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 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 two-fifths of a standard deviation less satisfied with their jobs and 10 percent less likely to remain with their employer for at least one year. Analysis of interview narratives using large language models reveals difficult interviews signal colleague ability whereas easy interviews convey a nonselective process. In a small-scale randomized field experiment, an exogenous increase in difficulty elevated perceived difficulty and boosted applicant engagement with the vacancy. 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. Nearly every worker, regardless of their age or experience, has had many job interviews, not just for the roles they currently have and have had in the past, but also roles for which they did not get an offer or received an offer and subsequently turned it down. Notwithstanding their prevalence and relevance, the *worker's* perspective on interviews remains largely unexplored, especially in economics. Can what the worker experiences during the interview process affect whether or not they decide to accept a job offer? Despite its simplicity, the answer to this question remains not well understood.

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 across 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 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-pecuniary 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,[2] it is especially pressing to understand what information workers gauge from the traditional interview process—and may miss out on if the process were fully automated.

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

[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]See, e.g., Mauer (2024), describing a survey of 2,366 HR professionals on their use of AI. One in four reported using AI for HR, of which two-thirds began using AI for that purpose within the last year.

a million interview reports from Glassdoor for high-wage occupations,[3] we fill this gap in the literature and establish a link between workers' interview experiences and their labor market outcomes. For each interview, we observe whether the worker received a job offer and whether they accepted it or turned it down. We also observe how difficult each worker perceived their interview process to be—a key metric we argue conveys valuable information about the employer 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 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 perceive the interview as easy are *more* likely to turn down an offer. And when the same worker is deciding between multiple offers at the same time, they are more likely to reject the firm whose interview they perceive to be easier. The effect is larger for increasingly high-paying jobs, as well as for interviews with technical assessments or that highlight the role's responsibilities, suggesting a role for perceptions of human capital development and career concerns. Moreover, consistent with workers learning about match quality through the interview, the penalty on offer acceptance associated with an easy interview is largest for small firms, which tend to have less-established reputations.

To better understand the information workers accrue through interviews, we turn to the free-response descriptions workers write about the interview process. We employ an LLM to annotate a number of relevant dimensions in the descriptions: (i) prospective colleagues being of high ability,[4] (ii) prospective colleagues being pleasant,[5] (iii) the interview experience being engaging, and (iv) the worker believing the firm "would hire anyone."[6] We start with perceptions of prospective colleagues. After an easy interview, job seekers are *two-to-three times* less likely to characterize the firm as employing high-ability colleagues and *four-to-five times* more likely to believe the firm would hire anyone. Indeed, workers who join after easy interviews seem disappointed by their peers: employer reviews following easy interviews are 25 percent more likely to highlight peers as a drawback of the workplace. Workers are also

[3]This includes management, finance, technology, engineering, healthcare, and law.

[4]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).

[5]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).

[6]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." We consider the role of realistic job previews in Section 5. See Wanous (1973) for an early discussion.

15–20 percent less likely to consider an easy interview as having been engaging, which we interpret as indicating reduced interest for the vacancy.

The perceptions workers derive about future colleagues through the interview process also tend to be accurate. Establishments with greater worker skill—as proxied for by the average worker fixed effect from an Abowd *et al.* (1999), or AKM, regression of log wages—more often evoke narrative reports about high-ability peers. Conversely, establishments with lower worker skill, and increased likelihoods of extending offers to candidates whom they interview, more often convey that the firm "would accept anybody." By credibly signaling the ability of prospective peers, interviews provide a channel for high-ability workers to discern which workplaces are comprised of other high-ability workers—facilitating sorting and potentially augmenting wage inequality (Song *et al.*, 2019).

If an interview offers the worker a preview for the job in question, we might anticipate impressions made during the interview process to predict realized match quality. For many workers in our data, we can look at job outcomes by linking their interviews to their resumes. We find that those who considered the interview easy are 10 percent less likely to remain with their employer for at least one year, consistent with a poorer match. Shorter spells could reflect increased layoffs due to poor performance or increased quits to pursue better matches. Using the employer reviews workers write on Glassdoor, we find that workers who joined after an easy interview have considerably lower job satisfaction than workers who joined after a not-easy interview. The effect size is about two-fifths of a standard deviation.[7] Given the established link between job satisfaction and voluntary turnover (Freeman, 1978; Akerlof *et al.*, 1988; Card *et al.*, 2012), along with workers increasingly alluding to *voluntarily* quitting in their employer reviews after easy interviews, we interpret the higher rate of turnover as reflecting poor match quality from the perspective of the worker, rather than that of the firm.

To complement the observational evidence, we conducted a pre-registered randomized field experiment in which interview difficulty was exogenously shifted. In the context of a real-world hiring process for a data scientist position at a university, we randomly varied the difficulty level of the technical assessment administered in a first-round interview ($N = 1,325$). This was a light-touch intervention, as the technical assessment asked only five questions and took around 10 minutes on average to complete. Nonetheless, the intervention substantially shifted applicants' perceived difficulty of the interview process, measured as one's belief about how *other* candidates would assess the difficulty of the process. This "first stage" effect—of objective difficulty shifting perceived difficulty—substantiates our in-

[7]For context, this penalty is larger than the effect of learning your employer engaged in corporate misconduct (Gadgil and Sockin, 2020) or accounting fraud (Zhou and Makridis, 2021).

terpretation of responses on Glassdoor reflecting both objective and subjective difficulty.

Our main goal in the experiment is to assess whether interview difficulty has a causal effect on the perceived value of the vacancy. We measure perceived value through post-treatment engagement with the position. First, candidates were asked two questions with open-text responses: why they are a good fit for the job, and do they have any questions for the employer? Applicants who experienced the easy technical assessment wrote significantly less text in these free-response fields. Second, at the end of the interview, candidates received a link to an "application checker" web page, where they could track the status of their application. Applicants who experienced the easy technical questions checked the status of their application significantly less often through this tracking page. These results provide causal evidence in support of our main interpretation of the observational data: Interview difficulty signals to workers the desirability of the vacancy.

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).[8] 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. Overall, the evidence is scant and mixed. While studies in organizational psychology demonstrate that recruiter behavior (Breaugh and Starke, 2000; Chapman *et al.*, 2005) and perceptions of selection procedures (Ryan and Ployhart, 2000) can affect candidate behavior, they largely focus on procedural factors such as fairness and communication style rather than rigor.

In economics, subjective interviews have been shown to facilitate discrimination by social class at elite multinationals (Shukla, 2025) and reduce attrition from medical school programs by improving match quality (Friedrich *et al.*, 2024), while AI-led interviews have been shown to improve hiring outcomes for low-wage service work (Jabarian and Henkel, 2025). Notably though, whereas Jabarian and Henkel (2025) focus on low-paying jobs, our work centers on high-paying jobs, 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,

[8]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.

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 learn about peer ability and opportunities for skill development.[9] 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. 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 partially inspection goods.

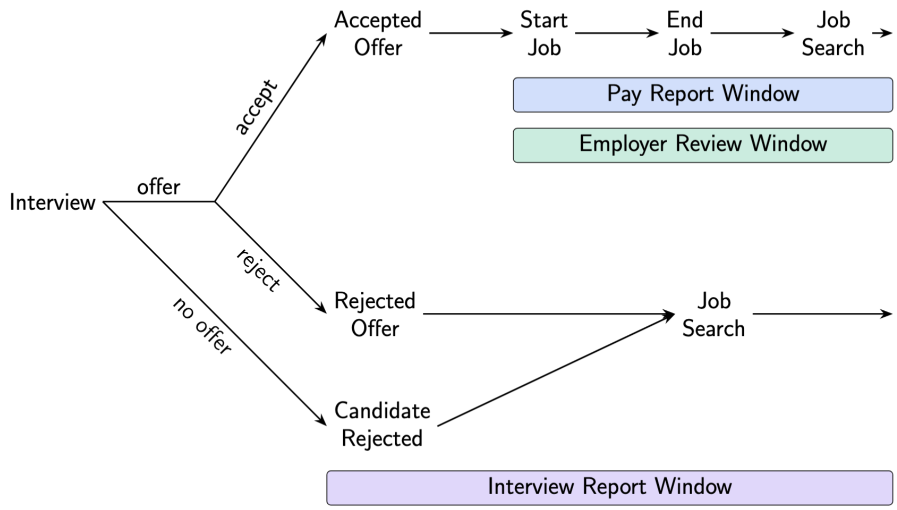
Third, the paper makes a contribution in terms of measurement, building on the growing literature in text algorithms for economics (Gentzkow *et al.*, 2019; Ash and Hansen, 2023). The use of aligned LLMs to label text datasets (in our case, interview narratives) is a relatively new approach that offers 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 details on how we compile our dataset of interview reports.

[9] 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, base wages are relatively transparent (Hall and Krueger, 2012), which reduces the need to discover pay during interviews.

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.

Platform Overview. Our data come from the website Glassdoor, an online platform where workers can anonymously share information about pay, job satisfaction, and 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.[10] Workers can satisfy the give-to-get requirement by 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. Our primary focus is interview reports, though we do incorporate pay reports and employer reviews in the analysis. 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 at 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, and for a free-response description of the interview process. Workers are also asked the difficulty level of the interview, to which they can respond by selecting one of five options: very easy, easy, average, difficult, or very difficult. Next, respondents state whether they received an offer for the job in question, and if they did, whether they accepted or rejected it. Respondents

[10]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).

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[11]), how many days the process took, and when the interview occurred. Appendix Figure A1 provides 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, what we observe is consistent with participants on Glassdoor reporting offer and acceptance decisions truthfully. First, among workers who report having accepted an offer, we can pinpoint the hiring firm on 34.0 percent of resumes (Appendix Figure A2). 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 H1) 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 pay, Appendix Table H2) than those who report not receiving an offer. Third, among those who report receiving an offer, 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 centers on high-paying occupations as identified by their Standard Occupational Classification (SOC) codes.[12] This restriction offers both practical and conceptual advantages. First, Glassdoor considerably over-samples from high-paying industries and occupations (Karabarbounis and Pinto, 2018; Liu *et al.*, 2022), such that we have particularly rich coverage of these jobs.[13] 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), which may be signaled during the interview process. Third, workers in these occupations tend to have career concerns and benefit from human capital accumulation through peer effects and on-the-job learning (Reagans *et al.*, 2005; Mas and Moretti, 2009; Jarosch *et al.*, 2021; Atkin *et al.*, 2022), such that a poor worker-firm match can be particularly costly. And fourth, these occupations have high marginal products, so firms will tend to expend more resources screening for them.[14]

[11]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.

[12]They are: management (11), business and financial operations (13), computer and mathematical (15), architecture and engineering (17), legal (23), and healthcare practitioners and technical (29).

[13]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 B1).

[14]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.

We take a number of steps to arrive at our interviews sample. The iterative procedure, along with the observations discarded at each step, is detailed in Appendix Table A1. We first restrict to interviews from 2008 through 2024. Then, since we are interested in the decision to accept 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. Then, to focus on matches that do not have a definite end date determined ex ante, we exclude interviews for internships—though, for internships as well, job seekers increasingly reject offers after easy interviews (Appendix C). 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 Appendix Table A2. In our sample, 20 percent of offers are rejected and the average interview process takes about 24 days until an offer is made.

Imputing Wages. Since workers do not disclose the wage they were offered in their interview reports, we impute offered wages using Glassdoor pay reports. For each firm $\times$ job title, we calculate the mean total pay 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 H3). 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 B2).

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 the link between job seekers' decisions to accept or reject job offers and their interview experiences, 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 concern is that individuals who disclose an interview report on Glassdoor 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 evaluate this concern, we take the database of Glassdoor pay reports and estimate an AKM regression with worker and firm fixed effects. Taking these worker fixed effects as proxies for ability, we plot the distribution for workers who report accepting an offer in the interviews sample and those in the pay reports database overall. While there is a small difference between the two—on the order of six percent of a standard deviation, consistent with some over-selection into contributing additional information on Glassdoor—the two distributions are almost identical (Appendix Figure B3). Workers who disclose interview reports may also be differentially selected on job satisfaction, as interviews are involved in job search. However, when we compare job satisfaction ratings from our interview sample to the broader sample, again the distributions look alike (Appendix Figure B4). Thus, the 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[15], major of study[16], 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 Appendix Table A2.

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 five-point scale, ranging from "very easy" to "very difficult." The distribution of interview

[15]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.

[16]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.

difficulty is plotted in Appendix Figure A3.[17] For ease of exposition, and to avoid concerns regarding heterogeneous interpretations of the five-point scale across sub-samples[18], we create an easy-interview indicator, which equals one if respondents record "very easy" or "easy" and zero otherwise. Roughly 35 percent of respondents perceived their interview as easy.

Reported difficulty in these interview reports will reflect both the objective structure of the firm's recruitment process and workers' subjective perceptions shaped by their ability, experience, and psychology. Perceived difficulty thus blends institutional rigor with self-assessed competence (Kukla, 1972). Objectively, a process may feel demanding because it is long or technically challenging. Subjectively, varying levels of preparation, experience, expectations, and perspectives can lead candidates to different judgments; two candidates may rate an identical assessment quite differently if, for instance, they vary in their beliefs about the effort that would be required to succeed in the associated job (Bandura, 1977).

Our controlled experiment illustrates both the objective and subjective dimensions of perceived interview difficulty (Section 7). First, we find that exogenously increasing the difficulty of a technical assessment shifts the distribution of reported difficulty. Second, we find that the same technical assessment receives widely different ratings of difficulty, underscoring the importance of subjective perception.

To get a broader sense of the sentiment associated with difficulty, Appendix Figure A4 depicts the words workers use in their interview narratives that are most associated—via an odds ratio—with easy interviews compared with difficult ones. Whereas workers tend to characterize easy interviews as "desperate" and providing a "chill" or "relaxing" interview experience that may have been a "scam" or "pyramid" "scheme", or just "misleading" or "sketchy", workers tend to characterize difficult interviews as "intensive" and a "rigorous" test of "reasoning", that required them to "dig" and "dive" into the details, which was "involved" and "rewarding" but also potentially "exhausting." These text patterns hint at some of the mechanisms we explore with an LLM.

As an alternative approach for interpreting the meaning of perceived interview difficulty, we surveyed 200 U.S. college graduates on Prolific. Each participant was presented with two vignettes in which job candidates described an interview. One vignette stated the interview was "very easy" or "easy," whereas the other vignette stated the interview was "average," "difficult," or "very difficult." Each respondent scored the two vignettes on a 0-5 Likert scale for eight provided statements. Appendix Figure A5 depicts how participants'

[17]The average difficulty rating is 2.67 (Appendix Table A2). 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).

[18]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).

scores for each statement varied between the former and the latter. The results demonstrate that individuals assign both objective and subjective aspects to difficulty. Whereas an easy interview reflects familiar questions and inviting impressions (more subjective) as well as a non-selective process (more objective), interviews that are not easy convey a sense of being demanding or uncomfortable (more subjective) as well as the firm testing reasoning and problem-solving while maintaining high hiring standards (more objective). These crowd-sourced interpretations from college graduates align with our interpretations of interview difficulty.

Given the focality of this measure of perceived difficulty, we take steps to internally and externally validate it. For internal validation, we record whether the job seeker mentions the word "easy" in their free-response narrative of the interview process and find the fraction that does monotonically declines with difficulty (Appendix Figure A6). For external validation, we turn to the website Onsites, which also collects summary information with regard 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 $\times$ job title we observe on Onsites, of which there are about 500, we calculate the average perceived difficulty. Then, in Appendix B, we compare Onsites' averages with those for the same firm $\times$ job title 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 whether perceived difficulty affects acceptance decisions, we examine whether and where there is variation in perceived difficulty. Appendix Table H4 summarizes the variation in our easy indicator between firms and workers. Perhaps unsurprisingly, the duration of the interview process is strongly correlated with difficulty, alone explaining 5 percent of the variation.[19] Incorporating firm fixed effects increases the explained variation to above 20 percent, demonstrating the hiring firm alone is not a perfect predictor of difficulty. The job seeker and hiring firm together can explain 80 percent of the variation, suggesting one-fifth of perceived difficulty is match-specific, e.g., which managers are involved or even possibly what the weather was.[20]

Last, we note which employers offer the most difficult interviews. Intuitively, we find

[19] This is observed across the entire wage distribution (Appendix Figure A7).

[20] While interviews become increasingly more difficult for the same worker over time, this largely reflects the different firms and job titles that workers interview with as their careers progress (Appendix Table H5).

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 A3). By comparison, firms in our sample with the least difficult interviews come from retail, food services, and insurance (Appendix Table A4).

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[21], 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, we randomly select 500 observations. If there are fewer than that in the sample for a 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 D.

To ensure the quality of the annotations produced by the LLM, we hired two freelancers with experience in 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 we 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 D1). The agreement rate of the LLM with the annotators is almost identical to the rate of 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.

[21] 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.

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, e.g., an indicator equal to one if the worker accepts a job offer and zero otherwise. 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's industry interacted with the vacancy's occupation, flexibly absorbing variation in acceptance rates and interview difficulty by industry and occupation. We also adjust for city-level seasonal variation by including fixed effects for the vacancy's metro area interacted with the calendar quarter. 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 the interview occurs and when the user discloses the associated data.[22] Additional fixed effects are included in follow-up specifications, including 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 or firm age, as indicated below.

We interpret 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 rich fixed effects described above adjust for many confounding sources, but they do not adjust for confounders that come from the specific worker $\times$ 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.

[22] 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 H1). Those who accepted the offer are significantly more likely to write the interview was easy, those who rejected the offer that it was difficult.

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 to the same firm who rated the interview as easy—which acts as a proxy for the interview's objective difficulty. With this alternative explanatory variable, 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. This leave-one-out regressor 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 alternative leave-one-out regressor as

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

which captures the average of 1(Easy interview) across all other workers that interviewed with the same firm, as desired. Naturally, we restrict the sample to firms with at least two applicants such that this index is defined.

We do not consider this variable as an instrument, given the unrealistic assumptions needed to satisfy the exclusion restriction. Still, it is helpful to estimate a "first stage" that regresses worker i's interview perception on 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).[23] As expected, others' perceptions for the same firm are highly predictive of one's own (Appendix Figure H2).

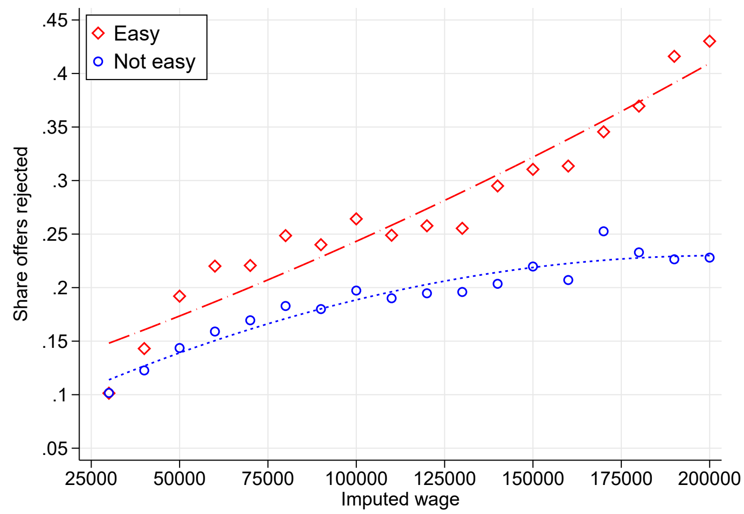
4 Interview Difficulty and Offer Acceptance

This section presents the main evidence on how workers respond to variation in the intensity of the interview process. Our focal regressions estimate the relationship between perceived interview difficulty and the probability of rejecting an offer, conditional on receiving an offer. The regressions include rich fixed effects and we report comprehensive robustness checks. To summarize, easy interviews increase the probability of rejected offers.

We first show our main result graphically. A primary consideration in offer acceptance is the offered wage, where one would expect that, all else equal, rejection rates would decrease

[23] Our conclusions are robust (Appendix Table H6) to alternative sets of other applicants, e.g., conditioning on location (same firm x metro) or occupation and time (same firm x occupation x year), as well as considering averages that are lagged or forward looking.

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 log 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."

with higher wages. In Figure 2, we plot the offer rejection rate for different wage levels, with separate plots for easy interviews and not-easy interviews.[24] We witness greater rejection rates at higher wages[25], and systematic differences in the rejection rate between easy and not-easy 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, rejection rates are upwards of 35 percent after easy interviews and below 25 percent after not-easy interviews. This would suggest interview difficulty itself is a valuable input into the decision to accept an offer—in particular that an easy interview is less favorable than a difficult one. Indeed, job seekers on average report greater dissatisfaction—i.e., a "thumbs-down" experience—with easy interviews than with not-easy interviews (Appendix Figure A8).

We begin with the cross-sectional estimates in Table 1. In column (1), compared with an acceptance rate of 81.8 percent among not-easy interviews, an easy interview is associated with a 4.9-percentage-point lower probability of offer acceptance. Column (2) shows this association is unchanged if instead we incorporate our leave-one-out measure from Equation (2), i.e., the fraction of other applicants who considered the firm's interviews to be easy. A potential concern with cross-sectional estimates is the composition of workers who per-

[24]We observe the same pattern if, in lieu of the imputed wage for 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 H3).

[25]This is not the case within worker, where higher wages are accepted more often (Appendix Table H7).

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

	1(Accepts job offer)							
	Cross-section sample		Within-worker sample			Within-worker-qtr sample		Within-vacancy sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(Easy interview)	-0.049***		-0.125***	-0.119***		-0.173***	-0.176**	-0.070***
	(0.002)		(0.009)	(0.014)		(0.032)	(0.077)	(0.008)
Fraction others' interviews easy		-0.050***			-0.121**			
		(0.006)			(0.051)			
Mean DV for not easy	0.818	0.818	0.732	0.732	0.732	0.560	0.560	0.818
N	421,112	421,112	20,135	20,135	20,135	2,521	2,521	35,628
Workers	407,909	407,909	9,421	9,421	9,421	1,185	1,185	35,187
R^2	0.09	0.08	0.25	0.76	0.76	0.52	0.83	0.51
Firm Observables	✓	✓	✓	✓	✓	✓	✓	
Worker FE				✓	✓			
Worker-Qtr FE							✓	
Firm-Job title-Metro-Qtr FE								✓

Notes: Table 1 summarizes the relation between the probability an offer is accepted and perceived difficulty of the interview with the iterated addition of fixed effects. Firm observables refer to industry x 20 five-percentile bins of firm age x 20 five-percentile bins of firm AKM pay premium. Each specification includes metro-quarter, 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%.

ceive interviews as easy and report such accepted or rejected offers to Glassdoor. To address compositional and selection concerns in the cross-section, columns (3)-(5) restrict the sample to workers with multiple job offers. Whether we include worker fixed effects—in which case our coefficient of interest is identified off of variation in perceptions of difficulty and offer acceptance for the same worker—or we do not, or we rely only on the perceptions of others, easy interviews are rejected about 12 percentage points more often.[26] In columns (6)-(7), we more narrowly pin down consideration sets by evaluating only workers who report multiple offers for the same quarter. When faced with both an easy interview and a not-easy interview that each resulted in an offer, the easy interview is rejected 17 percentage points more often. Last, in column (8), we narrow in on workers who all received offers for the same vacancy, i.e., a given firm × job title × metro × quarter—effectively fixing skill requirements. Again, workers who perceive the interview as easy reject the offer significantly more often.[27]

Robustness Checks. We next explore the robustness of this result. First, we demonstrate our results do not merely reflect differences in the ex ante desirability of firms. We consider four separate metrics along which workers may establish an ordinal ranking of firms. The first is the ease with which an offer can be secured, which we proxy for by the probability

[26] The shift in magnitude between the cross-section and within-worker samples in part reflects the latter comprising higher-wage jobs (Appendix Figure A9), which witness greater rates of rejection (Figure 2).

[27] Interview difficulty does not predict differences in realized wages within the same role, suggesting concerns with bargaining over compensation do not explain the lower offer acceptance rate (Appendix Table H8).

an interview results in an offer.[28] The second is the level of skill for the average worker at the firm—channeling the notion that more desirable firms can be more selective in hiring. Here, individual skill reflects the person fixed effects from an AKM regression on log pay. The third is relative job quality, which we capture through the firm fixed effects in an AKM regression on job satisfaction ratings from Glassdoor employer reviews. The fourth is interest in applying in the first place, which we capture through the probability a job seeker applies to a given vacancy conditional on seeing it.[29] Across all four metrics (Appendix Figure H4), easy interviews are rejected more often.

Next, we address a limitation of the estimates from the within-worker and within-worker-quarter samples. Those specifications are quite stringent, as they are identified only off of workers who disclosed on Glassdoor at least two interviews resulting in offers, where at least one interview was easy and another was not. Necessarily, these samples exclude candidates who only report one offer, potentially limiting their generalizability. Using data from workers' resumes, we can generate additional within-worker variation without requiring two offers to have been reported. The trick is that any job on a resume must necessarily have been the product of an offer that was accepted. So, for workers who report rejecting an offer—an aspect unique to Glassdoor interviews never observed in employee-employer matched administrative data—we can look at their resumes to see which firms they went to instead. We compare the rejected firm with the next firm listed on that worker's resume after the offer was rejected. Consistent with our main results, we find that interviews for the rejected firm are 20 percent more likely to be perceived as easy (Appendix Figure A11).

Another concern is that delayed reporting of interviews may add bias due to experiences on the job changing workers' retrospectives of the interview and its difficulty. This can occur because interviews are disclosed to Glassdoor retroactively (see Figure 1). To check if this is a pivotal issue in our analysis, we run a robustness check restricting the sample to rejected offers and accepted offers where the interview report was submitted to Glassdoor before the worker began the job in question (which we can observe from their resume). Reassuringly, easy interviews are still rejected more often within this subsample (Appendix Table H9).

We also explore a broader set of sensitivity and heterogeneity by re-estimating Equation (1) for various sub-samples. This includes aspects related to reporting on Glassdoor, such as time since the interview occurred; features of the interview process itself, such as whether managers or video communications were involved; worker demographics such as age, gender, and educational attainment; labor market status such as on-the-job or off-the-job search; and

[28]Higher-paying jobs have lower offer rates (Appendix Figure A10), consistent with more selective hiring at higher wages (Mueller *et al.*, 2023).

[29]We rely on data on vacancy-level application probabilities from Sockin and Sojourner (2023).

search behavior, such as prospective wage growth and breadth of firms considered. For every sub-sample, easy interviews are rejected significantly more often than not-easy interviews. For expositional purposes, we relegate a deeper discussion of these results to Appendix E.

5 Interviews as Learning Opportunities

Having established workers extract meaningful content from their interview experiences, we next explore a signaling channel. That is, during the interview process, workers learn about firm characteristics and 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.

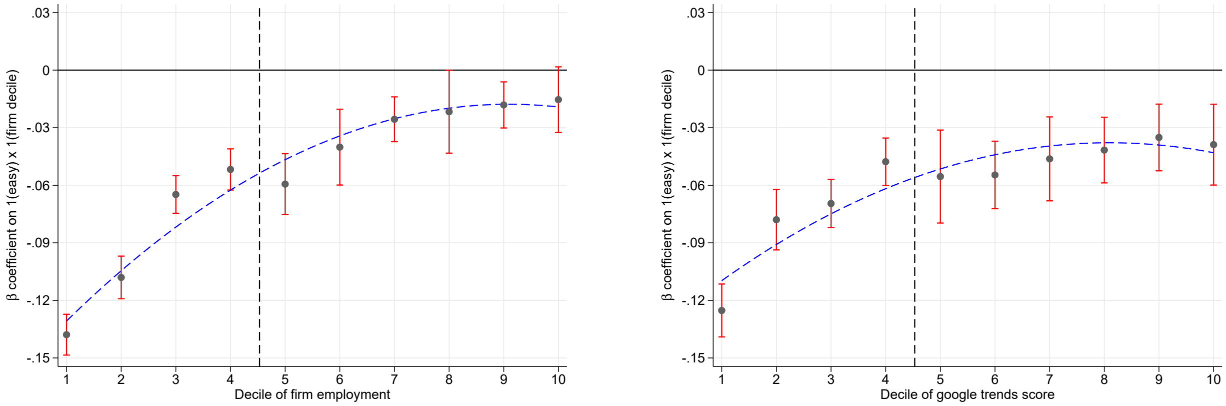
5.1 Heterogeneity by Employer Reputation

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 the employer's reputation. 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 well-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 rejected by interview difficulty within each decile 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 (Appendix Figure A12). While the rejection rate hovers around 16–20 percent across the distribution of firm size for not-easy interviews, the rejection rate rises to 20–24 percent for medium-sized firms and even further to 28–32 percent for the smallest firms. The coefficients from estimating the wedge in acceptance rates between easy and not-easy interviews by decile following the specification of Column (1) in Table 1 are plotted in panel (a) of Figure 3. 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 decile of the size distribution than those in the top decile.

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

Figure 3: Probability of Offer Acceptance by Perceived Difficulty and Firm Familiarity



(a) Firm size

(b) Google trends

Notes: Figure 3 relates offer acceptance to whether the job seeker perceived the interview to be easy or not, partitioned by the size of the employer (panel a) or how frequently the employer is searched on Google using data from Google Trends (panel b). Firms are partitioned into deciles in ascending order. Firm employment is based on a Glassdoor lookup table from January 2025. 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. Plotted coefficients correspond to $1(Easy) \times 1(Decile_k)$, 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%.

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 compared with more well-known firms. The raw differences are presented in Appendix Figure A12, while the corresponding regression coefficients are plotted in panel (b) of Figure 3. 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 and foreign graduates (Appendix Table H10). Presumably, workers who are referred by an employee are more familiar with the firm: By definition, they know at least one employee—meaning they have access to insider information about prospective peers and match quality. We anticipate a smaller penalty from easy interviews on offer acceptance for referrals. While referred job seekers are less likely to reject offers, consistent with Burks *et al.* (2015), and still more likely to reject easy interviews, the reduction in offer acceptance associated with an easy interview is less than half that observed for the full sample. Conversely, college graduates from universities outside the United States are twice as likely to reject an easy interview compared with the rest of the sample—consistent with such workers having less information about the quality of matches in U.S. labor markets ex ante.

5.2 Analysis of Interview Narratives

Drawing on interview narratives, we employed an LLM to parse the free-response text and identify whether and which signals are conveyed to job seekers during an interview, and how that varies with interview difficulty. In Section 3.1 above, we discussed the construction and validation of these LLM measures.

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 clarified compensation, clarified hours and scheduling, or detailed workplace amenities orthogonal to colleagues. The specific prompts asked of the LLM to do so are presented in Appendix D.

We first 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 Panel A of Table 2, suggest this is the case. Columns (1) and (2) show that while 3.7 percent of interview summaries describe potential colleagues as being of high ability following a not-easy interview, the fraction for easy interviews, either from one's own perception or the amalgamation of others', is about two percentage points lower—equivalent to a decline of roughly one-half relative to the baseline. When we narrow in on workers who report multiple offers and include worker fixed effects in columns (3) and (4), we observe that the same worker is significantly less likely to believe their colleagues will be of high ability after an easy interview. It is not simply though that job seekers are less likely to highlight colleagues in their interview summaries after easy interviews. If we instead look at job seeker beliefs about the pleasantness of prospective colleagues (Panel B), the association is small and not robust across specifications.

While considering whether an interview summary mentions high-ability colleagues captures positive perceptions of peer ability, job seekers could inversely develop negative perceptions of peer ability from an interview. To test for this possibility, 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 an 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 D. These estimates are reported in Panels C and D of Table 2, respectively. While only 1.2 percent

Table 2: Perceived Interview Difficulty and LLM Assessment of Workers' Beliefs

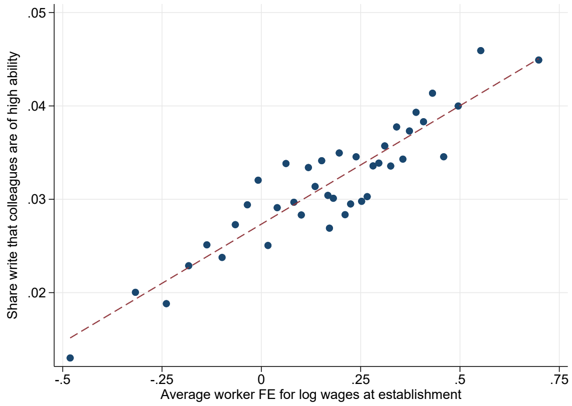
	Cross-section sample		Within-worker sample	
Panel A: DV = 1(High-ability colleagues)				
1(Easy interview)	-0.020***		-0.035***	-0.025***
	(0.001)		(0.003)	(0.006)
Fraction others' interviews easy		-0.022***		
		(0.002)		
Mean DV for not easy	0.037	0.037	0.054	0.054
Panel B: DV = 1(Pleasant colleagues)				
1(Easy interview)	0.003		-0.023***	-0.014
	(0.002)		(0.008)	(0.014)
Fraction others' interviews easy		-0.038***		
		(0.005)		
Mean DV for not easy	0.216	0.216	0.240	0.240
Panel C: DV = 1(Would accept anybody)				
1(Easy interview)	0.061***		0.043***	0.028***
	(0.001)		(0.003)	(0.005)
Fraction others' interviews easy		0.074***		
		(0.003)		
Mean DV for not easy	0.012	0.012	0.011	0.011
Panel D: DV = 1(Engaging experience)				
1(Easy interview)	-0.050***		-0.074***	-0.054***
	(0.002)		(0.008)	(0.015)
Fraction others' interviews easy		-0.073***		
		(0.006)		
Mean DV for not easy	0.292	0.292	0.313	0.313
N	421,112	421,112	20,627	20,627
Worker FE				✓

Notes: Table 2 summarizes the relation between workers' beliefs and perceived difficulty. Each specification includes fixed effects for metro-quarter, industry-occupation, year-quarter of interview x year-quarter submitted to Glassdoor, and firm industry x 20 five-percentile bins of firm age x 20 five-percentile bins of firm AKM pay premium. Included are additional text indicators produced by the LLM for aspects the interview process illuminated: compensation, hours or scheduling, and desirable workplace amenities. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

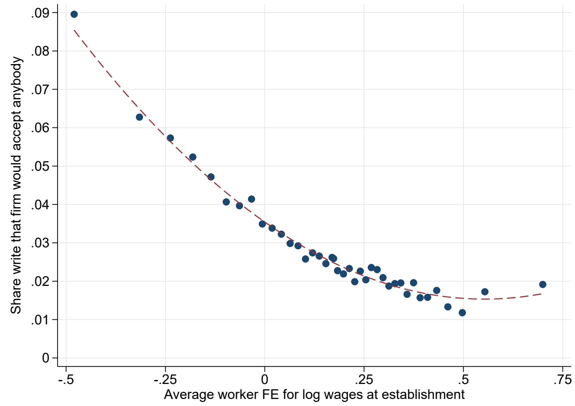
of workers write that the firm would accept anybody after not-easy interviews, column (1) shows the fraction is six percentage points higher after easy interviews—a six-fold increase. This disparity holds and remains large whether we only consider the perceptions of others rather than one's own in column (2), as well as looking between interviews that varied in perceived difficulty for the same worker in columns (3) and (4). This signal may in part stem from the interview process, which likely involves interactions with prospective peers, being less engaging or stimulating. Indeed, as shown in Panel D, easy interviews are less likely to be perceived as engaging experiences, with large coefficients relative to the baseline.

Inferences about prospective peers and engagement likely vary with the screening tools the hiring firm employs. For instance, requiring a skill or aptitude examination, or imposing

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.

job seekers funnel through additional rounds of interviewing, may induce a job seeker to infer prospective peers have all passed such screening and thus exceed some ability threshold. Using the free-response narratives, we examine whether such screening tools influence workers' perceptions. For a skills or qualifications assessment, we rely on an LLM to identify whether the candidate believed their skills or qualifications were directly assessed during the interview (specific prompt detailed in Appendix D). In Appendix Table H11, we show that such an assessment is associated with a reduced likelihood of perceiving the interview as easy—even when looking across interviews for the same worker—and an increased likelihood of perceiving prospective colleagues as high ability. And in Appendix Table H12, we show that—even for the same worker—firms that utilize additional interviewing rounds[30] have longer interviews, pay higher wages, have more difficult interviews, and 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 that prospective peers are of high ability and influences offer decisions.

[30]To approximate the number of rounds of interviewing, we first identify a sub-sample of workers who mention a specific number of rounds in their interview process and then calculate the average for each firm.

To further validate the mechanism that interview experiences serve as signals of prospective peer quality, we ask whether the elicited perceptions reflect accurate characteristics about the firm based on external sources. More specifically, we match up the text annotations for colleagues being of high ability and the firm accepting anybody, with measures of worker skill in those firms constructed via AKM-style wage regressions.[31] 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 that the interview-based text annotations for peer ability are informative about the skill levels in the associated firms. Compared with firms that have the highest levels of peer ability, firms with the lowest levels are *less than one-half* as likely to give the impression of having high-ability colleagues (panel a) and *more than four times* as likely to give the impression that the firm would accept anybody (panel b).[32] In turn, as shown in Appendix Figure A13, annotations of "would accept anybody" are highly positively correlated with the reported job offer rate. Thus, it is not just that certain firms or specific labor markets exhibit high-ability colleagues, but rather that 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 job's tasks and responsibilities

[31] We cannot directly observe one's (prospective) peers, but we can proxy for their ability using Glassdoor pay reports. First, taking the worker fixed effects from an AKM regression on log wages, we obtain a measure of individual skill. Then, taking the sample of pay reports as a snapshot of the pool of coworkers, we gauge peer ability by taking the average individual skill at each establishment (i.e., firm $\times$ metro) each year.

[32] Although we use the term peers broadly to refer to all colleagues, considering managers and non-managerial workers separately suggests it is the ability of the latter that largely drives these perceptions (Appendix Table H13). Further, we can disentangle the reputation of the parent firm from its establishments. We observe the same pattern when we look within establishments at the same firm, including firm and metro fixed effects (Appendix Table H14).

through realistic job previews. As highlighted in Appendix E, easy interviews in which the free-response narrative discussed responsibilities witness reduced offer acceptance rates compared to not-easy interviews. While suggestive evidence points to realistic job previews improving initial matches and reducing turnover (Wanous, 1973; Phillips, 1998), the literature has largely 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 D.

When 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 (Appendix Table H15). 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. Although workers value learning about job responsibilities through interviews, they appear to be partially deterred when such information is conveyed through an easy 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; in turn, workers may accept lower wages to have the opportunity to learn (Tambe *et al.*, 2020) or work for a startup (Roach and Sauermann, 2024), where they can be involved in cutting-edge and intellectually-stimulating work. If easy interviews signal limited potential for growth opportunities, candidates with career concerns may be particularly turned off by such 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 $\times$ job title we observe. So, for each firm $\times$ job title, we predict the average wage for the next job by taking the average imputed wage among all of the firm $\times$ job title pairs that occur next on workers' resumes. We repeat this exercise for the second next job and the third next job. Last, we create an indicator equal to one if the firm $\times$ job title for which the job seeker is interviewing is likely to be high wage, i.e., the average wage is above the

90th percentile, for any of the next three jobs, 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 H16, highlight that the decreased probability of accepting an offer after an easy interview is roughly twice as large for vacancies that lead to high-wage jobs in the future.

Outside Options. To proxy for 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 graduates 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 H17). 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, i.e., the monthly metro unemployment rate from the Bureau of Labor Statistics, offers further evidence outside options are a contributing factor (Appendix Table H18). When the unemployment rate rises, and workers subsequently have worse options amid increased competition, easy interviews are rejected less often.

Qualifications. Whether a job opening is a good fit for a worker may depend upon how much human capital the worker already has. For instance, a worker with many years of experience or education may learn through the interview they are "over-qualified" for the role, in which case they would likely find the interview easy and reject an offer if they received one. We find limited evidence in this regard. To proxy for a worker's relative qualifications, we consider how many years of potential experience (i.e., age) or actual experience (i.e., years employed on resume) a worker has compared with all other job seekers who received an offer for the same firm $\times$ job title. In Appendix Figures H5 and H6, we observe that workers with relatively more experience are *less* likely to believe the interview was easy, not more, and that relative experience does not clearly predict whether offers are rejected. This would suggest the easy-interview penalty on offer acceptance rates we document does not simply reflect observable mismatch with worker qualifications.

Learning About Self. One potential mechanism for the effect interview difficulty has on offer acceptance is that, rather than enabling candidates to learn about firms, more difficult interviews enable candidates to learn about their own abilities. While this mechanism could play a role to some extent in our setting, it is likely not a central factor. For one, the results for employee referrals (Appendix Table H10) and firm familiarity (Figure 3) are consistent with learning about firms rather than learning about self. Second, there is little evidence of heterogeneity by the worker's own human capital, e.g., age, alma mater, or grade point average (see Appendix E). And third, candidates with little prior work experience—those recruited through their university—and workers with relevant experience—those who have held a previous job in the same occupation—both increasingly reject easy interviews at comparable rates (Appendix Table H19). Together, these results are at odds with learning about oneself as the focal mechanism.

Behavioral Mechanisms. There are at least two potential behavioral mechanisms for our results. One is 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). A second is the theory of gift exchange or positive reciprocity (Akerlof, 1982). Through the lens of this theory, a "difficult" interview indicates costly effort by the employer—consistent with our evidence that workers perceive easy interviews as less engaging (Table 2, Panel D)—and the worker reciprocates by accepting the job offer.

While we cannot rule out these behavioral mechanisms, we believe they can explain neither the empirical evidence nor our preferred signaling interpretation. If effort justification or gift exchange were the main drivers, we would not observe heterogeneity in offer acceptance by, for example, employee referrals (Appendix Table H10) or firm familiarity (Figure 3). Further, these behavioral theories do not explain the evidence on how interview difficulty is associated with learning about high-ability colleagues (Table 2, Panel A).

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 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 particularly poor matches.

To test whether interview difficulty serves as a precursor for realized match quality, we turn to employee turnover. Firm tenure likely proxies for match quality since workers with poor matches will increasingly voluntarily quit (Akerlof *et al.*, 1988) and workers will pursue outside options if they believe them to be more appealing (Jäger *et al.*, 2024). To do so, we match interviews to tenure following accepted offers using workers' resumes. We consider each job listed on a worker's resume and identify for which (if any) the worker disclosed their interview to 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 estimate the specification from equation (1) and record the results in Table 3.[33]

Each specification supports the same narrative: Workers separate earlier if they had perceived the interview for that job to be easy.[34] The first three columns consider completed spells. Workers exit 16-18 percent earlier if they believed the interview was easy, even when we compare interviews across roles in column (1) or within roles in column (3). If everyone else believes the firm's interviews are easy, which again strongly predicts one's own beliefs, workers exit such firms roughly 21 percent earlier.[35] The latter three columns incorporate both ongoing and completed spells. Even when considering the same firm $\times$ job title, workers who accept after easy interviews are 7.3 percentage points less likely to remain in the match for at least one year, a nearly 10 percent decline relative to 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 proxy for a less-productive worker who is ultimately let go because of poor performance.

[33] 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 H20).

[34] 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 H21), we do not believe this to be the case.

[35] 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 interviews and incorporating each worker's fixed effect from an AKM regression on interview difficulty (Appendix Table H22).

Table 3: Tenure from Workers' Resumes After Offer Acceptance

	Logarithm of firm tenure			1(Firm tenure $\geq$ 12 months)		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Easy interview)	-0.170***		-0.195***	-0.082***		-0.073***
	(0.018)		(0.055)	(0.008)		(0.023)
Fraction others' interviews easy		-0.233***			-0.109***	
		(0.063)			(0.028)	
R^2	0.43	0.43	0.77	0.26	0.26	0.61
Mean DV for not easy	2.379	2.379	2.357	0.755	0.755	0.776
N	12,558	12,558	2,136	17,561	17,561	3,476
Firm Observables	✓	✓		✓	✓	
Firm-job title FE			✓			✓

Notes: Table 3 relates the length of firm tenure for a job using workers' resumes to their interview experiences for that same employer. Each specification includes metro, year-quarter in which the job began, industry-occupation, year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Firm observables refer to industry x 20 five-percentile bins of firm age x 20 five-percentile bins of firm AKM pay premium. Sample is restricted to workers who join the firm within one year of the interview. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

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 H22). Additionally, we can directly test for signs of poor match quality after an easy interview by turning to workers' job satisfaction reported 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.[36] 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.[37] We are able to match 46,000 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 and an interview

[36] Sockin (2022) shows Glassdoor ratings strongly correlate with satisfaction ratings from a representative survey across industries and occupations. For more details on Glassdoor reviews, see Marinescu *et al.* (2021).

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

Table 4: Job Satisfaction from Glassdoor Reviews After Offer Acceptance

	Overall rating				1(Mentioned in cons section)		
					Involuntary turnover	Voluntary turnover	Peers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1(Easy interview)	-0.598***		-0.486***	-0.341**	0.004	0.009**	0.030***
	(0.016)		(0.038)	(0.139)	(0.005)	(0.004)	(0.009)
Fraction others' interviews easy		-0.503***					
		(0.049)					
R^2	0.23	0.24	0.57	0.95	0.43	0.40	0.37
Mean DV for not easy	3.91	3.91	3.86	3.60	0.026	0.022	0.127
N	46,185	46,185	11,886	514	11,886	11,886	12,567
Firm Observables	✓	✓					
Firm-Job title FE			✓		✓	✓	✓
Worker FE				✓			

Notes: Table 4 relates job satisfaction to perceived interview difficulty for the same employer. 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 metro and the interview year-quarter x the year-quarter in which the review was written. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

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 B4), there is little difference between them.

As is shown in the first four columns of Table 4, easy interviews precede lower job satisfaction. Workers who accept offers after easy interviews are 0.6 stars less satisfied with their jobs—a disparity that is equivalent to two-fifths of a standard deviation and is larger in magnitude than the effect of learning your employer engaged in corporate misconduct (Gadgil and Sockin, 2020) or accounting fraud (Zhou and Makridis, 2021). Even when we consider workers who held the same job title at the same firm in column (3), or the same worker reporting their satisfaction for multiple jobs that differed in whether they followed easy or not-easy interviews in column (4), easy interviews are followed by lower satisfaction.

Since job dissatisfaction predicts turnover (Akerlof *et al.*, 1988; Card *et al.*, 2012), this evidence 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 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 40 percent more likely to mention *voluntary* turnover as a negative aspect of their workplace. Further evidence of voluntary turnover comes from measuring the frequency with which workers mention 'peers' in their reviews. Workers who accepted offers after easy interviews are 25 percent more likely to explicitly reference peers as a drawback of their jobs, consistent with the evidence above that easy interviews signal the firm "would accept anybody"—which is more often observed among workplaces with lower-ability peers (Figure 4, panel b).

7 Experimental Evidence on Interview Difficulty

To complement our observational evidence, we conducted a pre-registered, randomized field experiment that exogenously varied interview difficulty and measured its effect on applicant behavior. First, we show intervening on the objective difficulty of the interview process shifts perceived difficulty—validating our analysis of perceived difficulty in the observational data. Second, we find being randomly assigned an easy interview process reduces engagement and interest in the position, offering causal evidence in support of our main result.

Experiment Design. The experiment was implemented in the context of a real job advertisement posted for a data scientist position at a well-known university, listed for about two weeks in July 2025. The listed job title was simply "Data Scientist" with English fluency and Python/R programming skills listed as minimum qualifications. The ad specified that both full-time and part-time were possible, and that both in-person and remote work were possible. The position was advertised as lasting for at least one year and up to three years.

Applicants were asked to complete a survey through Qualtrics for the first-round interview. After first being asked to provide their personal information, including their resume, years of work experience, and educational background, applicants completed a technical assessment followed by retrospective questions about the interview. For a complete outline of the interview structure and summary statistics for the workers who applied for the position, see Appendix Tables F1 and F2, respectively.

The difficulty intervention was implemented through a technical assessment. Each candidate was randomly assigned with equal probability to one of two treatment arms: an "easy" arm and a "difficult" arm. In both arms, the assessment tested the same five technical areas: data, econometrics, probabilities, regular expressions, and coding. Within area, the difficulty of the associated question was significantly boosted in the difficult arm. For example, the "easy" regex task was: *Write a regular expression to detect if a sentence includes at least one question mark.* The "difficult" version was: *Write a regular expression to detect if a sentence* *includes at most one question mark* (emphasis added).

Directly after the technical assessment, candidates are asked two open-text questions: "*Why are you a good fit for this job?*" and "*Do you have any questions for us?*" The length of the responses to these questions is our first measure of engagement.

After these open-response questions, applicants are told the assessment portion is over and asked to complete a set of survey questions to facilitate future interview design. These survey questions gauged perceived difficulty of the interview—which, to mitigate image concerns, was framed as beliefs about others' perceptions. The first was, "*How many minutes do you believe it took other applicants on average to complete the interview?*" and the second was, "*How do you believe other applicants would rate the difficulty of the interview?*". The former allowed for a numerical response, the latter with one of the same five options as in the Glassdoor survey, either very easy, easy, average, difficult, or very difficult.

Upon completing the first-round interview, applicants received an email with a link to an application status checker. The link directed applicants to a web page where they could enter their email to track their application status. Visits to this website to check application status were logged as a continued measurement of applicant engagement.

This experimental design received ethics approval from the IRB at Cornell University and was pre-registered with the AEA RCT Registry. To ensure fairness in the hiring process, only materials provided before the randomization, i.e., applicants' resumes, were used in considering whom to advance to the next round of interviews. The hiring manager did not have access to answers for the technical assessment nor responses to the post-interview survey questions. Following IRB protocol, applicants were debriefed about the experiment after the interviewing period closed and allowed to opt out of having their responses considered for research purposes; about 2 percent of applicants chose to do so, and were subsequently dropped from the sample. The final sample consists of 1,325 applicants.

Treatment Effects. Considering first the distribution of perceived difficulty, Appendix Figure F1 shows that the distributions for the two treatment arms are not the same. Those who experienced the easy assessment were more likely to perceive the interview as easy or very easy, and less likely to perceive the interview as average or difficult. As intended, the difficult assessment appears to have been broadly perceived as more challenging, though there was still dispersion in perceptions, with about one-quarter of applicants believing the difficult assessment to have been easy or very easy.

This difference in perceived difficulty is statistically significant, as shown in Column (1) of Table 5. Applicants who experienced the easy assessment were 19 percentage points more likely to perceive the interview as easy compared with applicants who experienced

Table 5: Effects of Experimentally Induced Interview Difficulty

	1(Others would perceive interview as easy)	Predicted minutes it took others to complete interview	Standardized log length of why good fit and questions for us	Standardized count of application queries
1(Easy arm)	0.189***	-6.088***	-0.106*	-0.124**
	(0.026)	(0.856)	(0.058)	(0.061)
Mean DV difficult arm	0.241	25.703	0.053	0.054
Observations	1,325	1,325	1,309	1,325

Notes: Table 5 relates measures of perceived difficulty and of applicant engagement to whether the job seeker was assigned the easy technical assessment. Each specification includes fixed effects for experience category (0-2 years, 2-4 years, 4-6 years, 6+ years) × an indicator for post-Bachelor's degree × the day the interview was conducted. Robust standard errors reported in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

the difficult assessment—a 78 percent increase. Consistent with this shift, applicants who experienced the difficult assessment believed the interview required more effort, predicting it would take applicants on average six additional minutes to complete the first-round interview compared with applicants who experienced the easy assessment—a 31 percent increase. Appendix Figure F2 reports the full distribution of this measure. Evidently, even a light-touch intervention—five questions on a technical assessment that extended the interview by six minutes (Appendix Figure F3)—can meaningfully alter perceived difficulty.

This experimental evidence highlights how workers' perceptions of difficulty are not fixed before the interview occurs, as we observe a causal shift even when the vacancy is held constant—even for a job opening posted for a well-known university, for which most candidates would likely have a strong prior. Perceived interview difficulty, as in Glassdoor, thus reflects in part the objective difficulty of firms' interview processes—implying that variation in interview intensity in other real-world settings plausibly influences job seekers' own perceptions of difficulty.

Not only did the exogenous variation in interview difficulty affect perceived difficulty, it also appears to have altered the perceived desirability of the vacancy. We observe this pattern along two metrics of applicant engagement. First, applicants who experienced the easy assessment wrote significantly less text (10 percent of a standard deviation, Column 3) for the two open-response, non-technical questions. Evidently, when given the opportunity to signal interest at the cost of additional effort, a difficult assessment works to amplify that signal. Second, applicants who experienced the easy assessment checked the status of their application significantly less often than applicants who experienced the difficult assessment—on the order of 12 percent of a standard deviation. Although neither outcome guarantees applicants who experienced the easy arm would be more likely to reject an offer if they received one—the main outcome of the observational study—what we have documented is a reduction in applicant engagement even before any offer has been made. We interpret this as evidence that the observational results are not the product of confounding—say, due to reverse causality wherein candidates' perceptions of interview difficulty are colored by whether or not they received an offer—thereby bolstering the validity of a causal relation between interview difficulty and offer acceptance.

Limitations. Notwithstanding the useful contribution made by this evidence, we should acknowledge the limitations of the experiment design. The controlled setting of a Qualtrics survey abstracts from fundamental features of the full interview process—e.g., interactions with the hiring firm's employees, multiple rounds of interviewing, callbacks, etc. How these aspects interact with each other and contribute to candidates' perceptions, while important, is not in the scope of the experiment. Additionally, our intervention, while impactful, was relatively soft in scope, involving five technical questions and requiring only about 10-20 minutes of an applicant's time. Our experiment may not have external validity on how candidates would respond to a stronger intervention, e.g., an assessment or interview process that demanded multiple hours or days. Finally, our experiment was for a single job opening for a single well-established employer during a single time period. How applicants might respond to interview difficulty for other job titles, or other (possibly less established) employers, in other labor markets or at different periods in time may vary, and would be promising avenues for future interventions.

8 Conclusion

Interviews are a two-way dialogue, featuring interactions between workers and hiring managers. Yet, the (personnel) literature has largely adopted the perspective of the latter, exploring how interviews allow firms to screen workers (Benson and Shaw, 2024; Hoffman and Stanton, 2024). We take the opposite, underappreciated perspective. We ask, do workers form perceptions of the employer through interviews? Indeed, they do. We then ask, what do workers learn about the employer from the interview? They learn aspects that determine match quality yet are hard to gauge otherwise, such as the quality of future peers.

And yet, many questions remain. For one, we cannot speak to how workers' beliefs evolve since we do not observe their beliefs before interviewing. Qualitative methods that investigate workers' beliefs about employers (and their interviews) and how they evolve would be especially illuminating. Given our own text analysis, we suspect their views on prospective coworkers and opportunities for skill development shift with the difficulty of the interview, but perceptions of other aspects of the workplace, such as work-life balance or promotion opportunities, might shift as well—perhaps in response to difficulty or instead to a different feature of the interviewing environment, such as promptness or toxicity. Other work could also study to what extent different screening devices, such as IQ examinations, coding assignments, or personality tests alter 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 each affects worker beliefs and sorting. Such questions only take on heightened relevance as firms increasingly consider automating screening processes with AI.

These results highlight the importance of the manager's decision: which employees should conduct which interviews? On the one hand, if firms appear to benefit from signaling to job seekers—through difficult interviews—that they employ workers of high ability, then surely having higher-skilled workers conduct interviews will increasingly convey such signals. On the other hand, higher-skilled workers are more productive, and will have a greater opportunity cost to participating in interviewing. A trade-off thus arises, and it is one that will almost certainly vary with the job for which the worker is being recruited, e.g., an assistant professor compared with a full professor, or a junior consultant compared with a C-suite executive.

Further, it is unclear whether differences in interview practices pass through to differences in firm growth. Our findings suggest firms face a trade-off here as well: easy interviews result in more rejected offers and increased turnover, but difficult interviews require more time and resources. If interview practices have implications for firm growth, then to the extent that hiring practices are under managerial control, this would suggest there is another, understudied dimension by which managers contribute to differences in firm-level growth (Bloom and Van Reenen, 2010; Sadun *et al.*, 2025). In Appendix G, we provide a preliminary analysis in this direction, showing firms with more difficult interviews have faster wage growth in subsequent years, even after accounting for worker, industry, and occupation fixed effects. While these results suggest interview difficulty may be linked to faster productivity growth, establishing a causal link and identifying the underlying mechanisms—improved matching, reduced turnover, or greater innovation, for instance—remain open areas for research.

While this study considers interviews over the last fifteen years, it is plausible the nature of hiring will change. New technologies such as Zoom, for instance, have made remote interviews more commonplace. Further, the advent of AI now allows job boards to produce algorithmic recommendations of job openings for job seekers (Zhang and Kuhn, 2024). Whether such technologies will disrupt, ease, or distort hiring and the labor market more broadly is not yet known. We can only speculate as to what might happen if the interview process were to shift to being less "engaging" and more algorithmic. If this transition robs workers of these valuable signals of match quality, we may anticipate the labor market to become more inefficient—with heightened mismatch, reduced job satisfaction, and faster turnover. However, if it enables firms to better target candidates who would not find their interviews to be easy, or more acutely calibrate their interviews to match the expectations of job seekers who apply, the labor market may become more efficient through the same channels in reverse.

While the traditional interview process enables workers to better predict match quality, and sort accordingly, it also affords employers the opportunity to engage in discrimination, for instance, by sex (Mocanu, 2024) 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 will require balancing the potential loss in screening—for both workers and firms—with the potential gains from reducing bias and vacancy filling costs.

While our study is unique in its context, we believe it is quite broad in its scope. It is not just workers who do not want to form a match with a counterparty that would accept anyone. In higher education, high-ability students prefer courses that are more difficult and thought-provoking (Babad and Tayeb, 2003), reflecting a desire to learn more and avoid boredom (Martin *et al.*, 2008). In dating markets, individuals pursue partners more desirable than themselves (Bruch and Newman, 2018), and advances are requited less often when sent to someone who is more desirable (Bapna *et al.*, 2023). Although the motivations may differ across settings, the promise of a challenge appears to fuel engagement, not repel it. If interviewing truly is akin to courting, and workers do not want to be members of firms that want them, perhaps the future of hiring is not artificial intelligence, but a dating app.

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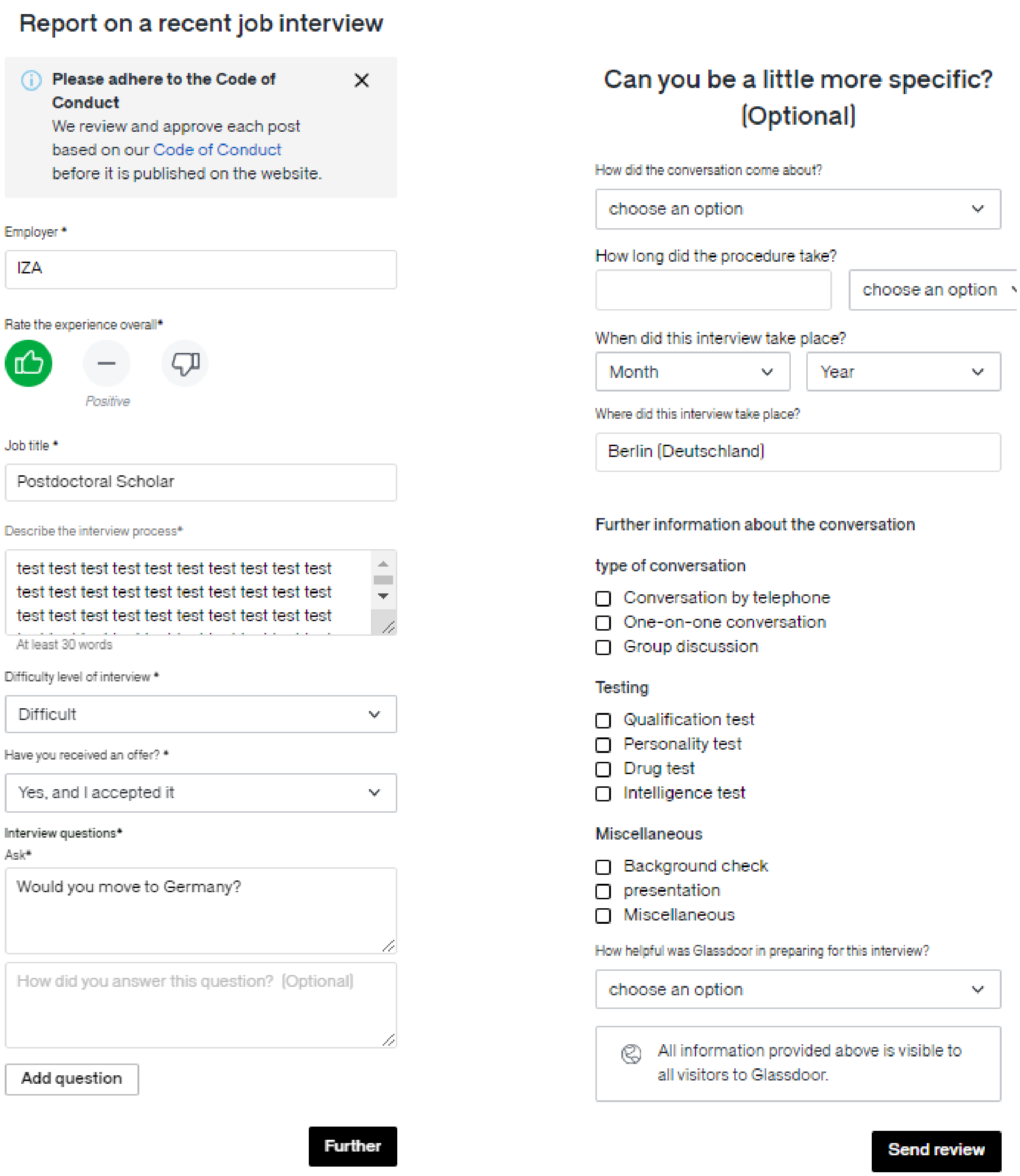
Appendix

Table of Contents

A Additional Summary Information

A.1 Glassdoor Interview Submission Process

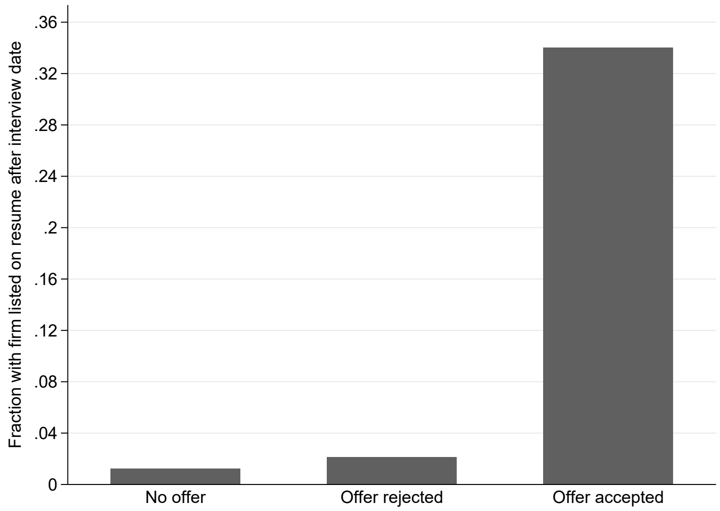
Figure A1: Screenshots of Interview Submission Form



Notes: Figure A1 provides a screenshot of the Glassdoor interview submission form from March 12, 2024. The left-hand panel is the first page where workers provide required information, and the right-hand panel is the second page where workers provide optional aspects.

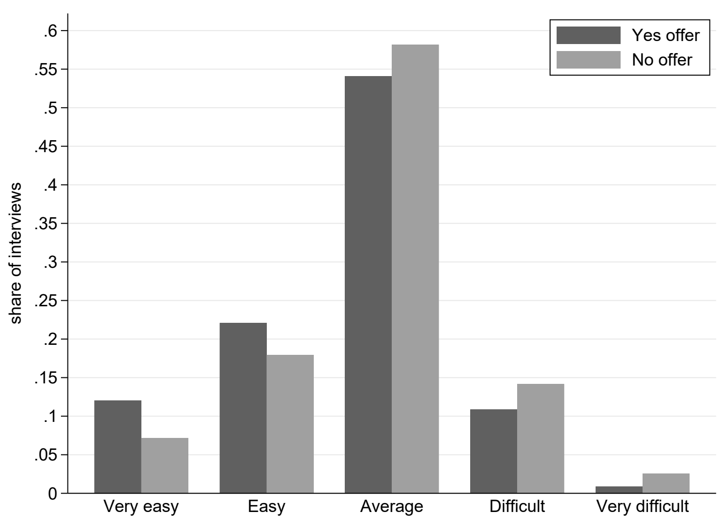
A.2 Figures Summarizing Glassdoor Interview Reports

Figure A2: Fraction of Workers for Whom Firm is on Resume by Reported Offer Status



Notes: Figure A2 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 A3: Sample Distribution of Perceived 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.

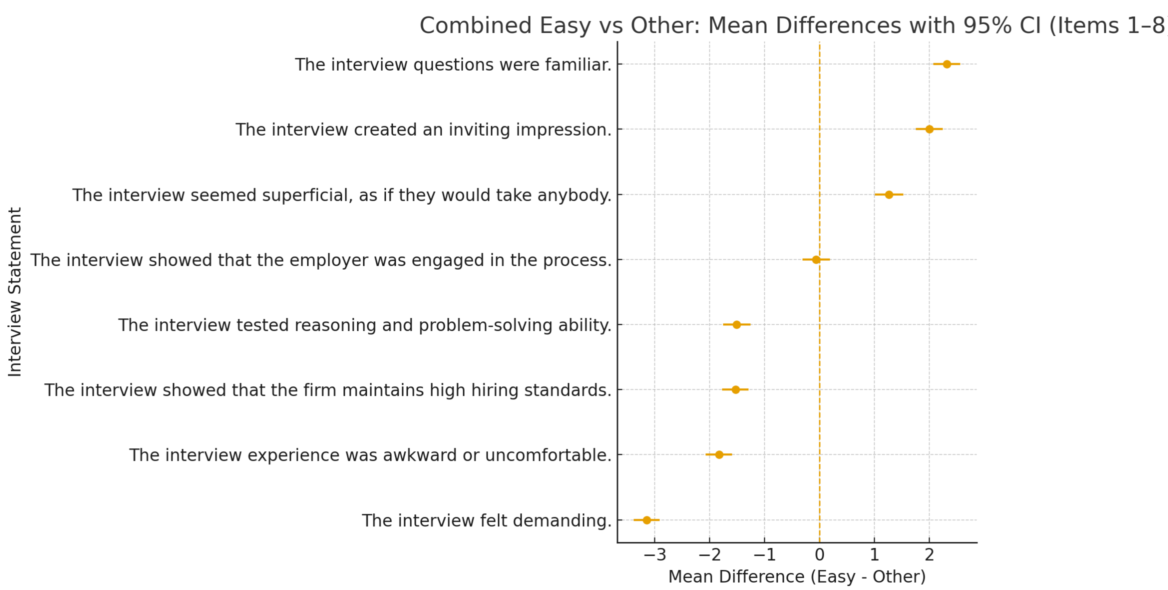
Figure A4: Words Associated with "Easy" or "Difficult" in Interview Descriptions

(a) "Easy" interviews

(b) "Difficult" Interviews

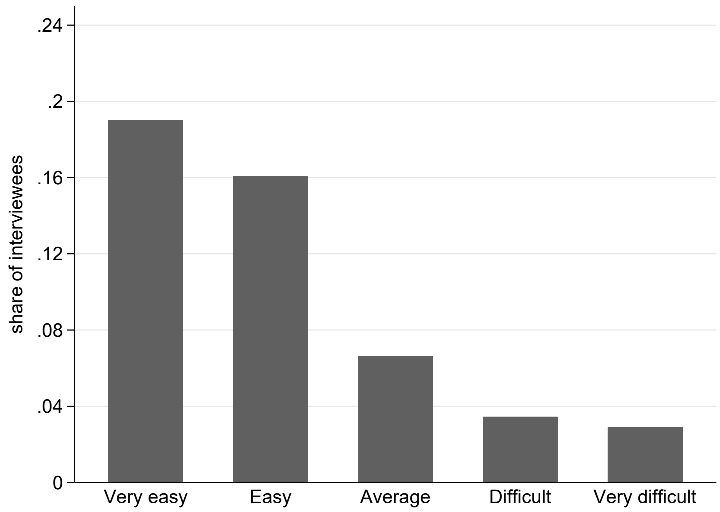
Notes: Figure A4 shows the top words in interview narratives by perceived difficulty. Panel (a) shows the words for "easy" and "very easy", while panel (b) shows the words for "difficult" and "very difficult". To make this graph, we started with interview descriptions for high-wage occupations, excluding internships. We sampled 50,000 narratives for the two categories: "easy" and "very easy" vs. "difficult" and "very difficult." The texts were tokenized into lists of nouns, verbs, and adjectives, all in lowercase. Word counts were then computed, and the vocabulary filtered to remove words appearing in fewer than 1 in 1,000 documents. Finally, word associations were calculated by the smoothed odds ratio for each category (easy vs. difficult). Each panel shows the top 100 words, with larger and darker words reflecting higher odds ratios.

Figure A5: What does an "Easy" Interview Imply? Crowd-Sourced Evidence



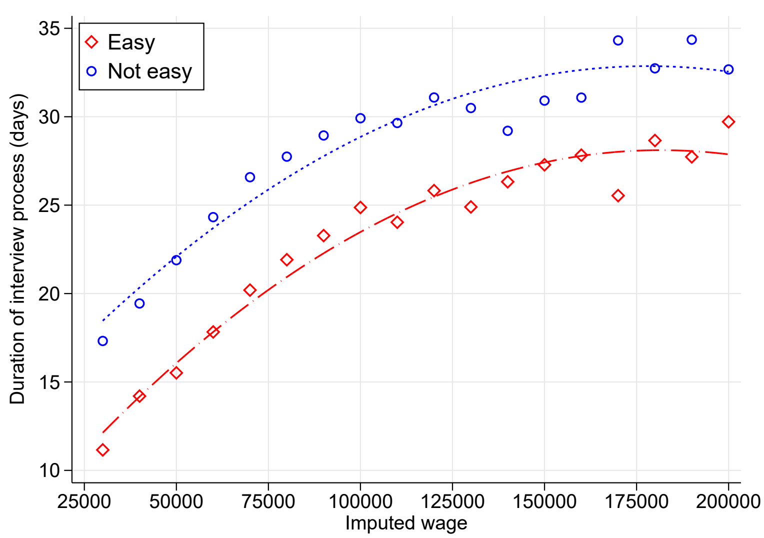
Notes: Figure A5 shows the difference in survey ratings of vignettes about job candidates along the eight associated dimensions (vertical axis labels). The difference is between vignettes describing the interview as "easy" or "very easy" versus vignettes describing the interview as "average," "difficult," or "very difficult." The horizontal scale goes from "associated with not-easy" (left) to "associated with easy" (right). To make this graph, we surveyed 200 college graduates on Prolific. They rated two vignettes (randomly ordered), one "easy" (75%) or "very easy" (25%), and another "average" (30%), "difficult" (60%), or "very difficult" (10%). For each vignette, they rated each of the eight dimensions (in random order) from zero to five. We then compute the within-subject difference and plot the mean and 95% confidence intervals across participants.

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



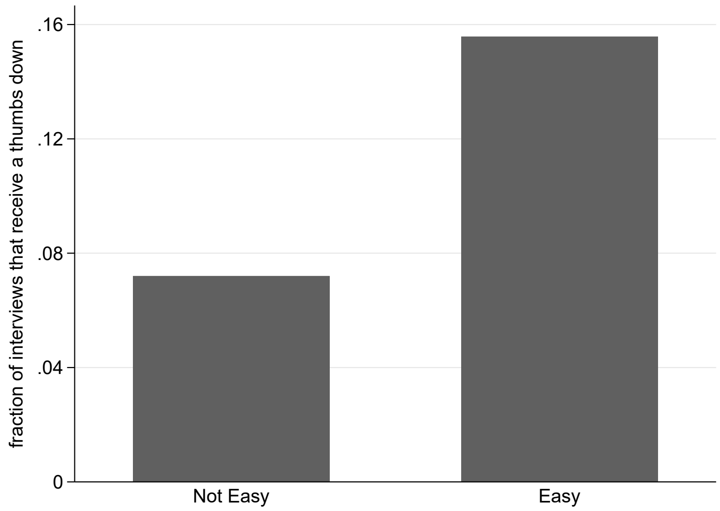
Notes: Figure A6 plots the share of interviews for each difficulty level (rated on a 1-5 scale: 1-very easy, 2-easy, 3-average, 4-difficult, 5-very difficult) that mentioned the word "easy" in the free-response description workers provided about the interview.

Figure A7: Interview Difficulty and Duration of the Entire Interview Process



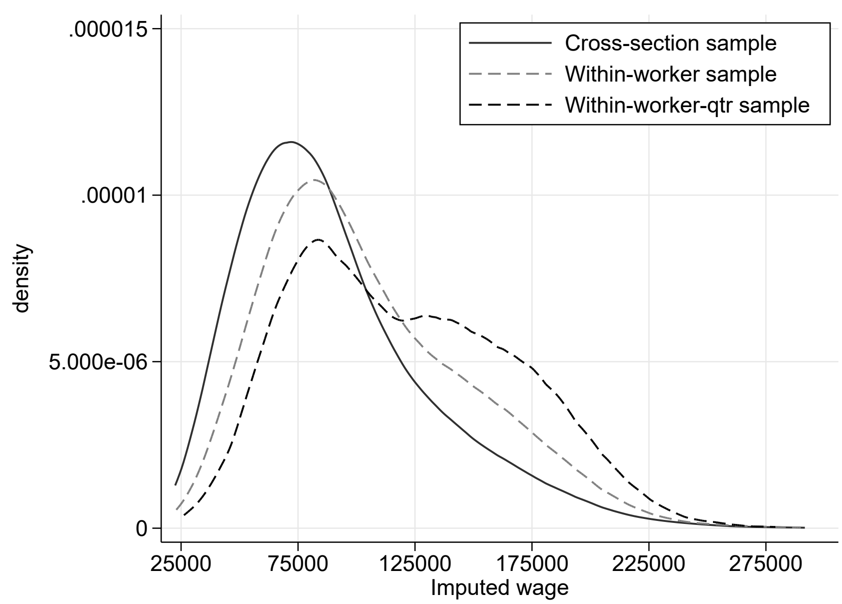
Notes: Figure A7 presents a binscatter of the average length of the interview process (in days) against the estimated wage of the vacancy, with each series indicating the self-reported difficulty rating as easy ("very easy" or "easy") and not easy ("average," "difficult," or "very difficult").

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



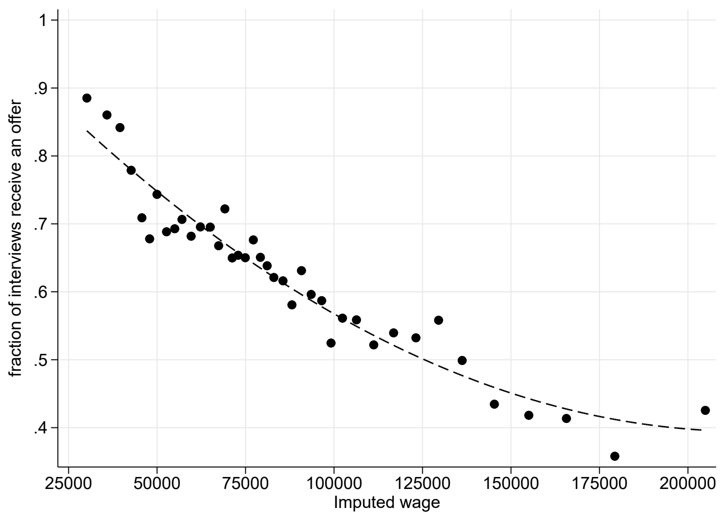
Notes: Figure A8 plots the share of interviews for each difficulty level (rated on a 1-5 scale: 1-very easy, 2-easy, 3-average, 4-difficult, 5-very difficult) that were characterized as negative experiences.

Figure A9: Distribution of Samples in Table 1 by Wage of Vacancy



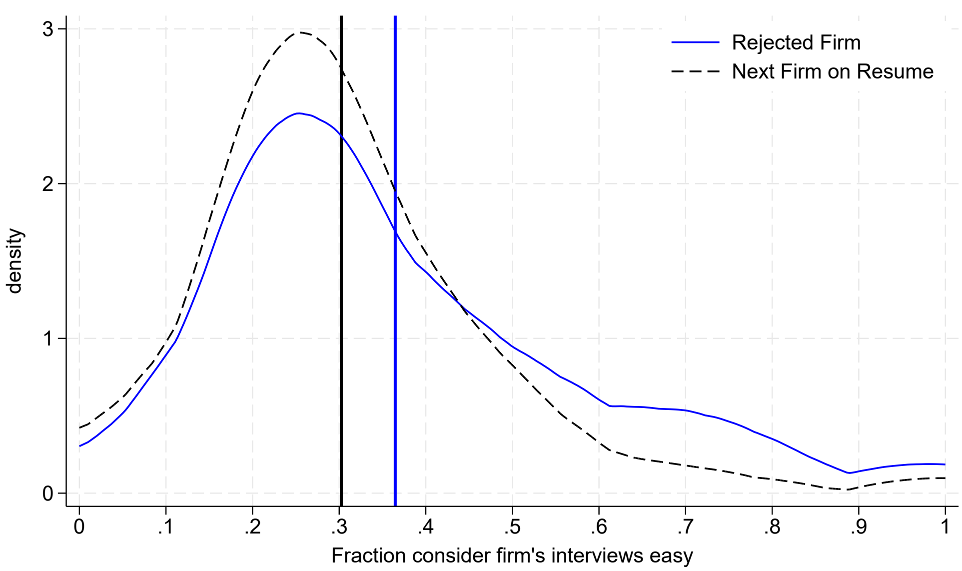
Notes: Figure A9 plots the distribution for the cross-section sample of job offers (solid line), the within-worker sample of job offers (dashed line), and the within-worker-quarter sample of job offers (dash-dot line) by the imputed wage of the vacancy.

Figure A10: Offer Rate by Imputed Wage of the Vacancy



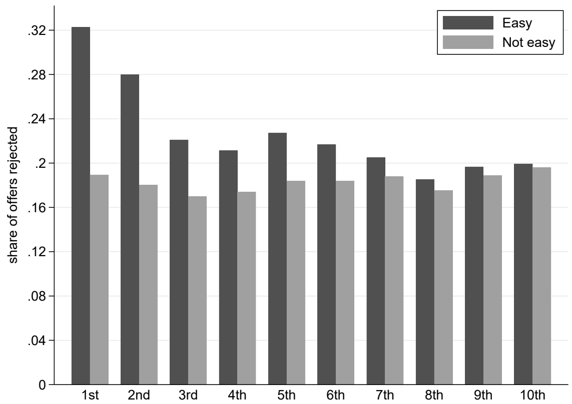
Notes: Figure A10 is a binscatter of the fraction of Glassdoor interviews that led to an offer by the imputed wage of the vacancy. Imputed wage reflects the average pay among Glassdoor pay reports for the given firm and job title. Wages are inflation-adjusted to 2021 dollars. Sample is restricted to firm-job title pairs with at least five interviews.

Figure A11: Comparison of Average Firm Interview Difficulty between Firms Whose Offers Were Rejected and the Next Firm on that Worker's Resume

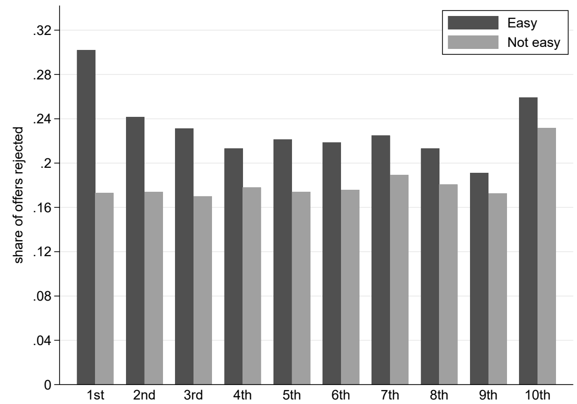


Notes: Figure A11 plots the distribution, among rejected offers (solid blue line) and the next firm that appears on the resume after an offer was rejected (dashed black line), of the fraction of the firm's interviews that were perceived as easy. Vertical lines indicate the mean of each distribution. Sample is restricted to firms that appear on resumes within six months of the rejected offer. There are 1,900 workers for whom we observe a rejected offer and a next firm on their resume.

Figure A12: Raw Rejection Rate by Perceived Difficulty and Firm Familiarity



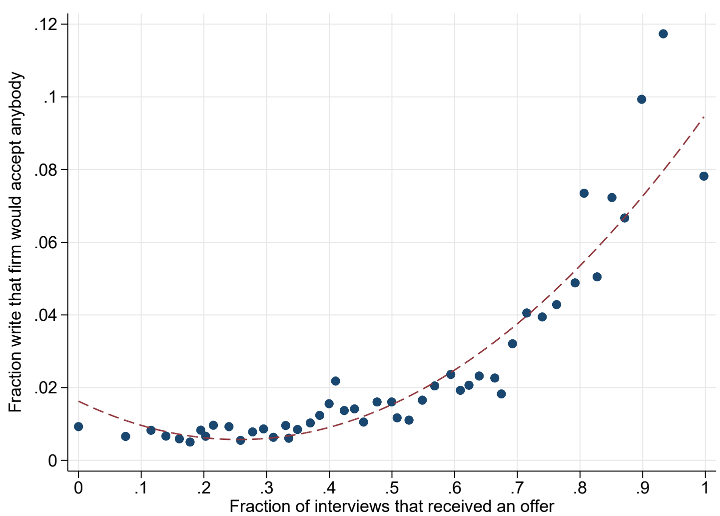
(a) Firm size



(b) Google trends

Notes: Figure A12 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 (panel a) or how frequently the employer is searched on Google using data from Google Trends (panel b). Firms are partitioned into deciles in ascending order. 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. Dashed blue line indicates a quadratic fit through the coefficients. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Figure A13: Actual Offer Rate and Interview-Based Perceptions of Accepting Anyone



Notes: Figure A13 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.

A.3 Tables Summarizing Glassdoor Interview Reports

Table A1: 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 A1 details the sample construction process and the observations dropped with each step.

Table A2: 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 difficulty 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
Panel C. Large language model labels				
1(High-ability colleagues)	507,522	0.027	0.000	0.162
1(Pleasant colleagues)	507,522	0.211	0.000	0.408
1(Would accept anybody)	507,522	0.042	0.000	0.201
1(Direct assessment)	507,522	0.217	0.000	0.412
1(Mentioned compensation)	507,522	0.056	0.000	0.230
1(Mentioned hours)	507,522	0.021	0.000	0.142
1(Mentioned desirable workplace amenities)	507,522	0.002	0.000	0.048
1(Engaging experience)	507,522	0.264	0.000	0.441
1(Realistic job preview)	507,522	0.296	0.000	0.457

Notes: Table A2 offers the mean, median, and standard deviation for each measure studied in our sample. Panel A pertains to aspects of the interview, Panel B covers worker demographics, and Panel C summarizes LLM-derived impressions of the interview narrative.

Table A3: 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 A3 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 A4: Firms with the Least Difficult Interviews

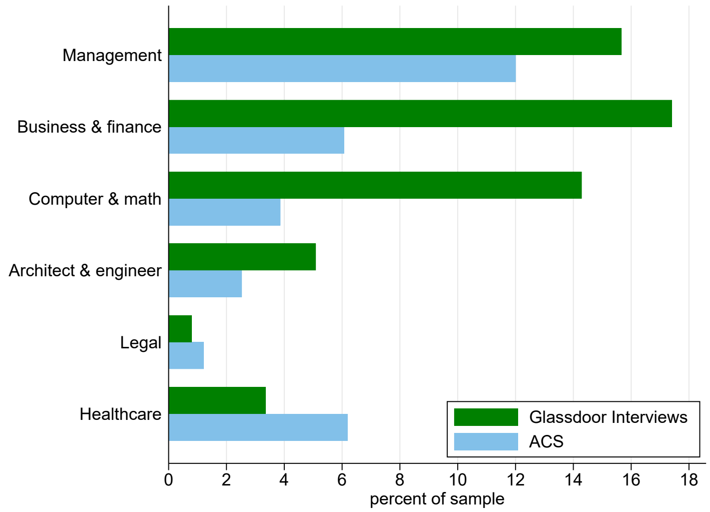
Ranking	Firm	Industry
1,149	Taco Bell	Restaurants & Food Service
1,150	Pizza Hut	Restaurants & Food Service
1,151	Advantage Solutions	Media & Communication
1,152	Dollar General	Retail & Wholesale
1,153	Jackson Hewitt	Retail & Wholesale
1,154	Aaron's	Retail & Wholesale
1,155	CROSSMARK	Retail & Wholesale
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 A4 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.

B Testing for Selection into Glassdoor Interviews

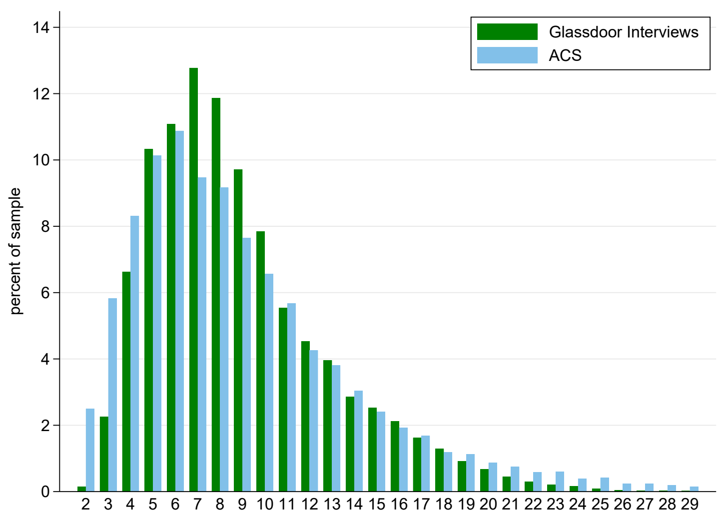
B.1 Glassdoor Comparison with the American Community Survey

Figure B1: Distribution of Glassdoor Interviews Database by Two-Digit Industry



Notes: Figure B1 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.

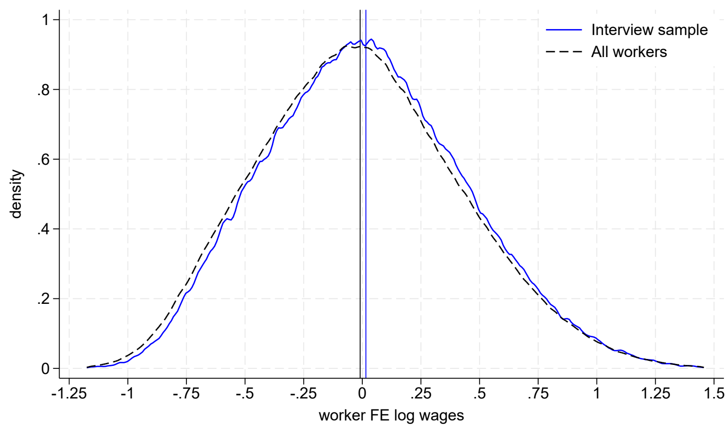
Figure B2: Distribution of Interviews Sample by Imputed Wage of the Vacancy



Notes: Figure B2 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.

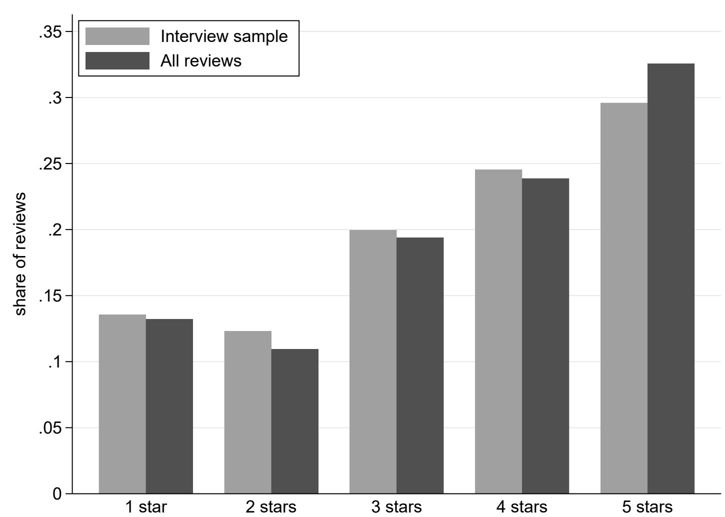
B.2 Glassdoor Interview Sample Comparison with Entire Glassdoor Database

Figure B3: Distribution of Worker AKM Fixed Effects from Accepted Offers Sample Compared with the Full Sample of Glassdoor Pay Reports



Notes: Figure B3 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 B4: Distribution of Job Satisfaction Ratings in Interviews Sample Compared with the Full Sample of Glassdoor Reviews



Notes: Figure B4 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.

B.3 Glassdoor Interview Sample Comparison with Onsites.fyi 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, however, 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-response 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 specifically for jobs 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 $\times$ job title we observe in Onsites. We then calculate the average difficulty level among Glassdoor interviews for the same firm $\times$ job title, and compare. The relationship between the two, summarized in Appendix Table B1, is reaffirming.

Greater interview difficulty on Glassdoor aligns with greater difficulty on Onsites. There are 117 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 0.53 additional levels of difficulty in Onsites. Excluding firm $\times$ 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 latent variation in interview difficulty.

Table B1: Average Interview Difficulty in Glassdoor and Onsites

	Mean interview difficulty on Onsites.fyi	
Mean interview difficulty on Glassdoor	0.529**	1.098***
	(0.234)	(0.248)
Firm-job title pairs	117	56
Onsites.fyi interviews	488	427
Weighted by Onsites.fyi count	✓	
Onsites.fyi count > 1		✓

Notes: Table B1 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%.

C Interviews for Internships

In this appendix section, we focus on a subset 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 Appendix Table C1. 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 percentage points decline in the probability the offer is accepted. Even when we compare interview reports for the same role, i.e., job title × firm × metro area, easy interviews are more often rejected (Column 3). Although the sample is particularly thin, we observe a marginally significant decline for easy interviews even for the same worker who chose between multiple internship offers (Column 4). Thus, for internships as well, interview difficulty is an important signal of match quality.

Table C1: 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
N	21,956	4,972	4,972	455
Industry-Occupation FE	✓	✓		
Firm-Job title-Metro FE			✓	
Worker FE				✓

Notes: Table C1 summarizes 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%.

D 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?

The frequency of overlap between the LLM and annotators for each prompt is presented in Appendix Table D1.

Table D1: 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 D1 lists, for each annotation, the fraction of overlap between the two annotators and between the LLM and the two annotators.

E Additional Heterogeneity Tests for Rejecting Easy Interviews

In this appendix, we explore heterogeneity by re-estimating Equation (1) for various subsamples of the interviews sample.

We first recognize Glassdoor skews toward young, college-educated workers in high-paying industries (Liu *et al.*, 2022). To show sample composition does not drive our results, we calculate representative weights from the American Community Survey (ACS) to match U.S. employment by industry, occupation, sex, metropolitan area, and pay. Even after reweighting, the coefficient is 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. Respondents also need not disclose the date when the interview occurred. Such interview reports comprise about two-fifths of the sample. For the main analysis, we impute a date based on the disclosure date. Considering only such interview reports produces an estimate similar to 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 E1, 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 a more meaningful signal for workers early in their careers.

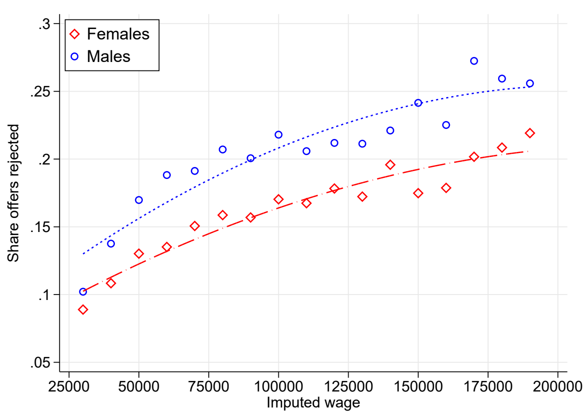
Turning to educational background, we consider workers with different majors, universities, grades, and degrees. Workers with STEM degrees as well as those with non-STEM degrees exhibit comparable negative responses to easy interviews. Though the coefficient is negative for both, graduates from universities with above-average college graduate quality, as defined in Martellini *et al.* (2024), exhibit a slightly larger decrease in offer acceptance 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. We also consider only workers with a post-Bachelor's degree and again find a sharp negative response to easy interviews.

We next consider heterogeneity by job search activity. 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 between jobs, both increasingly reject easy interviews. We determine whether a worker is searching on-the-job or off-the-job by examining whether the interview occurred during a job spell, or between two job spells, on their resume. Whether the job would likely constitute above-average or below-average pay growth, based on the most recent firm × job title on the worker's resume, acceptance rates are lower after easy interviews for both—though the wedge is considerably wider for the former. Last, we recognize workers may direct their search only toward firms with comparable interview difficulty; for such workers as well, where an ex ante ranking of candidate firms is more opaque, interviews perceived as easy are rejected more often.

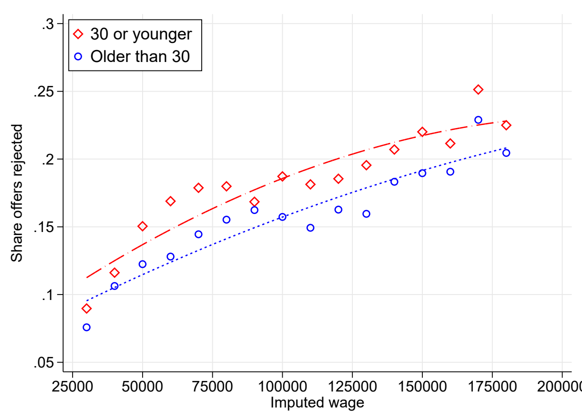
We also consider whether we observe the same pattern across interviews of varying characteristics. To identify each of the following aspects, we look whether they are explicitly mentioned in the free-response descriptions respondents provide in their reports. When the interview involves human resources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

For each sub-sample, the estimated coefficient and its 95 percent confidence interval are plotted in Appendix Figure E2.

Figure E1: Probability of Rejecting an Offer by Wage and Worker Demographics



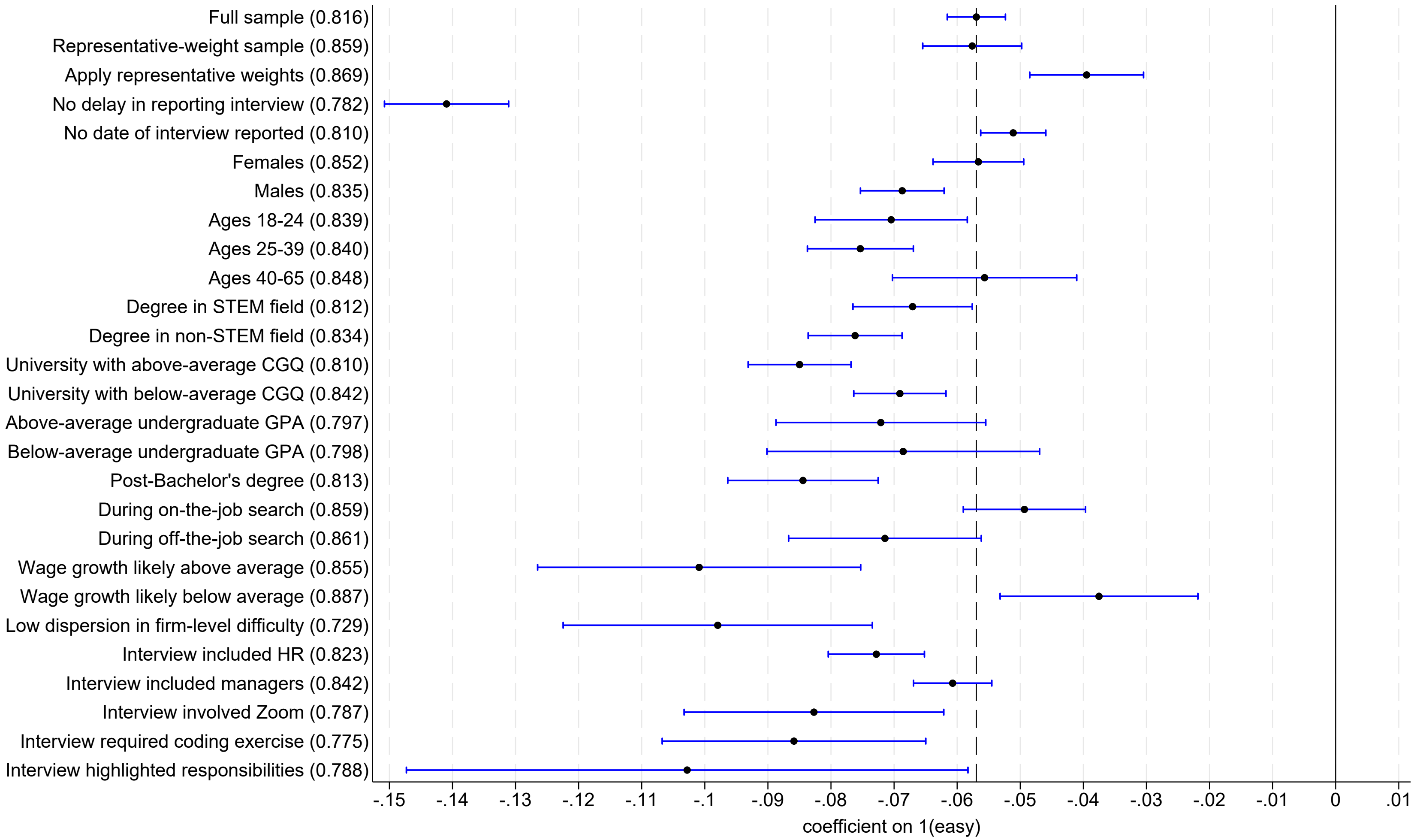
(a) By gender



(b) By age

Notes: Figure E1 depicts the share of rejected job offers plotted against the imputed wage of the vacancy. The sample is disaggregated by gender in panel (a) and age in panel (b). Each marker represents a $10,000 bin with at least 250 observations.

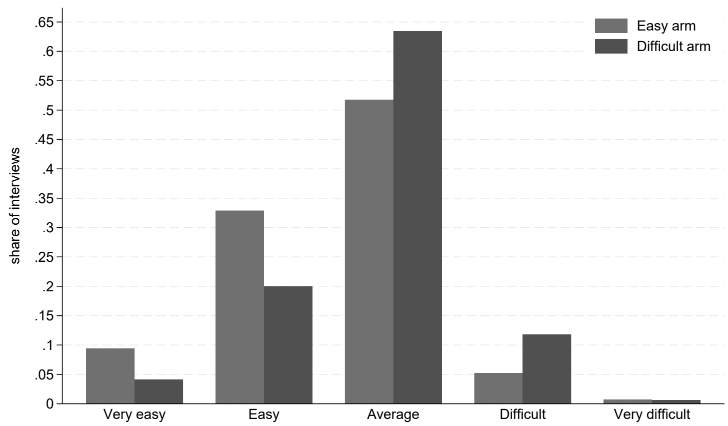
Figure E2: Interview Difficulty and Offer Acceptance for Different Sub-Samples



Notes: Figure E2 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 metro-quarter, 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.

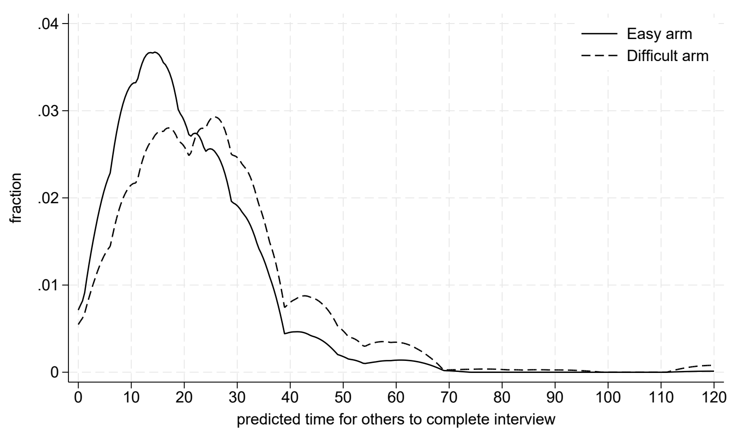
F Additional Information and Results from the Experiment

Figure F1: Experimentally Induced Difficulty and Interview Perceptions



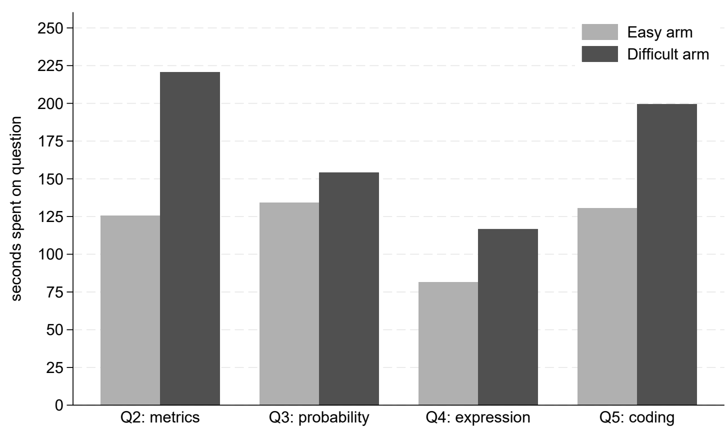
Notes: Figure F1 displays the fraction of applicants that reported each level of perceived difficulty by treatment arm. For a full characterization of the interview process for each treatment arm, see Appendix Table F1.

Figure F2: Predicted Time Needed to Complete Interview by Treatment Arm



Notes: Figure F2 shows the distribution of candidates' estimates (in minutes) of how long other applicants would need to complete the interview, by treatment arm. Two responses above 120 minutes were top-coded.

Figure F3: Seconds Spent Answering Each Free-Response Technical Question



Notes: Figure F3 shows the average number of seconds candidates spent per question by treatment arm. Since each question had a 10 minute time limit, the maximum number of seconds per question was 600.

Table F1: 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 F1 outlines the experiment and its two treatment arms.

Table F2: Summary Statistics for Interview Experiment

Measure	N	Mean	Median	Standard deviation	5th percentile	95th percentile
Start day	1,325	20.16	21.00	4.47	7.00	25.00
Duration (in seconds)	1,325	4149.00	1212.00	15335.00	337.00	11610.00
Post-Bachelor's degree	1,325	0.81	1.00	0.40	0.00	1.00
1(0-2 years experience)	1,325	0.32	0.00	0.47	0.00	1.00
1(2-4 years experience)	1,325	0.30	0.00	0.46	0.00	1.00
1(4-6 years experience)	1,325	0.20	0.00	0.40	0.00	1.00
1(6+ years experience)	1,325	0.19	0.00	0.39	0.00	1.00
1(Assigned easy arm)	1,325	0.52	1.00	0.50	0.00	1.00
Seconds to answer question 2	1,325	169.20	127.50	141.10	14.23	493.00
Seconds to answer question 3	1,325	142.00	92.49	132.50	6.16	435.30
Seconds to answer question 4	1,325	98.31	60.15	107.40	3.60	336.30
Seconds to answer question 5	1,325	160.10	109.10	152.40	5.26	502.10
Length of 'Why good fit?'	1,325	651.40	575.00	437.80	35.00	1541.00
Length of 'Questions for us?'	1,325	83.00	3.00	137.00	0.00	342.00
Number of application queries	1,325	0.29	0.00	1.33	0.00	2.00
Predicted completion time	1,325	22.61	20.00	15.05	5.00	45.00
1(Easy interview)	1,325	0.34	0.00	0.47	0.00	1.00
1(More interested in vacancy)	1,325	0.73	1.00	0.45	0.00	1.00

Notes: Table F2 shows summary statistics for key variables from the experiment.

G Implications of Interview Difficulty for Firm Growth?

In this appendix, we investigate whether firms differ in their growth rates by the difficulty of their interviews. 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 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 A3 and A4), and the sample is restricted to 2012-2016. Second, we ask whether this measure of early firm-level interview difficulty has predictive power for longer-run wages, i.e., the last five years of our sample 2020-2024. The estimating equation follows

$$\ln(\text{wage})_{i,k,t} = \psi \hat{D}_k \mathbb{1}_{\{2020 \leq t \leq 2024\}} + \lambda_i + \lambda_k + \mathbf{X}'_{i,k,t}\gamma + \epsilon_{i,k,t}. \tag{A1}$$

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 in the early sample period, by the relative difficulty of firm k's interviews in the early sample period. Put differently, equation (A1) is an AKM model that allows the firm's pay premium to drift over time with the firm's past interview difficulty. The results are presented in Appendix Table G1.

The results suggest interview difficulty is not inconsequential for firm growth. Firms with one standard deviation more difficult interviews 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 A3 and A4—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, and residualize difficulty by industry and firm age, this difficult-interview premium cannot be rationalized by sector-specific trends or 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, perhaps through improved job satisfaction (Sockin, 2022; Bellet *et al.*, 2024), or efficiency gains from the reduction in turnover and loss of firm-specific human capital, or the innovation and patenting that high-ability workers generate (Martellini *et al.*, 2024). Or, it may be that the firms that implement difficult interviews are the ones already on high-growth trajectories. While we do not attempt to disentangle these channels here, we hope future researchers will.

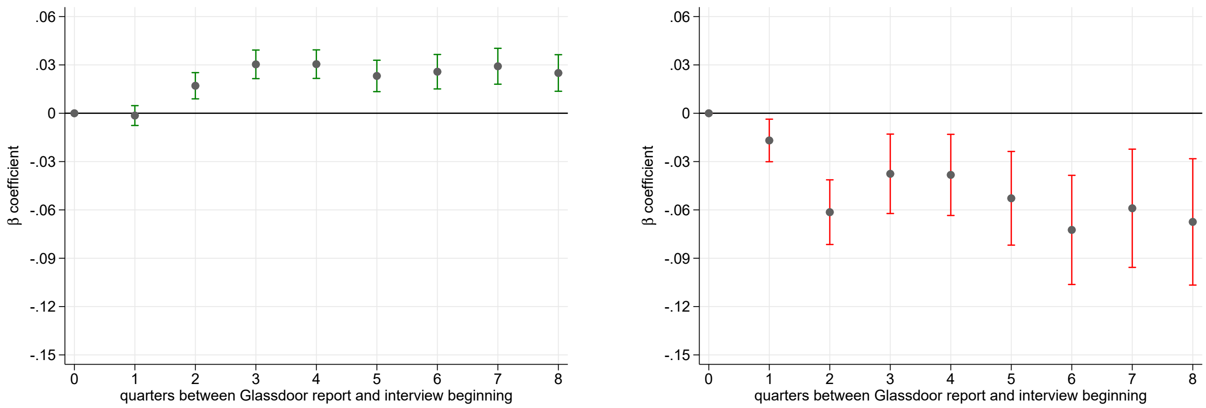
Table G1: Past Interview Difficulty and Future Pay Growth

	Ln(Total pay)			
	All firms		Firms founded from 2002-11	
	(1)	(2)	(3)	(4)
Firm's relative interview difficulty 2012-16 x 1(Pay in 2020-24)	0.008***	0.007***	0.012***	0.011***
	(0.001)	(0.001)	(0.004)	(0.003)
N	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 G1 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%.

H Sensitivity Exercises

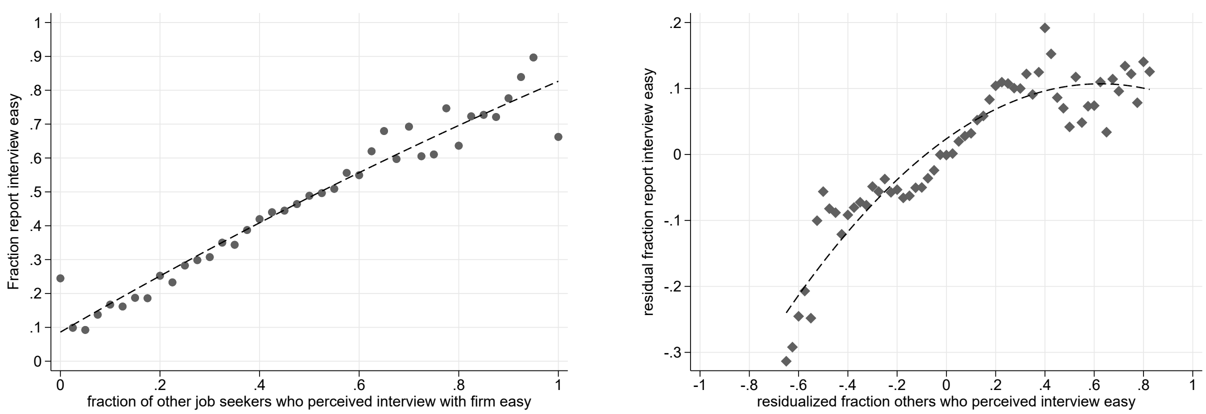
Figure H1: Difference in Perceptions of Interview Difficulty by Time Since Interview



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

Notes: Figure H1 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.

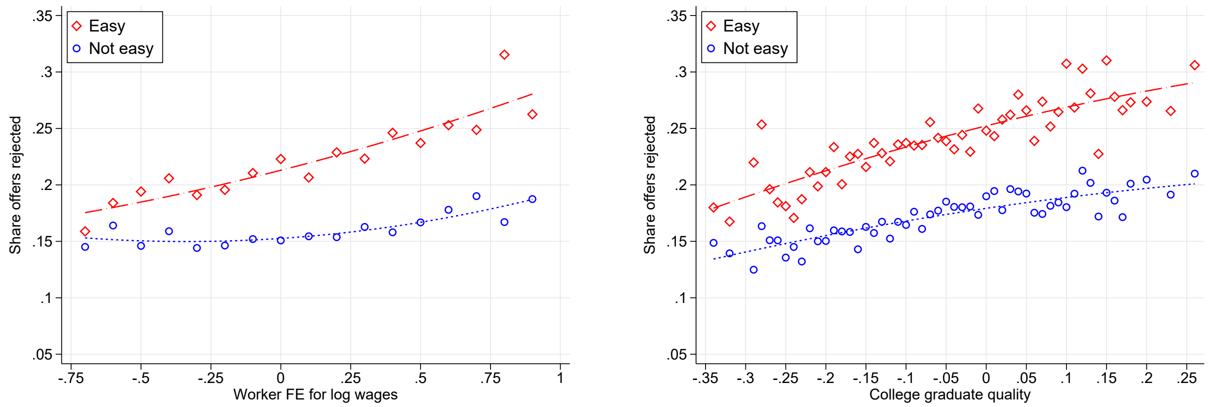
Figure H2: Perceived Interview Difficulty and the Perceptions of Other Job Seekers



(a) Unresidualized **(b)** Residualized

Notes: Figure H2 relates the perceived difficulty of others who interviewed for the same firm and one's own perceived difficulty. Panel (a) does not residualize, whereas in panel (b), both measures are residualized by the same fixed effects as in Column (2) of Table 1: industry x 20 five-percentile bins of firm age x 20 five-percentile bins of firm AKM pay premium, metro-quarter, industry-occupation, and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Each dot represents a 0.025-rounded bin with at least 25 observations. Dashed line represents a quadratic line of best fit.

Figure H3: Probability of Rejecting a Job Offer by Interview Difficulty and Alternative Measures of Worker Productivity

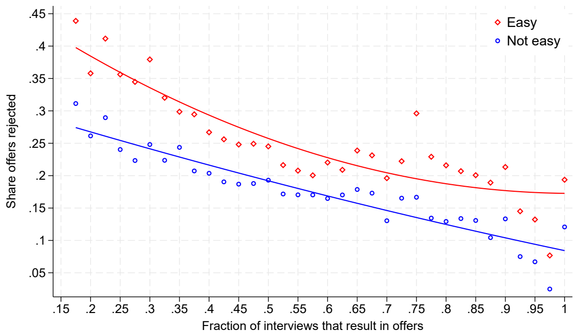


(a) Worker AKM FE

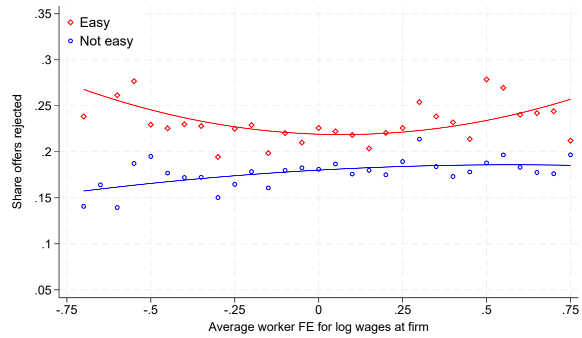
(b) College graduate quality

Notes: Figure H3 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 worker's university. College graduate quality (CGQ), a measure of the average human capital of a university's graduates, is from Martellini *et al.* (2024).

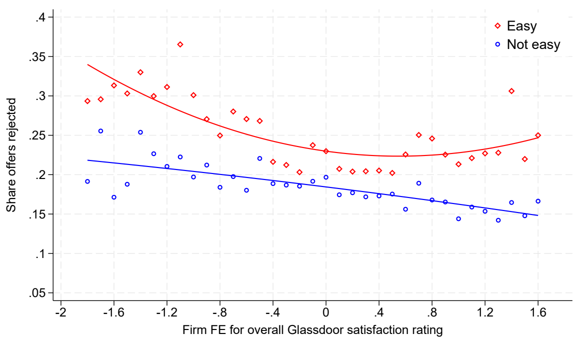
Figure H4: Probability of Offer Rejection by Interview Difficulty and Firm Desirability



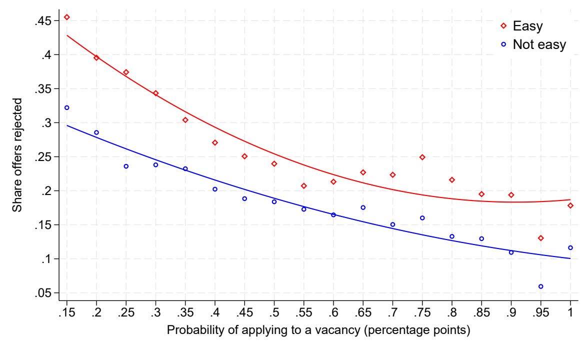
(a) Interview offer rate



(b) Median worker AKM FE



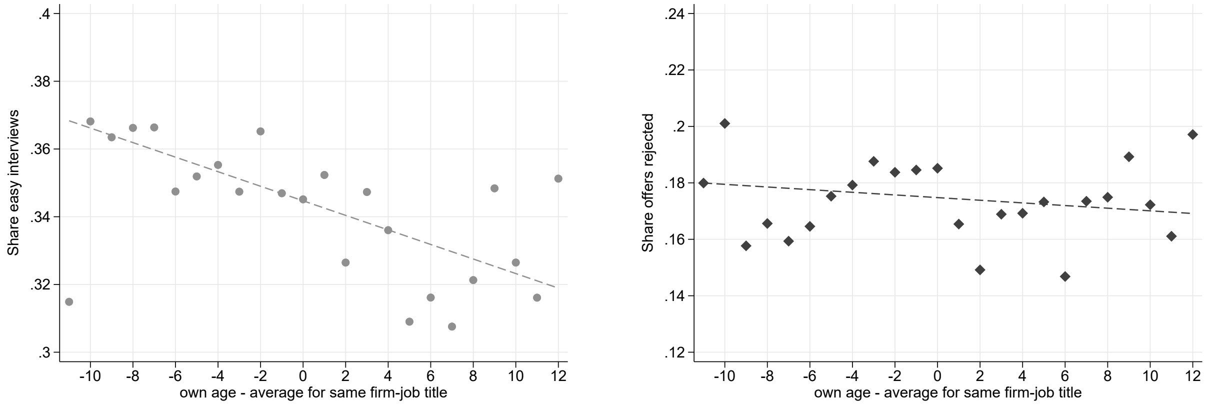
(c) Firm FE Glassdoor overall ratings



(d) Probability of applying

Notes: Figure H4 reflects a binscatter for the fraction of offers rejected, based on the worker's perception of interview difficulty and (a) the fraction of interviews for the firm that resulted in an offer, (b) the median worker fixed effect (from an AKM model of log wages) for the firm with which the worker is interviewing, (c) the firm fixed effect from an AKM model of Glassdoor overall ratings of job satisfaction, and (d) the probability of applying to a vacancy (firm x job title) conditional on being presented with the vacancy in search results. For further description and application of the data used in Panel (d), see Sockin and Sockin (2025). In each panel, each scatter point represents at least 250 interviews.

Figure H5: Relative Age as a Proxy for Under- or Over-Qualified

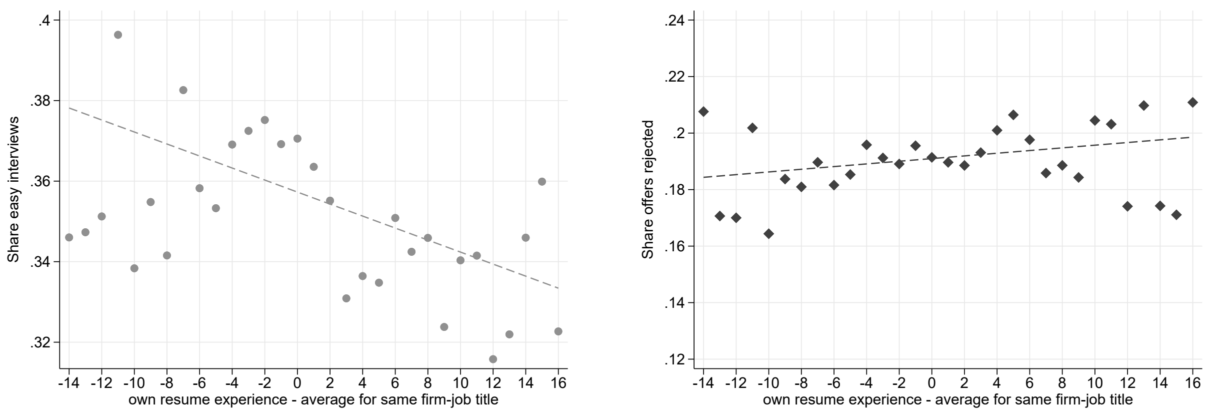


(a) Fraction easy interviews

(b) Fraction offers rejected

Notes: Figure H5 reflects the fraction of easy interviews (panel a) and offers rejected (panel b) by the age of the worker relative to all others who received offers for the same firm and job title. Each dot is a one-year bin with at least 250 interviews. Lines of best fit are weighted by sample count in each bin. The weighted correlations are –0.642 (p-value = 0.001) for panel (a) and –0.175 (p-value = 0.413) for panel (b).

Figure H6: Relative Experience on Resume as a Proxy for Under- or Over-Qualified



(a) Fraction easy interviews

(b) Fraction offers rejected

Notes: Figure H6 reflects the fraction of easy interviews (panel a) and offers rejected (panel b) by the years of prior experience on the worker's resume relative to all others who received offers for the same firm and job title. Each dot is a one-year bin with at least 250 interviews. Lines of best fit are weighted by sample count in each bin. The weighted correlations are –0.523 (p-value = 0.003) for panel (a) and 0.338 (p-value = 0.063) for panel (b).

Table H1: 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 H1 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 H2: 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 H2 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 H3: 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 H3 summarizes the relationship between a worker's actual wage from a Glassdoor pay report and the imputed wage 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 H4: Variation in Interview Difficulty Between Firms and Job Seekers

	1(Easy interview)				
Log length of interview duration	-0.088***	-0.055***	-0.064***	-0.045***	-0.033***
	(0.002)	(0.001)	(0.006)	(0.006)	(0.010)
N	280,451	280,451	7,339	7,339	7,339
R^2	0.053	0.219	0.090	0.381	0.799
Firm FE		✓		✓	✓
Job seeker FE					✓

Notes: Table H4 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 H5: 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 H5 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 H6: Alternative Sets of Other Interviewers' Perceived Difficulty and Offer Rejection

	1(Accepts job offer)				
	Leave-one-out firm	Leave-one-out firm-metro	Leave-one-out firm-occupation-year	1-year-lagged firm average	1-year-ahead firm average
	(1)	(2)	(3)	(4)	(5)
Fraction others' interviews easy	-0.050***	-0.030***	-0.028***	-0.021***	-0.024***
	(0.006)	(0.004)	(0.005)	(0.004)	(0.004)
R^2	0.08	0.08	0.08	0.09	0.09
Mean DV for not easy	0.818	0.818	0.805	0.815	0.820
N	421,112	376,458	366,426	350,224	338,619
Firm Observables	✓	✓	✓	✓	✓

Notes: Table H6 summarizes the relation between the probability an offer is accepted and the workers' perceived difficulty level of the interview for five different sets of other job seekers. Each instrument is listed in the header of each column. Firm observables refer to industry x 20 five-percentile bins of firm age x 20 five-percentile bins of firm AKM pay premium. Each specification includes metro-quarter, 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 H7: Probability of Accepting a Job Offer by Wage of Vacancy

	1(Accepts job offer)
Imputed log wage	0.425***
	(0.111)
Observations	1,839
Workers	867
R^2	0.67
Worker-Qtr FE	✓

Notes: Table H7 summarizes the relation between the probability an offer is accepted and the imputed log wage of the vacancy. The specification includes metro-quarter, 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 H8: 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 H8 relates the difficulty of the interview to the total pay the worker reports receiving. Sample is restricted to workers who 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 H9: 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	0.093	0.126	0.104
N	35,122	7,801	1,765
Firm-job title FE		✓	
Worker FE			✓

Notes: Table H9 summarizes 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 H10: Probability of Accepting a Job Offer by Perception of Interview Difficulty for Referrals and Foreign Graduates

	1(Accepts job offer)		
	Full sample	Employee referral	Attended foreign university
1(Easy interview)	-0.057***	-0.024***	-0.110***
	(0.002)	(0.004)	(0.009)
Mean DV for not easy	0.816	0.897	0.815
N	500,258	50,433	15,468

Notes: Table H10 summarizes the relation between the probability an offer is accepted and perceived difficulty of the interview for referrals and workers who attended university outside the United States. Each specification includes metro-quarter, 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 H11: Skills or Qualifications Assessment, Beliefs About Peers, and Offer Acceptance

	1(Easy)		1(High-ability colleagues)		1(Accepts job offer)	
1(Direct assessment)	-0.100***	-0.168***	0.013***	0.028***	0.015***	0.030**
	(0.003)	(0.014)	(0.001)	(0.007)	(0.002)	(0.015)
Mean DV with no assessment	0.376	0.402	0.025	0.029	0.810	0.714
N	271,241	14,187	271,241	14,187	271,241	14,187
Workers	264,688	6,604	264,688	6,604	264,688	6,604
Firm FE	✓		✓		✓	
Worker FE		✓		✓		✓

Notes: Table H11 summarizes the relation between the worker mentioning their skills or qualifications were directly assessed and perceived difficulty, perceived high-ability colleagues, and whether the job offer was accepted. Each specification includes metro, industry-occupation, and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects, and additional text covariates produced by the LLM, including indicators for aspects the interview process illuminated: compensation, hours or scheduling, and 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 H12: 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***	0.062***	-0.051***	0.010***	0.027***	0.023***
	(0.019)	(0.007)	(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	11.456	0.324	0.038	0.030	0.703
N	11,918	10,566	21,380	21,380	21,380	21,380
Workers	5,555	5,009	10,016	10,016	10,016	10,016
Worker FE	✓	✓	✓	✓	✓	✓

Notes: Table H12 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 H13: Beliefs about Peers and Actual Worker Ability of Managers and Non-Managers, Fixed Effects Model

	1(High-ability colleagues)		1(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 H13 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 H14: Beliefs about Peers and Actual Worker Ability, Fixed Effects Model

	1(High-ability colleagues)		1(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 H14 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 H15: 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 H15 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 aspects the interview process illuminated: compensation, hours or scheduling, and 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 H16: Probability of Accepting a Job Offer and Likely Wage of Future Jobs

	1(Accepts job offer)			
	(1)	(2)	(3)	(4)
1(Easy interview)	-0.034***	-0.033***	-0.043***	-0.038***
	(0.005)	(0.006)	(0.004)	(0.004)
1(Easy interview) x 1(Any of next three likely jobs high wage)		-0.029***		-0.045***
		(0.011)		(0.010)
1(Any of next three jobs likely high wage)		-0.014		
		(0.011)		
Fraction any of next three likely jobs high wage	0.147	0.147	0.146	0.146
N	120,702	120,702	109,801	109,801
Adjusted R^2	0.05	0.05	0.11	0.11
Industry-occupation FE	✓	✓		
Firm-job title FE			✓	✓

Notes: Table H16 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 H17: 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 H17 summarizes the relation between one's own human capital, as proxied for by the average human capital at the university where the worker received 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 H18: 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)
Mean DV for not easy	0.825	0.825	0.850	0.850
N	239,624	239,624	129,331	129,331
Firm FE		✓		✓

Notes: Table H18 summarizes the relation between the probability an offer is accepted and the workers' perceived difficulty level of the interview process interacted with the current unemployment 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 H19: Probability of Accepting a Job Offer by Perception of Interview Difficulty for University Recruits and Workers With Prior Occupational Experience

	1(Accepts job offer)		
	Full sample	Recruited through university	Previous experience in occupation
1(Easy interview)	-0.057***	-0.055***	-0.072***
	(0.002)	(0.006)	(0.004)
Mean DV for not easy	0.816	0.812	0.828
N	500,258	36,771	74,287

Notes: Table H19 summarizes the relation between the probability an offer is accepted and perceived difficulty of the interview for university recruits and workers who have had a prior job, based on their resume, in the same occupation. Each specification includes metro-quarter, 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 H20: 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)	-0.144***		-0.081***	
	(0.025)		(0.011)	
Fraction others' interviews easy		-0.250***		-0.124***
		(0.067)		(0.031)
Mean DV for not easy	2.435	2.443	0.755	0.759
N	5,770	5,396	8,071	7,614

Notes: Table H20 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 specification includes metro, year-quarter in which the job began, industry-occupation, and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Sample is restricted to workers who join the firm within one year of the interview. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table H21: Tenure from Resumes After Offer Acceptance by Firm Position on Resume

	Logarithm of firm tenure				1(Firm tenure $\geq$ 12 months)			
	Number of jobs on resume after job with matched interview							
	0	1	2	3+	0	1	2	3+
1(Easy interview)	-0.208***	-0.191***	-0.246***	-0.239***	-0.073***	-0.087***	-0.122***	-0.109***
	(0.024)	(0.026)	(0.043)	(0.059)	(0.009)	(0.014)	(0.024)	(0.035)
Mean DV for not easy	2.162	2.484	2.468	2.455	0.849	0.630	0.608	0.586
N	6,150	5,388	2,227	1,260	11,118	5,652	2,326	1,316

Notes: Table H21 examines the relationship between interview experiences and the length of firm tenure for a job using workers' resumes. Each specification includes metro, year-quarter in which the job began, industry-occupation, and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Sample is restricted to workers who join the firm within one year of the interview. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table H22: 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)	-0.162***	-0.180***	-0.060***	-0.060**
	(0.026)	(0.059)	(0.012)	(0.026)
Worker FE log wages	0.161***		0.104***	
	(0.040)		(0.016)	
Worker FE interview difficulty		0.026		0.005
		(0.041)		(0.017)
Mean DV for not easy	2.580	2.495	0.790	0.750
N	4,931	1,791	7,194	2,489

Notes: Table H22 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 specification includes metro, year-quarter in which the job began, industry-occupation, and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Sample is restricted to workers who join the firm within one year of the interview. "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 whether 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%.

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