To the extent that interviews reflect a medium for learning about employers and prospective peers, we anticipate the effect interviews have on offer acceptance rates to vary with how well-established are the employers. One way to proxy for employer reputation is firm size, in that job seekers are less likely to have interacted with small employers—either through their social networks or in product markets—than large employers. As such, small firms are less likely to have established reputations (Benson *et al.*, 2019; Sockin and Sojourner, 2023). Using an employer lookup table that includes a snapshot of firm employment as of January 2025, we partition firms into deciles by their size.

Looking at the fraction of offers that are rejected by interview difficulty within each decile in panel (a) of Figure 3 reveals a stark pattern. Whereas easy interviews are rejected at comparable, though still slightly higher, rates to not-easy interviews for large firms, easy interviews are rejected substantially more often for small firms. While the rate of rejection hovers around 16–20 percent across the distribution of firm size for not-easy interviews, the rejection rate rises to between 20–24 percent for medium-size firms and even further to 28–32 percent for the smallest firms. In panel (b), we estimate the wedge in acceptance rates between easy and not-easy interviews by decile following the specification of Column (1) in Table 1. Not only are easy interviews associated with lower offer acceptance rates for firms of all sizes, but the penalties are an order of magnitude larger for firms in the bottom, as opposed to the top, quintile of the size distribution.

An alternative approach to gauging firm reputation would be to categorize firms by how

Figure 3: Probability of Rejecting an Offer by Perception of Difficulty and Firm Size



(a) Raw means **(b)** Regression coefficients

Notes: Figure 3 displays the fraction of offers rejected by whether the job seeker perceived the interview to be easy or not, partitioned by the size of the employer. Firms are partitioned into deciles, with greater deciles indicating greater employment. Firm employment based on a Glassdoor lookup table from January 2025. Panel (a) represents the raw means, whereas panel (b) corresponds to the coefficients on $1(Easy) \times 1(Decile_k)$, when added to model (1) from Table 1, with the standalone indicators $1(Decile_k)$ included. Dashed blue line indicates a quadratic fit through the coefficients. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

well-known or popular they are. To proxy for firm popularity, we measure the frequency with which each firm is searched online using Google Trends. Using Boston Consulting Group as our comparison benchmark, we calculate the average Google Trends score over the sample period for the name of each firm we observe. By fixing the benchmark firm, we obtain a metric of relative firm popularity. Again, when we partition firms into deciles by their Google Trends score, the least well-known firms witness a significantly greater penalty from an easy interview on offer acceptance rates compared with more well-known firms (Appendix Figure A10). We interpret this result as further evidence that interviews are a particularly salient channel for learning about less well-known employers.

Further evidence workers learn about firms through interviews can be observed by studying referrals. Presumably, workers who are referred by an employee are more familiar with the firm: By definition, they know at least one current employee—meaning they have some ex ante inclination for the quality of prospective peers and access to insider information about opportunities for skill development. We thus anticipate a smaller effect of easy interviews on offer acceptance when the job seeker is referred to the job opening. While employee referrals are less likely to reject offers, consistent with Burks *et al.* (2015), and still more likely to reject offers after easy interviews, the reduction in offer acceptance associated with an easy interview is less than half that observed for the full sample (Appendix Figure A17).

5.2 Analysis of Interview Narratives

Drawing on interview narratives, we analyze three distinct but potentially complementary mechanisms: learning about potential colleagues, gaining insight into job responsibilities through realistic previews, and assessing career advancement potential. For each mechanism except the last, we employ a large language model (LLM) to parse the free-text interview descriptions and identify whether and which signals are conveyed to job seekers during interviews. See Section 3.1 above for more information on how the LLM variables were produced and validated with human annotations.

A key channel through which workers might learn about candidate employers is through interactions with prospective future colleagues during the interview process. To analyze whether the difficulty of the interview signals valuable information about colleague quality at the hiring firm, we employ an LLM to assess whether each free-response narrative suggests the job seeker perceived the employees at the hiring firm to be of high-ability or pleasant. To ensure perceptions of future colleagues are distinct from other attributes job seekers may try to gauge through the interview, we use the LLM to also detect whether, as controls, the interview process involved: direct assessment of skills or qualifications, clarified compensation, clarified hours and scheduling, or detailed workplace amenities orthogonal to colleagues. The specific prompts asked of the LLM to do so are available in Appendix A.

To test for this learning channel, we examine whether easy interviews are less likely to give the perception that the hiring firm's employees are of high ability. The results, presented in columns (1)-(4) of Table 2, suggest this is the case. Whereas about 18 percent of interview summaries describe potential colleagues as being of high ability following a not easy interview, the fraction for easy interviews is about 10 percentage points lower. In the IV specification (column 2), the coefficient for the LATE is significant and even larger in magnitude. This pattern persists even after including firm fixed effects (column 3), meaning that even though "superstar" (Autor *et al.*, 2020) or high-paying firms might have reputations for employing high-ability workers, the difficulty of the interview has informational content beyond that reputation. In column 4, when we narrow in on workers who report multiple interviews and include worker FE, we see a similarly large and significant decline in job seekers believing colleagues are of high ability after an easy interview.

Importantly though, it is not simply that job seekers are less likely to highlight future colleagues in their interview summaries after easy interviews. If we were to instead look at job seeker beliefs about the pleasantness of prospective colleagues, we do not find consistent effects of interview difficulty (columns (5)-(8)). The estimate is negative in the cross section, but flips positive with worker FE and is a tight zero when including worker FE.

While considering whether an interview summary mentions high-ability colleagues cap-

Table 2: Perceived Interview Difficulty and Colleague Skill or Pleasantness

	High-ability colleagues				Pleasant colleagues			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(Easy interview)	-0.024***	-0.075***	-0.018***	-0.016***	-0.007***	-0.113***	0.008***	0.003
	(0.001)	(0.004)	(0.001)	(0.005)	(0.002)	(0.018)	(0.002)	(0.014)
Specification	OLS	IV	OLS	OLS	OLS	IV	OLS	OLS
Cragg-Donald F statistic		3212.05				3212.05		
Mean DV for not easy	0.037	0.037	0.037	0.047	0.217	0.217	0.217	0.224
N	454,989	454,989	454,989	16,260	454,989	454,989	454,989	16,260
Additional text covariates	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE			✓	✓			✓	✓
Worker FE				✓				✓

Notes: Table 2 summarizes the relation between the interviewee's perception that the job offers colleagues who are of high ability (columns 1–4) or who are pleasant (columns 5–8), and the perceived difficulty of the interview. Each specification includes industry-occupation and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Additional text covariates include indicators for the interview process illuminated compensation, illuminated hours or scheduling, and illuminated desirable workplace amenities. For details on constructing the text-based measures, see Section 3.1. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

tures positive perceptions of peer ability, job seekers may instead develop negative perceptions of peer ability from an interview. To test for this consideration, we consider whether candidates perceive the interview as suggesting a nonselective hiring process or providing an engaging experience. Both of these can signal to workers their own degree of substitutability, but also the degree of substitutability of their peers. Using a LLM, we mark whether a job seeker's interview narrative suggests the firm would "accept anybody" or that the experience was engaging. The specific prompts asked of the LLM are displayed in Appendix A.

These estimates are reported in Table 3. Only 1 percent of job seekers state after not-easy interviews that the firm would "accept anybody," the fraction jumps 7 percentage points, a *seven-fold increase*, for easy interviews (column 1). This pattern persists with the IV (column 2), the addition of firm fixed effects (column 3), and even with worker FE (column 4). This signal may in part stem from the interview process, which likely involves interactions with future peers, being perceived as less engaging or stimulating. Indeed, in columns (5)-(8), we find easy interviews are less likely to be perceived as engaging experiences, with large coefficients relative to the baseline.

The extent to which candidates are able to draw inferences about prospective peers likely depends upon the screening tools the firm employs. If, for instance, the firm requires a skill or aptitude examination, or imposes that candidates funnel through additional rounds of interviewing, then a job seeker may reasonably infer employees of that firm have all passed such screening and are thus all above some ability threshold. Using the free-response descriptions candidates provide, we examine whether such screening tools influence candidates'

Table 3: Perceived Interview Difficulty and Whether Firm "Would Accept Anybody" or Whether the Interview was an Engaging Experience

	Would accept anybody				Engaging experience			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(Easy interview)	0.075***	0.248***	0.058***	0.017***	-0.064***	-0.203***	-0.041***	-0.033**
	(0.002)	(0.007)	(0.001)	(0.005)	(0.002)	(0.024)	(0.002)	(0.015)
Specification	OLS	IV	OLS	OLS	OLS	IV	OLS	OLS
Cragg-Donald F statistic		3212.05				3212.05		
Mean DV for not easy	0.013	0.013	0.013	0.011	0.292	0.292	0.292	0.294
N	454,989	454,989	454,989	16,260	454,989	454,989	454,989	16,260
Additional text covariates	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE			✓	✓			✓	✓
Worker FE				✓				✓

Notes: Table 3 summarizes the relation between the interviewee's perception that the employer would hire anyone (columns 1–4) or that the interview was an engaging experience (columns 5–8), and the perceived difficulty of the interview. Each specification includes industry-occupation and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Additional text covariates include indicators for the interview process illuminated compensation, illuminated hours or scheduling, and illuminated desirable workplace amenities. For details on constructing the text-based measures, see Section 3.1. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

perceptions of the interview process.

For a skills or qualifications assessment, we rely on a LLM to identify whether the candidate believed their skills or qualifications were directly assessed during the interview (specific prompt detailed in Appendix A). The results in Table 4 demonstrate that such an assessment is associated with a 10-17 percentage points reduction in the likelihood of perceiving the interview as easy—even when looking across interviews for the same worker—and a roughly 1 percentage point, equivalent to a 33-50 percent increase, in the likelihood of perceiving high-ability colleagues. For the number of rounds of interviewing, we first identify a subsample of workers who mention a specific number of rounds in their interview process and then calculate the average for each firm. In Appendix Table A12, we show that—even for the same worker—firms that utilize additional interviewing rounds have longer interviews, pay higher wages, have more difficult interviews, more strongly instill the beliefs that colleagues are of high ability and that the experience was engaging.

In both cases—whether the process includes a qualifications assessment or additional rounds of interviewing—job offers are accepted more often, even when narrowing in on the sample of workers who disclose multiple interviews. These results provide additional evidence that a more difficult interview, in this case the product of the firms' more objective screening decisions, signals peers that are of high ability and influences offer decisions.

Although workers form these perceptions of prospective colleagues through the interview process, it is another question entirely whether these beliefs are accurate. Although

Table 4: Assessment of Skills or Qualifications, Beliefs About Peers, and Offer Acceptance

	1(Easy)		1(High-ability colleagues)		1(Accepts job offer)	
1(Direct assessment)	-0.101***	-0.170***	0.009***	0.013***	0.018***	0.036***
	(0.003)	(0.009)	(0.001)	(0.004)	(0.002)	(0.009)
Mean DV with no assessment	0.370	0.389	0.023	0.026	0.801	0.712
Observations	454,989	30,581	454,989	30,581	454,989	30,581
Workers	440,511	14,232	440,511	14,232	440,511	14,232
Additional text covariates	✓	✓	✓	✓	✓	✓
Firm FE	✓		✓		✓	
Worker FE		✓		✓		✓

Notes: Table 4 summarizes the relation between the interviewee mentioning their skills or qualifications were directly assessed and whether the worker believed the interview was easy, perceived high-ability colleagues, and accepted the job offer. Each specification includes industry-occupation and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Additional text covariates include indicators for the interview process illuminated compensation, illuminated hours or scheduling, and illuminated desirable workplace amenities. For details on constructing the text-based measures, see Section 3.1. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

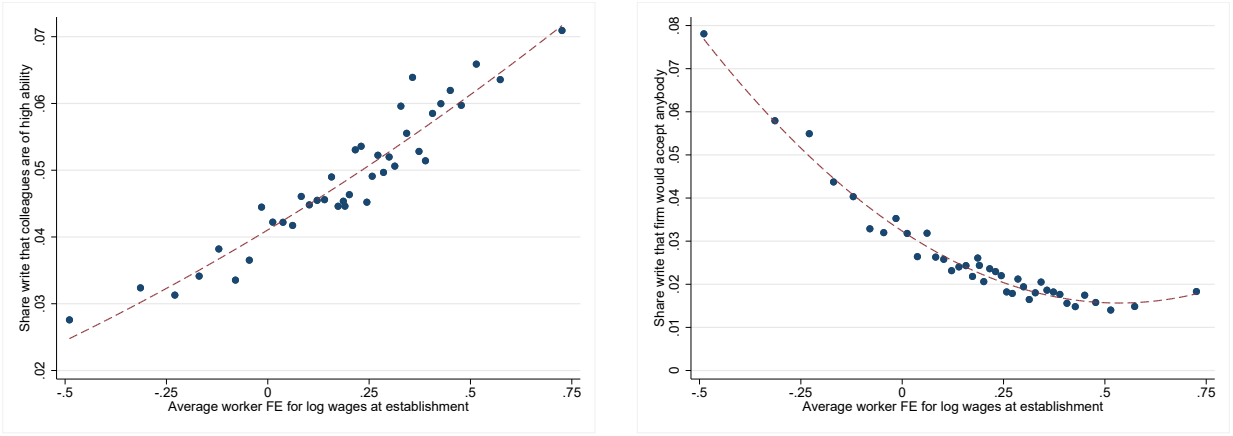
we cannot directly observe one's (prospective) peers, we can proxy for their ability using Glassdoor pay reports. First, taking the worker fixed effects from an AKM-style regression on log wages, we obtain a measure of individual skill. Then, taking the sample of Glassdoor pay reports as a snapshot of the pool of coworkers, we can gauge peer ability by taking the average level of individual skill at each establishment (i.e., firm-metro pair) each year. If the firm does indeed employ high-ability colleagues or would hire anyone, then we anticipate the frequency of perceiving the former to rise and the latter to fall with this measure of peer ability.

Figure 4 confirms this is the case. Compared with firms that have the highest levels of peer ability, firms with the lowest levels are more than four times as likely to give the impression that the firm would accept anybody, which itself is an accurate signal of the offer rate[30], and less than one-half as likely to give the impression of high-ability colleagues. This is not just about the interviewing firm though, but the specific establishment at which the worker interviews. To disentangle the reputation of the parent firm from its establishments, we can investigate the relations in Figure 4 when firm and metro fixed effects are incorporated. As shown in Appendix Table A18, the signals about peer ability persist.[31] Thus, it is not just that certain firms or specific labor markets exhibit high-ability colleagues, but rather that

[30] We test whether job seekers have accurate beliefs about the firm accepting anyone by considering how frequently interviews result in offers. Appendix Figure A12 reveals these impressions have merit. Job seekers are unlikely to believe the firm would accept anyone when the offer rate is below 70 percent; however, as the offer rate rises from 70 to 100 percent, job seekers increasingly believe the firm accepts anyone.

[31] Although we use the term peers broadly to refer to all colleagues, considering separately the ability of managers and non-managerial workers suggest it is the ability of the latter that largely drives these perceptions (Appendix Table A19).

Figure 4: Actual Peer Ability and Interview-Based Perceptions of Peer Ability



(a) 1(High-ability colleagues) **(b)** 1(Would accept anybody)

Notes: Figure 4 reflects a binscatter of the fraction of interviews that suggest, (a) peers are of high ability or (b) the firm would "accept anybody", against the average skill level of peers at the hiring firm. To proxy for the skill level of peers, we first estimate worker fixed effects from an AKM regression (that includes a fourth-order polynomial in experience) on log total pay using Glassdoor pay reports, and then calculate the median worker fixed effect for each firm x metro x year within the sample of Glassdoor pay reports. Sample is restricted to interviews for firm x metro x year bins for which the median is calculated from at least two workers. Fixed effects for metro x year-quarter of the interview are residualized out.

establishments differ in signaling high-ability colleagues.

From a macro perspective, that interviews can credibly relay signals of the ability of peers at hiring firms suggests interviews are a medium through which high-ability workers can sort into workplaces with other high-ability workers—which Song *et al.* (2019) argue accounts for about one-half of the increase in the variance of wages between firms in the United States since the late-1970s. From a micro perspective, that workers increasingly reject easy interviews and easy interviews less often signal high-ability colleagues highlights the importance of peer effects in the workplace (e.g., Mas and Moretti, 2009; Cornelissen *et al.*, 2017) and accords with recent work showing that opportunities for human capital development are among the most valued non-wage amenities (Maestas *et al.*, 2023).

5.3 Other Aspects of Employee-Employer Fit

Responsibilities. Beyond learning about colleagues and match quality, interviews may provide candidates with concrete information about the actual job responsibilities through realistic job previews. As highlighted in Appendix Figure A17, easy interviews in which the process highlighted the responsibilities of the role witness especially reduced offer acceptance rates. While suggestive evidence points to realistic job previews improving initial matches and reducing turnover (Wanous, 1973; Phillips, 1998), the literature has only studied their

effectiveness in reducing turnover among small cross-sections of workers for a given occupation. Given the interview narratives we observe and the breadth of the Glassdoor sample, we can examine the relation between realistic previews and interview difficulty across and within firms and workers. The prompt asked of the LLM for determining whether the job seeker experienced a realistic job preview is available in Appendix A.

In Table A25, we relate the decision to accept an offer with realistic job previews, interview difficulty, and their interaction. Counter to the limited evidence on offer acceptance rates (e.g., Wanous, 1973; Dean and Wanous, 1984), we find realistic job previews are associated with significantly higher offer acceptance rates, on the order of 7–10 percentage points. That said, this positive effect is somewhat diminished when the interview is easy. A realistic, but easy, job preview—even for the same firm—reduces this increase by 0.6 percentage point, or 9 percent. When we look at the same worker making multiple offer acceptance decisions, the drag from an easy interview is even more pronounced: While realistic previews witness acceptance rates that are 10 percentage points higher, the interview being easy blunts this relation by roughly two-fifths. Thus, while workers value learning about job responsibilities through interviews, they are deterred when such information is conveyed through an easy—presumably nonselective and less engaging—hiring process.

Career Concerns. Since workers are forward looking, they likely care not only about their current job opportunities, but also those that lie ahead. If workers do have such career concerns, they may place heightened value on skill development and learning on the job. In the information technology sector, workers, especially younger ones, value firms that invest in emerging technologies since they can acquire valuable skills and may in turn accept lower wages to have the opportunity to learn (Tambe *et al.*, 2020). Further, Roach and Sauermann (2024) show workers employed in startups accept lower wages to obtain the non-pecuniary benefits of startup employment, e.g., being involved in "cutting edge" and "intellectually challenging" work. If an easy interview signals limited potential for growth opportunities, candidates with career concerns may be particularly turned off to such job offers.

To proxy for workers' career concerns, we turn to the resumes workers upload to Glassdoor. With these resumes, we can follow the career trajectories of workers after any firm-job title pair we observe. So, for each firm-job title pair, we predict the average wage for the next job by taking the average imputed wage among all of the firm-job title pairs that occur next on workers' resumes. We repeat this exercise for the second next job and the third next job. Finally, we create an indicator equal to one if the firm-job title pair for which the job seeker is interviewing is one where at least one of the next three jobs is likely to be high wage, i.e., has an average imputed wage above the 90th percentile, and zero otherwise. We

then incorporate this indicator and its interaction with the easy interview indicator in Equation (1). The results, presented in Appendix Table A20, show that decreased probability of accepting an offer after an easy interview is roughly twice as large for vacancies that likely lead to a particularly high wage job in the future compared with vacancies that do not.

Outside Options. To proxy for the breadth of workers' outside options, we focus on undergraduate alma mater, leveraging the fact that there are differences in human capital between the graduates of each university (Martellini *et al.*, 2024). Differences across universities can translate into disparate labor market outcomes through, for instance, differences in skill (Dale and Krueger, 2011), access to firms (Dobbin and Zohar, 2023), or both. While workers who graduated from universities whose students tend to have greater human capital are more likely to perceive interviews as easy, and more likely to reject offers, they are no more likely to believe potential colleagues are of low ability (Appendix Table A23). Although this finding is consistent with the narrative that workers in high-paying occupations are more likely to reject offers after easy interviews, it does not appear to stem from concerns over potential colleagues. Looking at differences over the business cycle offers further evidence that outside options are a contributing factor (Appendix Table A24). When the unemployment rate rises, and workers subsequently have worse outside options amid increased competition for vacancies, easy interviews are rejected less often.

6 Interview Perceptions and Match Quality

If job seekers will reject offers because they experience easy interviews, it must be because the interview itself has predictive power—at least, in the eyes of the job seeker—for the quality of that potential match. If the interviews did not, workers would simply ignore any signals being cast by the interview experience and only focus on objective measures distinguishing vacancies, e.g., wages, hours, etc. Especially if workers learn about match quality over the duration of the match (Nagypál, 2007), having an informative ex ante signal can enable workers to sort away from obviously poor matches.

To test whether interview difficulty can serve as a precursor for eventual match quality, we study turnover behavior. Tenure length is a good measure of match quality since workers with poor match quality will voluntarily quit sooner (Akerlof *et al.*, 1988) and workers will pursue outside options if they believe them to be more appealing than their current match (Jäger *et al.*, 2024). To do so, we match workers' interview experiences to their accepted offers using their resumes. We consider all of the jobs listed on a worker's resume and identify for which (if any) the worker disclosed their interview experience on Glassdoor. We match

an interview to a job on a resume if the worker reported an interview for that firm within a year of the job beginning. For jobs with end dates listed on the resume, we can calculate tenure with the firm. Since not all jobs have ended, we also create an indicator for whether the match has survived at least twelve months. We then estimate differences in these two measures of firm tenure between workers who accepted offers after easy interviews and their counterparts who accepted offers after not-easy interviews. We use the main specification from Eq. (1) estimated with OLS.

The results for match quality are shown in Table 5.[32] Each specification supports the same narrative: Workers separate earlier if they had thought the interview they had *before* starting the job was easy.[33] The share of other candidates who rated interviews as easy (second row) is also negative (about -0.15 in columns 1-2 and -0.11 in columns 4-5), indicating shorter tenure when the broader applicant pool perceived the interview as easy. Even within the same industries and occupations, workers separate 20 percent faster after an easy interview (column 1). The result holds when using the IV specification instrumenting for easy interview with the leave-one-out-average from the firm (Column 2). We find similar OLS results looking within the same firm and job title (column 3).[34]

Columns 4-6 show consistent results when examining whether workers remain with their employer for at least one year. We observe a significantly lower probability after an easy interview for both OLS (column 4) and IV (column 5). Even when considering the same firm and job title, workers who accepted after easy interviews are about 6 percentage points (column 6) less likely to remain in the match for at least one year, a 15 percent reduction relative to the 78 percent share observed following not-easy interviews.

Of course, tenure is an equilibrium object. Faster turnover may reflect an increased propensity of voluntary quits just as easily as it could reflect a greater probability of layoffs. Depending upon which one dominates, the implications are drastically different. Under the former, the utility of the match is insufficient to dissuade the worker from pursuing outside opportunities. Indeed, others have shown that improved amenities, such as hybrid work arrangements (Bloom *et al.*, 2022), can induce workers to remain attached to their firms. If instead, faster turnover reflects a heightened probability of layoffs, an easy interview might

[32]Since we do not observe age for most respondents, we exclude age from our benchmark specification. That said, despite the thinner sample, the takeaways would be unchanged if we did (Appendix Table A15).

[33]Since workers may start using Glassdoor when searching for a new job, one may be concerned this result reflects selection of who simultaneously exits and reports to Glassdoor to facilitate job search. Since we observe reduced tenure following an easy interview for historical jobs, not just the most recent one on an individual's resume (Appendix Table A22), we do not believe this to be the case.

[34]Reassuringly, this result does not reflect unobserved selection of who inherently perceives interviews as easy. We draw the same conclusion restricting the sample to workers with multiple interview reports and incorporating each worker's fixed effect from an AKM-style regression on difficulty (Appendix Table A21).

Table 5: Tenure from Workers' Resumes After Offer Acceptance

	Logarithm of firm tenure			1(Firm tenure ≥ 12 months)		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Easy interview)	-0.201***	-0.488***	-0.199***	-0.084***	-0.382***	-0.061***
	(0.020)	(0.139)	(0.053)	(0.009)	(0.064)	(0.022)
Specification	OLS	IV	OLS	OLS	IV	OLS
Cragg-Donald F statistic		166.32			224.02	
Mean DV for not easy	2.491	2.492	2.364	0.787	0.789	0.785
Observations	8,817	8,514	2,264	12,718	12,339	3,540
Industry-occupation FE	✓	✓		✓	✓	
Firm-job title FE			✓			✓

Notes: Table 5 relates the length of firm tenure for a job using workers' resumes to their interview experiences for that same employer. Each column additionally includes fixed effects for the calendar year-month the job began × the calendar year-month the interview was submitted to Glassdoor. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

proxy for a less-productive worker who is ultimately let go because of poor performance.

Empirical evidence suggests the heightened turnover we observe after easy interviews reflects voluntary, as opposed to involuntary, separations. For one, if we were to proxy for each individual's skill using their own estimated fixed effect from an AKM regression on log wages (which itself is positively correlated with tenure), workers are still more likely to exit a job that had an easy interview faster (Appendix Table A21). Additionally, we can directly test whether the workers exhibit signs of poor match quality after an easy interview by turning to their reported levels of job satisfaction in Glassdoor employer reviews.

The reviews dataset is comprised of job satisfaction ratings where we observe the worker, their firm, and their job title. Glassdoor ratings are on an integral scale from 1–5 stars, and workers are incentivized to contribute through the give-to-get-mechanism introduced in Section 2.[35] Sockin (2022) shows Glassdoor satisfaction ratings across industries and occupations are strongly correlated with satisfaction reported in the National Longitudinal Survey of Youth 1997. To examine whether interview difficulty predicts job satisfaction, we match interviews in which the worker accepted the offer to their later-written Glassdoor review. We assign an employer review to an interview report if they are written by the same worker, are for the same firm in the same metropolitan area, and the review is provided after the interview occurred.[36] We are able to match 57,000 employer reviews to associated interview reports. With regard to this sample of employer reviews, one may be concerned that they are differently selected from Glassdoor reviews more broadly since the worker would have had to contribute at least two separate survey responses—an employer review

[35]For additional details about Glassdoor reviews, see Marinescu *et al.* (2021).

[36]We do not match on job title since workers may have been promoted or demoted in the interim.

Table 6: Job Satisfaction from Glassdoor Reviews After Offer Acceptance

					1(Mentioned in cons section)		
	Overall rating				Involuntary turnover	Voluntary turnover	Peers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1(Easy interview)	-0.695***	-1.688***	-0.436***	-0.345***	0.006	0.007*	0.032***
	(0.014)	(0.100)	(0.036)	(0.131)	(0.004)	(0.004)	(0.009)
Specification	OLS	IV	OLS	OLS	OLS	OLS	OLS
Cragg-Donald F statistic		841.20					
Mean DV for not easy	3.905	3.904	3.840	3.572	0.027	0.022	0.127
N	57,137	52,695	12,742	1,034	12,742	12,742	12,742
Industry-occupation FE	✓	✓					
Firm-Job title FE			✓		✓	✓	✓
Worker FE				✓			

Notes: Table 6 relates job satisfaction from workers' Glassdoor reviews to their interview experiences for the same position. Glassdoor reviews are matched to interviews if they are submitted by the same worker for the same firm in the same metro, and the interview was conducted before the review was submitted. Involuntary turnover is captured by the phrases 'fired,' 'laid off,' 'lay off,' 'layoff,' and 'let go.' Voluntary turnover is captured by the phrases 'quit' and 'resign.' Peers is captured by the phrases 'coworker,' 'colleague,' and 'people.' Each specification includes fixed effects for industry-occupation and the interview year-quarter and the year-quarter in which the employer review was written. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

and an interview report–for the same firm to be in the sample. However, when we look at the distribution of satisfaction ratings for this interview-paired sample compared with the entire database of reviews (Appendix Figure A16), there is little difference between them.

As is shown in Table 6, easy interviews precede *much worse* job satisfaction. Workers who accept offers after easy interviews are 0.70 stars less satisfied with their jobs (column 1). For context, this disparity is equivalent to one half of a standard deviation (1.41 stars) and is larger in magnitude than the effect of learning your employer engaged in corporate misconduct (Gadgil and Sockin, 2020) or received an Accounting and Auditing Enforcement Release from the U.S. Securities and Exchange Commission (Zhou and Makridis, 2021). This satisfaction gap between jobs accepted after easy and not-easy interviews holds for the leave-one-out IV specification (column 2) and persists when we compare workers evaluating the same firm and job title (column 3). Even when we consider the *same* worker reporting their satisfaction for multiple jobs that differed in whether they followed easy or not-easy interviews (column 4), that same worker reports 0.35 stars lower satisfaction, or one-fourth of a standard deviation, for the job that followed the easy interview.

Since job dissatisfaction predicts turnover (Akerlof *et al.*, 1988; Card *et al.*, 2012), such evidence strongly supports the narrative of more rapid quitting as opposed to more rapid layoffs. However, to further disentangle whether the reduced firm tenure we observe following easy interviews reflects voluntary or involuntary turnover, we turn to the free-response text

workers provide within their employer reviews. We identify specific terms that indicate involuntary turnover, such as 'fired' or 'laid off', or voluntary turnover, such as 'quit' or 'resign', and examine in columns (5) and (6) how the frequency with which such terms are mentioned in the 'cons' section of reviews varies with interview difficulty. Consistent with higher rates of workers choosing to leave, we find that workers who accepted offers after easy interviews are 32 percent more likely to mention *voluntary* turnover as a negative aspect of their workplace. Though this estimate is only significant at the 10 percent level, further evidence for this interpretation comes from identifying the frequency with which workers mention 'peers' in their reviews (column 7). Workers who accepted offers after easy interviews are 25 percent more likely to explicitly reference peers as a drawback of their job.

If easy interviews predict poor match quality and faster turnover, why would a job seeker choose to accept such an offer rather than continue searching for an alternative job with a less easy interview? One reason may be that the return to continuing their job search is low. This would be the case if workers were to increasingly accept offers after easy interviews as local labor markets slacken. Incorporating, from the Bureau of Labor Statistics, the metro area unemployment rate at the time of each interview, we find that a one standard deviation increase in the unemployment rate is associated with 0.7–1.1 percentage points greater likelihood of accepting an offer after an easy interview (Appendix Table A24). We interpret this result as further evidence that jobs which follow easy interviews are less desirable matches, as workers would increasingly reject such offers if they had better outside options.

7 Experimental Evidence on Interview Difficulty

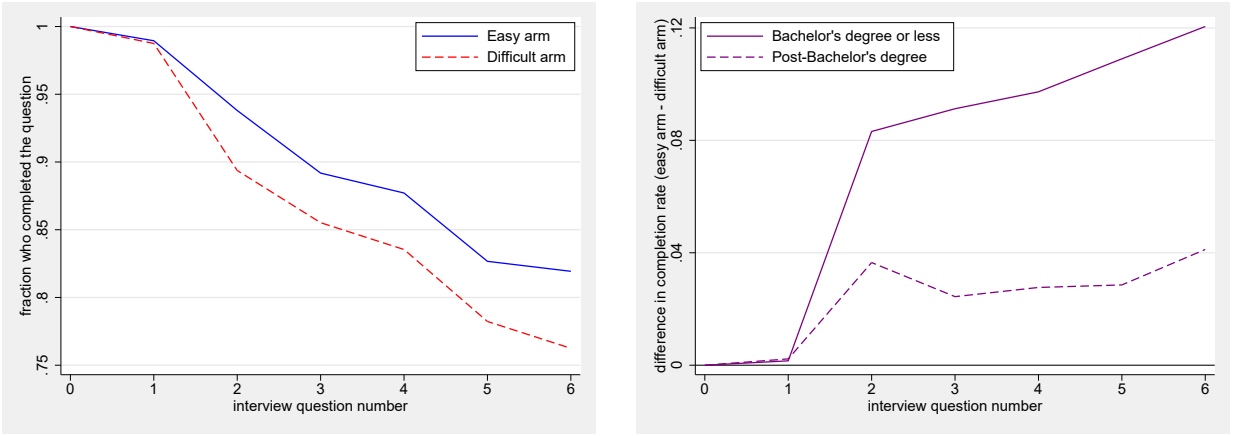
To complement our observational evidence, we conduct a pre-registered randomized field experiment that provides causal evidence on how interview difficulty affects candidate behavior. By randomly assigning job applicants to technical assessments of varying difficulty in the context of recruiting for a data scientist position at a university, we test whether interview difficulty directly influences candidate attrition and behavioral engagement with the vacancy. This experimental approach addresses two key limitations of our Glassdoor data: potential reverse causality (where offer decisions retrospectively shape difficulty perceptions) and selection bias from endogenous attrition (since we only observe candidates who complete the interview process). Though conducted in a simplified context—with no employee interactions or actual offers extended—the experiment provides controlled evidence that interview difficulty shapes labor market behavior.

Experiment Design. We posted a genuine job advertisement for a data scientist position at a university, attracting approximately 2,500 applicants. We focus the analysis on the 1,370 candidates who proceeded past the initial CV submission to begin the technical assessment—these individuals form our analysis sample. Before beginning the assessment, these candidates were randomly assigned with equal probability to one of two treatment arms. The "easy" arm received simpler technical tasks (e.g., working with 10MB files, interpreting linear regression, basic probabilities), while the "difficult" arm received more advanced tasks (e.g., working with 10GB files, explaining regression limitations, advanced probabilities). Appendix Table A26 provides the full assessment details and Appendix Table A27 reports summary statistics for key variables. As expected, candidates in the difficult arm spent significantly more time per question (Appendix Figure A21) and predicted others would need more time to complete the assessment (Appendix Figure A22). Importantly, to preserve the integrity of the randomization and avoid bias in actual hiring, the hiring manager did *not* observe applicants' responses to these randomized questions—actual first-round hiring decisions were based solely on CVs.

The interview consisted of five technical questions administered sequentially online. Upon completing the assessment, participants were surveyed about their perceived difficulty of the interview and how it affected their interest in the position. To mitigate self-image bias, we elicited perceived difficulty by asking how they believed *other* applicants would rate the interview, providing five options consistent with our Glassdoor data: very easy, easy, average, difficult, and very difficult. This framing successfully shifted the distribution of perceived difficulty between treatment arms (Appendix Figure A23). Candidates also provided written responses about why they were a good fit for the position and could submit questions for the employer—both serving as additional measures of engagement through response length and effort. Those who completed the assessment received an email containing a link where they could check their application status, which we track as a measure of continued interest. Together, these measures—stated interest, free-text responses, and status-checking behavior—allow us to examine how engagement relates to perceived interview difficulty without any offers being made.

Main Results. Figure 5 presents our first key finding from the Intent-to-Treat (ITT) analysis: differential attrition by treatment arm. Panel (a) shows how completion rates diverge sharply between treatment arms as candidates progress through the assessment. By the final question, only about 76% of those in the difficult arm remain, compared to 82% in the easy arm. Notably, most attrition occurs early—after just the first few questions—suggesting that candidates quickly form impressions about the interview's difficulty and make

Figure 5: Attrition During Interview Assessment by Relative Difficulty of the Assessment



(a) By treatment arm

(b) Between treatment arms

Notes: Figure 5 displays the fraction of applicants that complete each question of the technical assessment for each treatment arm in panel (a) and the difference between the two treatment arms by level of educational attainment in panel (b). For a description of each interview question, see Appendix Table A26.

immediate decisions about whether to continue.

There is substantial heterogeneity in this attrition pattern. Panel (b) disaggregates completion rates by educational attainment, showing strikingly different responses to treatment. Among candidates with a Bachelor's degree or less, the difficult assessment induces much higher differential attrition compared to the easy assessment: by question 6, the completion rate gap between easy and difficult arms reaches 12 percentage points. In contrast, candidates with post-Bachelor's degrees show significantly lower differential attrition—roughly 4 percentage points—suggesting that those with more human capital are less deterred by interview difficulty. Similar patterns emerge when disaggregating by years of work experience; see Appendix Figure A24.

These results highlight important selection dynamics. Relative to the easy assessment, the difficult assessment induces much higher attrition among candidates with less human capital. In contrast, those with more education persist for longer, suggesting they are less deterred by challenging assessments. This differential attrition implies that easy interviews fail to screen out candidates with less human capital (who complete at high rates) while difficult interviews successfully induce self-selection among this group. The welfare implications of such self-selection, however, remain ambiguous: such screening may benefit employers when candidates are plentiful but could exacerbate hiring challenges in tight labor markets.

Besides tackling selection bias, the other main identification challenge our experiment addresses is reverse causality, where candidates retrospectively reflect on interview difficulty after job offer decisions have been made. For example, candidates who decide to reject offers

might retrospectively rate interviews as "easy" to justify their decision. Moving beyond the ITT effects on candidate behavior, we examine the relationship between *perceived* difficulty and candidate interest in Table 7. While these perceptions are endogenous (and distinct from the random assignment), our experiment ensures they are measured *before* any offers are made—indeed, no offers are extended at all during the study period, nor do candidates engage with any employee. Therefore, this design isolates the real-time formation of interest from ex-post rationalization.

The results confirm that the link between perceived difficulty and stated interest emerges contemporaneously, before any hiring outcomes. Among those with post-Bachelor's degrees, who comprise nearly 80% of candidates who completed the interview assessment and the post-assessment survey, perceiving the interview as easy is associated with a 5.8 percentage point reduction in the probability of reporting increased interest in the vacancy—approximately 8% lower relative to the baseline rate of 74.7% among those who perceived the interview as not easy. The null effects in columns 1-6 suggest this isn't simply about overall engagement or effort; indeed we fail to reject the hypothesis that candidates who perceive the interview as easy write similar-length responses and check their application status equally often. Rather, the association appears specific to stated interest in the position itself. Appendix Table A28 presents complementary IV estimates using treatment assignment to instrument for perceived difficulty, though the estimates are less precise given the partial compliance with treatment.

This pattern provides evidence supporting a mechanism we observe throughout our Glassdoor analysis: the subjective experience of interview difficulty shapes candidate perceptions of match quality, particularly among those with high human capital. That this association emerges immediately after the interview assessment—before any offers, rejections, or ex-post rationalization—rules out reverse causality and suggests that candidates form real-time impressions about what interview difficulty signals regarding the job. For high human capital candidates, perceiving an assessment as easy appears to function as an immediate negative signal, consistent with our observational evidence linking easy interviews to perceptions of low selectivity and limited development opportunities.

The experiment thus complements and strengthens our observational evidence, while acknowledging important limitations. The controlled setting necessarily abstracts from key features of real job interviews—candidates interact with no employees and receive no actual offers during the study period. Yet despite these simplifications, we find responses consistent with our main findings. The ITT analysis reveals a causal behavioral effect—randomly assigned interview difficulty generates differential attrition by human capital—while attitudinal data show reduced interest among high-ability candidates who *perceive* assessments as

Table 7: Perceived Interview Difficulty and Interest in Vacancy

	Length why good fit		Length questions for us		Number of application queries		1(More interested in vacancy)	
	Full sample	Post-Bachelor's	Full sample	Post-Bachelor's	Full sample	Post-Bachelor's	Full sample	Post-Bachelor's
1(Easy interview)	-0.048	-0.058	0.041	0.071	0.026	0.012	-0.042	-0.058**
	(0.053)	(0.058)	(0.061)	(0.069)	(0.050)	(0.053)	(0.026)	(0.029)
Mean DV if not easy	0.326	0.363	0.159	0.156	0.199	0.192	0.740	0.747
Observations	1,370	1,094	1,370	1,094	1,370	1,094	1,370	1,094

Notes: Each specification includes fixed effects for the day on which the interview began. Standard errors are robust. Significance levels: * 10%, ** 5%, *** 1%.

easy. These results provide causal support for two critical insights from our observational analysis. First, the temporal sequence of our experiment—where difficulty perceptions and interest are measured before any hiring outcomes—rules out reverse causality as an explanation for our main results. Second, the heterogeneous effects by education reveal how interview difficulty serves distinct functions across the ability distribution, screening out some candidates through attrition while generating more interest in the vacancy among others. While we cannot claim that all mechanisms we posited through our Glassdoor analysis operate in this simplified experimental context, the emergence of similar patterns through random assignment strengthens our preferred interpretation that interview difficulty functions as a meaningful signal for candidates to gauge match quality.

8 Implications for Firm Growth

When it comes to interview difficulty, our results suggest firms face a trade-off: Easy interviews result in more rejected offers and increased turnover, but difficult interviews take more time—thereby requiring more resources—and can thin the pool of potential hires. If firms grow or evolve similarly regardless, it would render the decision inconsequential. However, if they do not, then it would suggest interviewing practices—in this case their difficulty—may help explain why some firms grow faster than others. To the extent that hiring practices are managerially-driven, this would suggest there is another, understudied dimension by which managers can contribute to differences in firm-level growth (Bloom and Van Reenen, 2010; Sadun *et al.*, 2025).

Although we observe neither employment nor productivity over time for firms in our sample to directly track growth, we do observe employee wages. Assuming that more productive firms will tend to pay higher wages—recognizing though that this mapping may not be one-to-one (Lochner and Schulz, 2024)—we can proxy for differences in productivity growth through differences in wage growth. To this end, we implement a two-step process.

First, we produce a firm-specific measure for interview difficulty $\hat{D}_k$ in the early years of the sample. The measure accounts for differences across job titles (as in Appendix Figures A4 and A5), and the sample is restricted to 2012-2016. Second, we ask whether this measure of early firm-level interview difficulty has predictive power for long-run wages in a future period, i.e., the last five years of our sample 2020-2024. The estimating equation follows

$$\ln(\text{wage})_{i,k,t} = \psi \times \hat{D}_k \times 1(2020 \leq t \leq 2024) + \lambda_i + \lambda_k + \mathbf{X}'_{i,k,t}\gamma + \epsilon_{i,k,t}. \tag{4}$$

The coefficient of interest ψ captures, for the same worker i, the degree to which wages in 2020-2024 differ relative to the firm's average wage level over the full sample period, by the relative difficulty of firm k's interviews in 2012–2016 compared with firms that were hiring for the same positions. Put differently, equation (4) is an AKM-model with an additional term for the firm's past degree of interview difficulty. The results are presented in Table 8.

What these results suggest is that interview difficulty is not inconsequential for firm growth. Firms whose interviews are perceived as one standard deviation more difficult pay wages five-to-ten years later that are 0.8 percent higher. This pattern holds when we account for cross-industry differences in interview difficulty—as evidenced by Appendix Figures A4 and A5—and even when we focus only on young firms with less-established reputations, where the relation rises to 1.2 percent greater wages per standard deviation of interview difficulty. Since we incorporate fixed effects for the worker, metro, and occupation, this difficult-interview premium cannot be rationalized by compositional shifts toward certain labor markets or occupations that may correlate with interview difficulty. Rather, it suggests faster productivity growth.

What mechanism is it that fuels this growth? Perhaps it is increased complementarity from the pooling of high-ability peers, or efficiency gains from the reduction in turnover and loss of firm-specific human capital, or increased productivity that results from improved job satisfaction (Bellet *et al.*, 2024), or the innovation and patenting that high-ability workers generate (Martellini *et al.*, 2024). Or, it may be the selection of firms that implement difficult interviews are the ones that are already on high-growth trajectories. While we do not attempt to disentangle these channels here, we hope future researchers will.

9 Conclusion

Interviews are a two-way dialogue, featuring interactions between hiring managers and workers. Yet, the (personnel) literature has almost exclusively adopted the perspective of *hiring managers*, exploring how interviews allow employers to screen workers (Benson and Shaw,

Table 8: Past Interview Difficulty and Future Pay Growth

	Ln(Total pay)			
	All firms		Firms founded from 2002-11	
	(1)	(2)	(3)	(4)
Firm's relative interview difficulty 2012-16 x 1(Salary in 2020-24)	0.008***	0.007***	0.012***	0.011***
	(0.001)	(0.001)	(0.004)	(0.003)
Observations	1,444,837	1,444,837	109,549	109,549
Adjusted R^2	0.86	0.86	0.89	0.89
Worker, firm, metro-year, and industry-occupation-year FE	✓	✓	✓	✓
Residualized relative interview difficulty		✓		✓

Notes: Table 8 relates interview difficulty to firm growth through workers' wages in future years. Firm relative interview difficulty from 2012-2016 is determined by regressing interview difficulty on firm and job title fixed effects for interviews from 2012–16, and then standardizing the firm fixed effects to have mean 0 and standard deviation 1. In columns (2) and (4), the firm fixed effects for interview difficulty are residualized by fixed effects for industry and year founded. The pay sample consists of Glassdoor pay reports spanning 2012 to 2024. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

2024; Hoffman and Stanton, 2024). In this paper, we take the opposite, underappreciated perspective. Do workers form perceptions of candidate employers through job interviews? They do. What exactly do workers learn through the interview process? Aspects that determine match quality yet are hard to gauge otherwise, such as the quality of future peers and their own degree of substitutability.

While this paper uniquely links workers' perceptions of the interview experience to their own labor market outcomes, many questions remain. For one, we cannot speak to how workers' beliefs evolve because we do not observe their expectations before their interviews begin. Qualitative methods that investigate workers' ex ante beliefs about employers (and their interviews) before, during, and after the interview process would be especially illuminating. Of particular interest is whether (or how) their perspectives shift based on the perceived difficulty of the interview. Given our own text analysis, we suspect their views on prospective coworkers and opportunities for skill development would shift, but those for other aspects of the workplace (such as work-life balance or promotion probabilities) might as well. Such qualitative methods could help shed light on whether there is a mismatch between workers' and hiring managers' perceptions throughout the interview process.

Other work could also study how employee screening could be structured and to what extent different screening devices, such as IQ examinations, coding assignments, or personality testsalter workers' perceptions of the employer and the job itself. While hiring managers have a battery of screening tools at their disposal, it is unclear how such evaluation methods causally shift the likelihood a worker will accept an offer, or even simply choose to continue with the interview process. These questions take on heightened relevance as firms

increasingly consider automating segments of their screening processes.

In light of these considerations, what are the broader implications of these findings for firms and society at large? That firms appear to benefit when high-wage workers face interviews perceived as difficult—whether by the candidates themselves or by the broader applicant pool, as difficult interviews are positively associated with offer acceptance, tenure, and satisfaction—invites moral hazard, i.e., strategic deception. If firms know workers rely on interviews to gauge match quality, then they have the incentive to disingenuously convey difficulty; firms may rely on only their most productive workers conducting interviews (to signal colleague ability) or include questions that are overly challenging (to offer the mirage of human capital development), when the role in reality promises neither. More broadly, it begs the question, which employees should be involved in the hiring process? And for whom? While higher-paid workers have greater opportunity costs for being involved in recruitment, they also are more likely to attract top talent to the firm.

For society, though, knowing workers' perceptions of the interview process may help reduce search costs and improve matching efficiency. If firms knew how their interviews were perceived by each candidate, they could make offers to workers who thought the interviews were more difficult and reduce turnover costs, as the workers who accept these offers would stay more attached to the firm due to improved match quality. This would have the potential to mitigate the deadweight loss that stems from high turnover and vacancy costs. What the implications are for sorting in the labor market depends upon the relative magnitude of these opposing forces: between more efficient matches through knowledge of amenities and colleague ability, and less efficient matches due to moral hazard through employer deception.

While this study considers interviews over the last fifteen years, it is plausible the nature of hiring will change. The advent of new technologies and the decentralization of hiring have intensified the use of automation in recruitment decisions. Artificial intelligence has already begun to alter the recruitment process through algorithmic recommendations (Zhang and Kuhn, 2024), while new technologies such as Zoom have made remote interviews commonplace. Whether such technologies will disrupt, ease, or distort employer recruitment is not yet known. But we can only begin to speculate what might happen if the interview process were to shift to being less interpersonal and more algorithmic. The quantifiable aspects of candidate assessment—skills tests, credentials, past performance—are natural targets for automation. But, our evidence suggests that the seemingly "inefficient" aspects of traditional interviews—the back-and-forth dialogue, the subtle signals about workplace culture, the perceived difficulty of the process—serve a valuable function in the matching process. This creates an interesting tension: the elements of interviews that are easiest to automate for firms may not be distinct from those that are most informative to job seekers.

At the same time though, the subjective nature of the traditional interview process affords employers the opportunity to engage in discrimination, for instance, by sex (Neumark *et al.*, 1996; Mocanu, 2024), caste (Shukla, 2025), or race (Kline *et al.*, 2022). While such biases may be detectable ex post from data on new hires or through audit studies, it may be difficult to detect absent such interventions. Determining the welfare effects from new technologies entering the interview process ultimately requires balancing the potential loss in screening—for both workers and firms—with the potential gains from reducing bias and vacancy-filling costs. While personnel economics has long been blind to the worker's information problem, workers evidently cling to what signals they can about match quality from choosing between candidate employers. Perhaps the old adage is true: knowledge is power; in this case, for workers, knowledge gained through interviewing is bargaining power.

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Appendix

A LLM Annotation Prompts

The following prompts were used to analyze the content of the interview descriptions. Before these prompts were introduced, the dialogue would always begin with "I will provide you with a text snippet that describes a job interview." followed by one of the prompts below. After the prompt, the dialogue would always conclude with "Read the description and provide a label "Definitely Yes," "Probably Yes," "Probably Not," "Definitely Not," or "N/A," followed by a semicolon (;) and then a short one-sentence explanation."

Colleague ability. Does the description say that prospective colleagues are highly able, intelligent, or competent? Determine whether the interview description explicitly mentions or strongly implies that colleagues at the employer are of high ability, intelligence, or competence. Do not answer 'Yes' solely because the process was described as being rigorous, long or difficult - difficulty and length alone do not necessarily mean that the prospective colleagues are of high ability. Likewise, do not view IQ tests, technical questions and coding challenges as being indicative of highly able colleagues.

Colleague pleasantness. Does the description say that prospective colleagues are friendly, pleasant, or interesting to spend time with for non-professional reasons? Determine whether the interview description explicitly mentions or strongly implies that colleagues at the employer are friendly, interesting, amiable, sociable, engaging, or have intriguing personalities. This does not include professional qualities like competence or skill, but rather focuses on personal interactions and social dynamics.

"They'd accept anybody". Does the description suggest, through explicit mention or clear implication, that the employer would hire anyone? That is, does it imply that the employer is desperate for employees and would accept any applicant regardless of qualifications or fit? Do not answer 'Yes' solely because the interview process is described as 'easy' - ease alone does not necessarily mean the employer would hire anyone.

Direct assessment. Was the interviewee directly assessed on their skills or qualifications? Determine whether the interview description indicates that the process involved a technical component, such as a coding exercise, qualification exam, technical test, or similar assessment.

Compensation. Does the description mention wages, salary, or compensation? For example, did the author learn during the interview process that compensation would be higher, lower, or

similar to what was expected?

Hours and scheduling. Does the description mention the expected hours or flexibility of the job? For example, did the author learn during the interview process that the job's hours, workload, or flexibility would be higher, lower, or similar to what was expected?

Workplace amenities. Your task is to determine whether the interview description suggests that the workplace will be a desirable environment with good amenities. For example: - Office facilities (e.g., modern workspace, ergonomic desks, well-equipped meeting rooms). - Leisure and recreational facilities (e.g., gym, game room, relaxation areas). - On-site services (e.g., cafeteria, childcare, fitness centers). - Flexible working arrangements (e.g., remote work options, flexible hours). Workplace amenities do not include qualities or attributes of colleagues, such as friendliness or professionalism. They do not include job features that are mainly intended to help you be more productive, such as better computer hardware or software. Does the text explicitly mention or clearly imply that the company has a desirable environment with good workplace amenities?

Interview engagement Does the description explicitly mention or strongly imply that the interview process was engaging? An interview is engaging if it involves: two-way communication with both the interviewer and candidate actively participating and listening to each other; the interviewer showing genuine interest in the candidate's background, experience and perspectives, while also sparking the candidate's interest.

Realistic job preview Does the description explicitly mention or strongly imply that the interview process provided the candidate with a realistic preview of what the job entails? Specifically, did the candidate leave the process with a better understanding of the work environment, job duties, and expectations?

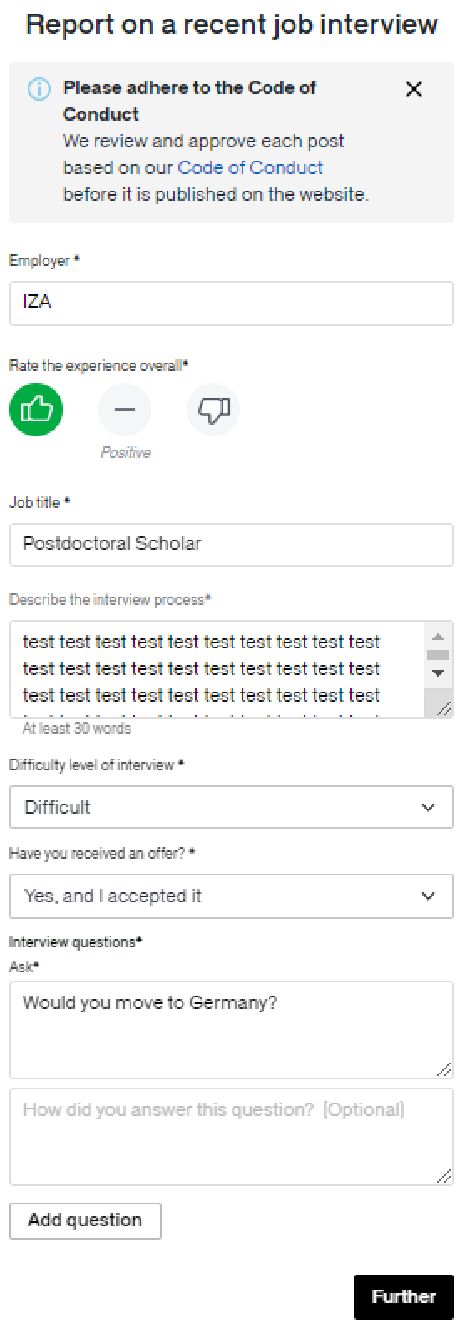
Table A1: Alignment between LLM-derived and Human-derived Annotations

Agreement between...	Colleague ability	Colleague pleasantness	Accept anyone	Assessment	Wages	Hours	Amenities	Engaging	RJP
Annotators 1 and 2	0.89	0.82	0.83	0.86	0.87	0.90	0.62	0.81	0.80
LLM and annotators	0.84	0.80	0.84	0.92	0.86	0.80	0.75	0.82	0.79

Notes: Table A3 lists, for each annotation, the fraction of overlap between the two annotators and between the LLM and the two annotators.

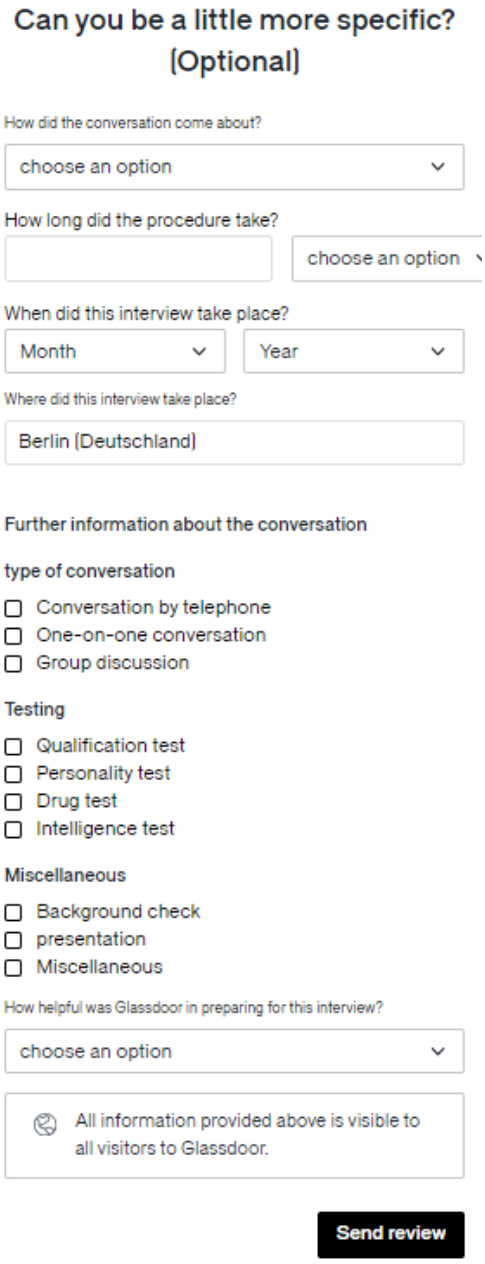
B Additional Summary Information

Figure A1: Screenshot of Interview Submission Process



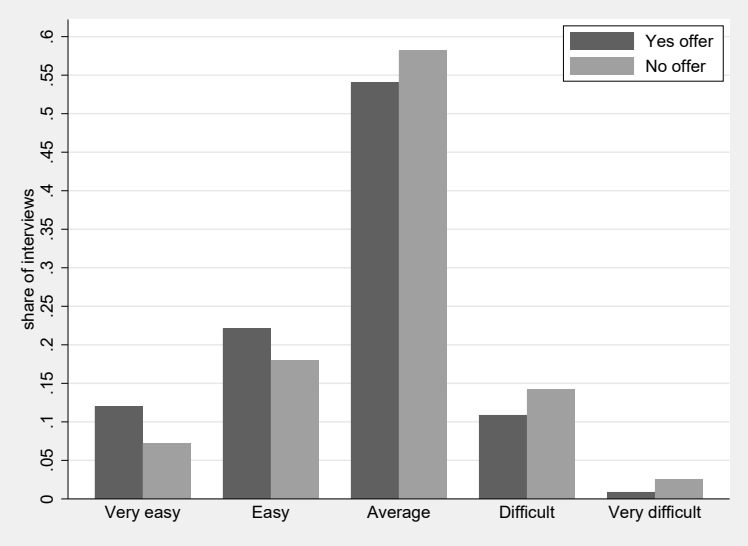
Notes: Figure A1 provides a screenshot of the Glassdoor interview submission form from March 12, 2024.

Figure A2: Screenshot of Additional, Optional Aspects of Interview Submission Process



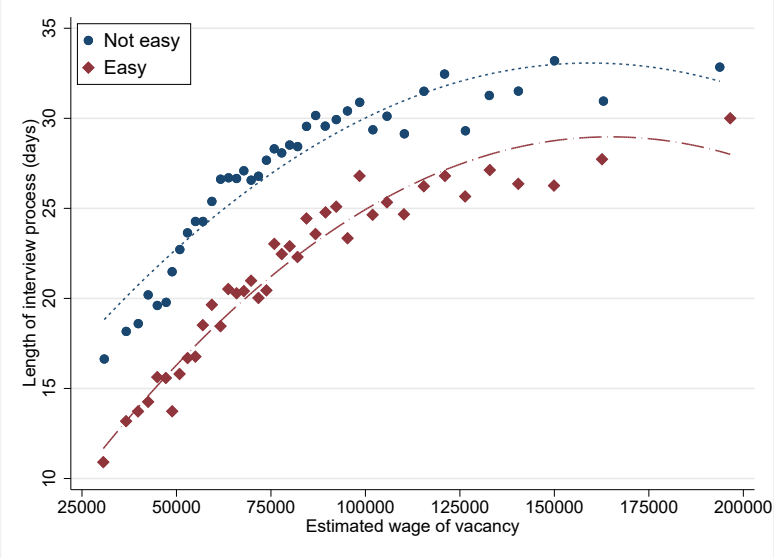
Notes: Figure A2 provides a screenshot of the optional aspects of a Glassdoor interview submission form that a respondent can provide from March 12, 2024.

Figure A3: Sample Distribution of Interview Difficulty, Including and Excluding Interviews That Did Not Result in Offers



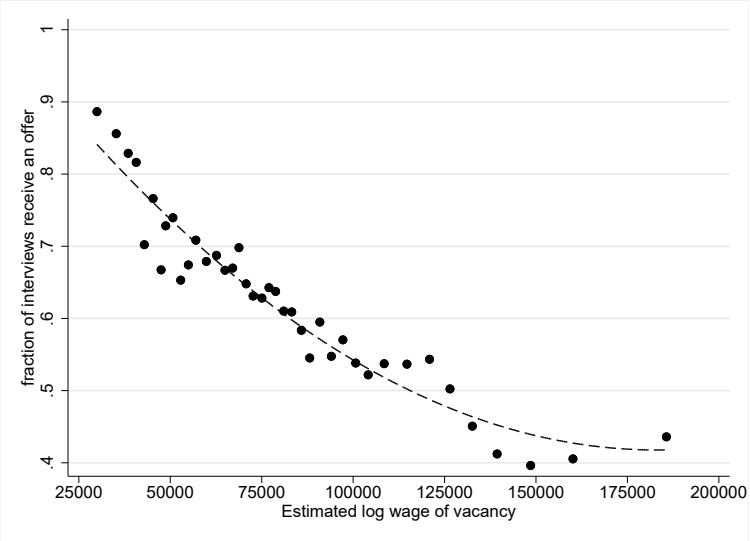
Notes: Figure A3 plots the fraction of interviews in the sample reporting each level of interview difficulty, split by interviews that received an offer and those that did not.

Figure A4: Interview Difficulty and Duration of the Entire Interview Process



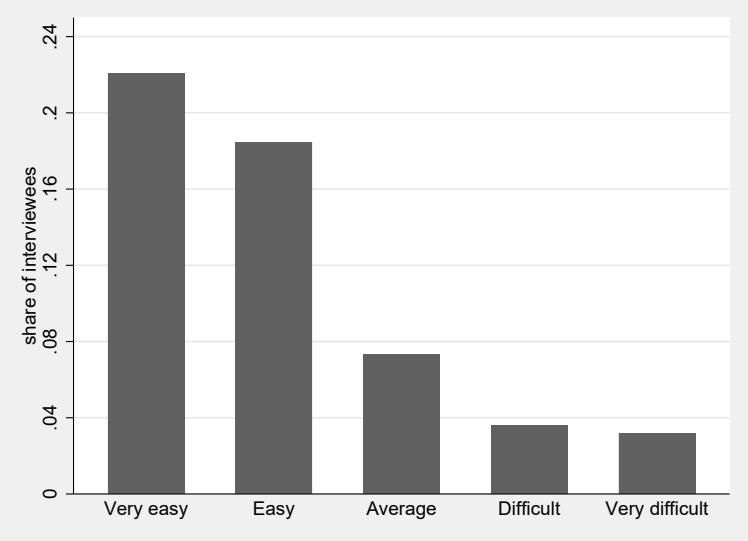
Notes: Figure A4 presents a binscatter of the average length of the interview process (in days) against the estimated wage of the vacancy, with each series indicating the self-reported difficulty rating as easy ("very easy" or "easy") and not easy ("average," "difficult," or "very difficult").

Figure A5: Offer Rate by Imputed Wage of the Vacancy



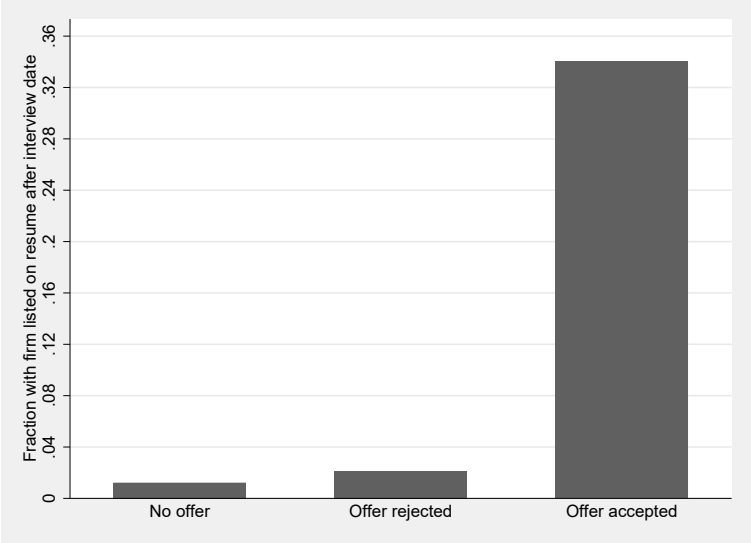
Notes: Figure A5 is a binscatter of the fraction of Glassdoor interviews that led to an offer by the imputed wage of the vacancy. Imputed wage reflects the average pay among Glassdoor pay reports for the given firm and job title. Wages are inflation-adjusted to 2021 dollars. Sample is restricted to firm-job title pairs with at least five interviews.

Figure A6: Fraction of Descriptions Mentioning "Easy" by Interview Difficulty



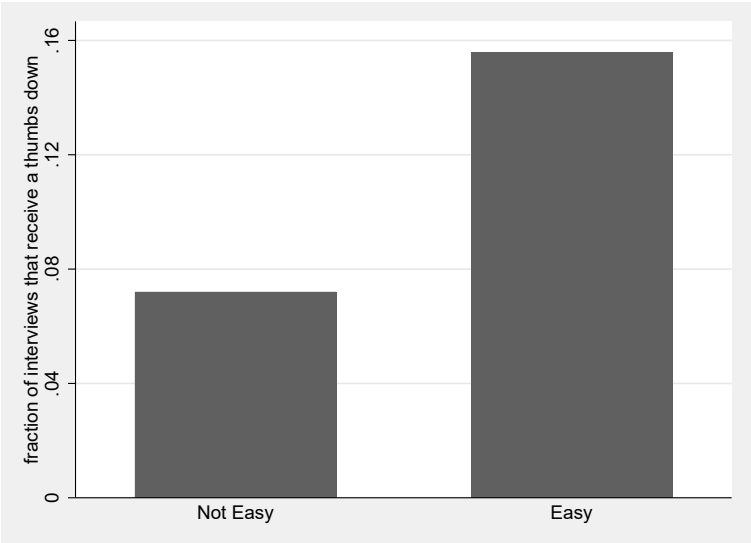
Notes: Figure A6 plots the share of interviews for each difficulty level (rated on a 1-5 scale: 1-very easy, 2-easy, 3-average, 4-difficult, 5-very difficult) that mentioned the word "easy" in the free-response description workers provided about the interview.

Figure A7: Fraction of Workers for Whom Firm is on Resume by Reported Offer Status



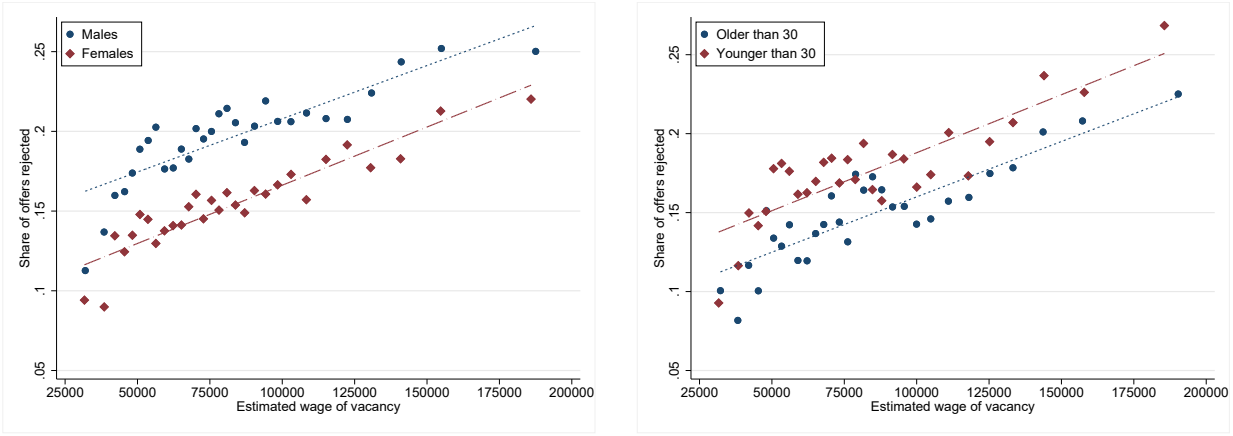
Notes: Figure A7 plots the share of interviews for which the hiring firm appears on the worker's resume, partitioned by whether the worker reported not receiving an offer, receiving an offer and rejecting it, or receiving an offer and accepting it. Sample is restricted to workers who upload a resume to Glassdoor after the date of the interview. Jobs that appear on resumes before the interview date are excluded.

Figure A8: Fraction Report Interview was a Negative Experience by Interview Difficulty



Notes: Figure A8 plots the share of interviews for each difficulty level (rated on a 1-5 scale: 1-very easy, 2-easy, 3-average, 4-difficult, 5-very difficult) that were characterized as negative experiences.

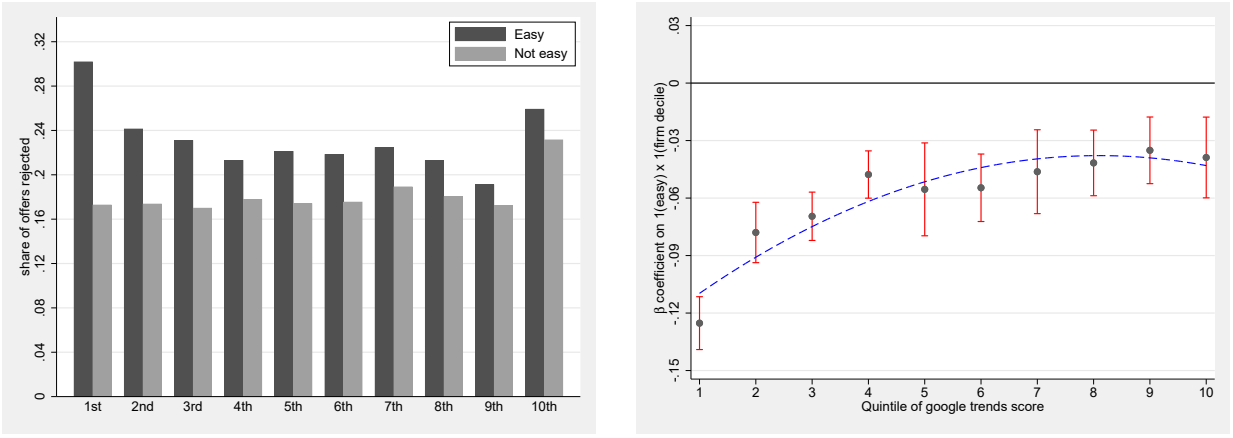
Figure A9: Probability of Rejecting an Offer by Wage and Worker Demographics



(a) By gender **(b)** By age

Notes: Figure A9 depicts a binscatter of the share of rejected job offers plotted against the estimated (log) wage of the vacancy. In panel (a), the sample is aggregated; panel (b) disaggregates by gender, and panel (c) by age group. The wage for each vacancy is *imputed* from Glassdoor pay reports for the same firm and job title, providing an approximate measure of what a hired worker would earn.

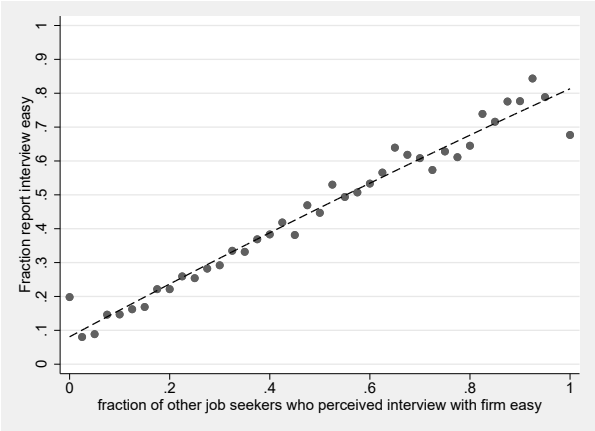
Figure A10: Probability of Offer Rejection by Perception of Difficulty and Firm Popularity



(a) Raw means **(b)** Regression coefficients

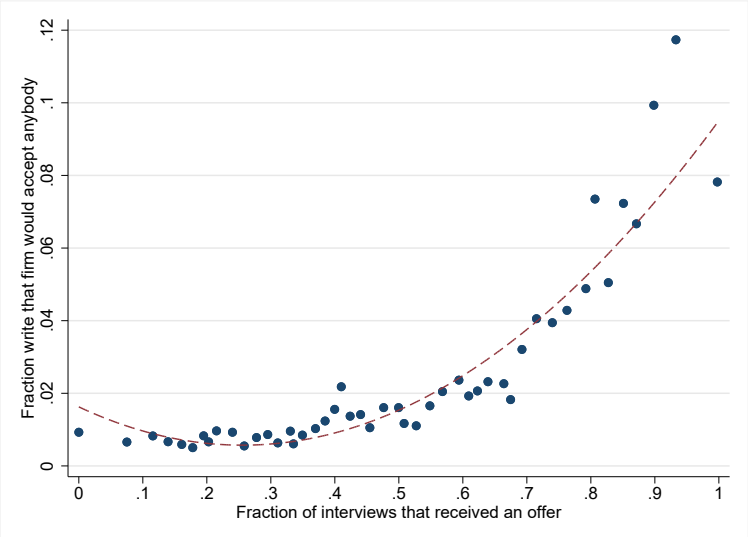
Notes: Figure A10 displays the fraction of offers rejected by whether the job seeker perceived the interview to be easy or not, partitioned by how frequently the employer is searched on google using data from Google Trends. Firms are partitioned into deciles, with greater declines indicating greater popularity in search. Google search popularity is taken by comparing the Google Trends score for each firm name with "Boston Consulting Group", and then averaging over the sample period. Panel (a) represents the raw means, whereas panel (b) corresponds to the coefficients on $1(Easy) \times 1(Decile_k)$, when added to model (1) from Table 1, with the standalone indicators $1(Decile_k)$ included. Dashed blue line indicates a quadratic fit through the coefficients. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Figure A11: Perceived Interview Difficulty and the Perception of Other Job Seekers



Notes: Figure A11 displays the fraction of interviews perceived as easy against the fraction of job seekers excluding oneself who perceived interviews for the hiring firm to be easy. Each dot represents a 0.025-rounded bin with at least 100 interviews, and the dashed line represents a quadratic line of best fit. Sample is restricted to firms with at least five interview reports.

Figure A12: Actual Offer Rate and Interview-Based Perceptions of Accepting Anyone



Notes: Figure A12 reflects a binscatter of the fraction of interviews that suggest the hiring firm would "accept anybody" against the fraction of interviews for the same firm x job title pair that resulted in an offer. Sample is restricted to firm x job title pairs for which at least 5 interview reports are observed.

Table A2: Iterative Procedure for Constructing Interviews Dataset

Step in sample cleaning process	N
1. Initial sample of U.S. interview reports	2,665,542
2. Drop interviews outside of 2008–2024 period	–18,048
=	2,647,494
3. Drop interviews that did not lead to an offer	–996,316
=	1,651,178
4. Drop interview reports with interview difficulty unavailable	–52,761
=	1,598,417
5. Drop interviews with two-digit NAICS industry unavailable	–104,387
=	1,494,030
6. Drop interviews not in six high-paying two-digit SOC occupations	–868,404
=	625,626
7. Drop interviews for internships	–23,513
=	602,113
8. Drop interview reports submitted more than two years after interview date	–94,548
= Final sample	507,565

Notes: Table A2 details the sample construction process, and the number of observations that are dropped with each step in the procedure.

Table A3: Summary Statistics for Interviews Dataset

Measure	Observations	Mean	Median	Standard deviation
Panel A. Interview characteristics				
Interview year	507,565	2,018.284	2,018.000	3.687
Interview month	507,565	6.279	6.000	3.491
Months after interview responded to Glassdoor	507,565	3.948	0.000	6.426
1(Rejected offer)	507,565	0.200	0.000	0.400
Interview difficulty level	507,565	2.665	3.000	0.858
1(Easy or very easy difficult level)	507,565	0.341	0.000	0.474
1(Employee referral)	412,608	0.130	0.000	0.336
1(University recruitment)	412,608	0.096	0.000	0.294
Interview duration in days	316,924	23.796	14.000	28.962
Imputed wage of the vacancy	297,148	83,939.774	77,027.984	36,201.786
Panel B. Job seeker demographics				
1(Female)	204,022	0.449	0.000	0.497
Age in years	108,267	30.445	28.000	9.007
1(Post-Bachelor's degree)	182,222	0.169	0.000	0.375
1(Attended university outside US)	182,222	0.093	0.000	0.290
College graduate quality of alma mater	156,818	-0.045	-0.040	0.152
1(STEM major)	135,361	0.409	0.000	0.492
Grade point average	22,548	3.578	3.600	0.283

Notes: Table A3 offers the mean, median, and standard deviation for each measure studied in our sample. Panel A pertains to aspects of the interview, Panel B to the demographics of the job seeker.

Table A4: Firms with the Most Difficult Interviews

Ranking	Firm	Industry
1	McKinsey & Company	Management & Consulting
2	Kearney	Management & Consulting
3	Boston Consulting Group	Management & Consulting
4	YipitData	Information Technology
5	Bridgewater Associates	Financial Services
6	SpaceX	Aerospace & Defense
7	Amazon Web Services	Information Technology
8	Bain & Company	Management & Consulting
9	Clearwater Analytics	Financial Services
10	Jane Street	Financial Services
11	Relativity Space	Aerospace & Defense
12	Google	Information Technology
13	D. E. Shaw & Co.	Financial Services
14	Oliver Wyman	Management & Consulting
15	Akuna Capital	Financial Services

Notes: Table A4 lists the 15 firms that offer the most difficult interviews. Ranking is based on the firm fixed effects from a regression on the full sample of interviews (offers and non-offers) that includes job title and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Sample restricted to firms for which we observe at least 100 interview reports.

Table A5: Firms with the Least Difficult Interviews

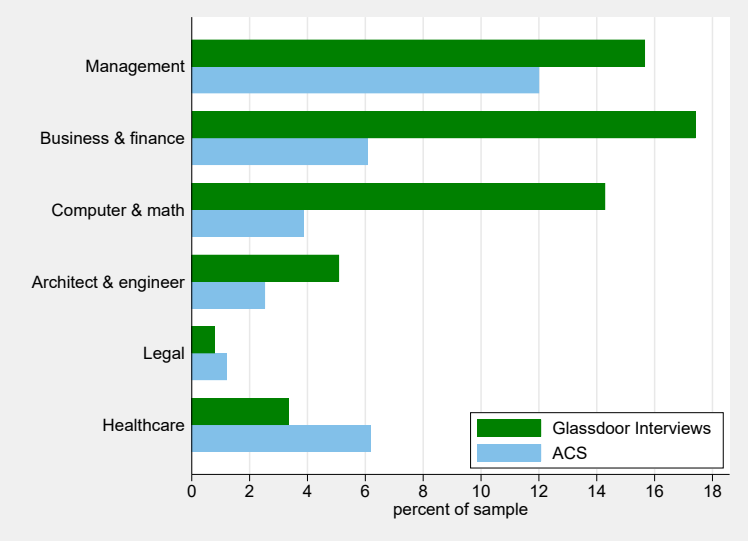
Ranking	Firm	Industry
1,149	Taco Bell	Restaurants & Food Service
1,150	Pizza Hut	Restaurants & Food Service
1,151	Advantage Solutions	Media & Communication
1,152	Dollar General	Retail & Wholesale
1,153	Jackson Hewitt	Retail & Wholesale
1,154	Aaron's	Retail & Wholesale
1,155	CROSSMARK	Retail & Wholesale
1,156	Family Dollar Stores	Retail & Wholesale
1,157	Menards	Retail & Wholesale
1,158	Dunkin'	Restaurants & Food Service
1,159	Marlabs	Information Technology
1,160	Aflac	Insurance
1,161	Globe Life Liberty National Division	Insurance
1,162	American Income Life	Insurance
1,163	Primerica	Insurance

Notes: Table A5 lists the 15 firms that offer the least difficult interviews. Ranking is based on the firm fixed effects from a regression on the full sample of interviews (offers and non-offers) that includes job title and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Sample restricted to firms for which we observe at least 100 interview reports.

C Selection into the Glassdoor Interviews Sample

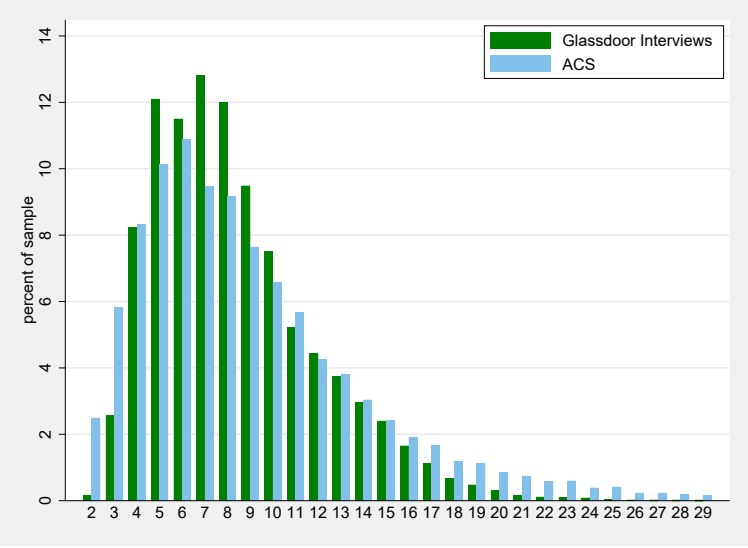
C.1 Comparison with the American Community Survey

Figure A13: Distribution of Glassdoor Interviews Database by Two-Digit Occupation



Notes: Figure A13 plots the fraction of interviews in the sample by each two-digit NAICS industry. Industries are assigned to each employer and come from a Glassdoor lookup table.

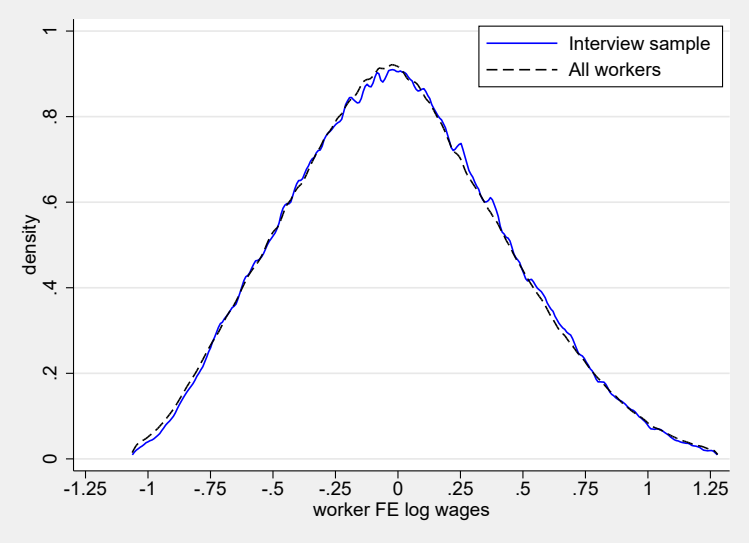
Figure A14: Distribution of Interviews Sample by Imputed Wage of the Vacancy



Notes: Figure A14 plots the fraction of interviews in the sample by the imputed wage of the vacancy within $10,000 bins. Imputed wage reflects the average pay among Glassdoor pay reports for the given firm and job title. Wages are inflation-adjusted to 2021 dollars.

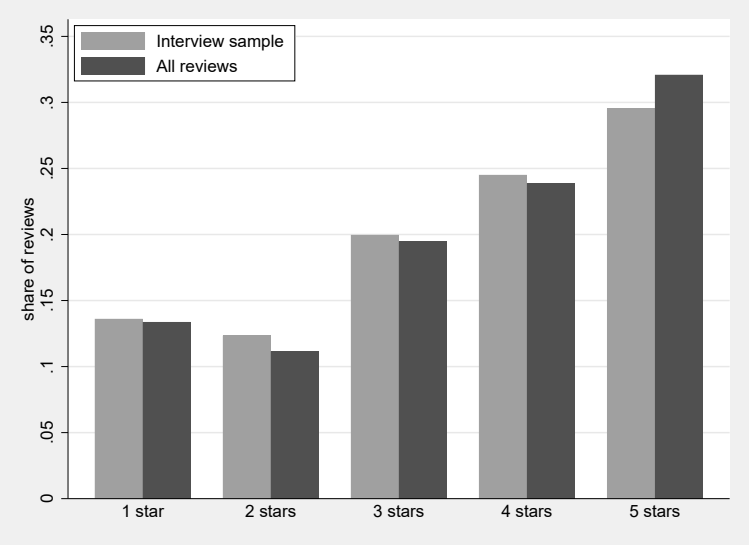
C.2 Comparison with the Entire Glassdoor Database

Figure A15: Distribution of Worker AKM Fixed Effects in Interviews Sample Compared with the Full Sample of Glassdoor Pay Reports



Notes: Figure A15 plots the distribution of the worker AKM fixed effects for the full sample of Glassdoor pay reports and the distribution of those that could be matched to an interview report.

Figure A16: Distribution of Job Satisfaction Ratings in Interviews Sample Compared with the Full Sample of Glassdoor Reviews



Notes: Figure A16 plots the distribution of the overall job satisfaction rating for the full sample of Glassdoor employer reviews and the distribution of those that could be matched to an interview report for analyzing match quality in Section 6.

D Comparison of Glassdoor with Onsites Database

In this section of the appendix, we provide additional detail on validating the Glassdoor data with the external data source, Onsites. Unlike Glassdoor which covers many employers across many industries, this website caters to jobs in software engineering for select companies generally in the information technology sector. As with Glassdoor, respondents are asked to rate the difficulty of the interview on a 5-level scale: easy, average, medium, difficult, and hard. We code these responses to reflect a 1–5 Likert scale similar to that in Glassdoor, with larger numbers indicating greater difficulty. In their free-text summaries of the interview experience, many respondents will state the exact job title for which they interviewed. Out of the roughly 1,400 interviews disclosed on Onsites, excluding interviews for internships, we are able to extract the job title for 700. The most common job titles are Software Development Engineer I, Software Development Engineer II, and Software Engineer, which together comprise about one-half of the sample. These 700 interviews span 42 employers; about one-third of the interviews are with Amazon or Microsoft.

As with Glassdoor, for each of these interviews, we observe the employer, job title, and perceived interview difficulty. We thus calculate the average difficulty level for each firm-job title pair we observe in Onsites. We then calculate the average difficulty level among Glassdoor interviews for the same firm-job title pairs, and compare. The relationship between the two, summarized in Table A6, is reaffirming. Greater interview difficulty on Glassdoor aligns with greater difficulty on Onsites.

There are 114 firm-job title pairs for which we can calculate an average in both datasets. When we weight by sample size in column 1, we find that one additional level of difficulty in Glassdoor is associated with, on average, about 0.52 additional levels of difficulty in Onsites. Excluding firm-job title pairs with only one observation in Onsites and giving each pair equal weight, we estimate an additional level in Glassdoor is associated with 1.10 additional levels in Onsites. This comparison with Onsites would suggest that the interview difficulty measure in Glassdoor, at least for software engineering jobs, captures true latent variation in interview difficulty.

Table A6: Average Interview Difficulty in Glassdoor and Onsites

	Mean interview difficulty on Onsites.fyi	
Mean interview difficulty on Glassdoor	0.515**	1.098***
	(0.233)	(0.248)
Firm-job title pairs	114	56
Onsites.fyi interviews	485	427
Weighted by Onsites.fyi count	✓	
Onsites.fyi count > 1		✓

Notes: Table A6 compares the average difficulty reported for interview reports submitted to Onsites.fyi and interview reports submitted to Glassdoor. Interview difficulty is measured on a 1-5 Likert scale in both datasets. Averages are calculated for firm-job title pairs. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

E Interviews for Internships

In this appendix, we focus on a sub-set of interviews that are not included in our main analysis, those for internships. We identify an interview as being for an internship if the word "Intern" is included in the job title. There are about 22,000 interview reports for internships in the high-paying occupations we consider. Internships increase earnings by about 6 percent (Margaryan *et al.*, 2022) and raise the probability of being invited for a job interview (Baert *et al.*, 2021), suggesting workers may accept internship offers regardless of the perceived difficulty of the interview. On the other hand, just as internships can be informative of idiosyncratic match quality to firms (Kuhnen and Oyer, 2016), so can they perhaps be for workers. In this case, job seekers may make internship acceptance or rejection decisions based on interview difficulty.

Taking our sample of interview reports for internships, we re-estimate variations of Equation (1), the results of which are summarized in Table A7. Looking at the cross-section of reviews, we observe that job seekers are 3–5 percentage points more likely to reject an offer if they perceived the interview to be easy. Compared with the average offer acceptance rates following not-easy interviews, this represents a 4–6 decline in the probability the offer is accepted. Even when we compare interview reports for the same role, i.e., job title at a firm in a metro area, easy interviews are more often rejected (Column 3). Although the sample is particularly thin, we observe a significant decline for easy interviews even for the same worker who made decisions over multiple internships (Column 4). Thus, for internships as well, interview difficulty is an important signal to workers of match fit.

Table A7: Probability of Accepting a Job Offer by Interview Difficulty for Internships

	1(Accepts job offer)			
	(1)	(2)	(3)	(4)
1(Easy interview)	-0.031***	-0.052***	-0.043***	-0.166*
	(0.006)	(0.012)	(0.012)	(0.099)
Mean DV for not easy	0.868	0.879	0.879	0.768
Observations	21,956	4,972	4,972	455
Industry-Occupation FE	✓	✓		
Firm-Job title-Metro FE			✓	
Worker FE				✓

Notes: Table A7 summarizes, for the relation between the probability an internship offer is accepted and the workers' perceived difficulty level of the interview process with the iterated addition of fixed effects for the firm, job title, and worker. Each specification includes year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

F Sensitivity Exercises

Table A8: Variation in Interview Difficulty Between Firms and Job Seekers

	1(Easy interview)				
Log length of interview duration	-0.088***	-0.055***	-0.065***	-0.045***	-0.033***
	(0.002)	(0.001)	(0.006)	(0.006)	(0.010)
N	280,490	280,490	7,395	7,395	7,395
R^2	0.053	0.219	0.091	0.383	0.800
Firm FE		✓		✓	✓
Job seeker FE					✓

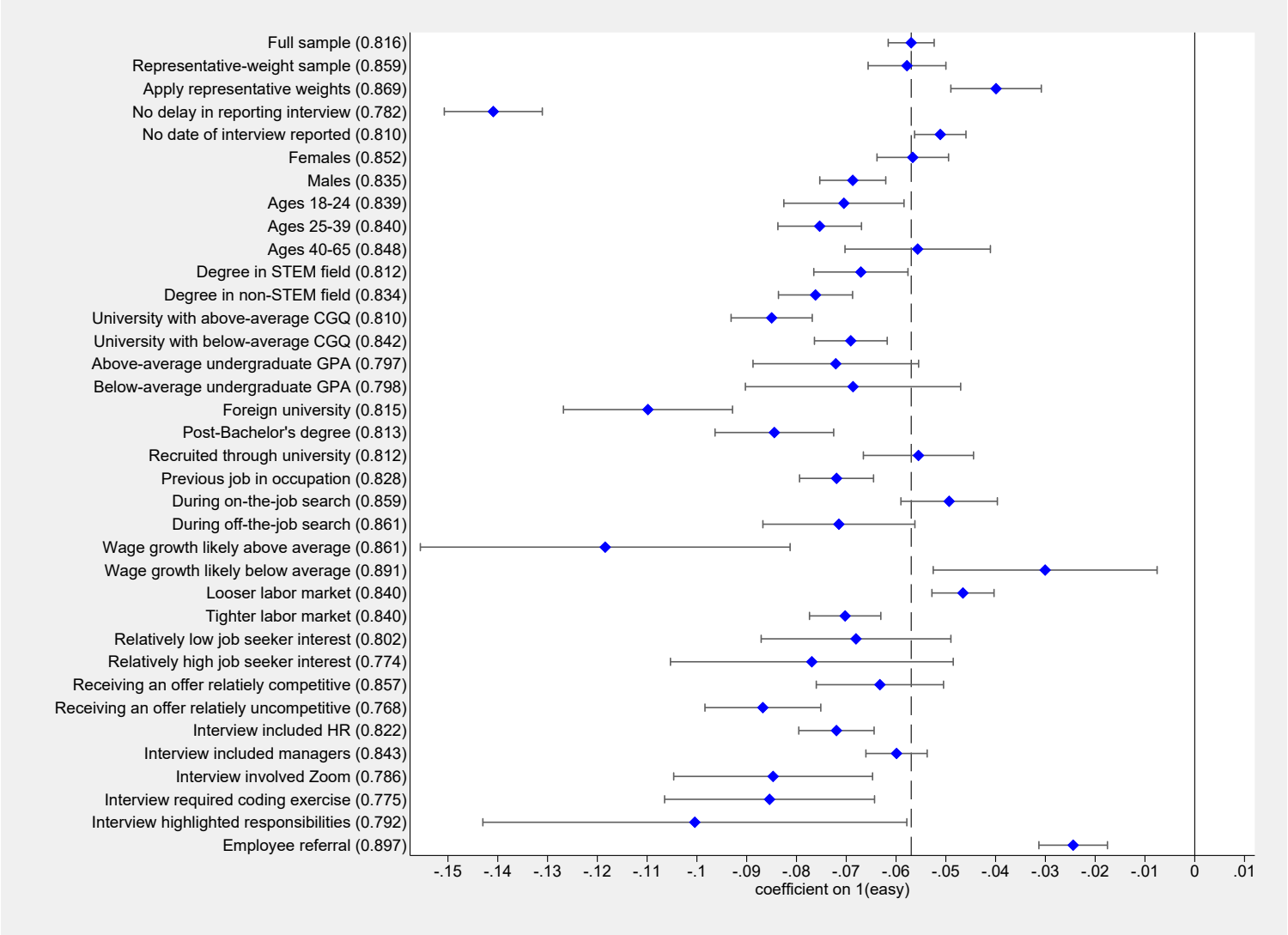
Notes: Table A8 reports how much of the variation in self-reported interview difficulty is accounted for by varying fixed effects models. Each column shows a regression of interview difficulty on the log length of the interview process, progressively adding job title, firm, and job seeker fixed effects. All specifications also include year-quarter fixed effects. The coefficients (and standard errors) correspond to the effect of log interview duration on difficulty. Significance levels: * 10%, ** 5%, *** 1%.

Table A9: Probability of Accepting and Interview Difficulty, by Two-Digit Occupation

	1(Accepts job offer)					
	Management	Business & finance	Computer & math	Architect & engineer	Legal	Healthcare
	(1)	(2)	(3)	(4)	(5)	(6)
1(Easy interview)	-0.079***	-0.073***	-0.056***	-0.032***	0.015	0.004
	(0.004)	(0.004)	(0.005)	(0.005)	(0.013)	(0.005)
Median annual pay	71,662	69,593	103,974	87,548	67,554	68,224
Mean DV for not easy	0.825	0.823	0.797	0.797	0.777	0.837
Observations	137,902	156,010	104,472	40,804	5,895	39,838
R^2	0.10	0.08	0.08	0.12	0.20	0.12
Metro-Quarter FE	✓	✓	✓	✓	✓	✓

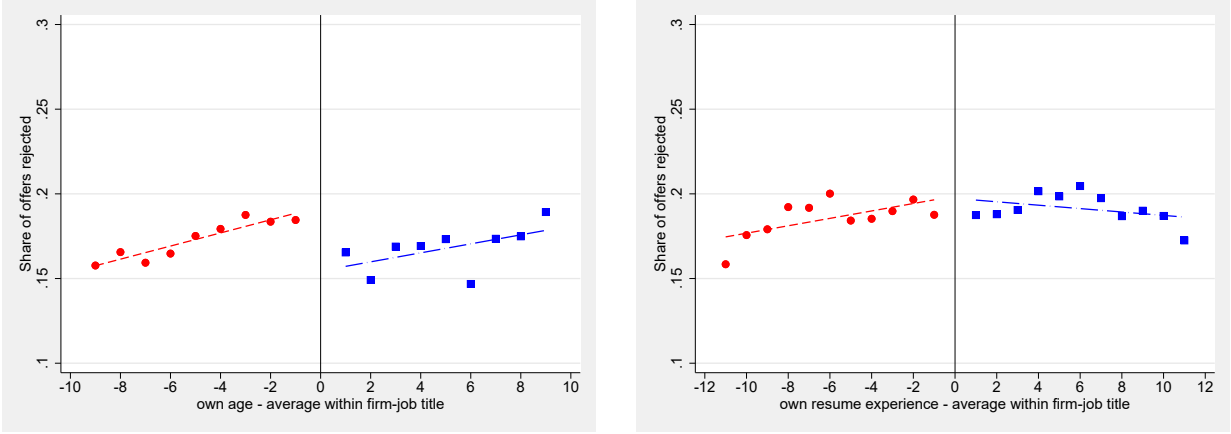
Notes: Table A9 summarizes the relation between the probability an offer is accepted and the workers' perceived difficulty level of the interview process, partitioned by occupation. Each specification includes industry and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Figure A17: Interview Difficulty and Offer Acceptance for Different Subsets of Workers



Notes: Figure A17 summarizes the relation between an easy interview and whether an offer is accepted. Each row represents a separate regression in which the sample is restricted to the subgroup listed. Each specification includes industry-occupation and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Representative weights match annual employment in the American Community Survey by two-digit NAICS industry, two-digit SOC occupation, sex, metropolitan area, and earnings rounded to the nearest $10,000. College graduate quality (CGQ) is from Martellini *et al.* (2024). The mean offer acceptance rate among not-easy interviews in each subsample is recorded in parentheses. Horizontal bars indicate 95% confidence intervals around each point estimate. Standard errors are clustered by firm.

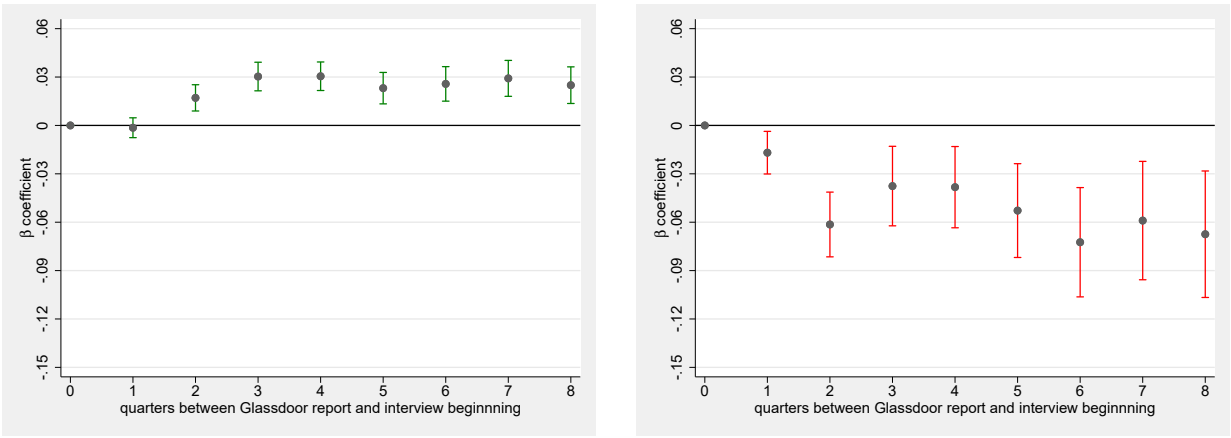
Figure A18: Proxies for Under- or Over-Qualified and Offer Rejection Rate



(a) Relative age **(b)** Relative resume experience

Notes: Figure A18 reflects the fraction of offers that are rejected by the relative age of the worker (panel a) and the relative years of prior experience on the worker's resume (panel b) to all others who received offers for the same firm and job title. Each dot represents a 0.20-rounded bin with at least 400 interviews.

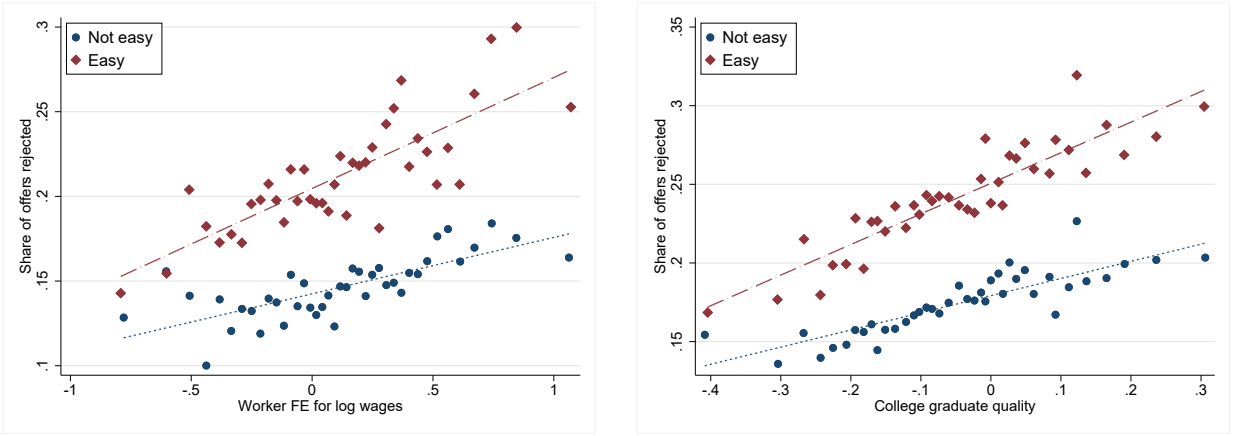
Figure A19: Difference in Perceptions of Interview Difficulty by Time Since Interview



(a) Accepted offers **(b)** Rejected offers

Notes: Figure A19 reflects the difference in the probability of reporting an interview as very easy or easy based on the time elapsed between the interview start date and when it was reported to Glassdoor. Results are shown separately for workers who accepted (panel a) and rejected (panel b) the job offer. Low- and high-paying jobs are defined as having average pay below or above the sample mean, respectively.

Figure A20: Probability of Rejecting a Job Offer by Interview Difficulty and Alternative Measures of Worker Productivity



(a) Worker AKM FE **(b)** College graduate quality

Notes: Figure A20 reflects a binscatter for the fraction of offers rejected, based on the worker's perception of interview difficulty and (a) the worker's AKM fixed effect on log pay or (b) the average graduate quality of the workerâs university. College graduate quality (CGQ), a measure of the average human capital of a university's graduates, is from Martellini *et al.* (2024).

Table A10: Predictive Power of Imputed Wages for Actual Wages

	Worker's actual wage	
	Levels	Logs
Worker's imputed wage	1.026***	1.014***
	(0.004)	(0.003)
N	26,671	26,671
R^2	0.873	0.879

Notes: Table A10 summarizes the relationship between a worker's actual wage disclosed in a Glassdoor pay report and the imputed wage we assign the interview based on the firm and job title. To assign the actual wage, we merge pay reports to interviews if the year of the pay report is the same as the interview year, and if they are for the same worker, firm, and job title. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A11: Interview Difficulty and Realized Wages

	Worker's actual wage	
	Levels	Logs
1(Easy interview)	-140.985	-0.007
	(724.250)	(0.008)
Mean DV	83,903.55	11.24
Fraction easy interviews	0.274	0.274
N	3,338	3,338
R^2	0.918	0.929
Firm-Job title-Metro FE	✓	✓

Notes: Table A11 relates the difficulty of the interview to the total pay the worker reports receiving. Sample is restricted to workers that provide both an interview report and a pay report for a given firm and job title. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A12: Interview Difficulty, Beliefs, and Offer Acceptance by Total Interview Rounds

	Ln(days)	Ln(pay)	1(Easy)	1(High-ability colleagues)	1(Engaging experience)	1(Accepts job offer)
Firm's average total interview rounds	0.085***	0.052***	-0.051***	0.010***	0.027***	0.023***
	(0.019)	(0.006)	(0.008)	(0.003)	(0.007)	(0.007)
Standard deviation interview rounds	0.72	0.69	0.72	0.72	0.72	0.72
Mean DV	2.910	11.397	0.324	0.038	0.030	0.703
Observations	11,918	10,611	21,380	21,380	21,380	21,380
Workers	5,555	5,030	10,016	10,016	10,016	10,016
Worker FE	✓	✓	✓	✓	✓	✓

Notes: Table A12 summarizes the relation between the estimated number of rounds the firm tends to conduct on average in its interviews and log length of the interview process, wages, interview difficulty, whether the worker perceived high-ability colleagues, whether the worker perceived an engaging experience, and offer acceptance. Each specification includes industry-occupation and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A13: Interview Difficulty for the Same Worker Over Time

	1(Easy interview)		
	(1)	(2)	(3)
Second interview observed	-0.039***	-0.028**	-0.021
	(0.007)	(0.012)	(0.019)
Third interview observed	-0.062***	-0.059**	-0.013
	(0.017)	(0.025)	(0.038)
Fourth interview observed	-0.107***	-0.072*	-0.015
	(0.033)	(0.041)	(0.063)
N	30,918	16,492	8,561
Job title FE			✓
Firm FE		✓	✓
Worker FE	✓	✓	✓

Notes: Table A13 summarizes the relationship between whether an interview is considered easy and the sequence of interviews experienced by the same worker over time. Sample is restricted to workers with more than one interview. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A14: Probability of Accepting a Job Offer by Interview Difficulty, Only Interview Reports for Accepted Offers Disclosed Prior to Joining the Firm

	1(Accepts job offer)		
1(Easy interview)	-0.043***	-0.033***	-0.040**
	(0.003)	(0.010)	(0.018)
Mean DV for not easy	0.092	0.126	0.104
Observations	35,117	7,801	1,765
Firm-job title FE		✓	
Job seeker FE			✓

Notes: Table A14 summarizes, for the relation between the probability an offer is accepted and the workers' perceived difficulty level of the interview process excluding interview reports where experience on the job after being hired may have influenced perceived difficulty. Each specification includes year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A15: Tenure from Resumes After Offer Acceptance, Accounting for Worker's Age

	Logarithm of firm tenure		1(Firm tenure $\geq$ 12 months)	
	(1)	(2)	(3)	(4)
1(Easy interview)	-0.125***	-0.130***	-0.054***	-0.080***
	(0.026)	(0.035)	(0.015)	(0.021)
Estimated log wage of vacancy		-0.086*		-0.012
		(0.052)		(0.029)
Mean DV for not easy	2.443	2.570	0.630	0.688
Observations	4,941	2,912	4,476	2,686
Adjusted R^2	0.25	0.22	0.15	0.12
Industry-occupation FE	✓	✓	✓	✓

Notes: Table A15 examines the relationship between interview experiences and the length of firm tenure for a job using workers' resumes. The sample is restricted to workers whose age is recorded in the Glassdoor database. Each column includes fixed effects for the worker's age and the interaction of the calendar year-month when the job began with the year-month the interview was submitted to Glassdoor. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A16: Difference in Interview Duration Between Offers and No Offers

	Ln(duration of interview process)	
	(1)	(2)
Received an offer	0.157***	
	(0.007)	
Received an offer and rejected it		0.137***
		(0.007)
Received an offer and accepted it		0.163***
		(0.008)
N	567,774	567,774
Firm FE	✓	✓

Notes: Table A16 relates the log length of the interview process to whether the worker received an offer and if so, whether they chose to reject or accept that offer. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A17: Difference in Worker Skill Between Those Who Do and Do Not Receive Offers

	Worker FE on log wages	
	(1)	(2)
Received an offer	0.188***	
	(0.014)	
Received an offer and rejected it		0.200***
		(0.018)
Received an offer and accepted it		0.185***
		(0.015)
N	30,574	30,574
Firm-Job title-Metro FE	✓	✓

Notes: Table A17 relates individual worker skill to whether the worker received an offer and if so, whether they chose to reject or accept that offer. Worker skill is proxied for by the individual's fixed effect in an AKM regression of log wages. Worker fixed effects are standardized across workers to have mean 0 and standard deviation 1. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A18: Beliefs about Peers and Actual Worker Ability, Fixed Effects Model

	High-ability colleagues		Would accept anybody	
	(1)	(2)	(3)	(4)
Standard median worker fixed effect	0.007***	0.005***	-0.016***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Mean DV for not easy	0.040	0.040	0.010	0.010
N	128,839	128,839	128,839	128,839
Adjusted R^2	0.01	0.03	0.02	0.07
Firm-interview year FE		✓		✓

Notes: Table A18 summarizes the relation between interviewee beliefs about the ability of peers and the actual ability of peers. Actual ability of peers is proxied for by worker FE from pay reports for employees at the interviewing firm and metro for the interviewing year. Sample is restricted to observations for which we can assign at least two workers' fixed effects. Each specification includes industry-occupation, metro-year of interview, and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A19: Beliefs about Peers and Actual Worker Ability of Managers and Non-Managers, Fixed Effects Model

	High-ability colleagues		Would accept anybody	
	(1)	(2)	(3)	(4)
Median worker FE for managers	-0.001	0.003**	-0.006***	-0.002
	(0.001)	(0.002)	(0.002)	(0.002)
Median worker FE for non-managers	0.006***	0.004***	-0.009***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.002)
Mean DV for not easy	0.037	0.037	0.008	0.008
N	75,042	75,042	75,042	75,042
Adjusted R^2	0.01	0.01	0.02	0.06
Firm-interview year FE		✓		✓

Notes: Table A19 summarizes the relation between interviewee beliefs about the ability of peers and the actual ability of managerial and non-managerial peers. Actual ability is proxied for by worker FE from pay reports for employees at the interviewing firm and metro for the interviewing year. Sample is restricted to observations for which we can assign at least two workers' fixed effects for managers and non-managers. Each specification includes industry-occupation, metro-year of interview, and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A20: Probability of Accepting a Job Offer and Likely Wage of Future Jobs

	1(Accepts job offer)			
	(1)	(2)	(3)	(4)
1(Easy interview)	-0.037***	-0.036***	-0.043***	-0.038***
	(0.006)	(0.006)	(0.004)	(0.004)
1(Easy interview) x 1(Any of next three likely jobs high wage)		-0.034***		-0.045***
		(0.012)		(0.013)
1(Any of next three jobs likely high wage)		-0.022**		
		(0.011)		
Fraction any of next three likely jobs high wage	0.143	0.143	0.143	0.143
Observations	105,657	105,657	97,745	97,745
Adjusted R^2	0.05	0.05	0.12	0.12
Industry-occupation FE	✓	✓		
Firm-job title FE			✓	✓

Notes: Table A20 summarizes the relationship between the probability of accepting an offer and the perceived difficulty of the interview process, considering whether any of the next three likely jobs are high wage. The 1st, 2nd, and 3rd next jobs are identified from workers' resumes, and their average wages are imputed based on firm-job title pairs. In this context, a high-wage job is a firm-job title pair for which the mean imputed wage falls above the 90th percentile of the distribution. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A21: Tenure from Workers' Resumes After Offer Acceptance, Accounting for Worker's Skill or Proclivity to Perceive Interviews as Easy

	Logarithm of firm tenure		1(Firm tenure $\geq$ 12 months)	
	(1)	(2)	(3)	(4)
1(Easy interview)	-0.178***	-0.202***	-0.069***	-0.065**
	(0.027)	(0.058)	(0.016)	(0.033)
Worker FE log wages	0.155***		0.120***	
	(0.039)		(0.022)	
Worker FE interview difficulty		0.010		0.014
		(0.038)		(0.022)
Mean DV for not easy	2.659	2.513	0.714	0.650
Observations	4,733	1,978	4,461	1,820
Industry-occupation FE	✓	✓	✓	✓

Notes: Table A21 relates the length of firm tenure for a job using workers' resumes to their interview experiences for that same employer, accounting for fixed unobservable characteristics of the worker. Each column additionally includes fixed effects for the calendar year-month the job began $\times$ the calendar year-month the interview was submitted to Glassdoor. "Worker FE interview difficulty" reflects the worker fixed effects from an AKM-style regression of worker and firm fixed effects on the 1-5 scale measure of interview difficulty, including an indicator for the worker received an offer and fixed effects for metro-quarter and the year-quarter of interview x year-quarter submitted to Glassdoor. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A22: Tenure from Resumes After Offer Acceptance by Firm Position on Resume

	Logarithm of firm tenure				1(Firm tenure ≥ 12 months)			
	Number of jobs on resume after job with matched interview							
	0	1	2	3+	0	1	2	3+
1(Easy interview)	-0.210***	-0.201***	-0.246***	-0.207***	-0.076***	-0.088***	-0.117***	-0.096***
	(0.024)	(0.026)	(0.042)	(0.051)	(0.009)	(0.014)	(0.023)	(0.031)
Mean DV for not easy	2.164	2.485	2.466	2.457	0.849	0.631	0.609	0.587
Observations	6,274	5,515	2,325	1,344	11,247	5,778	2,425	1,408
Industry-occupation FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Table A22 examines the relationship between interview experiences and the length of firm tenure for a job using workers' resumes. Each column includes fixed effects for the interaction of the calendar year-month when the job began with the year-month the interview was submitted to Glassdoor. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A23: Interview Difficulty, Beliefs, and Offer Acceptance by Own Human Capital

	1(Easy)	1(High-ability colleagues)	1(Accept anybody)	1(Accept offer)
College graduate quality of worker	0.009***	0.000	-0.000	-0.017***
	(0.002)	(0.001)	(0.001)	(0.001)
Observations	130,174	130,174	130,174	130,174
Workers	123,967	123,967	123,967	123,967
Firm FE	✓	✓	✓	✓

Notes: Table A23 summarizes the relation between one's own human capital, as proxied for by the average human capital among the university where the worker receive their Bachelor's degree (Martellini *et al.*, 2024), and interview outcomes. College graduate quality is standardized to have mean 0 and standard deviation 1. Each specification includes industry-occupation and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A24: Probability of Accepting a Job Offer and Local Labor Market Tightness

	1(Accepts job offer)			
	Full sample		Job seeker in metro	
	(1)	(2)	(3)	(4)
1(Easy interview)	-0.062***	-0.044***	-0.068***	-0.042***
	(0.006)	(0.005)	(0.007)	(0.005)
1(Easy interview) x metro unemployment rate	0.007***	0.005**	0.008***	0.006***
	(0.002)	(0.002)	(0.003)	(0.002)
Firm FE		✓		✓
Mean DV for not easy	0.825	0.825	0.850	0.850
Observations	239,624	239,624	129,331	129,331

Notes: Table A24 summarizes the relation between the probability an offer is accepted and the workers' perceived difficulty level of the interview process interacted with the current employment rate at the time of the interview in that metropolitan area. Each specification includes industry-occupation, metro x year-month of interview, and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by metro. Significance levels: * 10%, ** 5%, *** 1%.

Table A25: Probability of Accepting a Job Offer and Realistic Job Previews

	1(Accepts job offer)		
	(1)	(2)	(3)
1(Easy interview)	-0.039***	-0.032***	-0.075***
	(0.003)	(0.002)	(0.015)
1(Realistic job preview)	0.075***	0.068***	0.081***
	(0.002)	(0.002)	(0.014)
1(Easy interview) x 1(Realistic job preview)	-0.008**	-0.007**	-0.045*
	(0.003)	(0.003)	(0.025)
Mean DV for not easy	0.817	0.817	0.747
N	455,028	455,028	16,310
Adjusted R^2	0.07	0.11	0.28
Additional text covariates	✓	✓	✓
Firm FE		✓	✓
Worker FE			✓

Notes: Table A25 summarizes the relation between the interviewee's perception that the interview conveyed a realistic preview of what the job would entail and whether the worker accepted the job offer. Each specification includes industry-occupation and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Additional text covariates include indicators for the interview process illuminated compensation, illuminated hours or scheduling, and illuminated desirable workplace amenities. For details on constructing the text-based measures, see Section 3.1. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A26: Structure of Technical Assessment

	Easy assessment arm	Difficult assessment arm
Background	First name, last name, and email address	
Resume	Upload a resume	
Experience	Highest degree, field of study, university of study, and years of work experience	
Question 0	Prompt for technical assessment of 5 questions	
Question 1	Have you ever worked with data files with at least 1,000 observations?	Have you ever worked with data files with at least 1,000,000 observations?
Question 2	Suppose you are given a dataset with two variables: Years of Work Experience and Salary. You fit a linear regression where Salary is the dependent variable and Years of Work Experience is the independent variable. How would you interpret the slope coefficient in this model?	Suppose you are given a dataset with many observables (X1, X2, X3,...) and a continuous target variable (Y). You fit a multiple linear regression but the model performs poorly on unseen data. What are some possible reasons for poor generalization, and what are two alternative modeling approaches you could take?
Question 3	A deck of cards consists of 52 cards, where each card has a rank and a suit. There are 4 suits (clubs, diamonds, hearts, and spades) and each suit has 13 ranks (Ace, 2, 3, 4, 5, 6, 7, 8, 9, 10, Jack, Queen, King). If you pick 2 cards from the deck, what is the probability that you choose a 2 of any suit?	A deck of cards consists of 52 cards, where each card has a rank and a suit. There are 4 suits (clubs, diamonds, hearts, and spades) and each suit has 13 ranks (Ace, 2, 3, 4, 5, 6, 7, 8, 9, 10, Jack, Queen, King). Suppose there are two people and they each have their own deck. If each person draws 2 cards from their own deck, what is the probability that neither person picks a 2?
Question 4	Write a regular expression to detect if a sentence includes at least one question mark.	Write a regular expression to detect if a sentence includes at most one question mark.
Question 5	Write a function in Python or R called has_duplicate that does the following: Given a list of integers called MyList, return True if any value appears at least twice in the array. If every element in the input list is distinct, return False.	Write a function in Python or R called climb_stairs that does the following: You are attempting to climb a staircase with N many steps. If you can only go up the staircase, and can only go up either 1 or 2 stairs at a time, return the number of distinct ways you can climb to the top of the staircase.
Question 6	For the final question, we would like to know: Why are you a good fit for this job?	
Own Questions	Do you have any questions for us? Feel free to skip the question if you do not.	
Perceptions	How many minutes do you believe it took other applicants on average to complete the interview? How would you say your level of interest for the position now compares with your level of interest before the interview began? How do you believe other applicants would rate the difficulty of the interview?	

Notes: Table A26 outlines the experiment and its two treatment arms.

Table A27: Summary Statistics for Interview Experiment

Measure	Observations	Mean	Median	Standard deviation	5th percentile	95th percentile
Start day	1,912	20.22	21.00	4.44	8.00	25.00
Duration (in seconds)	1,912	5176.00	1106.00	18272.00	132.00	18216.00
Post-Bachelor's degree	1,912	0.80	1.00	0.40	0.00	1.00
1(0-2 years experience)	1,912	0.29	0.00	0.45	0.00	1.00
1(2-4 years experience)	1,912	0.30	0.00	0.46	0.00	1.00
1(4-6 years experience)	1,912	0.21	0.00	0.41	0.00	1.00
1(6+ years experience)	1,912	0.20	0.00	0.40	0.00	1.00
1(Assigned easy arm)	1,912	0.50	0.00	0.50	0.00	1.00
Finished question 1	1,912	0.99	1.00	0.11	1.00	1.00
Finished question 2	1,912	0.92	1.00	0.28	0.00	1.00
Finished question 3	1,912	0.87	1.00	0.33	0.00	1.00
Finished question 4	1,912	0.86	1.00	0.35	0.00	1.00
Finished question 5	1,912	0.80	1.00	0.40	0.00	1.00
Finished question 6	1,912	0.79	1.00	0.41	0.00	1.00
Seconds to answer question 2	1,751	158.70	116.00	139.20	8.53	469.10
Seconds to answer question 3	1,670	137.50	86.96	133.90	4.93	435.50
Seconds to answer question 4	1,637	95.89	57.96	107.30	2.90	336.30
Seconds to answer question 5	1,538	160.80	108.90	155.00	3.56	507.70
Length of 'Why good fit?'	1,912	501.30	445.50	467.50	0.00	1393.00
Length of 'Questions for us?'	1,912	61.45	0.00	122.70	0.00	306.00
Number of application queries	1,912	0.14	0.00	0.71	0.00	1.00
Predicted completion time	1,388	22.62	20.00	15.24	5.00	45.00
1(Easy interview)	1,374	0.34	0.00	0.47	0.00	1.00
1(More interested in vacancy)	1,382	0.72	1.00	0.45	0.00	1.00

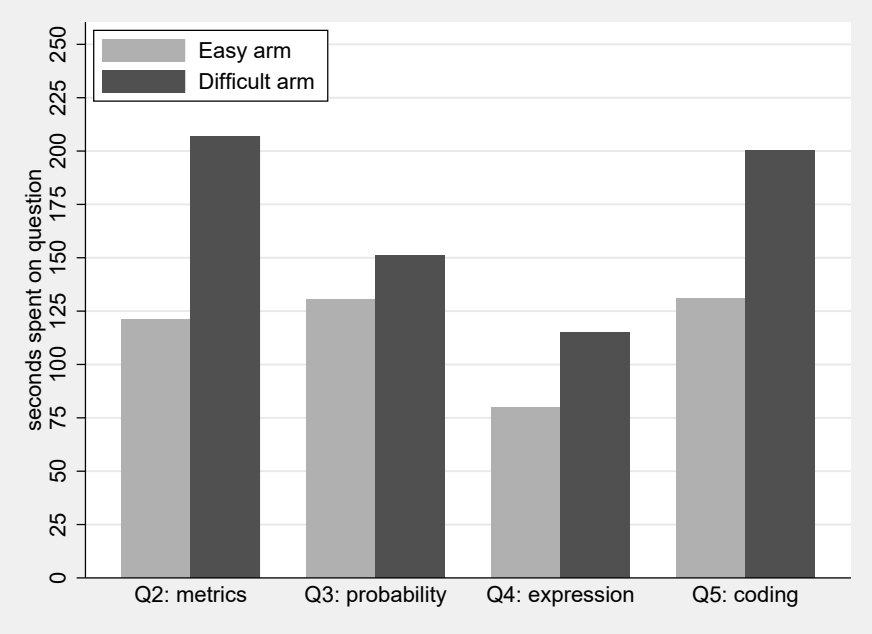
Notes: Table A27 shows summary statistics for key variables from the experiment.

Table A28: Treatment Arm as an IV for Perceived Difficulty and Interest in Vacancy

	Length why good fit		Length questions for us		Number of application queries		1(More interested in vacancy)	
1(Easy interview)	-0.401		-0.613*		-0.444		0.061	
	(0.276)		(0.337)		(0.274)		(0.130)	
Predicted completion time		0.182		0.283*		0.215*		-0.033
		(0.128)		(0.154)		(0.130)		(0.061)
Specification	IV	IV	IV	IV	IV	IV	IV	IV
Cragg-Donald F statistic	56.09	53.60	56.09	53.60	56.96	52.34	56.09	54.34
Observations	1,370	1,384	1,370	1,384	1,361	1,361	1,370	1,376

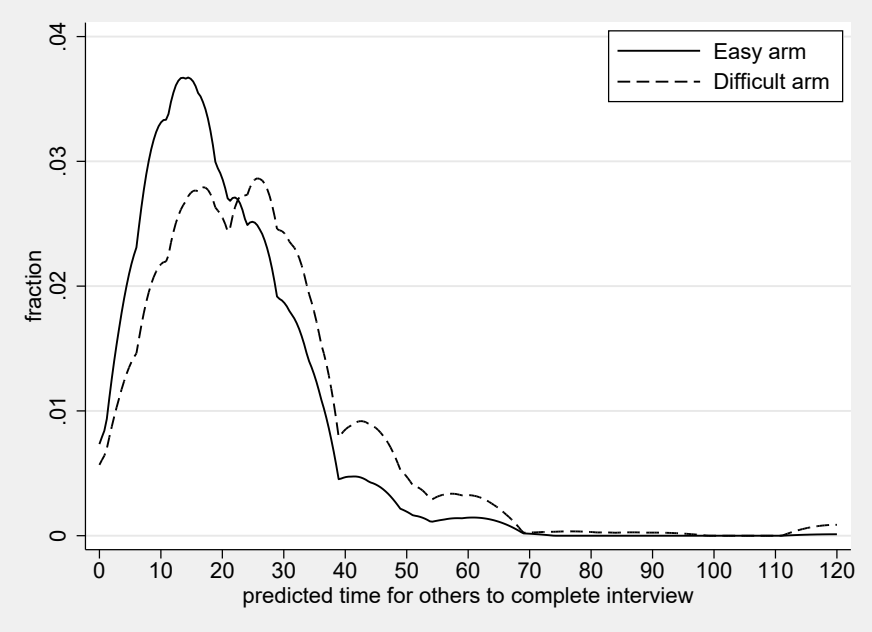
Notes: Each specification includes fixed effects for the day on which the interview began. Standard errors are robust. Significance levels: * 10%, ** 5%, *** 1%.

Figure A21: Seconds Spent Answering Each Question



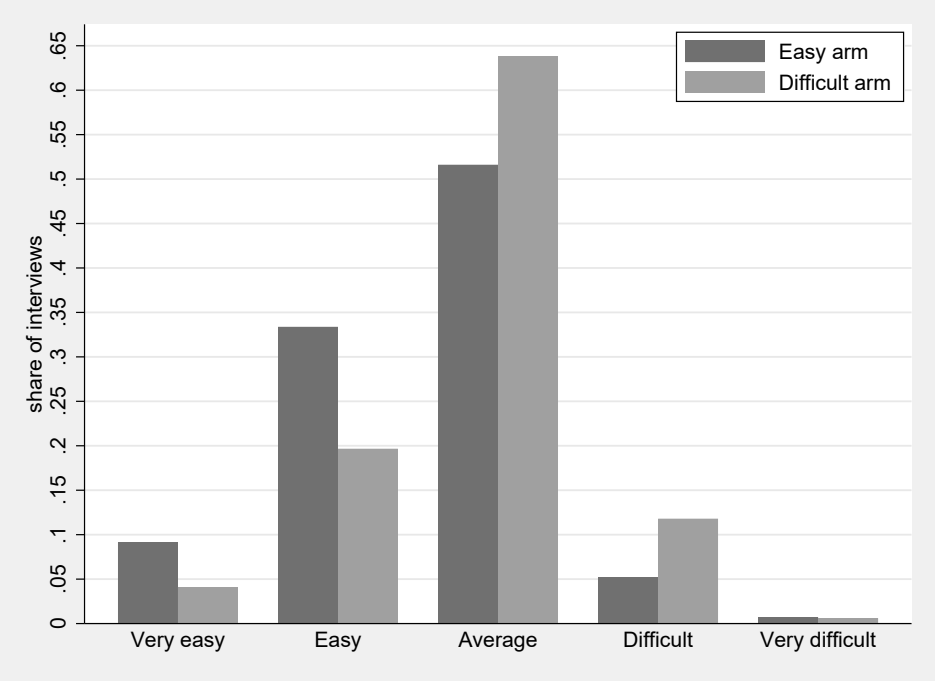
Notes: Figure A21 shows the average number of seconds candidates spent per question by treatment arm.

Figure A22: Predicted Time Needed to Complete Interview



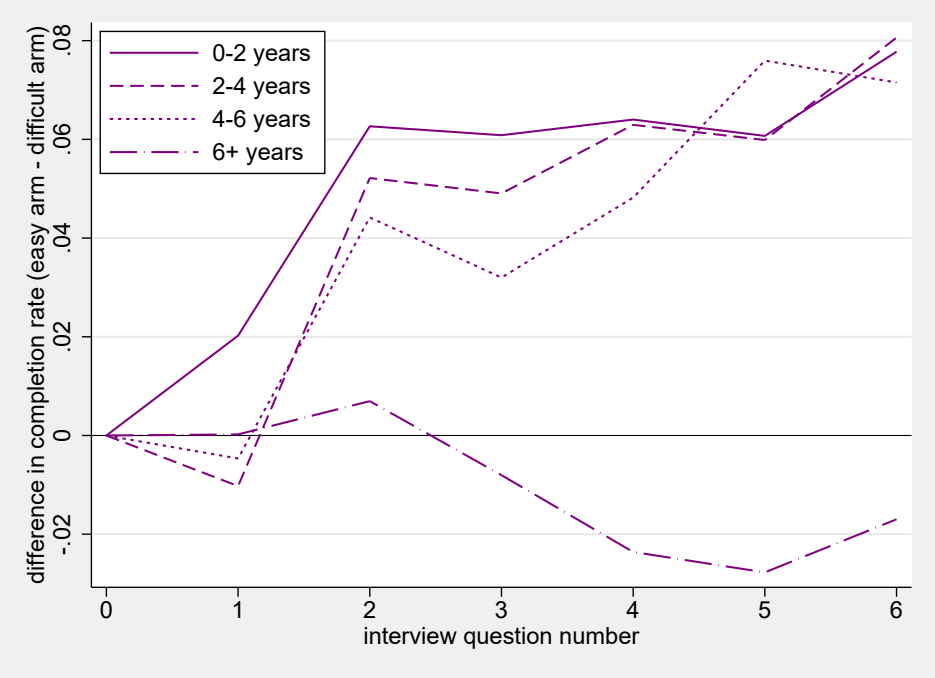
Notes: Figure A22 shows the distribution of candidates' estimates (in minutes) of how long other applicants would need to complete the interview, by treatment arm.

Figure A23: Distribution of Interview Difficulty by Treatment Arm



Notes: Figure A23 shows the distribution of perceived interview difficulty by treatment arm, where candidates rated how they believed other applicants would assess the difficulty.

Figure A24: Differential Attrition by Worker Experience



Notes: Figure A24 shows the difference in completion rates between treatment arms by years of work experience.

Supplementary References

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