

The Labor Hub

Discussion Paper No. 3

EASY INTERVIEWS

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Easy Interviews*

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Abstract

Do interviews enable workers to learn about firms? Using data on a half-million interviews, we find candidates for professional jobs more often reject job offers when they believe the interview was easy. 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 interview difficulty elevated perceived difficulty and boosted engagement with the vacancy. Interviews appear to preview match quality for workers, highlighting a novel channel through which labor markets may become less efficient if firms automate hiring with AI.

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Keywords: Interviews, peer effects, job satisfaction, large language models

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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 or 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 a job offer is accepted?

The answer to this basic question remains elusive—likely not for lack of want, but rather lack of data. A good answer 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 turn down those offers. Neither administrative employment data from government agencies nor internal data on hiring from firms could directly address this question: The former lack offers that were rejected, while the latter lack workers’ impressions of the interview process. With the advent of online job boards, however, such data exist. Through Glassdoor, we access rich data on job interviews for many workers across vacancies for many firms, with detailed information on the interview process, whether an offer was received, and whether an offer was accepted.

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.

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

²In a survey of 2,366 HR professionals regarding 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 (Maurer, 2024).

Whether interviews offer workers a meaningful glimpse into the workplaces they may join, to the best of our knowledge, has not been empirically established. We fill this gap in the literature by studying half a million interview reports for jobs in highly-educated professions and establishing 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. 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. Based on the heterogeneity we observe and additional survey evidence, we interpret perceived difficulty as capturing both objective and subjective aspects of the interview process. Workers also 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. Further, when the same worker is choosing between multiple offers at the same time, they increasingly reject the firm whose interview they perceived to be easier. Consistent with workers learning about prospective 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—and comparatively small for workers who are referred to the firm, who likely already have insider information. Moreover, the effect is larger for jobs that require interpersonal skills, suggesting a role for workers updating their beliefs about peers at the hiring firm.

To better understand the information workers accrue through interviews, we turn to the free-response narratives workers write about the interview process, building on the growing use of text algorithms in economics (Gentzkow *et al.*, 2019; Ash and Hansen, 2023). We employ an LLM to annotate a number of relevant dimensions, including prospective colleagues being of high ability,³ the worker believing the firm “would hire anyone”, the interview experience having been engaging, and the interview offering a realistic job preview.⁴

After an easy interview, job seekers are less than half as likely to characterize the firm as employing high-ability colleagues and six times as likely to believe the firm would hire anyone. Indeed, workers who join after easy interviews seem disappointed by their peers:

³High-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).

⁴The 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.” See Wanous (1973) for an early discussion.

employer reviews following easy interviews are nearly 25 percent more likely to highlight peers as a drawback of the workplace—contributing in part to workers who join after an easy interview exhibiting two-fifths of a standard deviation lower job satisfaction and being 10 percent less likely to remain with the firm for at least one year. Workers are also less likely to consider an easy interview as engaging, which we interpret as indicating reduced interest in the vacancy. Consistent with concerns over peers acting as a driving mechanism, we observe a larger effect of easy interviews on offer rejection in occupations that involve interpersonal relationships as a skill requirement.

These perceptions about future colleagues that workers derived through the interview process also appear to have been accurate. Establishments with greater worker skill—as proxied for by the average worker fixed effect from an AKM regression of log wages (Abowd *et al.*, 1999)—more often evoke narrative reports describing high-ability peers. Conversely, establishments with lower worker skill, and which more frequently make job offers to candidates they interview, increasingly 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).

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 10-20 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 interpretation of responses on Glassdoor reflecting both objective and subjective difficulty.

Our main goal with the experiment was to assess whether interview difficulty has a causal effect on the perceived value of the vacancy. We capture perceived value through applicants’ 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 whether they have any questions for the employer. Applicants who experienced the easy technical assessment wrote less text in these free-response fields. Second, at the end of the interview, candidates received an email with 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.

A heterogeneity analysis by the skill level of the applicants, according to the rank of their university, reveals that the experimental effects of interview difficulty on engagement are particularly pronounced for graduates from elite universities.

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](#)). 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 ([Breugh 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 in customer service, our work centers on professional jobs, for which tasks are more abstract and cognitively demanding, so labor is less substitutable. To our knowledge, no prior study has considered the worker’s perception of the interview process, in particular its difficulty, and documented 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. \(2019b\)](#), for instance, show that highly-rated employers receive increased labor supply in online labor markets, [Sockin and Sojourner \(2023\)](#) that improved Glassdoor ratings increase applications to small firms, [Bryan et al. \(2026\)](#) 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

gauge peer ability and opportunities for skill development.⁵ 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.

The third strand of literature pertains to firm hiring strategies and how the design of recruitment practices shapes labor market outcomes. Firms can fill vacancies through diverse channels—promoting from within ([Benson et al., 2019a](#)), soliciting external applications ([Chan, 1996](#)), or leveraging employee referrals ([Burks et al., 2015](#))—each of which involves a sequence of organizational decisions, from sourcing to screening to hiring ([Rynes, 1991](#); [Barber, 1998](#); [Oyer and Schaefer, 2011](#)). On the sourcing side, employee referrals have been shown to yield higher-quality and longer-lasting matches ([Brown et al., 2016](#)), while the design of job advertisements can alter the volume and composition of the applicant pool ([Belot et al., 2022](#); [Burn et al., 2022](#)). With regard to screening, statistical discrimination may induce firms to screen out workers on observable characteristics ([Agan and Starr, 2017](#); [Doleac and Hansen, 2020](#)), whereas algorithmic recommendations can improve match quality by surfacing candidates that firms might otherwise overlook ([Horton, 2017](#); [Hoffman et al., 2018](#)). We add to this literature by focusing on the acceptance margin—whether candidates take the offers they receive—and how that is influenced by firm hiring practices.⁶ Along this margin, whereas [Coffman et al. \(2017\)](#) inform applicants about the average rejection rate and [Jabarian and Henkel \(2025\)](#) use AI interviewers, we focus on interview rigor—and the signals it communicates to workers about the firm.

2 Data

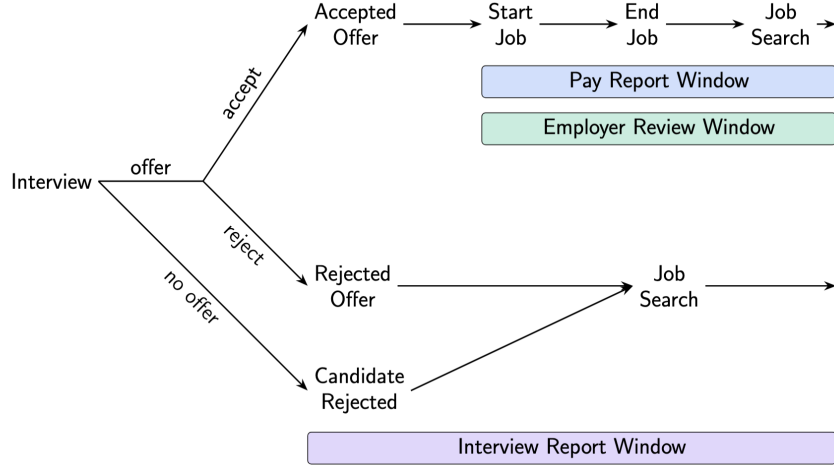
This section sets the stage with background information on Glassdoor and details on how we compile our dataset of interview reports.

Platform Overview. Our data come from the website Glassdoor, an online platform where workers can anonymously share information about pay, job satisfaction, and interview

⁵Workers may also use the interview to learn whether the firm is willing to bargain over wages ([Caldwell et al., 2026](#)); however, in many knowledge-worker settings, base wages are relatively transparent ([Hall and Krueger, 2012](#)), which reduces the need to discover pay during interviews.

⁶There is also indirect evidence in economics on offer acceptance, e.g., by gender ([Cortés et al., 2023](#)).

Figure 1: Timeline of Glassdoor Reports



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

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.⁷ 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, and 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 where the interview took place, but this is not required. Since the 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. Respondents are asked whether they received an offer for the job in question, and if they did, whether they accepted or rejected it. Respondents also have the option to disclose a number of additional aspects of the interview process, including how they received the interview (e.g., an employee referral⁸), how many days the entire

⁷For additional details regarding this give-to-get mechanism, see [Marinescu et al. \(2021\)](#).

⁸Referrals may enter with different expectations about the firm and its amenities. For instance, [Hampole et al. \(2026\)](#) find female MBA students discover female-friendly firms from women in their social network.

interview 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 38 percent of resumes (Appendix Figure A2). Among those who report rejecting the offer, the share is 2 percent; among those who did not receive an offer in the first place, 1 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 I1) 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 regression of log pay, Appendix Table I2) than those who report not receiving an offer. And 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. We restrict our attention to workers in professional occupations, identified by Standard Occupational Classification (SOC) codes: management (11); business and financial operations (13); computer and mathematical (15); architecture and engineering (17); life, physical, and social science (19); community and social service (21); and legal (23). Glassdoor has comprehensive coverage and large samples of interviews from these occupations, such that we have particularly rich information across employers and within workers.⁹ For most other occupations, coverage on Glassdoor is lower and sampling is sparse.

Further, professional occupations offer the most interesting setting for our research question regarding interviews. Workers in professional occupations are highly educated (Deming and Kahn, 2018) and specialize in abstract, non-routine cognitive tasks (Acemoglu and Autor, 2011).¹⁰ In turn, workers in such occupations generally have high marginal products and command high wages, so firms will tend to expend more resources screening for them.¹¹ Finally, workers in professional occupations tend to have career concerns and accumulate human capital through peer effects and on-the-job learning (Reagans *et al.*, 2005; Mas and Moretti, 2009; Jarosch *et al.*, 2021; Atkin *et al.*, 2022), so a poor worker-firm match can be

⁹While these occupations represent 29 percent of full-time employment in the representative American Community Survey, they represent 57 percent of Glassdoor interviews (Appendix Figure C1).

¹⁰According to job postings data from Lightcast, the seven occupations we study exhibit the highest rates of requiring an advanced degree—with more than three-quarters of ads for each one requiring a post-secondary education. Authors’ own calculations, available upon request.

¹¹Looking 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 ones.

particularly costly for one’s career.

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 nearly two-fifths of interview reports where the worker was not offered the job. We next exclude interviews for which either perceived difficulty, occupation, or industry is unavailable, and restrict the sample to the seven highest-educated professional occupations. To focus on matches that do not have a definite end date determined *ex ante*, we next exclude interviews for internships.¹² 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 of interviews that led to offers includes 502,400 interview reports. If we were to include interviews that did not lead to offers, there are 1,012,600 reports. Summary statistics for the former are available in the first three columns of Table 1, while those for the latter are in the final three columns. 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 incorporate these averages into our interviews data. Through this process, we are able to impute a wage for 297,400 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, 2026), and universities (Martellini *et al.*, 2024)—and for our interviews sample, the distribution of imputed wages closely tracks the distribution of wages for these occupations in the American Community Survey (ACS), particularly for higher wages (Appendix Figure C2). Three, for a subset of workers, we observe their actual wage since they submitted a Glassdoor pay report for the same firm, job title, and year after accepting the offer. For this subset of 26,000 workers, we estimate an elasticity of realized wages with respect to imputed wages close to one, with imputed wages explaining about 85 percent of the variation in realized wages (Appendix Table I3).

¹²Though, for internships as well, workers increasingly reject offers after easy interviews (Appendix B). This would suggest our results are not solely the product of workers knowing the quality of their outside options since prospective interns, as new labor market entrants, have less information about their own abilities and the market value of their skills.

Table 1: Summary Statistics for Glassdoor Interviews Dataset

Measure	Offers			Offers & Non-Offers		
	N (1000s)	Mean	Standard deviation	N (1000s)	Mean	Standard deviation
Panel A. Interview characteristics						
Interview year	502.4	2018.25	3.69	1012.6	2018.65	3.70
Interview month	502.4	6.27	3.49	1012.6	6.28	3.49
Months between interview and disclosure	502.4	3.99	6.46	1012.6	2.98	5.44
1(Rejected offer)	502.4	0.20	0.40	1012.6	0.10	0.30
Interview difficulty level	502.4	2.68	0.85	1012.6	2.78	0.85
1(Easy interview)	502.4	0.33	0.47	1012.6	0.29	0.45
1(Thumbs-up impression)	502.4	0.76	0.43	1012.6	0.56	0.50
1(Employee referral)	408.8	0.13	0.34	825.5	0.10	0.30
1(University recruitment)	408.8	0.10	0.30	825.5	0.10	0.29
Interview duration in days	315.0	24.15	29.28	616.4	24.31	29.02
Imputed wage of the vacancy	297.4	88349.92	40330.89	575.6	97321.98	43557.28
Panel B. Job seeker demographics						
1(Female)	203.7	0.44	0.50	391.1	0.43	0.50
Age in years	108.5	30.29	8.91	212.0	30.84	9.07
1(Post-Bachelor’s degree)	183.5	0.18	0.38	389.6	0.21	0.41
1(Attended university outside US)	183.5	0.10	0.30	389.6	0.12	0.32
College graduate quality of alma mater	159.3	-0.04	0.15	339.6	-0.04	0.15
1(STEM major)	136.6	0.42	0.49	293.2	0.44	0.50
Grade point average	23.0	3.58	0.28	51.3	3.59	0.28
Panel C. Large language model labels						
1(High-ability colleagues)	502.4	0.03	0.16	1012.6	0.02	0.14
1(Would accept anybody)	502.4	0.04	0.20	1012.6	0.03	0.16
1(Engaging experience)	502.4	0.27	0.44	1012.6	0.20	0.40
1(Realistic job preview)	502.4	0.30	0.46	1012.6	0.21	0.41
1(Mentioned compensation)	502.4	0.06	0.23	1012.6	0.05	0.22
1(Mentioned hours)	502.4	0.02	0.14	1012.6	0.02	0.13
1(Mentioned desirable workplace amenities)	502.4	0.00	0.05	1012.6	0.00	0.05
1(Direct assessment)	502.4	0.22	0.42	1012.6	0.26	0.44

Notes: Table 1 offers the sample size, mean, and standard deviation for each measure studied in our sample, separately for interviews that led to offers and all interviews regardless of outcome. Panel A pertains to aspects of the interview, Panel B covers worker demographics, and Panel C summarizes LLM-derived impressions of the interview narrative.

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 workers’ decisions to accept job offers and their interview experiences, few comparisons exist. With regard to interview difficulty, one such comparison is the website [Onsites.fyi](https://onsites.fyi). On this website, individuals also disclose interview experiences, though primarily for jobs in software engineering. When we compare the reported level of difficulty between Onsites and Glassdoor, we find considerable overlap (more on this below).

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 on log annual pay. Taking the worker fixed effects from this model 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 C3). This evidence suggests that the interviews sample is not meaningfully differently selected on ability.

Demographic Observables. When creating a profile on the website, users are asked to provide their gender and age. We observe gender for 203,700 offers and age for 108,500. For workers who uploaded a resume to Glassdoor, we additionally observe their educational background. This includes, if listed, their university of study, major of study,¹³ undergraduate grade point average (GPA), and any post-Bachelor’s degree. From the university of study, we can ascertain college graduate quality, as measured by [Martellini *et al.* \(2024\)](#), and whether the worker attended university outside the United States. In summary, we observe educational histories for 183,500 interviews, for which we observe college graduate quality for 159,300, major of study for 136,600, and GPA for 23,000. Summary statistics for these demographics are available in Panel B of Table 1.

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 difficulty is plotted in Appendix Figure A3.¹⁴ For ease of exposition, and to avoid concerns regarding heterogeneous interpretations of the five-point scale across sub-samples,¹⁵ we create an easy-interview indicator, which equals one if respondents record “very easy” or “easy” and zero otherwise. Roughly one-third of interviews that led to offers were perceived 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,

¹³We 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.

¹⁴Appendix Figure A3 shows 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 interviews more cumbersome).

¹⁵The 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](#)).

experience, and psychology. Perceived difficulty blends institutional rigor with self-assessed competence (Kukla, 1972). Objectively, a process may feel demanding because it is arduous or technically challenging. Subjectively, varying levels of preparation, experience, expectations, and perspectives can lead candidates to form 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 6). With regard to the former, we find that exogenously increasing the difficulty of a technical assessment shifts the distribution of reported difficulty. And as for the latter, we find that the same technical assessment receives widely different ratings of perceived difficulty, underscoring the importance of subjective perception.

To get a broader sense of the sentiment associated with difficulty, Appendix Figure A4 depicts the words used in interview narratives 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” in, and 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 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,” the other that the interview was “average,” “difficult,” or “very difficult.” Respondents scored the vignettes on a 0–5 Likert scale for eight provided statements. Appendix Figure A5 depicts how scores for each statement varied between the former and the latter. The results demonstrate individuals assign 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 align with our interpretations of interview difficulty.

Given the focality of perceived difficulty for our analysis, we examine its internal and external validity. For internal validation, we consider the free-response narratives workers write about the interview process and find the fraction of workers who mention the word “easy” declines monotonically with difficulty (Appendix Figure A6). For external validation, we turn to the website Onsites, which also collects summary information from interview experi-

ences. Since Onsites caters primarily to jobs in software engineering for technology firms, we caveat that comparison with Onsites cannot necessarily speak to the validity of difficulty for other occupations and industries on Glassdoor. For this website as well, respondents record the difficulty 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 C, for the same firm $\times$ job title, we compare average difficulty on Onsites with average difficulty on Glassdoor. A one-level increase in difficulty on Glassdoor corresponds to a statistically significant increase of 0.5–1.1 levels on Onsites. Glassdoor interview difficulty thus appears to capture latent differences in difficulty between interviews.

Since we are interested in whether perceived difficulty influences acceptance decisions, we examine whether and where there is variation in perceived difficulty. Appendix Table I4 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.¹⁶ 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 worker 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.¹⁷

Last, we note which employers offer the most difficult interviews. Intuitively, we find that difficult interviews are prevalent among 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 A2). By comparison, firms in our sample with the least difficult interviews come from retail, food services, and insurance (Appendix Table A3).

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.

¹⁶This is observed across the entire wage distribution (Appendix Figure A7).

¹⁷While interviews become increasingly more difficult for the same worker over time, this reflects the different firms and job titles for which workers interview as their careers progress (Appendix Table I5).

3.1 Text Analysis of Interview Narratives

We first narrow our focus to observations with interpretable text,¹⁸ 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 eight dimensions of interest. They are: colleague ability, 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.

Then, 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.¹⁹ Summary statistics on the text annotations for the full sample of interviews are reported in Panel C of Table 1.

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 randomly sampled interview descriptions and asked them the same prompts 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 D). The agreement rate of the LLM with the annotators is almost identical to the rate of agreement between the two annotators themselves, 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 (Calderon *et al.*, 2025).

To empirically validate these text-based variables, we show in Appendix E that they correlate as expected with external data by considering the frequency with which interview narratives convey that colleagues are of high ability or that the firm “would accept anybody.”

¹⁸We exclude observations where the text contains fewer than eight words of at least three letters or more, which trims the dataset by about 1 percent.

¹⁹The use of aligned LLMs in this fashion, coupled with deep learning (Dell, 2025), offers a scalable, reproducible alternative to human annotation (Ash *et al.*, 2024; Ludwig *et al.*, 2025).

Drawing on two separate measures of individual skill—from Glassdoor pay reports and from workers’ resumes—we find that establishments with high-ability peers tend to signal colleagues are of high ability, whereas establishments with low-ability peers increasingly signal the firm would accept anybody. Further, the frequency with which workers characterize the hiring firm as accepting anybody jumps sharply as the fraction of interviews that result in offers for a given firm $\times$ job title rises above 70 percent.

3.2 Estimation Strategy

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

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

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, e.g., the firm’s industry $\times$ the vacancy’s occupation, or the vacancy’s metro area $\times$ the calendar year-quarter of the interview. Since interviews are reported ex post, to flexibly absorb variation across time both in terms of when the interview occurred and when the user disclosed the associated data, each specification includes calendar year-quarter of the interview $\times$ calendar year-quarter of the Glassdoor submission.²⁰ Since we observe multiple interviews for some workers, in some specifications we are able to incorporate worker FE, and even worker $\times$ calendar year-quarter of the interview FE. $\mathbf{X}_{i,k,t}$ can include other worker or firm covariates, e.g., the imputed wage or firm age, as indicated below.

We interpret our treatment as the impact of a firm characteristic—interview difficulty—on workers’ decisions. For each interview, we measure the perceived difficulty of the hiring firm. The rich fixed effects described above adjust for many confounding sources, but 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 outcomes such as offer acceptance.

To adjust for this source of confounding, we construct a firm-level measure of interview difficulty that purges the experience of worker i . Specifically, we construct a leave-one-out

²⁰About 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, recollection of the interview experience by workers who accepted the offer 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 I1): Those who accepted the offer are significantly more likely to write the interview was easy; those who rejected the offer are significantly more likely to write that the interview was difficult.

“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 the 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

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

which captures the average of $1(\text{Easy interview})$ across all other workers that interviewed with the same firm, as desired. Naturally, we restrict the sample to firms with at least two recorded interviews such that this index is defined. As expected, others’ perceptions for the same firm are highly predictive of one’s own (Appendix Figure I2).²¹

4 Interview Difficulty and Offer Acceptance

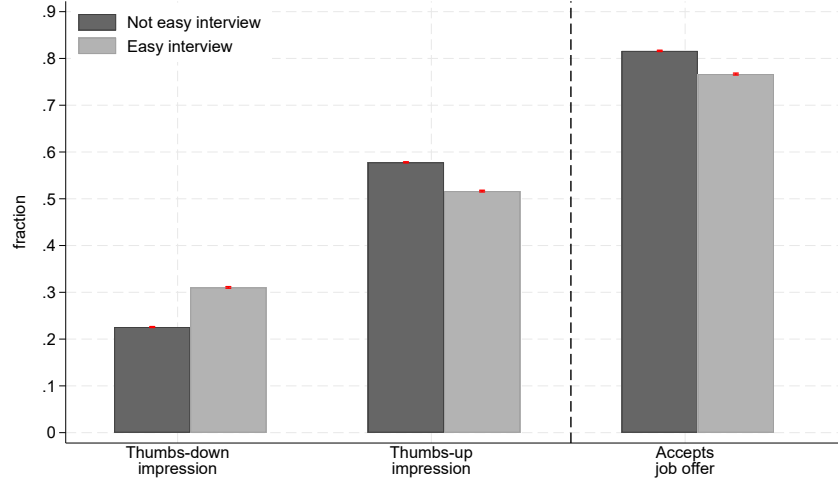
This section presents the main evidence on how workers respond to variation in the rigor of the interview process. Our focal regressions estimate the relationship between perceived interview difficulty and the probability of accepting an offer, conditional on receiving an offer. The regressions include rich fixed effects and we report comprehensive robustness checks.

We first show our main result graphically. In Figure 2, we plot the fraction of workers who characterize their interview as leaving a “thumbs-up” or “thumbs-down” impression, as well as the fraction who accept a job offer conditional on receiving one, partitioned by whether the worker perceived the interview to have been easy. Across the full sample of interviews, workers who perceive the interview as easy are 8.5 percentage points more likely to record a “thumbs-down”, or unfavorable, impression of the interview. Among interviews that led to offers, workers who perceive the interview as easy are 5.0 percentage points less likely to accept the offer.

Turning to a regression framework, we begin with the cross-sectional estimates for accepting an offer in Panel A of Table 2. 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-

²¹Our conclusions are robust (Appendix Table I6) to alternative sets of other applicants, e.g., conditioning on location (same firm $\times$ metro) or occupation and time (same firm $\times$ occupation $\times$ year), as well as considering averages that are lagged or forward looking.

Figure 2: Interview Experience and the Fraction of Offers Accepted, by Interview Difficulty



Notes: Figure 2 displays the distribution of workers’ impressions of the interview process and the fraction that accept the offer, by whether the interview was considered easy. Workers can report the interview as a “thumbs-up”, “thumbs-down”, or “neutral” impression—with the latter omitted from the figure. ‘Easy’ corresponds to difficulty levels “very easy” and “easy” whereas ‘Not easy’ corresponds to difficulty levels “average,” “difficult,” and “very difficult.” The sample for impressions (left of the dashed line) reflects the full sample of interviews, for offer acceptance (right of the dashed line) the sample of interviews that led to offers. Intervals around the sample proportions reflect 95% Binomial exact confidence intervals.

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. Both of these specifications account for the firm’s industry, age, and relative pay premium, meaning our estimates do not reflect any of these observable differences across firms. A potential concern with cross-sectional estimates though is the composition of workers who perceive interviews as easy and report accepted or rejected offers to Glassdoor.

To address such compositional and selection concerns in the cross-section, columns (3)-(5) restrict the sample to workers with multiple offers. Whether we include worker fixed effects—in which case our coefficient of interest is identified off variation in perceived 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 10–13 percentage points more often.²² In columns (6)-(7), we more narrowly pin down consideration sets by evaluating workers who report multiple offers for the same year-quarter. When faced with both an easy interview and a not-easy interview that each resulted in an offer, the easy interview is rejected 13–15 percentage points more often. Last, in column (8), we narrow in on workers who all received offers for the same

²²The shift in magnitude between the cross-section and within-worker samples in part reflects the latter comprising higher-wage jobs (Appendix Figure A8), which witness greater rejection rates—a purely cross-sectional result. Within worker, higher-paying jobs are accepted more often (Appendix Table I7).

vacancy, i.e., firm $\times$ job title $\times$ metro $\times$ year-quarter—effectively fixing skill requirements. Again, workers who perceive the interview as easy reject the offer more often.²³

Table 2: Probability of Accepting a Job Offer by Perception of Interview Difficulty

Panel A: 1(Accepts job offer Offer)								
	Cross-section sample		Within-worker sample			Within-worker-qtr sample		Within-ad sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(Easy interview)	-0.049*** (0.002)		-0.114*** (0.007)	-0.101*** (0.011)		-0.132*** (0.023)	-0.153*** (0.047)	-0.073*** (0.008)
Fraction others' interviews easy		-0.050*** (0.006)			-0.132*** (0.038)			
Mean DV for not easy	0.818	0.818	0.735	0.735	0.735	0.549	0.549	0.817
N	423,961	423,961	23,860	23,860	23,860	3,344	3,344	34,889
Workers	410,305	410,305	11,147	11,147	11,147	1,569	1,569	34,455
R ²	0.07	0.07	0.18	0.71	0.71	0.36	0.75	0.51
Panel B: 1(Thumbs-up)								
	Cross-section sample		Within-worker sample			Within-worker-qtr sample		Within-ad sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(Easy interview)	-0.064*** (0.003)		-0.096*** (0.003)	-0.059*** (0.004)		-0.090*** (0.005)	-0.066*** (0.007)	-0.032*** (0.009)
Fraction others' interviews easy		-0.025*** (0.006)			-0.027** (0.011)			
Mean DV for not easy	0.573	0.573	0.405	0.405	0.405	0.333	0.333	0.577
N	875,841	875,841	145,955	145,955	145,955	44,040	44,040	111,145
Workers	787,116	787,116	57,889	57,889	57,889	16,877	16,877	107,277
R ²	0.05	0.05	0.10	0.62	0.62	0.15	0.66	0.45
Firm Observables	✓	✓	✓	✓	✓	✓	✓	
Worker FE				✓	✓			
Worker-Qtr FE							✓	
Firm-Job title-Metro-Qtr FE								✓

Notes: Table 2 summarizes the relation between (i) the probability an offer is accepted conditional on receiving an offer in Panel A, and (ii) the probability of a “thumbs-up” impression in Panel B, with the perceived difficulty of the interview and iteratively incorporating fixed effects. Firm observables refer to industry $\times$ 20 five-percentile bins of firm age $\times$ 20 five-percentile bins of firm AKM pay premium. Each specification includes metro, industry-occupation and year-quarter of interview $\times$ year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

As additional supporting evidence, we consider an alternative outcome: whether the worker offered a positive, “thumbs-up” impression of the interview—as opposed to a neutral or negative impression of the interview. Although these impressions are less tangible and lower stakes than the decision to accept an offer, they offer the advantage of being observed for *all* interviews, not just those that led to offers, and being more comparable to the outcomes of worker engagement from the field experiment in Section 6. Among all interviews—offers and non-offers—56 percent of interviews receive a “thumbs-up” impression from the worker

²³Interview difficulty does not predict differences in realized wages within the same role, suggesting concerns with bargaining over wages do not explain the lower rate of offer acceptance (Appendix Table I8).

(see columns 4-6 of Panel A in Table 1 for summary statistics on this sample). In Panel B of Table 2, we re-estimate the same specifications as in Panel A, but no longer restrict the sample to interviews that led to offers and use an indicator for a “thumbs-up” impression as the outcome of interest. When an interview is easy, or other workers report the firm has easy interviews, there is a reduced likelihood of a “thumbs-up” impression, even for the same worker who rates multiple interviews they had in the same quarter. This pattern is observed among interviews that led to offers and those that did not (Appendix Table I9), bolstering our key insight that an easy interview offers a negative signal about the hiring firm.

Application and Screening Behavior Ex Ante. It is important to note that since we study interviews and the subsequent acceptance of job offers, our estimation sample is necessarily restricted to workers who must have attained an interview for the job in question—which, in turn, reflects only a subset of those who applied. Naturally, this implies there are strategic considerations among both parties involved that happen prior. First, workers must decide to which jobs they will apply. Second, firms must decide, among the pool of applicants, whom to interview. If both of these strategic decisions correlate with interview difficulty, then the estimates from equation (1) may not be externally valid to candidates who chose not to apply for the vacancy or were not chosen to be interviewed. In other words, we never observe offers that are never made but would have been rejected had they been made, and any such behavior may differ between easy and difficult interviews.

To understand the direction of any such bias for estimating the effect of an easy interview on offer acceptance, we examine how the ability distribution of the pool of interviewees differs across firms of varying interview difficulty. In Appendix Table I10, we record how the 10th, 50th, and 90th percentiles of worker ability—i.e., the fixed effect from an AKM regression on log pay or the college graduate quality (Martellini *et al.*, 2024) of workers’ alma maters—evolve with the fraction of interviews perceived as easy by those firms. Evidently, firms that practice increasingly easy interviews interview lower-ability workers across the entire distribution. For instance, firms for which 10–20 percent of interviews are considered easy interview workers that are on average 0.3–0.5 standard deviation higher ability compared with firms for which 40–50 percent of interviews are considered easy.

Our interpretation of this evidence is that, if anything, we underestimate the negative effect that easy interviews have on offer acceptance. Based on Appendix Table I10, we potentially omit outcomes for: (i) lower-ability workers at firms with more difficult interviews, and (ii) higher-ability workers at firms with less difficult interviews. Assuming that firms prefer to hire workers with more ability as opposed to less, relatively low-ability workers will tend to be screened out by the firm, such that they would not receive an interview or

offer were they to apply. In the case of the former then, it is likely that we are not missing offers that would have arisen had these workers applied. Again, assuming that firms prefer to hire workers with more ability as opposed to less, relatively high-ability workers will increasingly receive interviews, such that the lack of interviews among high-ability workers at firms with less difficult interviews likely reflects such workers choosing not to apply to these firms as opposed to them being screened out.²⁴ In the case of the latter then, it is likely that we are missing offers that would have arisen had these high-ability workers applied to easy-interviewing firms. By revealed preference, these offers would more than likely have been rejected—otherwise, high-ability candidates would have applied and been accepted.

Robustness Checks. We next explore the robustness of our main results. First, we demonstrate our estimates do not merely reflect differences in the ex ante desirability of firms. We consider four 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 an interview results in an offer.²⁵ The second is the level of skill (i.e., the AKM-derived worker fixed effect) for the average worker at the firm—channeling the notion that more desirable firms can be more selective in hiring. The third is relative job quality, which we capture through the firm fixed effects from an AKM regression on job satisfaction ratings from the full database of Glassdoor employer reviews, as in [Sockin \(2022\)](#). 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, as in [Sockin and Sojourner \(2023\)](#). Across all four metrics (Appendix Figure I3), 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 workers who disclosed at least two interviews that resulted 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 intuition 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 that is seldom, if ever, observed in employee-employer

²⁴Although it is possible that high-ability workers do apply to these firms and the firm chooses not to interview them, if firms prefer to hire workers with more ability as opposed to less, then this must reflect the firm believing such a worker would not accept an offer if they were extended one. Given that this centers around firms with less difficult interviews, this belief would necessarily stem from workers turning down offers after easy interviews—which is precisely the result we propose.

²⁵Higher-paying jobs have lower offer rates (Appendix Figure A9), consistent with more selective hiring at higher wages ([Mueller et al., 2023](#)).

matched administrative data—we can examine their resumes to see which firms they went to instead. We then compare the rejected firm with the next firm listed on that worker’s resume after the offer was rejected. Consistent with our main result, interviews for the rejected firm on average are 20 percent more likely to be perceived as easy compared with interviews for the “accepted” firm (Appendix Figure A10).

Another concern is that the delayed reporting of interviews—since interviews are disclosed to Glassdoor retroactively (see Figure 1)—may add bias due to experiences on the job corrupting workers’ retrospectives of their interviews. To examine whether this is a pivotal issue for our analysis, we run a robustness check restricting the sample to either rejected offers or accepted offers where the interview report was submitted to Glassdoor *before* the worker started the job in question (which we can observe from their resume). Still, within this subsample, easy interviews are rejected more often (Appendix Table I11).

We also explore a broader set of sensitivity and heterogeneity analyses by re-estimating equation (1) for various sub-samples. This includes aspects related to reporting, 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 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 discussion of these results to Appendix F.

5 Interviews as Learning Opportunities

Having established that workers extract meaningful content from interviews, we next explore a signaling channel. That is, during the interview process, what aspects of the firm and potential match quality do workers gauge? To this end, we consider differences by the reputation of the employer, and incorporate LLM-based annotations 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.*, 2019b; Sockin and Sojourner, 2023). Using an employer lookup table in the Glassdoor database that includes a snapshot of firm

employment as of January 2025,²⁶ 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 than not-easy interviews for large firms, easy interviews are rejected substantially more often for small firms (Appendix Figure A11). While the rejection rate for not-easy interviews hovers around 16–20 percent across the distribution of firm size, the rejection rate for easy interviews 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 firm size decile (following the specification of column (1) in Table 2) 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 penalty is an order of magnitude larger for firms in the bottom decile of the size distribution compared with those in the top decile.

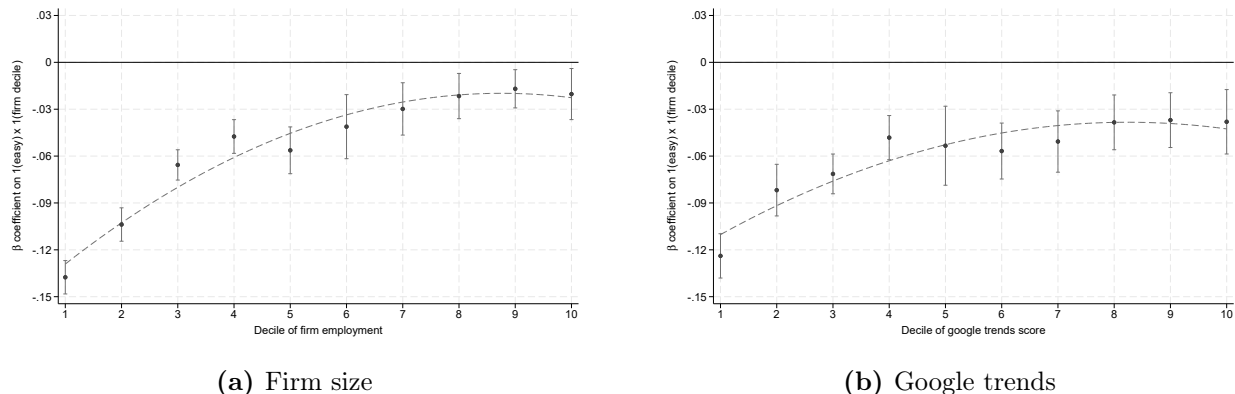
An alternative approach to gauging firm reputation would be to categorize firms by how well-known or popular they are. To proxy for firm popularity, we measure the frequency with which each firm is searched online using Google Trends. Using “Boston Consulting Group” as our comparison benchmark, we calculate the average Google Trends score over the sample 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 averages are presented in Appendix Figure A11, 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.

To complement these two cross-sectional measures of across-firm heterogeneity, we consider an alternative measure of firm salience that has variation over time: the number of employer reviews—both as a stock and an annual flow—that the firm has publicly available on Glassdoor compared with other firms. Appendix Figure I4 shows that, consistent with the between-firm results with firm size or Google search trends, when the same firm accumulates more Glassdoor reviews—indicating there is more information publicly available at the firm—there is a smaller penalty of an easy interview on offer acceptance.

Further evidence workers learn about firms through interviews can be observed by studying referrals and foreign graduates (Appendix Table I12). 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

²⁶Since this lookup table is dynamically updated, we do not have a time series, only the most recent value.

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



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 $1(\text{Easy}) \times 1(\text{Decile}_k)$, when added to model (1) from Table 2, with the standalone indicators $1(\text{Decile}_k)$ included. Coefficients are from a regression with metro, industry-occupation and year-quarter of interview $\times$ year-quarter submitted to Glassdoor fixed effects. Dashed blue line indicates a quadratic fit through the coefficients. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

match quality. We thus 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 nearly twice as likely to reject an easy interview compared with the full sample—consistent with such workers having less information about the quality of matches in U.S. labor markets ex ante.

5.2 Learning about Peers

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 interview difficulty signals valuable information about colleague quality at the hiring firm, we use an LLM to assess whether a given narrative suggests the job seeker perceived the hiring firm’s employees as high ability. 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 are presented in Appendix D.

Table 3: Perceived Interview Difficulty and LLM Assessment of Workers’ Beliefs

Panel A: DV = 1(High-ability colleagues)				
	Cross-section sample		Within-worker sample	
	(1)	(2)	(3)	(4)
1(Easy interview)	-0.021*** (0.001)		-0.031*** (0.003)	-0.025*** (0.004)
Fraction others’ interviews easy		-0.023*** (0.002)		
Mean DV for not easy	0.038	0.038	0.052	0.052
Panel B: DV = 1(Would accept anybody)				
	Cross-section sample		Within-worker sample	
	(1)	(2)	(3)	(4)
1(Easy interview)	0.060*** (0.001)		0.041*** (0.003)	0.031*** (0.004)
Fraction others’ interviews easy		0.071*** (0.003)		
Mean DV for not easy	0.012	0.012	0.011	0.011
Panel C: DV = 1(Engaging experience)				
	Cross-section sample		Within-worker sample	
	(1)	(2)	(3)	(4)
1(Easy interview)	-0.051*** (0.002)		-0.070*** (0.007)	-0.055*** (0.011)
Fraction others’ interviews easy		-0.074*** (0.006)		
Mean DV for not easy	0.293	0.293	0.312	0.312
N	423,961	423,961	24,461	24,461
Worker FE				✓

Notes: Table 3 summarizes the relation between workers’ beliefs and perceived difficulty. Each specification includes fixed effects for metro, 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%.

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 3, suggest this is the case. Columns (1) and (2) show that while 3.8 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 that of others, is about two percentage points lower—equivalent to a decline of more than one-half relative to the baseline. When we narrow in on workers who report multiple offers 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.

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 an 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 B and C of Table 3, respectively. While only 1.2 percent 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 500 percent increase. This disparity holds and remains large both when we only consider the perceptions of others rather than one’s own in column (2), and when we compare interviews that varied in perceived difficulty for the same worker in columns (3) and (4). This signal may in part stem from less engaging or stimulating interactions with prospective peers; as shown in Panel C, easy interviews are less likely to be perceived as engaging experiences, with large coefficients relative to the baseline for not-easy interviews.

Beliefs about prospective peers may also vary with the screening tools the hiring firm deploys; requiring an aptitude examination or imposing additional rounds of interviewing may induce job seekers to infer that each of the hiring firm’s employees exceeds some ability threshold. We consider whether such screening tools influence workers’ perceptions by measuring technical assessments and interview rounds from the interview narratives (see Appendix D). An aptitude assessment is associated with a reduced likelihood of perceiving the interview as easy and an increased likelihood of perceiving prospective colleagues as high ability (Appendix Table I13). Firms that require additional interviewing rounds not only have longer and more difficult interviews, but more strongly instill the belief that colleagues are of high ability and that the experience was engaging (Appendix Table I14). Both are associated with job offers being accepted more often, providing additional evidence that a more difficult interview signals high-ability peers and affects offer decisions.

If colleague ability is indeed a key mechanism through which interview difficulty influences offer decisions, then we would anticipate there to be larger effects in settings where personal interactions and relationships are more central to the job. To test for this, we consider heterogeneity in the relation between easy interviews and the rate of offer rejection by the degree to which interpersonal skills are required of the job, channeling [Goldin \(2014\)](#) and looking across three-digit SOC occupations. We interact our easy-interview indicator with

Table 4: Interview Difficulty, Interpersonal Skills Required, and Offer Rejection

	1(Rejects job offer)		
	Cross-section sample		Within-worker sample
	(1)	(2)	(3)
1(Easy interview)	0.050*** (0.002)		0.104*** (0.008)
1(Easy interview) x Interpersonal relationships index	0.012*** (0.002)		0.016** (0.008)
Fraction others' interviews easy		0.047*** (0.006)	
Fraction others' interviews easy x Interpersonal relationships index		0.016*** (0.006)	
Mean DV for not easy	0.182	0.182	0.266
N	423,955	423,955	31,254
Workers	410,299	410,299	14,527
Firm Observables	✓	✓	
Worker FE			✓

Notes: Table 4 summarizes the relation between the probability an offer is rejected and perceived difficulty of the interview, allowing for a differential slope by the degree to which the job requires interpersonal skills. Firm observables refer to industry x 20 five-percentile bins of firm age x 20 five-percentile bins of firm AKM pay premium. Interpersonal skills are assigned by three-digit SOC occupation, standardized, and reflect the measure used in [Goldin \(2014\)](#). Each specification includes metro, industry × three-digit SOC occupation, and year-quarter of interview × year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

this continuous index of interpersonal skill requirements and re-estimate equation (1). The results, recorded in Table 4, are consistent with a peers-based mechanism: The likelihood of a worker rejecting an easy interview is significantly larger in occupations that require more interpersonal relationships. We observe this pattern both across and within workers, as well as when focusing solely on the perceptions of others who interviewed with the same firm.

Taken one step further, if this is not just about peers but really *learning* about peers, we would anticipate heterogeneity by the intensity of interpersonal relationships to be redoubled when the firm is less well-known. Building on the discussion of employer reputation in Section 5.1, we interact the intensity of interpersonal relationships required for the job with the size of the firm. Appendix Table I15 records the results. While the previous heterogeneity results hold—rejections are more likely after easy interviews for small firms and more relationship-oriented occupations—the triple interaction, easy interview × small firm × the intensity of interpersonal relationships, is also positive, significant, and non-trivial.

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](#)). From a macro perspective, that interviews can credibly relay signals of peer ability 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.

5.3 Learning about Pay

The firm’s pay premium. It is well established that the same worker can receive different wages working for different firms ([Abowd *et al.*, 1999](#)). If workers recognize firm-specific pay premia exist but have imperfect information over their magnitudes ([Caldwell *et al.*, 2026](#)), the interview process may provide new information on pay premia. In particular, a more intense interview process—which is typically more costly for a firm to implement—may be perceived as more difficult while signaling to the worker that the firm would offer greater pay. If this is the case, then workers may reject easy-interviewing firms because they are concerned about receiving lower pay compared with other employers.

To analyze this dynamic, Table 5 regresses the propensity for a worker to consider an interview with the firm as easy on the firm’s objective pay premium (as captured by a fixed effect on log wages). We observe a negative coefficient: a one-standard-deviation increase in firm-specific wages is associated with a roughly 6-percentage-point lower likelihood of perceiving an interview as easy. This significantly negative relation holds even when comparing multiple interviews for the same job seeker, and when adjusting for observable predictors of interview difficulty and pay, such as industry, firm age, firm size, and location.

These results offer evidence consistent with workers learning, and in turn updating their beliefs, about wages as a potential channel for rejecting offers after easy interviews. However, we believe this is neither the only, nor the main, mechanism for our results. For one, the reduction in offer acceptance we observe among easy interviews holds when flexibly controlling for the hiring firm’s objective pay premium (see the firm observables in Table 2). Moreover, if learning about pay premia were the only channel, we would expect easy interviews to increasingly witness offer rejections when they are for objectively lower-paying firms—as the easy interview would thus (credibly) signal a wage discount and a not-easy interview signal the opposite. However, we find the reverse: the penalty on offer acceptance following easy interviews is largest for high-paying firms, not low-paying ones (Appendix Figure I5).

Table 5: Probability of an Easy Interview by Hiring Firm’s Relative Wage Premium

	1(Easy interview)			
	(1)	(2)	(3)	(4)
Firm AKM wage premium	-0.064*** (0.002)	-0.045*** (0.002)	-0.055*** (0.003)	-0.044*** (0.003)
Mean DV	0.279	0.279	0.303	0.303
N	825,939	825,939	119,563	119,563
Workers	746,160	746,160	47,839	47,839
R ²	0.03	0.10	0.52	0.60
Firm and job covariates		✓		✓
Worker FE			✓	✓

Notes: Table 5 summarizes the relation between the probability an interview is easy and the firm’s relative pay premium as measured by the firm fixed effect in an AKM model of log wages with worker fixed effects. Firm AKM wage premium is normalized into standard deviations. Firm and job covariates include industry x 20 five-percentile bins of firm age x 20 five-percentile bins of firm size, metro, job title, and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Future trajectory of pay. Workers who are forward looking presumably will care not only about current job opportunities but also those that lie ahead. If workers have such career concerns, they may place heightened value on skill development and on-the-job learning in order to access high-paying firms and jobs in the future.²⁷ If easy interviews signal limited opportunities for skill development, candidates who are motivated by career concerns will likely be particularly averse to accepting such offers. We explore whether concern over future pay is a potential mechanism through two complementary approaches.

First, we examine whether easy interviews are turned down more often for jobs that have steep pay trajectories. To this end, we again incorporate workers’ resumes. We predict, for each firm × job title, the wage of the next job by taking the mean imputed wage among all subsequent jobs that appear next on workers’ resumes. Repeating this exercise for the second and third next jobs, we create an indicator equal to one if the firm × job title of the interview has an expected wage 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 I19, 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.

Second, we test whether there are rational career-related reasons to avoid working for an easy-interviewing firm by studying the panel of workers we observe in Glassdoor pay

²⁷In the information technology sector, for instance, younger workers may accept lower wages to have the opportunity to develop skills through experience with emerging IT systems (Tambe *et al.*, 2020).

reports. More specifically, we predict aspects of a worker’s next employment opportunity given the interview difficulty of their current firm. The results, presented in Appendix Table I20, demonstrate that workers employed in easy-interviewing firms achieve lower wages in the future, with sorting into lower-paying firms and lower-paying job titles explaining about three-fifths of this penalty. We observe a pay penalty even conditional on the worker’s university and major, as well as their current firm’s pay premium, consistent with slower accumulation of human capital at easy-interviewing firms, potentially due to weakened peer effects alongside lower-ability colleagues.

5.4 Learning about Match Quality

Job Satisfaction. Workers may choose to reject offers after easy interviews because it is not just a signal of peer ability, but a precursor for how satisfied they will be with the job. To empirically test whether interview difficulty signals eventual match quality, we turn to employer reviews on Glassdoor, which include job satisfaction ratings on an integral scale from 1–5 stars.²⁸ We match an interview report for which the offer was accepted to a later-written Glassdoor review 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.²⁹ We are able to match 46,300 employer reviews to an interview report.³⁰

The first three columns of Table 6 relate interview difficulty to job satisfaction and show easy interviews precede lower job satisfaction. Workers who accept after easy interviews are 0.6 stars less satisfied with their jobs—a disparity equivalent to two-fifths of a standard deviation and larger in magnitude than the effect of learning your employer engaged in corporate misconduct ([Gadgil and Sockin, 2026](#)) or accounting fraud ([Zhou and Makridis, 2021](#)). Even among workers with the same job title at the same firm, reduced job satisfaction follows easy interviews. This dissatisfaction appears to at least in part reflect disappointment with peers. In their employer reviews, workers who accept offers after easy interviews are approximately 25 percent (3.0 percentage points off a baseline of 12.9 percent) more likely to explicitly mention peers as a drawback of their workplace, consistent with the evidence above that easy interviews signal the firm “would accept anybody”—which is more often

²⁸Workers are incentivized to contribute through the give-to-get mechanism introduced in Section 2. [Sockin \(2022\)](#) shows Glassdoor ratings strongly correlate with satisfaction ratings from a representative survey across industries and occupations. For more on Glassdoor reviews, see [Marinescu et al. \(2021\)](#).

²⁹We do not match on job title since workers may have been promoted or demoted in the interim.

³⁰With 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 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 C4), they are highly similar.

Table 6: Job Satisfaction and Realized Firm Tenure After Offer Acceptance

	Data Source: Employer reviews						Data Source: Resumes		
	1(Mentioned in cons section)						1(Firm tenure $\geq$ 12 months)		
	Overall rating			Peers	Involuntary turnover	Voluntary turnover			
	(1)	(2)	(3)				(7)	(8)	(9)
1(Easy interview)	-0.589*** (0.016)		-0.479*** (0.036)	0.030*** (0.009)	0.005 (0.005)	0.009** (0.004)	-0.074*** (0.008)		-0.059*** (0.019)
Fraction others' interviews easy		-0.508*** (0.050)						-0.086*** (0.028)	
R ²	0.23	0.24	0.57	0.42	0.44	0.40	0.25	0.24	0.60
Mean DV for not easy	3.92	3.92	3.86	0.129	0.027	0.022	0.756	0.756	0.779
N	46,323	46,323	11,932	11,932	11,932	11,932	17,792	17,792	3,426
Firm Observables	✓	✓					✓	✓	
Firm-Job title FE			✓	✓	✓	✓			✓

Notes: Table 6 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 $\times$ the year-quarter in which the review was written. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

observed among workplaces with lower-ability peers (Appendix E).

Since job dissatisfaction has been found to induce voluntary turnover (Akerlof *et al.*, 1988; Card *et al.*, 2012), we also test whether interview difficulty predicts faster job separation rates. Suggestive evidence for this channel first comes from the text of employer reviews. Workers who accept offers after easy interviews are 40 percent (0.9 percentage points off a baseline of 2.2 percent) more likely to mention *voluntary* turnover as a negative aspect of their workplace. More direct evidence of faster turnover comes from workers’ resumes. We consider each job listed on a worker’s resume and identify those for which the worker uploaded an interview report for that firm to Glassdoor within a year of the job beginning. We then estimate equation (1) with an indicator for firm tenure lasting at least 12 months as the outcome.³¹ The results, displayed in the last three columns of Table 6, indicate workers separate earlier if they perceived the interview to be easy; for the same firm $\times$ job title, workers are 5.9 percentage points (relative to a baseline of 77.9 percent) less likely to remain in the match for at least one year after an easy interview. This evidence supports the narrative of workers increasingly turning down offers after easy interviews because they

³¹We do not account for age since it is unobserved for most respondents, though the takeaways would be unchanged if we did (Appendix Table I16). This result does not reflect unobserved selection of who perceives interviews to be easy, as we draw the same conclusion when we incorporate each worker’s fixed effect from an AKM regression on interview difficulty (Appendix Table I17). It also does not reflect selection on worker ability as we observe the same pattern when we include each worker’s fixed effect from an AKM regression on log wages (Appendix Table I17). Further, this result does not appear to reflect selection of who simultaneously exits and reports to Glassdoor to facilitate job search, as we observe the same pattern for historical jobs, not just the most recent one listed (Appendix Table I18).

foresee dissatisfaction with the job, which may necessitate having to search for a new job.

Over- or Under-Qualified? Learning about responsibilities and requirements though appears distinct from the worker learning they are under- or over-qualified compared with other candidates. A worker with many years of experience or education may plausibly learn through the interview they are “over-qualified” for the role—in which case they would likely find the interview easy and reject the offer if they were to receive one. We find limited evidence for this behavior. 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 I6 and I7, 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 does not simply reflect (observable) mismatch based on the worker’s qualifications.

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 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 I22). Although this finding is consistent with the narrative that workers in professional occupations are more likely to reject offers after easy interviews, in this case 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 that outside options are a contributing factor (Appendix Table I23). We estimate that a one standard deviation increase in the local unemployment rate is associated with a reduction in the easy-interview penalty on offer acceptance of roughly 10 percent. Thus, when the unemployment rate rises and workers subsequently have worse opportunities amid increased competition, easy interviews are rejected less often.

5.5 Learning Channels and Behavioral Responses that Are Less Plausible

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 I12) 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 F). 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 I24). Together, these results are at odds with learning about oneself as the focal mechanism.

Failing to Learn Relevant Information? Interviews offer candidates the opportunity to obtain concrete information about tasks and expectations of the job. When an interview does so, it is considered a realistic job preview.³² If workers accept offers more often when the interview provides a realistic preview of the job, then it could be the case that easy interviews are rejected more often because they less often convey relevant information for the job. Given the interview narratives we observe and the breadth of our sample, we can relate the decision to accept an offer with whether the interview offered a realistic job preview, interview difficulty, and their interaction. To do so, we ask the LLM to determine whether the job seeker experienced a realistic job preview, for which the prompt used is available in Appendix D; 30 percent of interviews that result in offers are labeled as having been realistic job previews (Panel C of Table 1).

Relating realistic job previews to offer acceptance, we find that such interviews are associated with significantly greater rates of offer acceptance, on the order of about 8 percentage points (Appendix Table I21). This is the case even when looking across offers for the same worker. That said, even though easy interviews that lead to offers are significantly less likely to be deemed realistic job previews (correlation of -0.1), there is no clear interaction effect that arises with regard to rejecting the offer when it is a realistic job preview that the worker also perceives to have been easy. In other words, easy interviews are more often rejected, regardless of whether the interview offers a realistic preview of the job. This suggests that interview difficulty is not simply an imperfect proxy for the relevance of the content that is

³²Suggestive evidence points to realistic job previews as improving initial matches and reducing turnover among small cross-sections of workers for a given occupation (Wanous, 1973; Phillips, 1998).

relayed throughout the interview.

Behavioral Responses. 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 the lens of effort justification, effort adds value (Inzlicht *et al.*, 2018). A second is the theory of gift exchange or positive reciprocity (Akerlof, 1982). Through the lens of gift exchange, a “difficult” interview indicates costly effort by the employer—consistent with workers perceiving easy interviews as less engaging (Table 3, Panel C)—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 I12) 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 3, Panel A).

6 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 as-

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 G1 and G2, 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* (emphasis added). The “difficult” version was: *Write a regular expression to detect if a sentence includes at most one question mark* (emphasis added). For the coding component, to ensure the “easy” and “difficult” prompts were believable candidates for coding exercises in a first-round technical assessment for a data scientist, we sourced candidate questions from [DataLemur](#).

Directly after the technical assessment, candidates were 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?*” 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 a response corresponding with the same five options as in Glassdoor, either very easy, easy, average, difficult, or very difficult.³³

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 by the

³³We also asked about the applicant’s change in self-reported interest: “How would you say your level of interest for the position now compares with your level of interest before the interview began?”, with three possible responses: “Just as interested”, “Less interested”, or “More interested”. Since only 1.5 percent of respondents answered “Less interested”—possibly reflecting a hesitancy to relay explicitly negative feedback—there was limited variation. We therefore decided not to include this variable as a measure of engagement.

hiring manager in considering whom to advance to the next round of interviews. This meant that the hiring manager had access to responses for neither the technical assessment nor the post-interview survey. Applicants were made aware that the latter would be blind to the hiring manager, but to ensure the interview was taken seriously, not the former. 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 interview difficulty, Appendix Figure G1 illustrates 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.

To test whether differences across the two arms are statistically significant, we estimate

$$Y_i = \rho \times 1(\text{Easy arm})_i + \mathbf{X}_i' \gamma + \varepsilon_i. \quad (3)$$

where i indexes each participant. The coefficient of interest ρ captures the effect of being in the “easy questions” treatment arm. The covariates $\mathbf{X}_i$ include pre-treatment controls, for better precision: work experience, college attainment, and date the assessment was completed. The tables report heteroskedasticity-robust standard errors and associated significance calculations. To get at worker heterogeneity, we also estimate equation (3) separately for workers with degrees from high-ranked colleges and those from lower-ranked colleges.

The results for the full applicant sample are presented in Panel A of Table 7. As shown in Column (1), the difference in perceived difficulty is statistically significant. Applicants who experienced the easy assessment were 19 percentage points more likely to perceive the interview as easy compared with applicants who experienced the difficult assessment—a 78 percent increase (Column 1). Consistent with the increase in perceived difficulty, applicants assigned 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 (Column 2). Appendix Figure G2 reports the full distribution of this measure. Evidently, even a light-touch intervention—five questions on a technical assessment that extended the

Table 7: 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)	(2)	(3)	(4)
Panel A: All applicants				
1(Easy arm)	0.189*** (0.026)	-6.088*** (0.856)	-0.110* (0.058)	-0.124** (0.061)
Mean DV difficult arm	0.241	25.703	0.058	0.054
Observations	1,325	1,325	1,325	1,325
Panel B: Lower-skilled applicants				
1(Easy arm)	0.165*** (0.038)	-5.738*** (1.274)	-0.108 (0.073)	-0.091 (0.089)
Mean DV difficult arm	0.243	24.980	0.129	0.058
Observations	655	655	655	655
Panel C: Higher-skilled applicants				
1(Easy arm)	0.225*** (0.060)	-5.427*** (1.512)	-0.304*** (0.113)	-0.347** (0.175)
Mean DV difficult arm	0.261	25.082	0.241	0.188
Observations	311	311	311	311

Notes: Table 7 relates measures of perceived difficulty and of applicant engagement to whether the job seeker was assigned the easy technical assessment. To proxy for an applicant’s skill, we map their university to the measure of college graduate quality from [Martellini *et al.* \(2024\)](#). Higher-skilled applicants are those for whom college graduate quality is in the top tercile, lower-skilled applicants the bottom two terciles. Each specification includes fixed effects for experience category (0-2 years, 2-4 years, 4-6 years, 6+ years) $\times$ an indicator for post-Bachelor’s degree $\times$ the day the interview was conducted. Robust standard errors reported in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

interview by six minutes (Appendix Figure G3)—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 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 interview difficulty.

Not only did the exogenous variation in interview difficulty shift 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 less text (11 percent of a standard deviation, Column 3) for the two open-response, non-technical questions.³⁴ This would suggest that, 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

³⁴Sixteen respondents did not fill out either free-text question, so we impute a zero for these respondents; excluding these respondents produces identical results.

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 (Column 4).

While the response length and application checker outcomes proxy for engagement with the position, we recognize that they do not directly indicate whether an applicant would have rejected a job offer had they received one. Relative to our observational data, these outcomes are most akin to whether the worker attributed a “thumbs-up” impression to the interview—a measure of engagement we observe regardless of whether an offer was made (Appendix Table I9). The experiment documents a reduction in workers’ impressions of the vacancy even before an offer has been made.

Since employers value not just the number of applicants who are interested in a vacancy but also the quality of said applicants, we examine heterogeneity in our treatment effects by worker ability. We proxy for each applicant’s ability using their university of study; for 73 percent of applicants, we are able to assign the human-capital-based ranking of universities from [Martellini *et al.* \(2024\)](#). We partition the sample into lower-skilled and higher-skilled applicants, the latter reflecting the upper tercile according to this ranking, the former the lower two terciles. The results for these two groups are recorded in Panels B and C of Table 7, respectively. Whereas both groups increasingly perceived the easy arm as such and believed the easy arm would require fewer minutes to complete, highly-skilled applicants in particular disengaged after the easy assessment.³⁵ According to both outcomes, highly-skilled applicants who completed the easy assessment exhibited roughly 30–35 percent of a standard deviation less engagement with the vacancy. For lower-skilled applicants, while the estimates are negative, we cannot reject the hypothesis of no effect.

Broader Context. The controlled setting of our experiment, while useful for identification, necessarily abstracts away from other aspects of the hiring process, such as face-to-face interactions with the hiring firm’s employees, multiple rounds of interviewing, and callbacks. How these other aspects interact with one another and with interview difficulty to influence candidates’ perceptions of the hiring firm would be interesting to study as well. Additionally, our intervention was relatively mild in scope, requiring only about 10–20 minutes of an applicant’s time. Candidates may respond differently to a more involved intervention with greater opportunity cost, e.g., an assessment or presentation 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 respond to interview difficulty for other roles, or other (possibly less-established) employers, in other labor markets or at different points

³⁵These results rule out a compensatory-effort story in which lower-ability workers try to compensate for weak interview performance by engaging more through text responses.

over the business cycle may vary. Studying this variation would be a promising avenue for future interventions.

7 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, 2025; Hoffman and Stanton, 2025). 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 as to which employees should conduct which interviews. On the one hand, if firms appear to benefit from signaling to job seekers—through more difficult interviews—that the firm employs workers of high ability, then surely having higher-skilled workers participate in interviewing will increasingly convey such signals to job seekers. On the other hand, higher-skilled workers are more productive, and will have a greater opportunity cost of conducting interviews. 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: while easy interviews

result in more rejected offers and increased turnover, 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 points to another, understudied dimension by which managers contribute to differences in firm-level growth (Bloom and Van Reenen, 2010; Sadun *et al.*, 2025). In Appendix H, 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, they 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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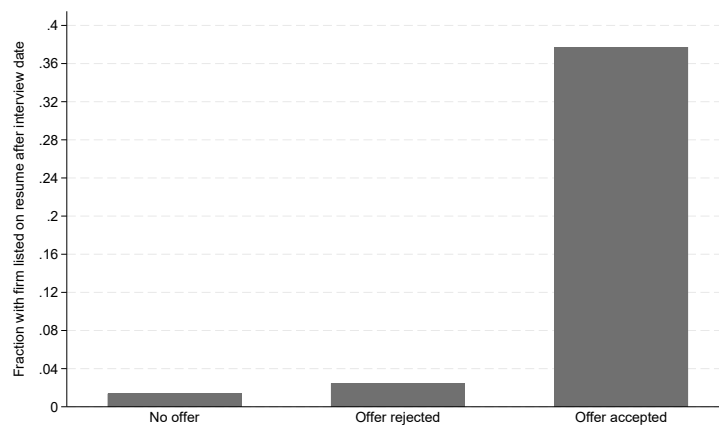
A.1 Glassdoor Interview Submission Process

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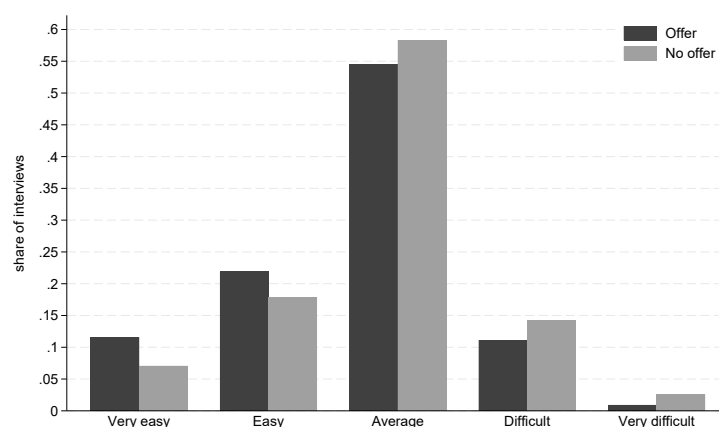
A.2 Figures Summarizing Glassdoor Interview Reports

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



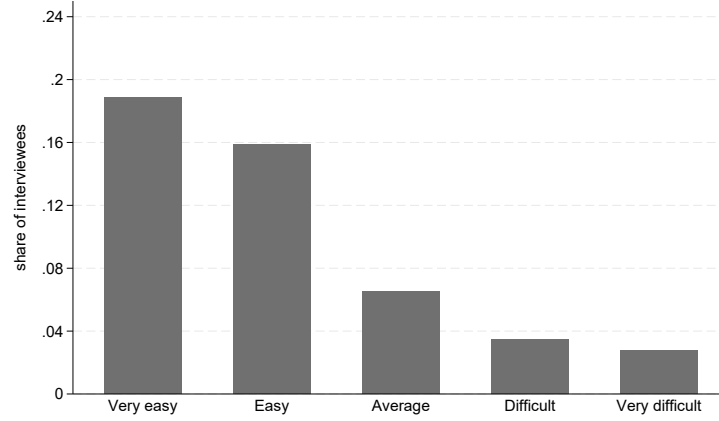
Notes: Figure A2 plots the share of interviews for which the hiring firm appears on the worker's resume, partitioned by whether the worker reported not receiving an offer, receiving an offer and rejecting it, or receiving an offer and accepting it. Sample is restricted to workers who upload a resume 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



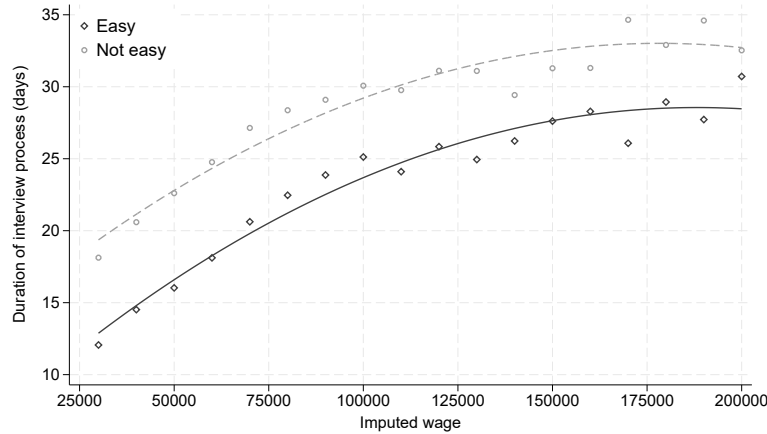
Notes: Figure A3 plots the fraction of interviews in the sample reporting each level of interview difficulty, split by interviews that received an offer and those that did not.

Figure A6: Fraction of Descriptions Mentioning “Easy” by Interview Difficulty



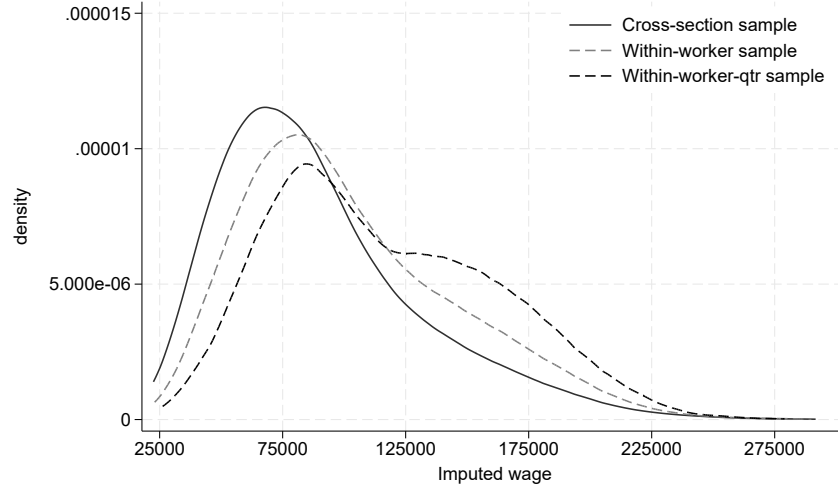
Notes: Figure A6 plots the share of interviews for each difficulty level (rated on a 1-5 scale: 1-very easy, 2-easy, 3-average, 4-difficult, 5-very difficult) that mentioned the word “easy” in the free-response description workers provided about the interview.

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



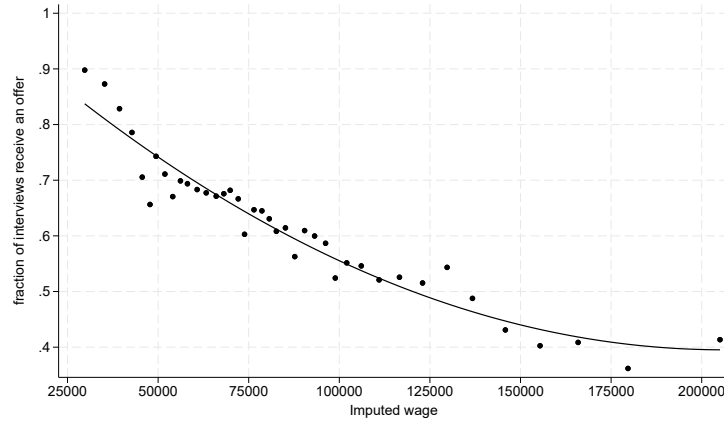
Notes: Figure A7 presents a binscatter of the average length of the interview process (in days) against the estimated wage of the vacancy, with each series indicating the self-reported difficulty rating as easy (“very easy” or “easy”) and not easy (“average,” “difficult,” or “very difficult”).

Figure A8: Distribution of Samples in Table 2 by Wage of Vacancy



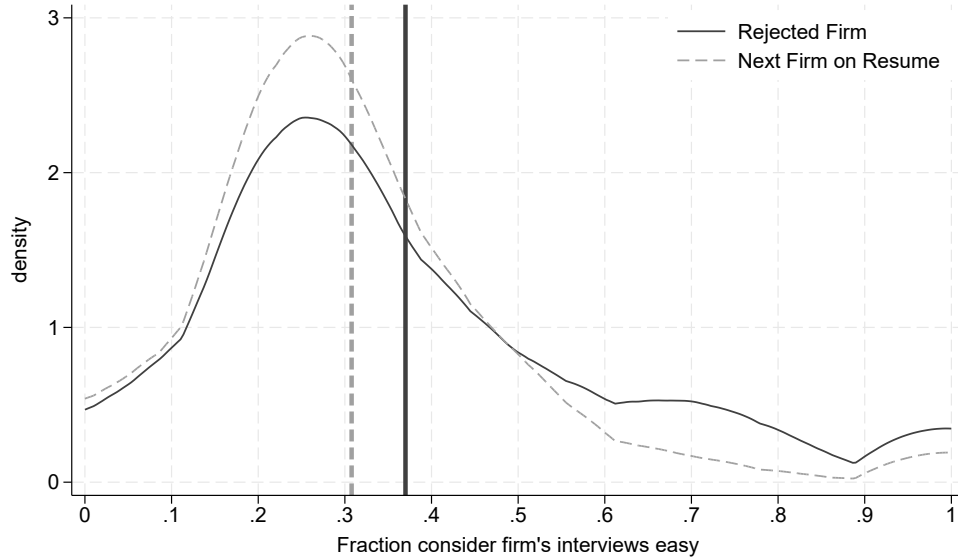
Notes: Figure A8 plots the distribution for the cross-section sample of job offers (solid line), the within-worker sample of job offers (dashed line), and the within-worker-quarter sample of job offers (dash-dot line) by the imputed wage of the vacancy.

Figure A9: Offer Rate by Imputed Wage of the Vacancy



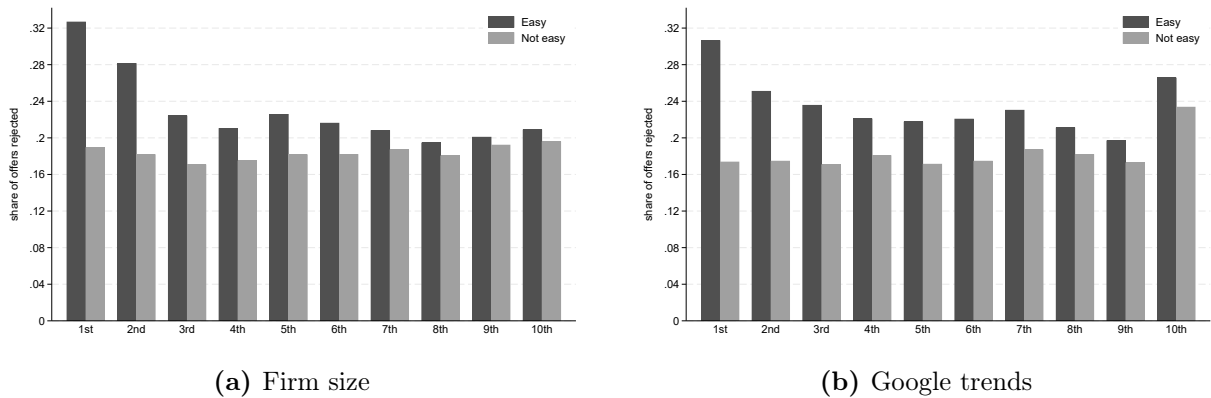
Notes: Figure A9 is a binscatter of the fraction of Glassdoor interviews that led to an offer by the imputed wage of the vacancy. Imputed wage reflects the average pay among Glassdoor pay reports for the given firm and job title. Wages are inflation-adjusted to 2021 dollars. Sample is restricted to firm-job title pairs with at least five interviews.

Figure A10: Comparison of Average Firm Interview Difficulty between Firms Whose Offers Were Rejected and the Next Firm on that Worker’s Resume



Notes: Figure A10 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 3,089 workers for whom we observe a rejected offer and a next firm on their resume.

Figure A11: Rejection Rate by Perceived Difficulty and Firm Familiarity



Notes: Figure A11 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.

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 industry and occupation unavailable	–335,569
=	1,262,848
6. Drop interviews in other occupations	–642,127
=	620,721
7. Drop interviews for internships	–23,689
=	597,032
8. Drop interview reports submitted more than two years after interview date	–94,599
= Final sample	502,433

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

Table A2: 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	Bridgewater Associates	Financial Services
5	SpaceX	Aerospace & Defense
6	YipitData	Information Technology
7	Bain & Company	Management & Consulting
8	Amazon Web Services	Information Technology
9	Relativity Space	Aerospace & Defense
10	Jane Street	Financial Services
11	Clearwater Analytics	Financial Services
12	Google	Information Technology
13	Oliver Wyman	Management & Consulting
14	AKUNA CAPITAL	Financial Services
15	D. E. Shaw & Co.	Financial Services

Notes: Table A2 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) for the seven occupations we consider 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 A3: Firms with the Least Difficult Interviews

Ranking	Firm	Industry
1,169	Allied Universal	Management & Consulting
1,170	Pizza Hut	Restaurants & Food Service
1,171	Advantage Solutions	Media & Communication
1,172	Dollar General	Retail & Wholesale
1,173	Jackson Hewitt	Retail & Wholesale
1,174	Aaron's	Retail & Wholesale
1,175	Family Dollar Stores	Retail & Wholesale
1,176	CROSSMARK	Retail & Wholesale
1,177	Menards	Retail & Wholesale
1,178	Dunkin'	Restaurants & Food Service
1,179	Marlabs	Information Technology
1,180	Aflac	Insurance
1,181	American Income Life	Insurance
1,182	Globe Life Liberty National Division	Insurance
1,183	Primerica	Insurance

Notes: Table A3 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) for the seven occupations we consider 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 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 professional occupations we consider. Internships have been found to 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, whether a job seeker accepts an offer for an internship may vary with the difficulty of the interview.

Taking our sample of interview reports for internships, we re-estimate variations of equation (1), the results of which are summarized in Table B1. Looking at the cross-section of reviews, workers are 3–5 percentage points more likely to reject an offer if they perceived the interview to be easy, relative to a baseline offer acceptance rate for not-easy interviews of 87–88 percent. Even when we compare interview reports for the same role, i.e., job title $\times$ firm $\times$ metro, easy interviews are rejected 4 percentage points more often, relative to a baseline offer acceptance rate for not-easy interviews of 88 percent (Column 3). Although the sample is particularly thin, we observe a significant penalty on offer acceptance following easy interviews even for the same worker choosing between multiple internship offers (Column 4). Thus, for internships as well, easy interviews are rejected more often.

Table B1: Probability of Accepting a Job Offer by Interview Difficulty for Internships

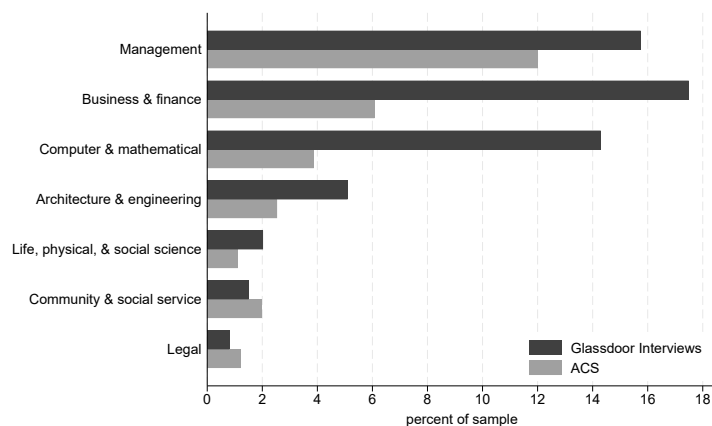
	1(Accepts job offer)			
	(1)	(2)	(3)	(4)
1(Easy interview)	-0.031*** (0.006)	-0.054*** (0.012)	-0.044*** (0.013)	-0.194** (0.098)
Mean DV for not easy	0.867	0.879	0.879	0.765
N	22,138	4,980	4,980	469
Industry-Occupation FE	✓	✓		
Firm-Job title-Metro FE			✓	
Worker FE				✓

Notes: Table B1 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. Each specification includes year-quarter of interview $\times$ year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

C Testing for Selection into Glassdoor Interviews

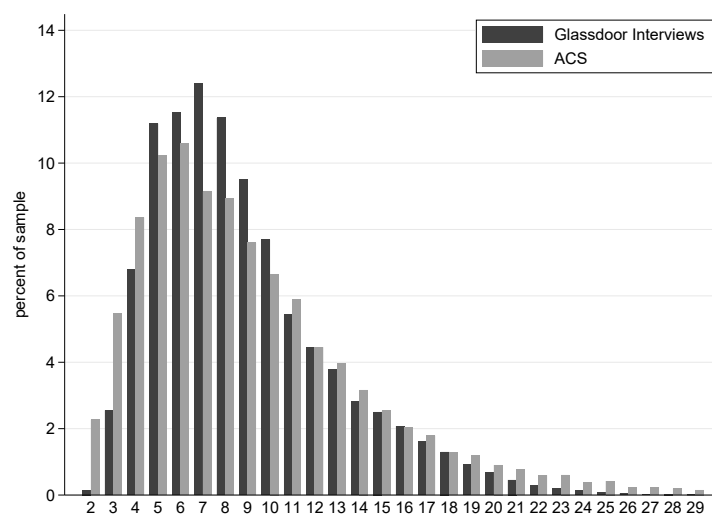
C.1 Glassdoor Comparison with the American Community Survey

Figure C1: Distribution of Glassdoor Interviews Database by Two-Digit Occupation



Notes: Figure C1 plots the fraction of interviews in the sample by each two-digit SOC occupation. Industries are assigned to each employer and come from a Glassdoor lookup table.

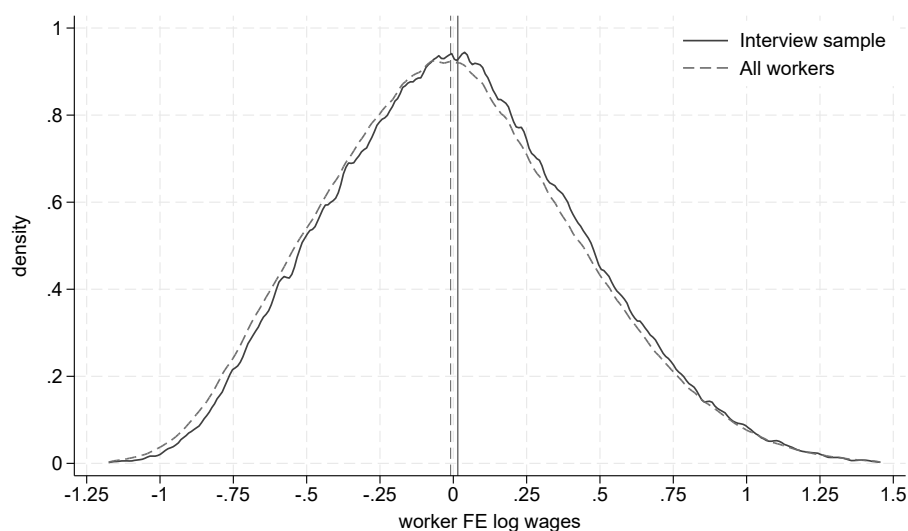
Figure C2: Distribution of Interviews Sample by Imputed Wage of the Vacancy



Notes: Figure C2 plots the fraction of interviews in the sample by the imputed wage of the vacancy within \$10,000 bins. Imputed wage reflects the average pay among Glassdoor pay reports for the given firm and job title. Wages are inflation-adjusted to 2021 dollars.

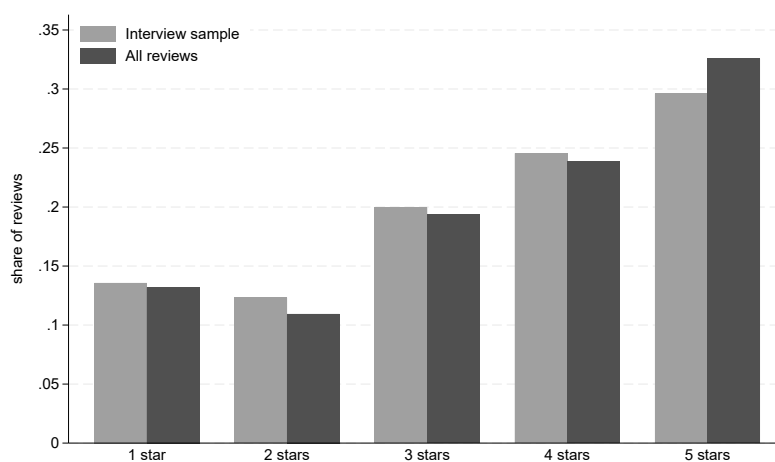
C.2 Glassdoor Interview Sample Comparison with Entire Glassdoor Database

Figure C3: Distribution of Worker AKM Fixed Effects from Accepted Offers Sample Compared with the Full Sample of Glassdoor Pay Reports



Notes: Figure C3 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 C4: Distribution of Job Satisfaction Ratings in Interviews Sample Compared with the Full Sample of Glassdoor Reviews



Notes: Figure C4 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.

C.3 Glassdoor Interview Sample Comparison with Onsites.fyi Database

In this appendix section, we provide additional detail on validating the Glassdoor data with an external data source, Onsites. Unlike Glassdoor, which covers many employers across many industries, Onsites caters to software engineering jobs for select companies, generally in the information technology sector. As with Glassdoor, respondents are asked to rate the difficulty of their 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 are for Amazon or Microsoft.

As with Glassdoor, for each interview, we observe the firm, job title, and perceived interview difficulty. We thus calculate the average difficulty for each firm $\times$ job title in Onsites, and the average difficulty for the same firm $\times$ job title in Glassdoor, and compare. The relationship between the two, summarized in Appendix Table C1, is reassuring. Greater difficulty on Glassdoor aligns with greater difficulty on Onsites. There are 120 firm-job title pairs for which we can calculate an average in both datasets. When we weight by sample size in column (1), one additional difficulty level in Glassdoor is associated with, on average, 0.51 additional levels of difficulty in Onsites. Equally weighting firm $\times$ job title pairs with more than one observation in Onsites produces a larger estimate close to 1, specifically 1.06. 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 C1: Average Interview Difficulty Across Jobs on Glassdoor and Onsites

	Onsites mean difficulty	
	(1)	(2)
Glassdoor mean difficulty	0.509** (0.229)	1.057*** (0.241)
Firm-job title pairs	120	59
Onsites interviews	511	450
Weighted by Onsites count	✓	
Onsites count > 1		✓

Notes: Table C1 compares the average difficulty for interview reports on Onsites.fyi and interview reports on 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%.

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.

“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 the two annotators, as well as between the annotators themselves, for each prompt is presented in Table D1.

Table D1: Alignment between LLM-derived and Human-derived Annotations

Agreement between...	Ability	Anyone	Assessment	Wages	Hours	Amenities	Engaging	RJP
Annotators 1 and 2	0.89	0.83	0.86	0.87	0.90	0.62	0.81	0.80
LLM and annotators	0.84	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. Ability refers to Colleague ability, Anyone to “They’d accept anybody”, Assessment to Direct assessment, Wages to Compensation, Hours to Hours and scheduling, Amenities to Workplace amenities, Engaging to Interview engagement, and RJP to Realistic job preview.

E Empirical Validation of LLM Prompts for Peer Ability

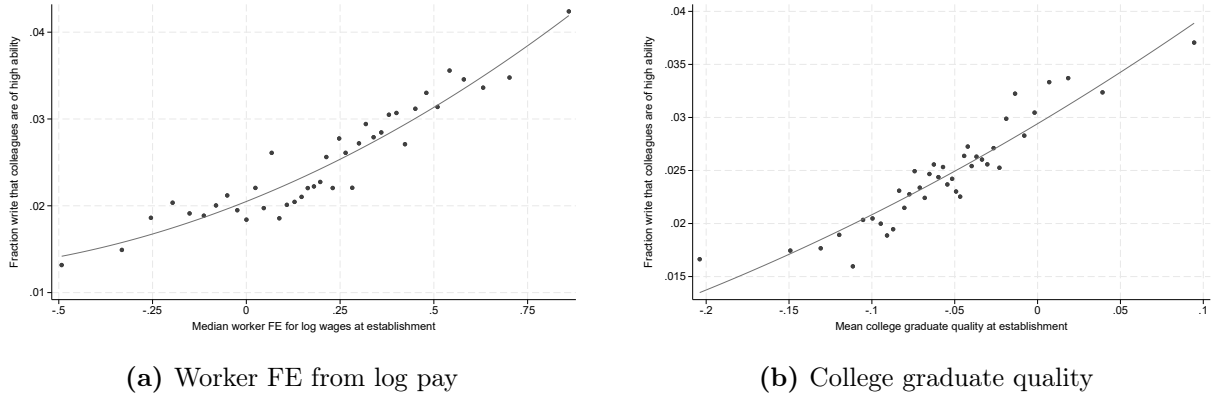
In this appendix, we further validate that interview experiences can signal prospective peer quality by asking whether the elicited perceptions workers draw from the interview reflect empirical characteristics about the firm based on external sources. Here, we consider all interview reports, offers and non-offers, not just those that received an offer.

First, we match up the LLM-based annotations for high-ability colleagues and ‘would accept anybody’ with establishment-level measures of peer ability. We proxy for peer ability through two measures. First, we use Glassdoor pay reports and estimate worker fixed effects from an AKM regression on log wages. Taking the sample of pay reports as a snapshot of the pool of coworkers, we calculate the median worker fixed effect at each firm $\times$ metro $\times$ year. Second, we use workers’ resumes, and based on their Bachelor’s degree, assign them their alma mater’s college graduate quality (Martellini *et al.*, 2024). We then calculate the mean college graduate quality among the set of workers that we observe, among our sample of resumes, at each firm $\times$ metro.

Figures E1 and E2 affirm that these interview-based text annotations of peer ability are informative about latent worker ability within the hiring firm. Compared with firms that have the highest levels of peer ability, firms with the lowest levels are (*less than*) *half* as likely to give the impression of high-ability colleagues and *more than three times* as likely to give the impression that the firm would accept anybody. 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 (Table E1). Further, we can disentangle the reputation of the parent firm from its establishments. We observe the same pattern for both proxies of peer ability when we look between establishments of the same firm by including firm $\times$ year and metro $\times$ year fixed effects (Table E2). Thus, it is not just that certain firms or specific labor markets exhibit high-ability colleagues, but rather that establishments, which differ in coworker ability, differ in signaling high-ability colleagues.

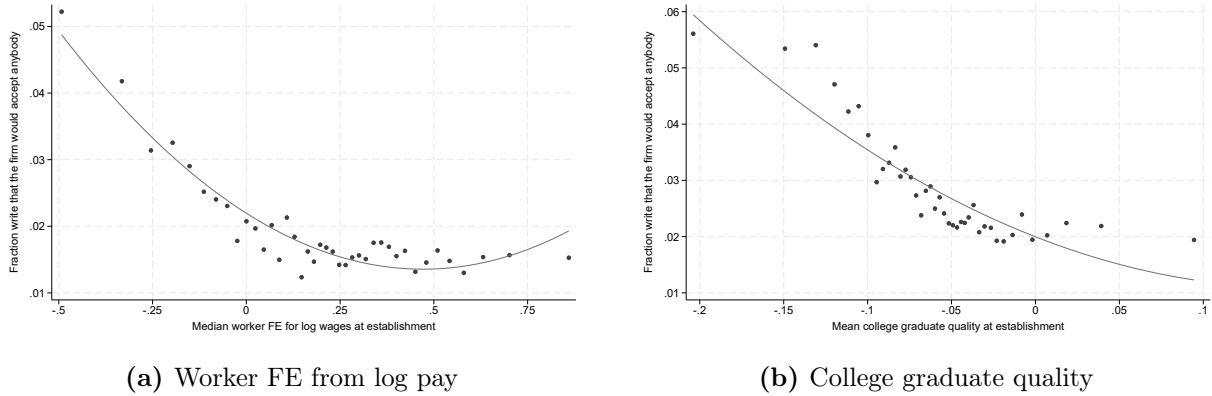
Second, we relate the frequency with which interview narratives suggest the firm would accept anybody and the firm’s observed offer rate in the Glassdoor interviews database. For the latter, we calculate the fraction of interview reports in Glassdoor that resulted in an offer for each firm $\times$ job title. We find, in Figure E3, that annotations of “would accept anybody” are robustly correlated with the reported job offer rate. When the fraction of interviews that lead to offers is below 70 percent, about 1-2 percent of interviews characterize the firm as accepting anybody. As the offer rate rises above 70 percent, the frequency rises sharply, with upwards of 8-12 percent of interviews characterizing the firm as accepting anybody when the offer rate exceeds 90 percent.

Figure E1: Actual Peer Ability and Perceptions of High-Ability Colleagues



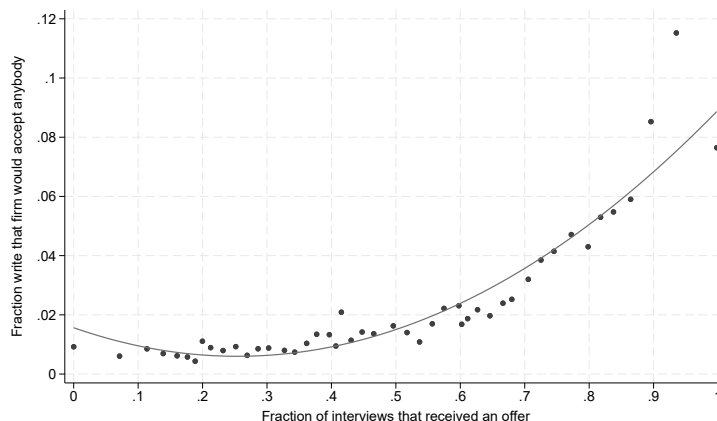
Notes: Figure E1 reflects a binscatter of the fraction of interviews that suggest peers are of high ability against the average skill level of peers at the hiring firm, where the skill level of peers is measured by workers' fixed effects from log pay in panel (a) or their college graduate quality in panel (b). For panel (a), 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 by firm $\times$ metro $\times$ year within the sample of pay reports. For panel (b), we calculate the mean college graduate quality (Martellini *et al.*, 2024) among workers we observe at each firm $\times$ metro based on their resumes. Sample is restricted to cells for which at least two workers are observed. Fixed effects for metro are residualized out.

Figure E2: Actual Peer Ability and Perceptions of Accepting Anyone



Notes: Figure E2 reflects a binscatter of the fraction of interviews that suggest the firm “would accept anybody” against the average skill level of peers at the hiring firm, where the skill level of peers is measured by workers' fixed effects from log pay in panel (a) or their college graduate quality in panel (b). For panel (a), 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 by firm $\times$ metro $\times$ year within the sample of pay reports. For panel (b), we calculate the mean college graduate quality (Martellini *et al.*, 2024) among workers we observe at each firm $\times$ metro based on their resumes. Sample is restricted to cells for which at least two workers are observed. Fixed effects for metro are residualized out.

Figure E3: Actual Offer Rate and Interview-Based Perceptions of Accepting Anyone



Notes: Figure E3 reflects a binscatter of the fraction of interviews that suggest the hiring firm “would accept anybody” against the fraction of interviews for the same firm x job title pair that resulted in an offer. Sample is restricted to firm x job title pairs for which at least 5 interview reports are observed.

Table E1: Beliefs about Peers and Actual Ability of Managers and Non-Managers

	1(High-ability colleagues)		1(Would accept anybody)	
	(1)	(2)	(3)	(4)
Median worker FE for managers	0.000 (0.001)	0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
Median worker FE for non-managers	0.004*** (0.001)	0.003*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)
Mean DV	0.024	0.024	0.014	0.014
N	167,493	167,493	167,493	167,493
Firm-interview year FE		✓		✓

Notes: Table E1 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 E2: Beliefs about Peers and Actual Ability of Peers, with Firm $\times$ Year Fixed Effects

	1(High-ability colleagues)		1(Would accept anybody)	
	(1)	(2)	(3)	(4)
Panel A: Worker fixed effects from log pay				
Standardized median among peers	0.004*** (0.001)	0.003*** (0.001)	-0.011*** (0.001)	-0.007*** (0.001)
Mean DV	0.026	0.026	0.018	0.018
N	284,197	284,197	284,197	284,197
Panel B: College graduate quality				
Standardized median among peers	0.007*** (0.001)	0.001* (0.001)	-0.011*** (0.001)	-0.003*** (0.001)
Mean DV	0.026	0.026	0.026	0.026
N	379,145	379,145	379,145	379,145
Firm-interview year FE		✓		✓

Notes: Table E2 summarizes the relation between interviewee beliefs that colleagues are of high ability or the firm “would accept anybody” and the actual ability of peers. The skill level of peers is measured by workers’ fixed effects from log pay in panel A and their college graduate quality in panel B. 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 $\times$ year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

F 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 to match U.S. employment by industry, occupation, sex, metropolitan area, and pay. After re-weighting, the coefficient remains negative and statistically significant, albeit somewhat attenuated.

Next, we consider that there may be recall bias in perceptions of difficulty for those who disclose their interviews on Glassdoor with a delay. When we restrict the sample to only interview reports submitted within one month of the interview process ending, easy interviews are rejected 14 percentage points more often—a marked 18 percent decline relative to the acceptance rate after not-easy interviews. As measurement error induced by delayed reporting biases our estimates toward zero, our benchmark estimates in Table 2 are likely conservative lower bounds. 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 the interview year and month based on the disclosure date. Considering only interview reports without disclosed dates 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 (Figure F1, 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 similarly negative responses to easy interviews. Graduates from universities with above-average college graduate quality, based on the ranking by Martellini *et al.* (2024), exhibit a slightly larger decline in offer acceptance after an easy interview compared with graduates from other universities, though the estimate is negative and significant for both groups. For workers with above-average and below-average GPAs, the estimates are significantly negative and not dissimilar. We also consider only workers with post-Bachelor’s degrees and again find a sharp negative response to easy interviews.

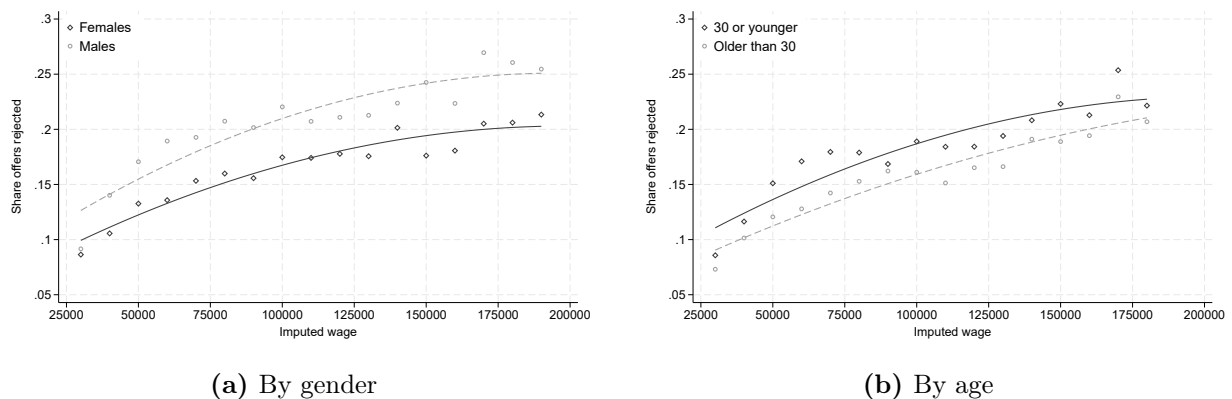
We next consider heterogeneity by job search activity. We first determine whether a worker is searching on-the-job or off-the-job by examining whether the interview occurred

during a job spell, or between two job spells, on their resume. Whether workers are searching on-the-job or off-the-job, workers in both cases are more likely to reject offers after an easy interview. Whether the job would likely constitute above-average or below-average pay growth, based on the most recent firm $\times$ 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 at whether they are explicitly mentioned in each interview narrative. Whether the interview involves HR or includes management, easy interviews are increasingly rejected for both. If the interview involved a video component conducted remotely over Zoom, included a coding exercise, or highlighted the responsibilities that would be required, easy interviews are rejected a marked 8–10 percentage points more often than not-easy interviews—suggesting interviews may be especially important barometers for assessing the hiring firm when workplace attributes are more opaque, or when opportunities for skill development are relayed.

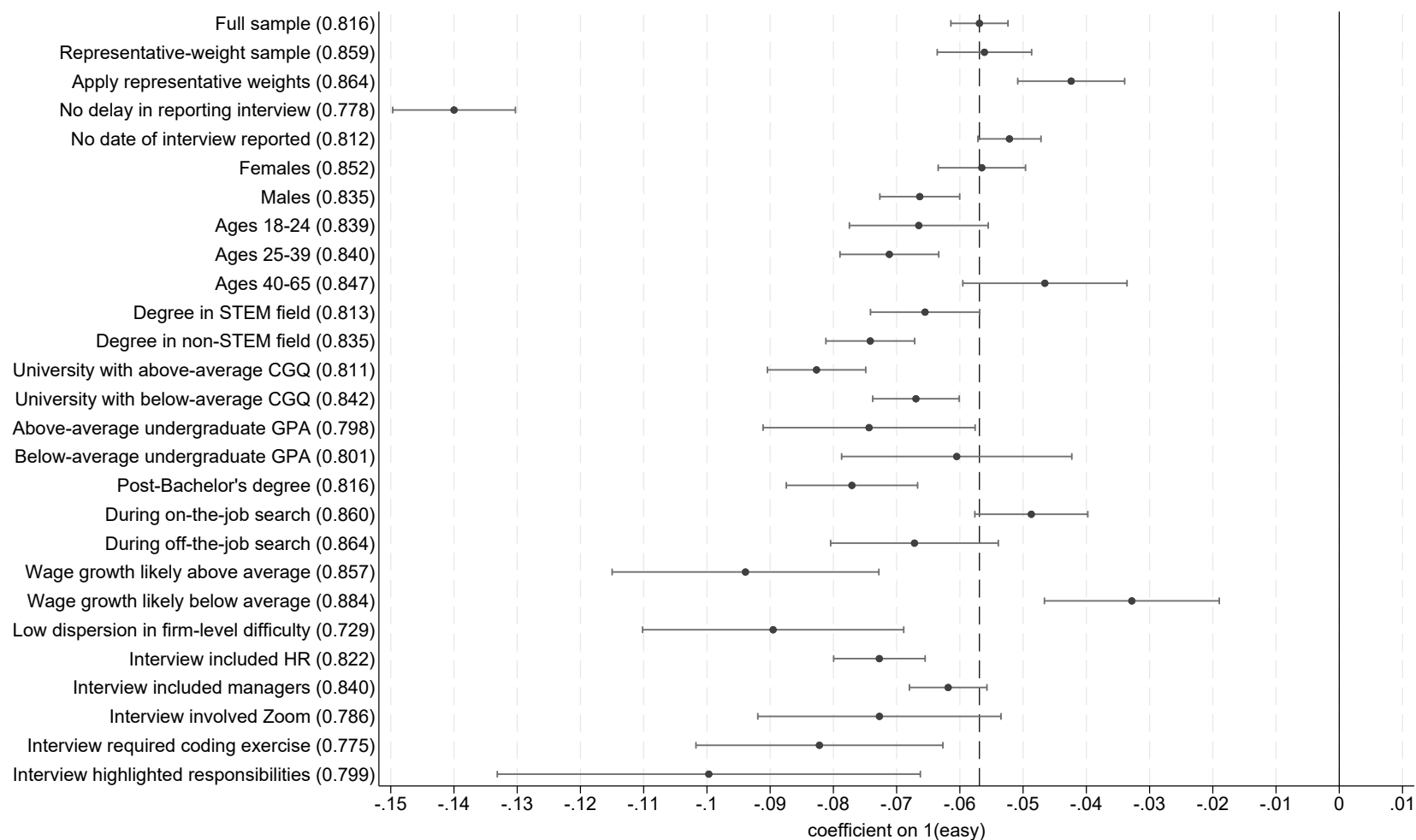
For each sub-sample, the estimated coefficient and its 95 percent confidence interval are plotted in Figure F2.

Figure F1: Probability of Rejecting an Offer by Wage and Worker Demographics



Notes: Figure F1 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.

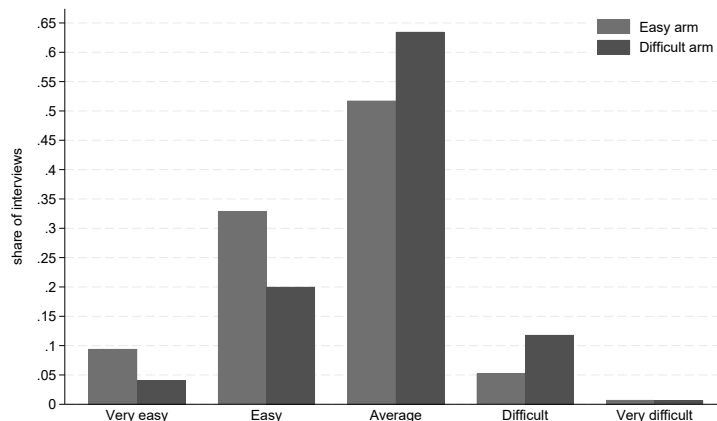
Figure F2: Interview Difficulty and Offer Acceptance for Different Sub-Samples



Notes: Figure F2 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, 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.

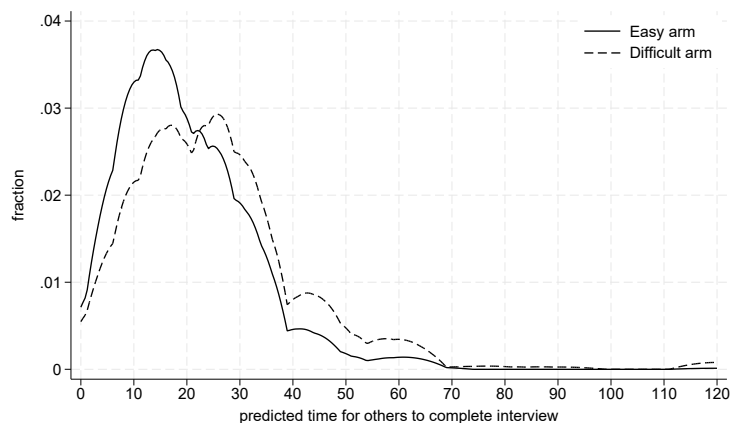
G Additional Information and Results from the Experiment

Figure G1: Experimentally Induced Difficulty and Interview Perceptions



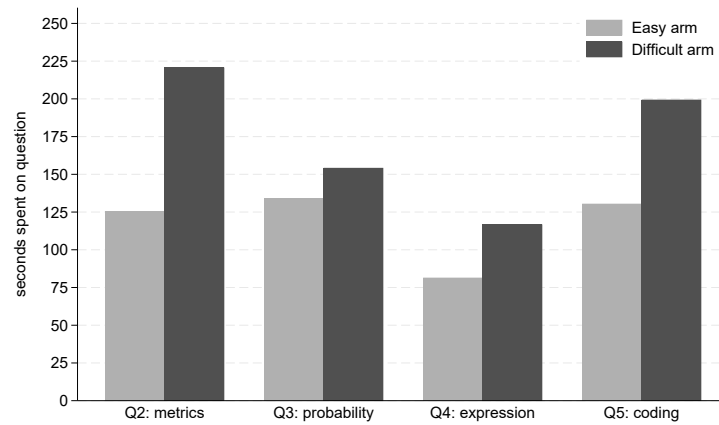
Notes: Figure G1 displays the fraction of applicants that reported each level of perceived difficulty by treatment arm. For a full characterization of the interview process for each treatment arm, see Appendix Table G1.

Figure G2: Predicted Time Needed to Complete Interview by Treatment Arm



Notes: Figure G2 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 G3: Seconds Spent Answering Each Free-Response Technical Question



Notes: Figure G3 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 G1: Structure of Technical Assessment

	Easy assessment arm	Difficult assessment arm
<i>Background</i>	First name, last name, and email address	
<i>Resume</i>	Upload a resume	
<i>Experience</i>	Highest degree, field of study, university of study, and years of work experience	
<i>Question 0</i>	Prompt for technical assessment of 5 questions	
<i>Question 1</i>	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?
<i>Question 2</i>	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?
<i>Question 3</i>	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?
<i>Question 4</i>	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.
<i>Question 5</i>	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.
<i>Question 6</i>	For the final question, we would like to know: Why are you a good fit for this job?	
<i>Own Questions</i>	Do you have any questions for us? Feel free to skip the question if you do not.	
	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?	
<i>Perceptions</i>	How do you believe other applicants would rate the difficulty of the interview?	

Notes: Table G1 outlines the experiment and its two treatment arms.

Table G2: 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

Notes: Table G2 shows summary statistics for key variables from the experiment.

H 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 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 Glassdoor sample. The measure accounts for differences across job titles (as in Appendix Tables A2 and A3), 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

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

where λ is a vector of group-specific fixed effects that includes worker, firm, metro $\times$ year, and two-digit North American Industry Classification System (NAICS) industry $\times$ two-digit SOC occupation $\times$ year fixed effects, and $\mathbf{X}_{i,k,t}$ is a vector that includes a fourth-order polynomial in years of experience.

The coefficient of interest ψ captures, for the same worker i , the degree to which wages in the period 2020–2024 differ relative to the firm’s average wage level in earlier years before this period, by the relative difficulty of firm k ’s interviews in the beginning of the sample period, 2012–2016. 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 Table H1.

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—which are evident in Appendix Tables A2 and A3—and even when we focus only on young firms with less-established reputations, where the relation rises to 1.3 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.

Table H1: Past Interview Difficulty and Future Pay Growth

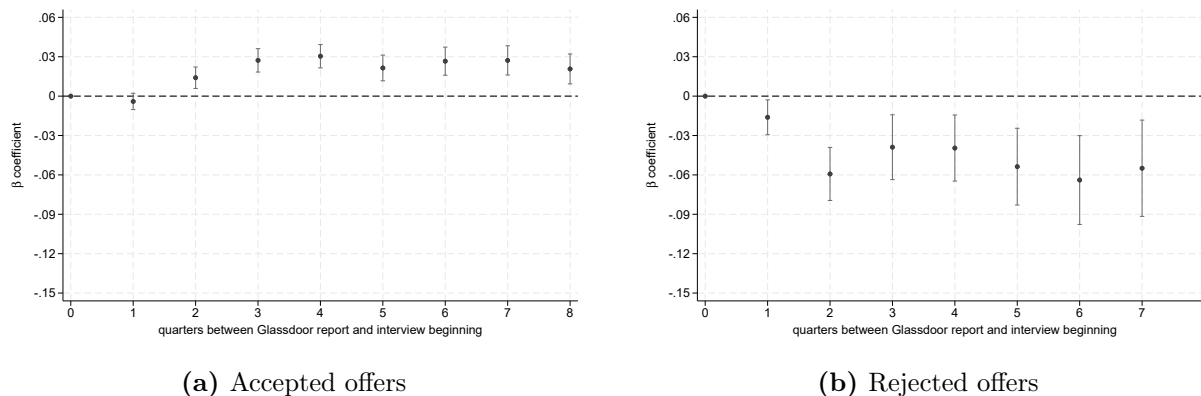
	Ln(Total pay)			
	All firms		Firms founded from 2002-11	
	(1)	(2)	(3)	(4)
Firm's relative interview difficulty 2012-16 x 1(Pay in 2020-24)	0.008*** (0.001)	0.006*** (0.001)	0.013*** (0.004)	0.012*** (0.003)
N	1,439,200	1,439,200	114,798	114,798
Adjusted R ²	0.86	0.86	0.89	0.89
Worker, firm, metro-year, and industry-occupation-year FE	✓	✓	✓	✓
Residualized relative interview difficulty		✓		✓

Notes: Table H1 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%.

What mechanism is it that fuels this faster growth? Perhaps it is increased complementarity from the pooling of high-ability peers, perhaps through improved satisfaction (Bellet *et al.*, 2024), or efficiency gains from the reduction in turnover and the mitigated loss of firm-specific human capital (Becker, 1962), or the innovation and patenting that high-ability workers generate (Martellini *et al.*, 2024). Or, perhaps firms that implement difficult interviews are the firms that are already set on high-growth trajectories. While we do not attempt to disentangle these channels here, we hope future researchers will.

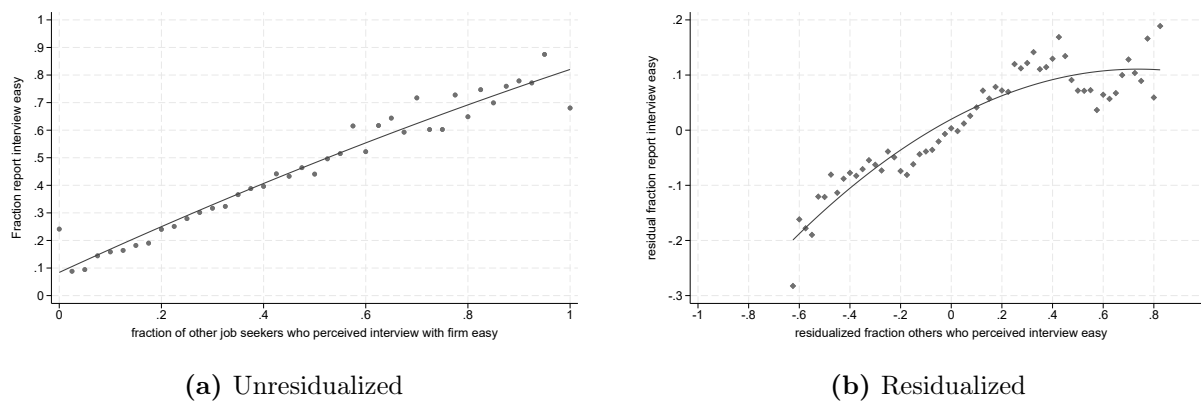
I Sensitivity Exercises

Figure I1: Difference in Perceptions of Interview Difficulty by Time Since Interview



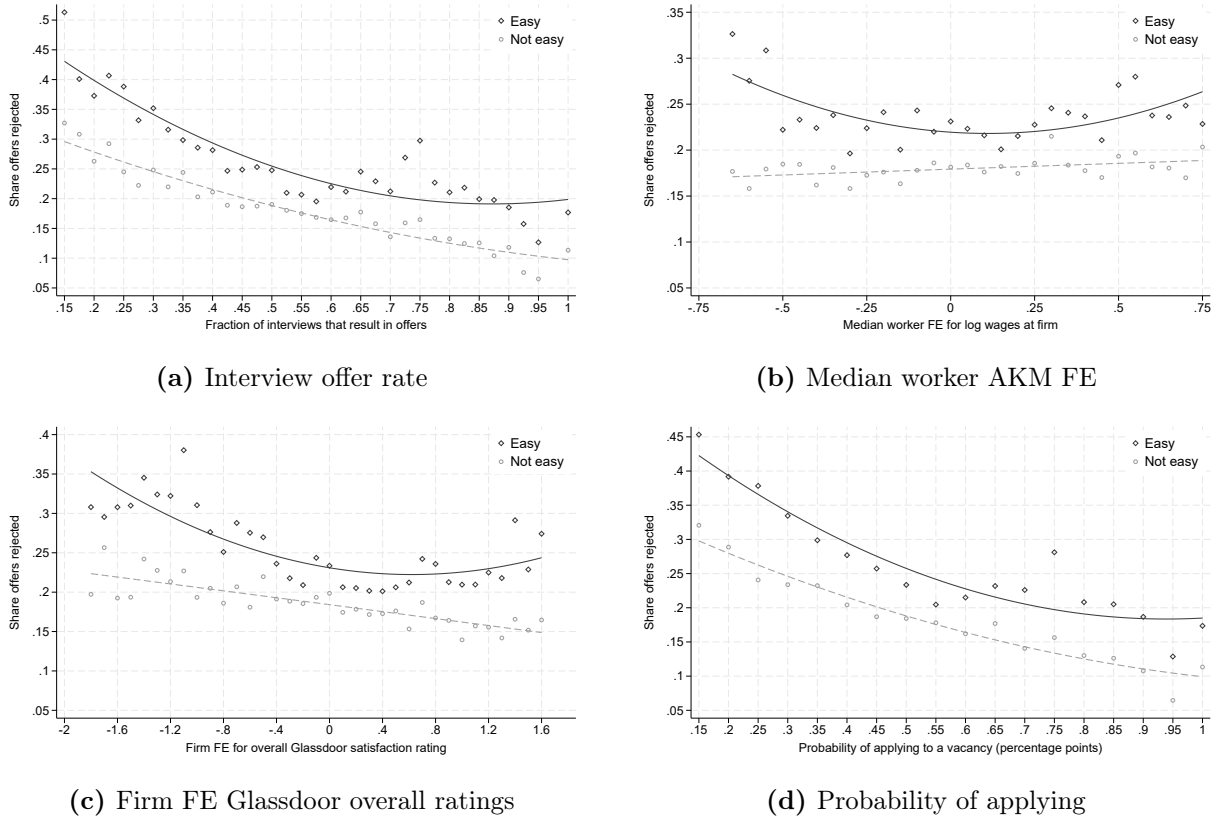
Notes: Figure I1 reflects the difference in the probability of reporting an interview as very easy or easy based on the time elapsed between the interview start date and when it was reported to Glassdoor. Results are shown separately for workers who accepted (panel a) and rejected (panel b) the job offer.

Figure I2: Perceived Interview Difficulty and the Perceptions of Other Job Seekers



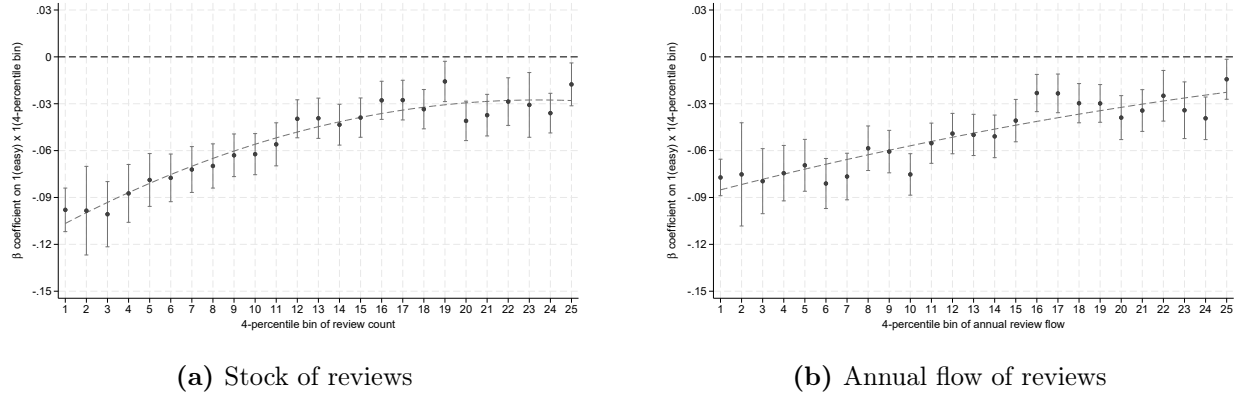
Notes: Figure I2 relates the perceived difficulty of others who interviewed for the same firm and one's own perceived difficulty. Panel (a) does not residualize, whereas in panel (b), both measures are residualized by the same fixed effects as in Column (2) of Table 2: industry x 20 five-percentile bins of firm age x 20 five-percentile bins of firm AKM pay premium, metro, 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 I3: Probability of Offer Rejection by Interview Difficulty and Firm Desirability



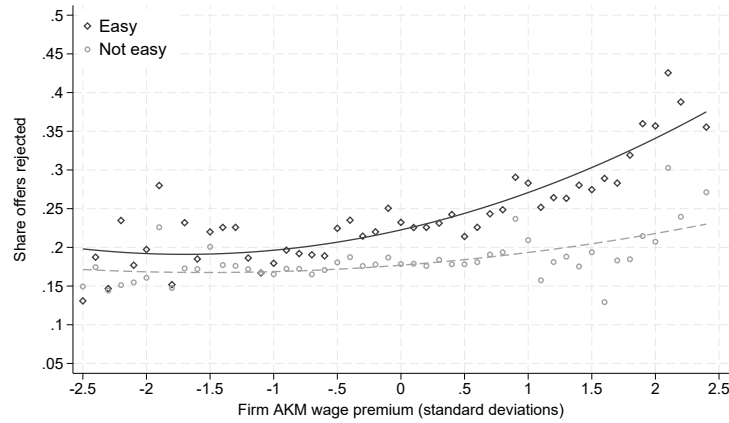
Notes: Figure I3 reflects a binscatter for the fraction of offers rejected, based on the worker's perception of interview difficulty and (a) the fraction of interviews for the firm that resulted in an offer, (b) the median worker fixed effect (from an AKM model of log wages) for the firm with which the 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 I4: Probability of Offer Acceptance by Perceived Difficulty and the Firm’s Relative Number of Glassdoor Reviews, Within-Firm Variation



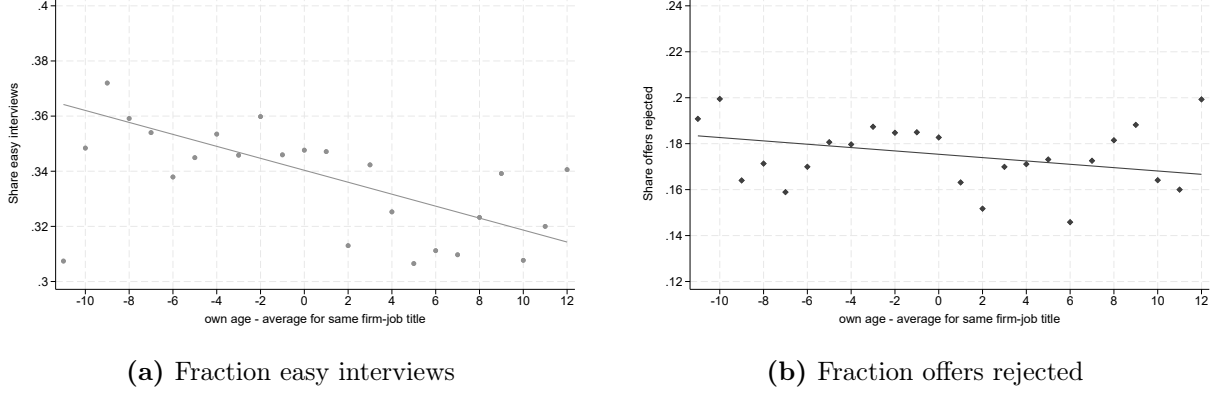
Notes: Figure I4 relates offer acceptance to whether the job seeker perceived the interview to be easy or not, partitioned by the total number of Glassdoor reviews submitted on the platform by the time of the interview (panel a) or the number of new Glassdoor reviews written within the last year (panel b). Firms are partitioned into 25 four-percentile bins within each calendar year in ascending order. Plotted coefficients correspond to $1(Easy) \times 1(Bin_k)$, when added to model (1) from Table 2, with the standalone indicators $1(Bin_k)$ included—with the addition of firm fixed effects. Regression includes firm, metro, industry-occupation, and year-quarter of interview $\times$ year-quarter submitted to Glassdoor fixed effects. Dashed blue line indicates a quadratic fit through the coefficients. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Figure I5: Probability of Offer Rejection by Interview Difficulty and Firm Pay Premium



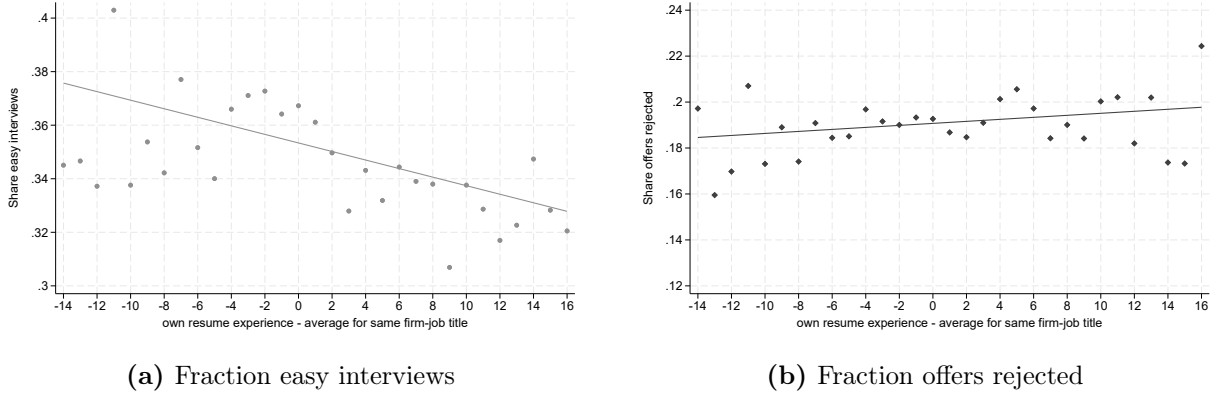
Notes: Figure I5 reflects a binscatter for the fraction of offers rejected, based on the worker’s perception of interview difficulty and the firm’s fixed effect from an AKM model of log wages. Each scatter point represents a 0.1-rounded bin.

Figure I6: Relative Age as a Proxy for Under- or Over-Qualified



Notes: Figure I6 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 I7: Relative Experience on Resume as a Proxy for Under- or Over-Qualified



Notes: Figure I7 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 I1: Difference in Interview Duration Between Offers and No Offers

	Ln(duration of interview process)	
	(1)	(2)
Received an offer	0.158*** (0.007)	
Received an offer and rejected it		0.139*** (0.007)
Received an offer and accepted it		0.163*** (0.008)
N	571,608	571,608
Firm FE	✓	✓

Notes: Table I1 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 I2: Difference in Worker Skill Between Those Who Do and Do Not Receive Offers

	Worker FE on log wages	
	(1)	(2)
Received an offer	0.192*** (0.014)	
Received an offer and rejected it		0.202*** (0.017)
Received an offer and accepted it		0.189*** (0.015)
N	31,883	31,883
Firm-Job title-Metro FE	✓	✓

Notes: Table I2 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 I3: Predictive Power of Imputed Wages for Realized Wages

	Worker's actual wage	
	Levels	Logs
Worker's imputed wage	1.042*** (0.006)	1.016*** (0.003)
N	25,770	25,770
R^2	0.84	0.86

Notes: Table I3 summarizes the relationship between a worker's realized wage from a Glassdoor pay report and the imputed wage based on the firm and job title. To assign the realized 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 I4: Variation in Interview Difficulty Between Firms and Job Seekers

	1(Easy interview)				
Log length of interview duration	-0.085*** (0.002)	-0.055*** (0.001)	-0.061*** (0.006)	-0.045*** (0.006)	-0.028*** (0.010)
N	279,046	279,046	7,543	7,543	7,543
R^2	0.052	0.217	0.085	0.376	0.799
Firm FE		✓		✓	✓
Worker FE					✓

Notes: Table I4 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 I5: Interview Difficulty for the Same Worker Over Time

	1(Easy interview)		
	(1)	(2)	(3)
Second interview observed	-0.042*** (0.007)	-0.026** (0.011)	-0.025 (0.021)
Third interview observed	-0.052*** (0.017)	-0.036 (0.025)	-0.018 (0.043)
Fourth interview observed	-0.117*** (0.034)	-0.049 (0.044)	-0.006 (0.079)
N	31,320	16,642	8,613
Job title FE			✓
Firm FE		✓	✓
Worker FE	✓	✓	✓

Notes: Table I5 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 I6: Alternative Sets of Other Interviewees' Perceived Difficulty and Offer Acceptance

	1(Accepts job offer)				
	Leave-one-out firm (1)	Leave-one-out firm-metro (2)	Leave-one-out firm-occupation-year (3)	1-year-lagged firm average (4)	1-year-ahead firm average (5)
Fraction others' interviews easy	-0.050*** (0.006)	-0.028*** (0.004)	-0.026*** (0.005)	-0.019*** (0.004)	-0.024*** (0.004)
R ²	0.07	0.07	0.07	0.07	0.07
Mean DV for not easy	0.818	0.817	0.804	0.815	0.820
N	423,961	378,888	367,335	352,155	341,001
Firm Observables	✓	✓	✓	✓	✓

Notes: Table I6 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, 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 I7: Probability of Accepting a Job Offer by Wage of Vacancy

	1(Accepts job offer)
Imputed log wage	0.392*** (0.084)
N	2,417
Workers	1,140
R ²	0.62
Worker-Qtr FE	✓

Notes: Table I7 summarizes the relation between the probability an offer is accepted and the imputed log wage of the vacancy. The specification includes metro, 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 I8: Interview Difficulty and Realized Wages

	Worker's actual wage	
	Levels	Logs
1(Easy interview)	-517.719 (833.308)	-0.011 (0.009)
Mean DV	91,674.73	11.31
Fraction easy interviews	0.273	0.273
N	3,157	3,157
R ²	0.88	0.90
Firm-Job title-Metro FE	✓	✓

Notes: Table I8 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 I9: Probability of a “Thumbs-up” by Perception of Interview Difficulty

	1(Thumbs-up)							
	Cross-section sample		Within-worker sample			Within-worker-qtr sample		Within-ad sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Interviews That Led to Offers								
1(Easy interview)	-0.097*** (0.002)		-0.129*** (0.008)	-0.099*** (0.011)		-0.120*** (0.021)	-0.103*** (0.037)	-0.069*** (0.008)
Fraction others' interviews easy		-0.113*** (0.006)			-0.147*** (0.036)			
Mean DV for not easy	0.813	0.813	0.794	0.794	0.794	0.783	0.783	0.843
N	423,961	423,961	23,860	23,860	23,860	3,344	3,344	34,889
Workers	410,305	410,305	11,147	11,147	11,147	1,569	1,569	34,455
R ²	0.07	0.06	0.18	0.71	0.71	0.38	0.83	0.51
Panel B: Interviews That Did Not Lead to Offers								
1(Easy interview)	-0.061*** (0.002)		-0.078*** (0.003)	-0.045*** (0.004)		-0.072*** (0.005)	-0.055*** (0.008)	-0.020 (0.012)
Fraction others' interviews easy		-0.043*** (0.006)			-0.048*** (0.012)			
Mean DV for not easy	0.369	0.369	0.231	0.231	0.231	0.208	0.208	0.409
N	451,243	451,243	85,071	85,071	85,071	29,724	29,724	51,632
Workers	398,004	398,004	32,563	32,563	32,563	11,234	11,234	49,870
R ²	0.05	0.05	0.09	0.60	0.60	0.14	0.65	0.42
Firm Observables	✓	✓	✓	✓	✓	✓	✓	
Worker FE				✓	✓			
Worker-Qtr FE							✓	
Firm-Job title-Metro-Qtr FE								✓

Notes: Table I9 summarizes the relation between the probability a worker reports that the interview was a “thumbs-up” impression and perceived difficulty of the interview with the iterated addition of fixed effects. Panel A restricts the sample to interviews that led to offers, while Panel B restricts the sample to interviews that did not lead to offers. 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, 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 I10: Distribution of Worker Ability Among Interviews by Firm Interview Difficulty

Fraction of firms' interviews easy	Worker FE from log wages				College graduate quality			
	N	p10	p50	p90	N	p10	p50	p90
0–10%	5,821	-0.98	0.26	1.49	10,870	-1.05	0.35	1.75
10–20%	35,450	-1.00	0.29	1.54	66,806	-1.18	0.23	1.53
20–30%	53,070	-1.15	0.09	1.36	97,112	-1.26	0.10	1.31
30–40%	29,036	-1.32	-0.09	1.22	54,366	-1.31	-0.06	1.13
40–50%	11,056	-1.45	-0.25	1.05	21,939	-1.31	-0.13	1.03
50–60%	3,995	-1.67	-0.46	0.92	8,150	-1.30	-0.17	1.03
60–100%	2,916	-1.82	-0.69	0.59	7,994	-1.35	-0.28	0.99

Notes: Table I10 partitions firms by the fraction of their interviews that are perceived to be easy, and calculates the distribution of worker ability within each partition among workers who receive an interview. We consider two measures of worker ability: (i) individual fixed effects from an AKM regression on log pay, and (ii) the college graduate quality from [Martellini *et al.* \(2024\)](#) of the worker's university. We report the number of workers represented (N), the 10th percentile (p10), the 50th percentile (p50), and the 90th percentile (p90). Both measures have been normalized into standard deviations.

Table I11: Probability of Accepting a Job Offer by Interview Difficulty, Excluding Interview Reports for Accepted Offers That Were Disclosed to Glassdoor After Joining the Firm

	1(Accepts job offer)		
1(Easy interview)	-0.043*** (0.003)	-0.052*** (0.011)	-0.035** (0.018)
Mean DV for not easy	0.092	0.137	0.105
N	37,761	5,117	1,787
Firm-job title-metro FE		✓	
Worker FE			✓

Notes: Table I11 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 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 I12: 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*** (0.002)	-0.024*** (0.003)	-0.105*** (0.008)
Mean DV for not easy	0.816	0.897	0.819
N	502,337	53,606	17,662

Notes: Table I12 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, 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 I13: 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*** (0.003)	-0.165*** (0.014)	0.012*** (0.001)	0.027*** (0.007)	0.015*** (0.002)	0.031** (0.014)
Mean DV with no assessment	0.370	0.398	0.026	0.030	0.809	0.710
N	268,743	14,366	268,743	14,366	268,743	14,366
Workers	262,139	6,687	262,139	6,687	262,139	6,687
Firm FE	✓		✓		✓	
Worker FE		✓		✓		✓

Notes: Table I13 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 I14: 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	0.084*** (0.019)	0.061*** (0.007)	-0.054*** (0.007)	0.010*** (0.003)	0.026*** (0.007)	0.022*** (0.006)
Standard deviation interview rounds	0.73	0.70	0.72	0.72	0.72	0.72
Mean DV	2.925	11.450	0.321	0.038	0.028	0.700
N	12,184	10,939	21,822	21,822	21,822	21,822
Workers	5,673	5,186	10,214	10,214	10,214	10,214
Worker FE	✓	✓	✓	✓	✓	✓

Notes: Table I14 summarizes the relation between the estimated number of rounds the firm interviews for on average 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 I15: Probability of Rejecting a Job Offer by Perception of Interview Difficulty, Degree of Interpersonal Skills Required for the Job, and Firm Size

	1(Rejects job offer)		
	(1)	(2)	(3)
1(Easy interview)	0.057*** (0.002)		0.027*** (0.004)
1(Easy interview) x Interpersonal relationships index	0.019*** (0.002)		0.008*** (0.003)
1(Easy interview) x 1(Smaller firm)		0.084*** (0.003)	0.055*** (0.005)
1(Easy interview) x 1(Smaller firm) x Interpersonal relationships index			0.017*** (0.003)
1(Smaller firm)		-0.023*** (0.004)	-0.015*** (0.005)
1(Smaller firm) x Interpersonal relationships index			-0.008*** (0.002)
Mean DV for not easy	0.184	0.184	0.184
N	502,334	502,334	502,334

Notes: Table I15 summarizes the relation between the probability an offer is rejected and perceived difficulty of the interview, firm size, and the degree to which the job requires interpersonal skills. Interpersonal skills are assigned by three-digit SOC occupation, standardized, and reflect the measure used in [Goldin \(2014\)](#). Smaller firm reflects below-median firm size. Each specification includes metro, industry $\times$ three-digit SOC occupation, and year-quarter of interview $\times$ year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table I16: Tenure from Resumes After Offer Acceptance, Accounting for Worker's Age

	1(Firm tenure $\geq$ 12 months)	
	(1)	(2)
1(Easy interview)	-0.078*** (0.011)	
Fraction others' interviews easy		-0.112*** (0.031)
Mean DV for not easy	0.755	0.759
N	8,242	7,790

Notes: Table I16 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 $\times$ 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 I17: Tenure from Workers' Resumes After Offer Acceptance, Accounting for Worker's Skill or Proclivity to Perceive Interviews as Easy

	1(Firm tenure $\geq$ 12 months)	
	(1)	(2)
1(Easy interview)	-0.067*** (0.012)	-0.080*** (0.025)
Worker FE log wages	0.101*** (0.016)	
Worker FE interview difficulty		-0.001 (0.018)
Mean DV for not easy	0.795	0.752
N	7,352	2,740

Notes: Table I17 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 the 1-5 scale measure of interview difficulty on worker and firm fixed effects, including an indicator for whether the worker received an offer and fixed effects for metro and the year-quarter of interview x year-quarter submitted to Glassdoor. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table I18: Tenure from Resumes After Offer Acceptance by Firm Position on Resume

	1(Firm tenure $\geq$ 12 months)			
	Jobs on resume after job with matched interview			
	0	1	2	3+
1(Easy interview)	-0.069*** (0.009)	-0.086*** (0.014)	-0.118*** (0.023)	-0.119*** (0.034)
Mean DV for not easy	0.848	0.629	0.607	0.598
N	11,261	5,722	2,386	1,330

Notes: Table I18 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 I19: Probability of Accepting a Job Offer and Likely Wage of Future Jobs

	1(Accepts job offer)			
	(1)	(2)	(3)	(4)
1(Easy interview)	-0.037*** (0.005)	-0.035*** (0.006)	-0.046*** (0.003)	-0.041*** (0.004)
1(Easy interview) x 1(Any of next three likely jobs high wage)		-0.033*** (0.011)		-0.048*** (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	118,963	118,963	107,911	107,911
Adjusted R ²	0.05	0.05	0.12	0.12
Industry-occupation FE	✓	✓		
Firm-job title FE			✓	✓

Notes: Table I19 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 I20: Future Employment Outcomes as a Function of Firm's Interview Difficulty

	Percentile of future...		Ln(Future total pay)				
	Firm pay rank	Job title pay rank					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm's fraction of interviews easy	-8.562*** (0.445)	-3.747*** (0.216)	-0.172*** (0.007)	-0.098*** (0.005)	-0.072*** (0.003)	-0.073*** (0.010)	-0.047*** (0.011)
Firm's percentile of firm pay rank							0.001*** (0.000)
Standard deviation of firm's fraction	0.165	0.165	0.165	0.165	0.165	0.158	0.158
N	625,695	625,695	625,695	625,695	625,695	65,956	65,956
R ²	0.24	0.42	0.45	0.58	0.73	0.72	0.72
Current job title x year FE	✓	✓	✓	✓	✓	✓	✓
Future metro x year FE	✓	✓	✓	✓	✓	✓	✓
Future firm FE				✓	✓	✓	✓
Future job title FE					✓	✓	✓
Bachelor's university x major FE						✓	✓

Notes: Table I20 summarizes how the interview difficulty of the worker's previous firm correlates with the worker's current employment, including their firm, job title, and pay. Firm pay rank reflects the firm fixed effect from an AKM regression on log total pay in ascending order. Job title pay rank reflects the average wage by job title in ascending order. Firm pay rank and job title pay rank are then partitioned into 100 percentiles, which are the outcomes of columns (1) and (2), respectively. Column (6) is restricted to workers for whom we observe their Bachelor's degree alma mater. Standard errors are clustered by the previous firm. Significance levels: * 10%, ** 5%, *** 1%.

Table I21: Probability of Accepting a Job Offer and Realistic Job Previews

	1(Accepts job offer)		
	(1)	(2)	(3)
1(Easy interview)	-0.037*** (0.003)	-0.035*** (0.002)	-0.084*** (0.012)
1(Realistic job preview)	0.075*** (0.002)	0.074*** (0.002)	0.083*** (0.012)
1(Easy interview) x 1(Realistic job preview)	-0.005 (0.003)	-0.004 (0.003)	0.007 (0.021)
Mean DV for not easy	0.818	0.818	0.732
N	429,107	429,107	24,057
Firm observables		✓	✓
Worker FE			✓

Notes: Table I21 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. 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, industry-occupation, and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects, as well as indicators that 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 I22: 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*** (0.002)	0.000 (0.001)	-0.000 (0.001)	-0.017*** (0.001)
Observations	132,576	132,576	132,576	132,576
Workers	126,178	126,178	126,178	126,178
Firm FE	✓	✓	✓	✓

Notes: Table I22 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 I23: Probability of Accepting a Job Offer and Local Labor Market Tightness

	1(Accepts job offer)			
	Full sample		Worker is in metro	
	(1)	(2)	(3)	(4)
1(Easy interview)	-0.063*** (0.006)	-0.045*** (0.005)	-0.068*** (0.007)	-0.043*** (0.005)
1(Easy interview) x metro unemployment rate	0.007*** (0.002)	0.005*** (0.002)	0.008*** (0.003)	0.006*** (0.002)
Mean DV for not easy	0.825	0.825	0.850	0.850
N	237,000	237,000	127,522	127,522
Firm FE		✓		✓

Notes: Table I23 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 I24: 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*** (0.002)	-0.050*** (0.005)	-0.070*** (0.004)
Mean DV for not easy	0.816	0.814	0.827
N	502,337	40,624	77,228

Notes: Table I24 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, 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%.

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