Interviews*

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Abstract

Interviews allow employers to learn about workers, but do they also enable workers to learn about firms? Using data on hundreds of thousands of interview reports from Glassdoor, we find that candidates for high-paying jobs are 9 percent more likely to reject a job offer if they believe the interview was easy. Easy interviews appear to convey poor "fit" as those who accept offers after easy interviews are one-half of a standard deviation less satisfied with their jobs and 14 percent less likely to remain with their employer for at least one year. Analysis of interview narratives using a large language model reveals that difficult interviews signal colleague ability and opportunities for skill development, whereas easy interviews convey a nonselective process. Interviews offer workers a preview of match quality, highlighting a unique channel through which labor markets may become less efficient if firms fully automate their hiring processes with AI.

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1 Introduction

It is hard to imagine a more ubiquitous feature of the labor market than the job interview. Almost every worker, regardless of age or experience, has had many interviews, not just for the job they currently have but also for roles where they did not get an offer and the employer turned them away, or they 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 the job interview itself determine whether a candidate will decide to accept or reject an offer?

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

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

Whether interviews offer workers a meaningful glimpse into the workplaces they may join, to the best of our knowledge, has not been empirically established.[2] Studying half a million interview reports from Glassdoor, we fill this gap in the literature and establish a link between workers' interview experiences and their labor market outcomes. For each

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

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

interview reported, we observe whether the worker received a job offer and whether they accepted the position or turned it down. We also observe how difficult each worker perceived their interview process to be—a key metric we will show signals valuable information to job seekers. Further, workers provide a free-response description characterizing the interview process, which we analyze using a large language model (LLM) to explore the mechanisms behind our results. Altogether, these data shed new light on whether—and how—interview impressions steer workers toward or away from employers.

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

We begin by considering acceptance and rejection decisions. Even for the same vacancy—the same firm, job title, local labor market, and quarter—candidates who thought the interview was easy are 9 percent more likely to reject the job offer. Notably, interviews that are conducted remotely, involve technical exercises, or highlight the role's responsibilities experience outsize declines in offer acceptance rates if they were considered easy—suggesting a role for perceptions of skill development and non-wage amenities traditionally gauged through onsite visits. When a worker has more than one offer in the same quarter, they are 13–25 percentage points more likely to reject the offer from the firm whose interview they perceived as easier; We estimate, based on the sample of workers who report multiple offers, the decline in the probability of offer acceptance associated with an easy interview to be equivalent to that associated with a marked 42 log points (35 percentage points) lower wage.

Critically, it is one's own subjective perception of interview difficulty, not necessarily objective difficulty, that predicts offer acceptance, Although we cannot observe firms' actual hiring practices to gauge objective interview difficulty, we can reliably make this claim based off two empirical facts. First, although employers may have reputations for implementing relatively difficult interviews—for instance, prestigious consulting firms such as McKinsey and Boston Consulting, finance firms such as Bridgewater and Jane Street, or information

technology firms such as Amazon and Google—the patterns we document all persist when we include firm fixed effects. Second, if we calculate the average difficulty reported by all other job seekers interviewing for the same position, that metric does not predict offer acceptance. However, taking one's *own* perceived difficulty relative to this average of others does: A job seeker who perceives the interview as relatively easy compared with other applicants increasingly turns down the job offer. This supports the interpretation that workers are learning about their own idiosyncratic match quality with the firm.

In this respect, we anticipate interview impressions—as an ex ante precursor—to track realized match quality. Since many workers upload their resumes to Glassdoor when creating a profile, we can link, for those who accepted an offer, their interview with the corresponding job on their resume. Comparing workers who list on their resumes the same job title at the same firm, those who considered the interview easy exhibit firm tenures that are considerably shorter, on the order of 18 percent. This translates into a 14 percent lower likelihood of remaining with the firm for at least one year. Thus, we can conclude that perceptions of the interview process predict not just immediate outcomes (e.g., offer acceptance) but also longer-run outcomes (e.g., retention).

The marked gap in tenure between workers who interviewed for the same job but perceived the interviews to be of varying difficulty naturally raises the question, why? Are workers who perceive the interview to be easy more likely to be laid off due to poor performance, or more likely to voluntarily quit to pursue better matches? Since many visitors to Glassdoor also submit reviews of their employers in which they disclose their job satisfaction, we can link, for those who accepted an offer, their interview report to their subsequent employer review. Drawing on these reviews, we find compelling evidence for the latter. Workers who accept an offer after perceiving the interview to be easy report job satisfaction that is a remarkable 35–50 percent lower than their peers. For context, this penalty is larger than the effect of learning your employer engaged in corporate misconduct (Gadgil and Sockin, 2020) or received an Accounting and Auditing Enforcement Release from the U.S. Securities and Exchange Commission (Zhou and Makridis, 2021). Given the established link between job satisfaction and voluntary turnover (Freeman, 1978; Akerlof *et al.*, 1988; Card *et al.*, 2012), we interpret the higher rate of turnover following easy interviews as more likely reflecting poor match quality from the perspective of the worker than that of the firm.

To better understand the information workers accrue through interviews, we turn to free-response descriptions workers write about the interview process. We employ a LLM to determine whether a description indicates: (i) prospective colleagues being of high ability[3],

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

(ii) prospective colleagues being pleasant[4], (iii) the interview experience being engaging, (iv) the worker believing the firm "would hire anyone," and (v) the interview offering a "realistic job preview."[5] Job seekers are *two-to-three times* more likely to characterize the firm as employing high-ability colleagues if they believed the interview was not easy; They are no more likely though to believe the firm employs pleasant colleagues—distinguishing opportunities for human capital growth from social amicability. By contrast, after an easy interview, job seekers are *four-to-five times* more likely to believe the firm would hire anyone, and 15–20 percent less likely to consider the interview process engaging. Further, although realistic job previews generally raise offer acceptance rates, the increase is 12–16 percent shallower for easy interviews than not-easy ones. Thus, while a challenging interview can convey the positive signal of human capital development and meaningful job content, an easy interview may signal a nonselective, disengaged process. By signaling the ability of prospective peers, interviews provide a unique channel through which high-ability workers can discern which workplaces are comprised of other high-ability workers—facilitating sorting and potentially augmenting inequality in earnings (Song *et al.*, 2019).

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 (Highhouse, 2008; Dana *et al.*, 2013; Rivera, 2012, 2015).[6] Studies in such fields have highlighted the potential for interviews to result in hiring disparities along socioeconomic status, or their tendency to detract from the hiring process by adding extraneous, non-diagnostic information on candidates that fails to predict performance. In economics, Shukla (2024) demonstrates that subjective interviews afford employers the opportunity to discriminate against minorities in entry-level recruitment. To the best of our knowledge, no study prior has considered the worker's perception of the interview experience, in particular its difficulty level, and shown it affects labor market outcomes—initial sorting as well as firm tenure and job satisfaction thereafter.

The second strand of literature pertains to how workers respond to the revelation of information about employers when engaged in job search. Benson *et al.* (2019), for instance, show that highly-rated employers receive increased labor supply in online labor markets, Sockin and Sojourner (2023) that improved Glassdoor ratings increase applications to small

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

[5]The U.S. Office of Personnel Management writes that a realistic job preview can "provide candidates a richer description of the agency and the job (e.g., work environment, duties, expectations) to help them decide if they are a good match." See Wanous (1973) for an early discussion of realistic job previews.

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

firms, Bryan *et al.* (2022) that workers, especially high-quality ones, sort towards startups with better quality science and business models when such information is available, and Ward (2022) that job seekers sort away from companies with below-average levels of employee happiness when such information is revealed. Our work demonstrates that job interviews are another information-revelation mechanism by which workers will sort, as workers can learn about peer ability and opportunities for skill development.[7] Our findings thus relate to the broader literature on search-and-matching frictions in the labor market (e.g., Diamond, 1982; Mortensen and Pissarides, 1994) by highlighting the *two-sided* nature of the interview process.[8] We demonstrate that perceived interview difficulty can reduce uncertainty around match quality, much as workers in classic job-matching models learn about the quality of an employer (Jovanovic, 1979). That interviews help explain which matches form in the short run and endure in the long run suggests jobs are not entirely experience goods (Nelson, 1970; Menzio and Shi, 2011), as interviews may render them quasi-inspection goods.

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

2 Data

In this section, we offer background information on Glassdoor and detail how we compile our dataset of interview reports, which includes implementing an imputation process for assigning a wage to each job offer.

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

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

Platform Overview. Our data come from the website Glassdoor, an online labor market platform where workers can anonymously share information about pay, job satisfaction, and their interview experiences. Visitors to Glassdoor are incentivized to contribute through a "give-to-get" mechanism, whereby they gain access to the information others have provided once they themselves contribute.[9] Workers can satisfy the give-to-get requirement by submitting one of four surveys: a pay report, an employer review, a benefits rating, or an interview report. Access expires after a year, which can be refreshed with an additional contribution. Although we do incorporate pay reports and employer reviews in the analysis, our primary focus is the interview reports. Workers are assigned unique identifiers, allowing us to link individuals across surveys.

Interview Reports. When disclosing an interview experience, each respondent is asked for their employer and job title. They can also provide the location in which the interview took place but this is not required. Since this survey is a summary of their interview experience, workers are asked: whether they had a positive, neutral, or negative experience overall, for a free-response description of the interview process, and to recall any particular interview questions they were asked. Workers are also asked the difficulty level of the interview, to which they can respond very easy, easy, average, difficult, or very difficult. We translate this measure of difficulty into a 1-5 integer scale, which is increasing in difficulty, and we create an indicator for "the interview was easy," equaling one for very easy and easy responses and zero otherwise. Next, respondents state whether they received an offer for the job in question, and if they did, whether they chose to accept or reject it. Respondents also have the option to disclose a number of additional aspects of the interview process, including how they received the interview (e.g., an employee referral[10]), how many days the process took, when the interview occurred, the form(s) the interview took (e.g., a phone discussion), and any testing that occurred (e.g., personality test, drug test). Appendix Figures IA1 and IA2 provide snapshots from a sample Glassdoor submission form.

Main Sample. Our analysis focuses only on *high-paying occupations*, identified by their Standard Occupational Classification (SOC) codes.[11] This restriction offers both practical

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

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

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

and conceptual advantages. First, Glassdoor considerably over-samples from these occupations such that we have particularly rich coverage of these jobs.[12] Second, high-wage workers have strong preferences for non-wage amenities (e.g., Sockin, 2022; Colonnelli *et al.*, 2023; Maestas *et al.*, 2023; Cullen *et al.*, 2025) and since these occupations feature relatively transparent base pay (Hall and Krueger, 2012), interview experiences may be especially relevant in shaping perceptions over amenities. Third, workers in these occupations tend to have career concerns and benefit from human capital accumulation through peer effects and on-the-job learning (e.g., Jarosch *et al.*, 2021) such that a poor worker-firm match can be quite costly. And fourth, these occupations have high marginal products, so firms will tend to expend more resources screening for them.[13]

We take a number of additional steps to arrive at our ultimate dataset. The iterative procedure, along with the number of observations discarded at each step, is detailed in Appendix Table IA1. We first restrict the sample to interviews from 2008 through 2024. Then, since we are interested in the decision to accept or reject an offer, we exclude the 38 percent of interview reports where the worker was not offered the job. We then exclude interviews for which either perceived difficulty or the industry of the firm are unavailable. Next, we restrict the sample to the six high-paying occupations of interest, which reduces the sample by about two-thirds. Next, to focus on matches that do not have a definite end date determined ex ante, we exclude interviews that correspond to internships—though, for internships as well, job seekers increasingly reject offers after easy interviews (Internet Appendix C). Finally, to reduce measurement error in the recollection of past interview experiences, of the remaining interview reports, we exclude the 15 percent that are submitted to Glassdoor more than two years after the interview date. The final sample includes 508,000 interview reports. Summary statistics for characteristics of the interviews are available in panel A of Table IA2. In our sample, 20 percent of offers are rejected and 80 percent accepted.

Imputing Wages. Since workers are not asked to disclose the wages they were offered when submitting their interview reports, we impute offered wages using Glassdoor pay reports. For each firm–job title pair, we calculate the mean base pay from these reports and merge these averages with our interviews data. Through this process, we are able to impute a wage for 297,000 interviews. We believe these imputed averages are valid proxies for posted wages for three reasons. One, job titles explain more than 90 percent of the variance in posted wage ranges (Marinescu and Wolthoff, 2020). Two, Glassdoor wages align well with

[12] While these occupations represent 32 percent of full-time employment in the representative American Community Survey, they represent 57 percent of the Glassdoor interviews database (Appendix Figure IA9).

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

representative data across industries (Karabarbounis and Pinto, 2018), occupations (Gibson, 2021), and universities (Martellini *et al.*, 2024). And three, for a subset of workers, we can assign them their actual wage since they submitted a Glassdoor pay report for the same firm, job title, and year of the interview after accepting the offer. For this subset of 27,000 workers, we estimate an elasticity of imputed wages to actual wages close to one, and imputed wages explain about 88 percent of the variation in actual wages (Appendix Table IA5). Further, the distribution of imputed wages in our interviews sample closely tracks the distribution of wages for these occupations in the American Community Survey (ACS), particularly for higher wages (Appendix Figure IA10).

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

A separate potential concern is that Glassdoor interview reports are differentially selected from the rest of the Glassdoor database. For instance, workers who disclose interview reports may be positively or negatively selected on ability. To check this concern, we take the database of Glassdoor pay reports and estimate a regression with worker and firm fixed effects in the style of Abowd *et al.* (1999). Taking these worker fixed effects as proxies for ability, we plot the distribution for workers in the interviews sample and those in the database overall. The two distributions are nearly identical (Appendix Figure IA11). Further, workers who disclose interview reports may be less satisfied with their jobs, as many of them are searching for new jobs. However, when we compare job satisfaction ratings from our interview sample to the broader sample, again the distributions look alike (Appendix Figure IA12). Thus, our interviews sample does not appear differently selected on ability or sentiment.

Demographic Observables. When creating a profile on the website, users are asked to provide their gender and age. We observe gender for 204,000 interviews and age for 108,000. For workers who uploaded a resume to Glassdoor, we additionally observe their

educational background. This includes, if listed, their university of study[14], major of study[15], undergraduate grade point average (GPA), and any post-Bachelor's degree. In summary, we observe educational histories for 182,000 interviews, for which we observe college graduate quality for 157,000, major of study for 135,000, and GPA for 23,000. Summary statistics for these demographics are available in panel B of Table IA2.

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 IA3.[16] For ease of exposition, and to avoid concerns regarding heterogeneous interpretations of the five-point scale across sub-samples[17], we create an easy-interview indicator, which equals one if respondents record easy or very easy and zero otherwise. Roughly 35% of respondents believe their interview was easy.

Given the import of this measure, we take steps to internally and externally validate reported interview difficulty. First, we extract whether the job seeker mentions the term "easy" in their free-response descriptions of the interview process. We observe that the fraction of interviews that mention "easy" monotonically decreases with interview difficulty (Appendix Figure IA6); about 22 percent of interviews deemed "very easy" mention it compared with only about 8 percent for those rated "average" and 4 percent for those rated "difficult." Next, we evaluate which employers offer the most difficult interviews. Intuitively, we find that difficult interviews are experienced with elite employers in management consulting, finance, and technology. This includes prestigious consulting firms (Weinstein, 2022) such as McKinsey and Bain & Company, as well as "superstar" firms (Autor *et al.*, 2020) such as Amazon and Google (Table IA3).

For external validation, we turn to a different website, Onsites, that also collects summary information with regards to interview experiences. Onsites caters primarily to jobs in software engineering for technology firms; as such, we caveat that comparison with Onsites cannot necessarily speak to the validity of interview difficulty for other occupations and industries on Glassdoor. For this website as well, respondents are asked to record the difficulty

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

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

[16]The average difficulty rating is 2.67 (Appendix Table IA2). Also plotted is the distribution of interview difficulty for interviews that did not culminate in an offer, which are excluded from our sample but may reasonably exhibit a different distribution across difficulty levels (e.g., rejected candidates finding the interview more cumbersome).

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

level of their interview on a five-point scale. For each firm and job title pair we observe on Onsites, of which there are about 500, we calculate the average perceived difficulty level. Then, in Appendix I, we compare Onsites' averages with those for the same firm-job title pairs in Glassdoor. A one-level increase in difficulty on Glassdoor corresponds to a statistically significant increase of 0.5–1.1 levels in Onsites. Glassdoor interview difficulty thus appears to capture latent differences in difficulty between interviews.

Since we are interested in how perceptions of the interview process affect acceptance decisions, understanding whether and where there is variation in interview difficulty is necessary; if all job seekers thought interviews were easy, there would be no variation off of which to identify differences. Table 1 investigates how much variation there is in our easy indicator between firms and and workers. First, we recognize that the length of the interview process is strongly correlated with difficulty in column 1, alone explaining about 5 percent of the variation.[18] Incorporating firm fixed effects (column 2) increases the explained variation to above 20 percent, demonstrating that knowing the hiring firm alone is not a perfect predictor of difficulty. Adding job title fixed effects increases the explained variation only slightly to still below 30 percent.[19] Knowing the job seeker and the hiring firm together can explain 80 percent of the variation (column 5). This suggests about one-fifth of interview difficulty is match-specific and can vary within person and firm, e.g., which managers are involved, which questions are asked, or even possibly what the weather was.[20] Thus, there is considerable variation and individual subjectivity in this measure.

3 The Decision to Reject an Offer and Interview Difficulty

While we observe an overall offer rejection rate of 17 percent, there may be meaningful heterogeneity between different types of workers. One particularly salient aspect is the offered wage, though the direction is not obvious. Since job seekers increasingly apply to vacancies that advertise greater wages (Marinescu and Wolthoff, 2020; Belot *et al.*, 2022), one might expect workers to accept high-wage offers at greater rates. On the other hand, firms may invest more resources screening for high-wage jobs, such that low-wage workers receive more offers and subsequently make more rejections. In Figure 1, we plot the offer rejection

[18] This is true across the entire wage distribution (Appendix Figure IA4).

[19] Worker demographics have limited predictive power after conditioning on firm and job title (Appendix Table IA7). Job seekers from universities whose graduates have more human capital on average are modestly more likely to consider the interview easy, employee-referred job seekers less likely to do so.

[20] We find little evidence of for learning-by-doing when it comes to interview difficulty. Although interviews appear to get progressively harder over time for workers, this largely reflects the different firms and job titles workers interview with as their careers progress (Table IA7).

Table 1: Variation in Interview Difficulty Between Firms and Job Seekers

	1(Easy interview)				
Log length of interview duration	-0.091***	-0.049***	-0.042***	-0.056***	-0.033***
	(0.002)	(0.002)	(0.002)	(0.009)	(0.010)
N	128,623	128,623	128,623	7,395	7,395
R^2	0.059	0.229	0.289	0.652	0.800
Firm FE		✓	✓		✓
Job title FE			✓		
Job seeker FE				✓	✓

Notes: Table 1 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%.

rate for different wage levels separately for easy interviews and not-easy interviews.[21]

As is evident, offer rejection rates differ systematically between the two. Across the wage distribution, at each wage level above the very bottom, rejection rates are higher after easy interviews. For the highest-paying jobs, we witness rejections rates upwards of 35 percent after easy interviews but below 25 percent after not-easy interviews. This would suggest that the interview process itself is a valuable input into the decision to accept or reject an offer—in particular that an easy interview is less favorable to a difficult interview. Indeed, job seekers on average report greater dissatisfaction (i.e., a "thumbs-down" experience overall) with easy interviews than not-easy interviews (Appendix Figure IA7).

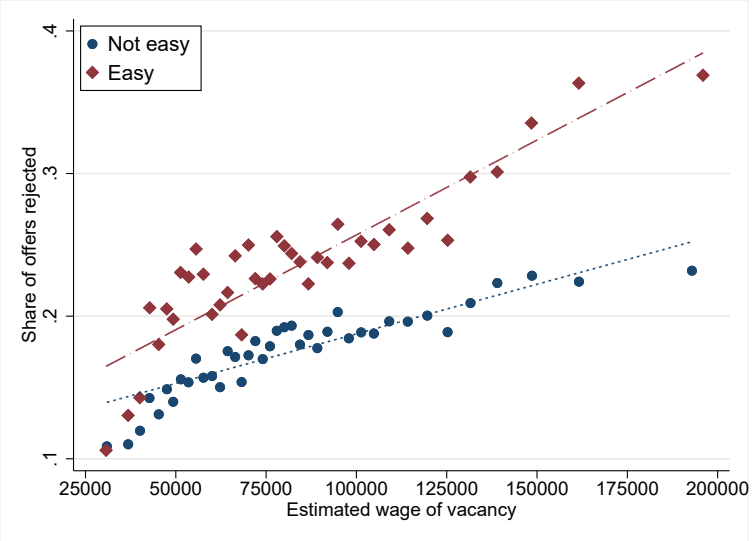
To formalize the relation between interview difficulty and the decision to accept or reject an offer, and account for various covariates, we estimate

$$1(\text{Accepts})_{i,k,t} = \beta 1(\text{Easy interview})_{i,k,t} + \lambda_{\iota(k),o(i,k,t)} + \lambda_{m(i,t),t} + \lambda_{t,\tau(i,k,t)} + \varepsilon_{i,k,t} \qquad (1)$$

where $1(\text{Accepts})_{i,k,t}$ is an indicator equal to one if worker i accepts the offer from firm k after an interview in calendar quarter t and zero otherwise. We include fixed effects for firm k's industry $\iota(k)$ cross the vacancy's occupation $o(i,k,t)$, $\lambda_{s(k),o(i,k,t)}$, and for the metropolitan area of the vacancy $m(i,t)$ cross the calendar quarter t, $\lambda_{m(i,t),t}$. While about one-half of interview reports are submitted to Glassdoor in the same calendar quarter the interview process began, one half are submitted retroactively thereafter. To account for possible bias in the recollection of the interview experience over time, included are fixed effects $\lambda_{t,\tau(i,k,t)}$

[21] We observe the same pattern if, in lieu of the estimate wage of the vacancy, we partitioned interviews according to other proxies of match productivity, e.g., the worker's AKM-derived fixed effect or the college graduate quality of the job seeker's alma mater (Appendix Figure IA17).

Figure 1: Probability of Rejecting a Job Offer by Wage and Interview Difficulty



Notes: Figure 1 displays a binscatter of the fraction of offers that are rejected against the imputed wage of the vacancy and the worker's perceived interview difficulty. The imputed wage reflects the average pay reported on Glassdoor for the given firm and job title. 'Easy' corresponds to difficulty levels "very easy" and "easy" whereas 'Not Easy' corresponds to difficulty levels "average," "difficult," and "very difficult."

for the calendar quarter of the interview t cross the calendar quarter the interview was submitted on Glassdoor $\tau(i,k,t)$.[22] Estimating Equation (1) as a linear probability model, the coefficient of interest β captures the mean difference in the probability of accepting an offer after an easy interview compared with a not-easy interview, among job seekers who interviewed within the same industry and occupation, accounting for local labor market trends over time. We cluster standard errors by firm and record the results in Table 2.

The first column introduces the baseline specification. The coefficient β is an economically and statically significant -0.06, indicating that easy interviews are rejected 6 percentage points more often than not easy interviews.[23] Given a baseline rejection rate of 16.7 percent for not-easy interviews, this wedge equates to a roughly one-third increase in offer rejection rate. In column (2), we incorporate the length of the interview process, since this measure is highly correlated with interview difficulty (see Table 1) and may correlate with offer acceptance. The coefficient of interest falls only modestly. In column (3), we tighten the comparison to workers interviewing for the same vacancy by incorporating firm cross job

[22]Individuals may have rosier or murkier memories if an interview happened in the past, especially if they did not accept the offer. Moreover, if a worker accepted the offer, their interview experience may be clouded by experiences on the job since then. Indeed, there are perceptible differences for those who submit reviews after more time has passed since the interview (Appendix Figure IA16). Those who accepted an offer are significantly more likely to write the interview was easy, those who rejected it that it was difficult.

[23]Estimating Equation 1 separately by occupation reveals this effect is driven by management, business and finance, computer and mathematical, and architecture and engineering jobs (Appendix Figure IA13).

title cross metropolitan area cross calendar quarter fixed effects. Though this considerably thins the sample, even after fixing the vacancy—which effectively pins down the skill requirements, compensation, and responsibilities of the job—easy interviews are rejected 7.0 percentage points more often. Given a the mean acceptance rate of 81.8 percent among not-easy interviews for this sample, workers who perceive the interview as easy for the same vacancy are 9 percent less likely to accept the offer.

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

	1(Accepts job offer)					
	(1)	(2)	(3)	(4)	(5)	(6)
1(Easy interview)	-0.060***	-0.057***	-0.070***	-0.248***	-0.131**	-0.163***
	(0.003)	(0.002)	(0.008)	(0.047)	(0.054)	(0.037)
Log duration of interview process		0.008***				
		(0.001)				
Imputed log wage of vacancy						0.385***
						(0.086)
Mean DV for not easy	0.833	0.833	0.818	0.637	0.637	0.562
Observations	310,124	310,124	35,695	1,919	1,919	2,563
R^2	0.09	0.09	0.51	0.64	0.84	0.61
Metro-Quarter FE	✓	✓		✓		
Firm-Job title-Metro-Quarter FE			✓			
Worker-Quarter FE				✓	✓	✓
Firm FE					✓	

Notes: Table 2 summarizes the relation between the probability an offer is accepted and the workers' perceived difficulty level of the interview process with the iterated addition of fixed effects for the location, firm, job title, and worker. Each specification includes industry-occupation and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

While these analyses focus on the cross-section of workers in our sample, comparing acceptance and rejection decisions between workers who had easy interviews and others who had not-easy interviews, we do observe a number of workers who receive multiple offers. To abstract from concerns regarding differential selection of which job seekers accept an offer and disclose the decision on Glassdoor compared with job seekers who reject an offer and disclose it on Glassdoor, we can look at variation in acceptance and rejection decisions within worker. Further, to account for differences in labor market conditions, preferences, or human capital that may evolve over time for the same worker, we narrow in on workers who report multiple job offers around the same time by including worker cross calendar quarter fixed effects, $\lambda_{i,t}$, in column (4). In this specification, identification of β stems from workers who experience both an easy interview and a not-easy interview; in other words, what is required is within-worker variation in perceived difficulty—which assuages concerns

that what we identify in the cross-section is differences in reporting functions rather than realized interview experiences (Bond and Lang, 2019). Although our sample is only about 2,000 interviews, the same worker is a staggering 25 percentage points more likely to reject easy interviews. Even if we were to account for differences between firms—as some firms may have a reputation for more difficult interviews than others—this within-worker estimate remains large at 13 percentage points.

Finally, to gauge how much workers value interview difficulty, in column (6) we incorporate the imputed wage for each vacancy into our within-worker model. Two takeaways are worth highlighting. First, although we observe greater rejection rates for higher-paying jobs in Figure 1, this result is purely cross-sectional. Once we narrow in on the same worker's choice set, greater wages are associated with increased offer acceptance rates. Second, given a coefficient of 0.39 on the logarithm of the imputed wage, this translates into an easy interview decreasing the probability of acceptance by the same magnitude as a 42 log points (35 percentage points) reduction in the wage.

Sensitivity and Heterogeneity We next demonstrate the ubiquity of this result that easy interviews increasingly produce rejected offers by re-estimating Equation (1) for various sub-samples of interviews. The resulting estimates are available in Appendix Figure IA14.

We first recognize that Glassdoor skews toward young, college-educated workers in high-paying industries (Liu *et al.*, 2022). To show the composition of our sample does not drive our results, we take representative weights from the American Community Survey (ACS) such that re-weighing would match U.S. employment by industry, occupation, sex, metropolitan area, and pay. Even after re-weighting, the coefficient remains negative and statistically significant, albeit somewhat attenuated. We also recognize that there may be recall bias in perceptions of difficulty or the interview process more broadly for those who report their interviews to Glassdoor with a delay. Indeed, when we restrict the sample to only interviews reports that are submitted within one month of the interview process ending, the effect is even larger. For these interviews that are submitted contemporaneously, we estimate that easy interviews are rejected 14 percentage points more often—a marked 18 percent lower than the acceptance rate for not-easy interviews. Since measurement error induced by delayed reporting biases estimates toward zero, this would suggesting our benchmark estimates are conservative lower bounds. Respondents also need not disclose the date when the interview occurred. When we restrict the sample to only such interview reports, which comprise about two-fifths of the sample, the estimate is similar to under the benchmark.

We next consider demographics. Although we observe across the wage distribution that men are more likely to reject offers than women (Appendix Figure IA8: panel a) and younger

workers more than older workers (panel b), both men and women are similarly more likely to reject easy interviews, as are workers across the age spectrum. Younger workers are somewhat more responsive to easy interviews than older workers, suggesting interview difficulty may be an especially meaningful signal for workers early in their careers.

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

We next consider each job seeker's prior work experience. Whether it is workers with little experience, i.e., were recruited through their university, or workers with relevant experience, i.e., a previous job on their resume was for the same occupation as the vacancy, both increasingly reject easy interviews. Whether workers are searching on-the-job, i.e., conduct the interview while employed, or searching off-the-job, i.e., conduct the interview while unemployed, both increasingly reject easy interviews.[24] We also consider whether the worker would likely be receiving an above-average pay raise or a below-average pay raise (based on the most recent firm and job title on their resume before the interview) if they were to accept the offer; again, for both, we observe reduced acceptance rates following easy interviews—though the effect is considerably stronger for the former.

Next, we narrow in on competition for the job. We first merge in monthly metropolitan area unemployment rates from the Bureau of Labor Statistics and partition labor markets into above-average (looser) and below-average (tighter) labor markets. Although we observe negative reactions to easy interviews in looser and tighter markets, the decline in acceptance rates is twice the magnitude among the latter—consistent with workers exhibiting more bargaining power and rejecting offers when available labor is scarce. We next partition interviews by whether the vacancy attracts a relatively high or low amount of job seeker

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

interest.[25] For vacancies that are highly sought after by job seekers ex ante as well those that are less sought after, we observe similarly negative coefficients. Last, we consider whether the vacancy is a competitive interview process, in that it is relatively challenging to receive a job offer. For this exercise, we incorporate interviews that did not result in an offer, and for each firm and job title pair, we calculate the fraction of interviews that result in offers.[26] Again, both sets—vacancies that are relatively competitive for ultimately receiving an offer and those that are not so competitive—witness greater rejection rates after easy interviews; however, we do observe a more negative response to an easy interview among the latter—a mechanism we return to in Section 4.

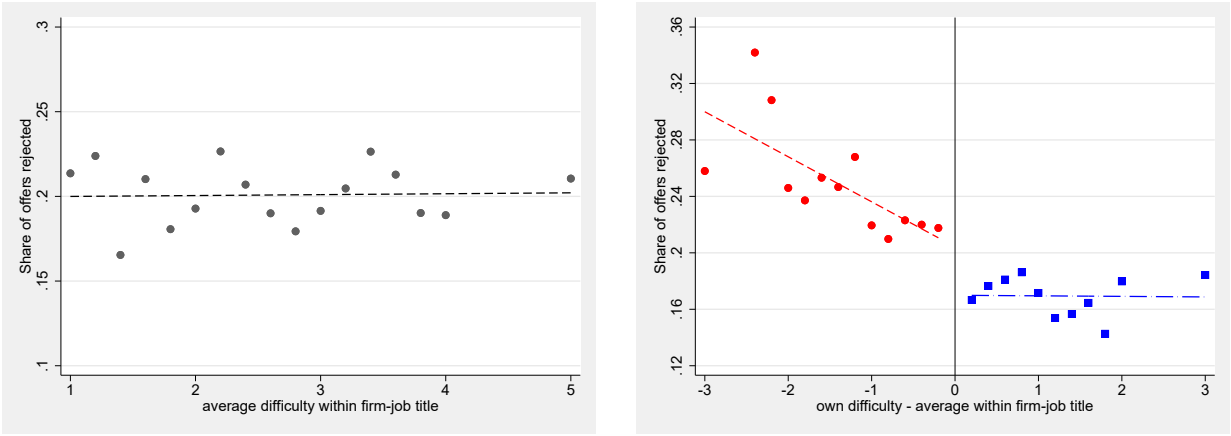
Last, we consider whether we observe the same pattern across interviews of varying characteristics. To identify each of the following aspects, we look whether they are explicitly mentioned in the free-response descriptions respondents provide in their reports. When the interview involves human resources or includes management, easy interviews are increasingly rejected for both. And, if the interview involved a video component conducted remotely over Zoom, included a coding exercise, or highlighted the responsibilities that would be required, we observe particularly negative effects of 8–10 percentage points—suggesting that interviews may be especially important barometers when workplace attributes are more opaque and when skill development is relayed.

Subjective or Objective Difficulty? Since perceived interview difficulty is a meaningful predictor of offer acceptance decisions, the question arises whether the mechanisms at play pertain to the objective difficulty of the interview process, the subjective nature of it, or both. Distinguishing between the two can help disentangle whether it is the hiring aspects all candidates face, or the individual's *own* unique experience, that drives this behavior. While we cannot actually observe how difficult each interview truly was, we can proxy for it by leveraging the collective experiences of similar job seekers. Since objectively easy interviews will, almost tautologically, be perceived as generally being easy, we can proxy for objective difficulty by taking the average difficulty level among all *other* job seekers, excluding one's self, who interviewed for the same firm and job title. Objectively easy interviews should witness lower averages and objectively not-easy interviews higher ones. We can then investigate whether the experience of others has any bearing on one's own acceptance or rejection decision. Panel (a) of Figure 2 suggests that objective interview difficulty has little bearing on this decision, as offer rejection rates appear similar regardless: The rejection

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

[26] Appendix Figure IA5 relates imputed wages to interview outcomes, showing high-paying jobs have lower offer rates, consistent with more selective hiring at higher wages (Mueller *et al.*, 2023; Bassier *et al.*, 2023).

Figure 2: Probability of Rejecting a Job Offer by Own Perception of Difficulty Compared with Other Job Seekers



(a) Difficulty of others **(b)** Relative difficulty to others

Notes: Figure 2 displays the fraction of offers rejected by the average interview difficulty reported by others for the same firm-job title pair (panel a) and the difference between one's own interview difficulty and the aforementioned average (panel b). Each dot represents a 0.20-rounded bin with at least 400 interviews.

rate is around the sample average of 20 percent for vacancies where the consensus is the interviews were easy as well as ones where the consensus is they were difficult.

To parse out the role of subjective difficulty, we take the measures of objective difficulty and take the difference to one's own reported difficulty level. Panel (b) illustrates how this difference between one's own perception and consensus predicts offer rejection rates.[27] Job seekers who perceive the interview as being relatively easy will exhibit values below zero, whereas those who perceive the interview as being relatively hard will record values above zero. Evidently, there are strikingly different patterns by relative difficulty. Among candidates who find interviews relatively more difficult (positive values), rejection rates are flat at about 17 percent. Among candidates though who find interviews relatively easy (negative values), we observe a change in level and slope. Not only is there a discrete 5-percentage-points jump in rejection rates just below zero, but rejection rates rise as the difference becomes more negative (i.e, as candidates find interviews increasingly relatively easy)—reaching rejection rates upwards of 30 percent. Thus, it is primarily the candidate's *own* perception of the interview process that influences their decision, suggesting workers are making inferences about their own match quality.

[27]Relative difficulty does not appear to proxy for being relatively over- or under-qualified compared with the rest of the applicant pool. If we were to consider instead one's own human capital (age or previous work experience) relative to the average for the same firm and job title (Appendix Figure IA15), the bifurcation observed in panel (b) of Figure 2 between positive and negative values does not materialize.

4 Potential Mechanisms

Having established workers extract meaningful content from their interview experiences, we now examine several specific channels through which this learning might occur. Drawing on interview narratives, we analyze four distinct but potentially complementary mechanisms: (1) learning about potential colleagues' abilities and temperament, (2) inferring overall match quality, (3) gaining insight into job responsibilities through realistic previews, and (4) assessing career advancement potential. For each mechanism except the last, we employ a large language model (LLM) to parse the free-text interview descriptions and identify whether and which specific signals are conveyed to job seekers during an interview. To ensure the annotations produced by the LLM are reliable, we compare them with those produced by human inspection. Reassuringly, the annotations agree about 80 percent of the time for each dimension considered. For further details about the comparison process, see Appendix II.

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

To test for this learning channel, we examine whether easy interviews are less likely to give the perception that the hiring firm's employees are of high ability. The results, presented in columns (1)-(3) of Table 3, reveal this is indeed the case. Whereas about 18 percent of interview summaries describe potential colleagues as being of high ability following a not easy interview, the fraction for easy interviews is about 10 percentage points lower. This pattern persists even after including firm fixed effects, meaning that even though "superstar" (Autor *et al.*, 2020) or high-paying firms might have reputations for employing high-ability workers, the difficulty of the interview has informational content beyond that reputation. This not just observed in the cross-section; narrowing in on workers who report multiple interviews and conducting a within-worker analysis (Appendix Table IA8) reveals a similarly large and significant decline in the frequency with which job seekers believe colleagues are of high

ability after an easy interview.

Table 3: Perceived Interview Difficulty and Colleague Skill or Pleasantness

	High-ability colleagues			Pleasant colleagues		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Easy interview)	-0.115***	-0.099***	-0.079***	-0.010***	-0.013***	0.006***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Mean DV for not easy	0.178	0.178	0.178	0.247	0.247	0.247
N	424,114	424,114	424,114	424,114	424,114	424,114
Adjusted R^2	0.05	0.08	0.11	0.02	0.03	0.07
Additional text covariates		✓	✓		✓	✓
Firm FE			✓			✓

Notes: Table 3 summarizes the relation between the interviewee's perception that the job offers colleagues who are of high ability (columns 1–3) or who are pleasant (columns 4–6) and the perceived difficulty of the interview. Each specification includes industry-occupation and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Additional text covariates include indicators for the interview process illuminated compensation, illuminated hours or scheduling, illuminated desirable workplace amenities, and included a skills assessment. For details on constructing the text-based measures, see Appendix II. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

From a macro perspective, that interviews can relay signals of the ability of peers at hiring firms suggests interviews are a medium through which high-ability workers can sort into workplaces with other high-ability workers—which Song *et al.* (2019) argue accounts for about one-half of the increase in the variance of wages between firms in the United States since the late-1970s. From a micro perspective, that workers increasingly reject easy interviews and easy interviews less often signal high-ability colleagues highlights the importance of peer effects in the workplace (e.g., Mas and Moretti, 2009; Cornelissen *et al.*, 2017) and accords with recent work showing that opportunities for human capital development are among the most valued non-wage amenities (Maestas *et al.*, 2023). Importantly though, it is not simply that job seekers are less likely to highlight future colleagues in their interview summaries after easy interviews. If we were to instead look at the relation between interview difficulty and whether the job seeker believes their prospective colleagues would be pleasant in column (4)-(6), we find statistically significant but economically small effects of about one percentage point relative to a baseline of 25 percent among not easy interviews.

4.2 Learning About Match Quality

To understand whether interviews reveal information about overall match quality, we next consider whether candidates perceive the interview as suggesting a nonselective hiring process or providing an engaging, substantive experience. Both of these can signal to workers their own degree of substitutability, as well as how desperate an employer is to fill the vacancy. To

this end, we employ a LLM to determine whether each job seeker's narrative of the interview process suggests the firm would effectively "accept anybody" or whether the experience was engaging. Again, the specific prompts asked of the LLM are available in Appendix II.

To test for this learning channel, we examine whether easy interviews convey that the hiring firm is being nonselective and would "accept anybody." The results, presented in columns (1)-(3) of Table 4, highlights this is very much the case. Whereas only about 3 percent of job seekers state after not-easy interviews that the firm would "accept anybody," the fraction jumps 11–14 percentage points, a *four-to-five fold increase*, for easy interviews. This pattern persists with the addition of firm fixed effects, highlighting the subjective nature of these beliefs. This signal may in part stem from the interview process being perceived as less engaging when the job seeker considers it to be easy. Indeed, in columns (4)-(6), we find easy interviews are 5–7 percentage points less likely to be perceived as engaging experiences, a 15–23 percent decline relative to a baseline of about 32 percent for not easy interviews. Both of these relations attenuate somewhat but persist when we consider a within-worker comparison of easy and not easy interviews (Appendix Table IA8).

Table 4: Perceived Interview Difficulty and Whether Firm "Would Accept Anybody"

	Would accept anybody			Engaging experience		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Easy interview)	0.138***	0.131***	0.109***	-0.073***	-0.074***	-0.048***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Mean DV for not easy	0.032	0.032	0.032	0.322	0.322	0.322
N	424,114	424,114	424,114	424,114	424,114	424,114
Adjusted R^2	0.08	0.09	0.13	0.04	0.04	0.09
Additional text covariates		✓	✓		✓	✓
Firm FE			✓			✓

Notes: Table 4 summarizes the relation between the interviewee's perception that the employer would hire anyone (columns 1–3) or that the interview was an engaging experience (columns 4–6) and the perceived difficulty of the interview. Each specification includes industry-occupation and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Additional text covariates include indicators for the interview process illuminated compensation, illuminated hours or scheduling, illuminated desirable workplace amenities, and included a skills assessment. For details on constructing the text-based measures, see Appendix II. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

This conclusion resonates with prior work demonstrating that recruitment practices can influence how applicants judge match quality (Friedrich *et al.*, 2024). In this sense, a hiring process perceived as "too easy" communicates weak standards or minimal screening efforts, thereby diminishing appeal to job seekers. Inversely, more demanding and engaging interviews appear to cultivate the opposite, even conditional on the hiring firm.

4.3 Learning about Responsibilities through Realistic Job Previews

Beyond learning about colleagues and match quality, interviews may provide candidates with concrete information about the actual job responsibilities through realistic job previews (RJPs). As highlighted in Appendix Figure IA14, easy interviews in which the process highlighted the responsibilities of the role witness especially reduced offer acceptance rates. While suggestive evidence points to RJPs improving initial matches and reducing turnover (Wanous, 1973; Phillips, 1998), the literature has only studied their effectiveness in reducing turnover among small cross-sections of workers for a given occupation. Given the interview narratives we observe and the breadth of the Glassdoor sample, we can examine the relation between RJPs and interview difficulty across and within firms and workers. The specific prompt asked of the LLM for determining whether the job seeker perceived the interview process as a RJP is available in Appendix II.

In Table 5, we present evidence on how the decision to accept an offer varies with realistic job previews, interview difficulty, and their interaction. Interestingly, counter to the limited evidence on RJPs and offer acceptance rates (e.g., Wanous, 1973; Dean and Wanous, 1984), we find that RJPs are associated with significantly higher job offer acceptance rates, on the order of 7–10 percentage points. That said, this positive effect is somewhat diminished when the interview is easy. A realistic, but easy, job preview—even for the same firm—reduces this increase by 0.6 percentage point, or 9 percent. When we look at the same worker making multiple offer acceptance decisions, the drag from an easy interview is even more pronounced: While RJPs experience acceptance rates that are 10 percentage points higher, the interview being easy blunts this relation by roughly two-fifths. Thus, while workers value learning about job responsibilities through interviews, they are deterred when such information is conveyed through an easy—presumably nonselective and less engaging—hiring process.

4.4 Career Concerns

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

Table 5: Probability of Accepting a Job Offer and Realistic Job Previews

	1(Accepts job offer)			
	(1)	(2)	(3)	(4)
1(Easy interview)	-0.048***	-0.039***	-0.032***	-0.077***
	(0.003)	(0.003)	(0.002)	(0.010)
1(Realistic job preview)		0.075***	0.068***	0.099***
		(0.002)	(0.002)	(0.010)
1(Easy interview) x 1(Realistic job preview)		-0.008**	-0.006*	-0.040**
		(0.003)	(0.003)	(0.018)
Mean DV for not easy	0.821	0.821	0.821	0.739
N	424,114	424,114	424,114	24,675
Adjusted R^2	0.06	0.07	0.12	0.29
Additional text covariates	✓	✓	✓	✓
Firm FE			✓	
Worker FE				✓

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

career concerns may be particularly turned off to such job offers.

To proxy for workers' career concerns, we turn to the resumes workers upload to Glassdoor. With these resumes, we can follow the career trajectories of workers after any firm-job title pair we observe. So, for each firm-job title pair, we predict the average wage for the next job by taking the average imputed wage among all of the firm-job title pairs that occur next on workers' resumes. We repeat this exercise for the second next job and the third next job. Finally, we create an indicator equal to one if the firm-job title pair for which the job seeker is interviewing is one where at least one of the next three jobs is likely to be high wage, i.e., has an average imputed wage above the 90th percentile, and zero otherwise. We then incorporate this indicator and its interaction with the easy interview indicator in Equation (1). The results are recorded in Table 6.

For jobs that offer high future wage growth, an easy interview has an especially large drag on offer acceptance rates. For interviews with vacancies that do not likely lead to a high wage job in the future, easy interviews are rejected 3.6 percentage points more often than not easy interviews. On the other hand, for vacancies that do, easy interviews are rejected an additional 3.4 percentage points often—roughly doubling the easy-interview penalty on offer rejection rates. This pattern persists even when we compare workers who interviewing for the same roles through firm-job title fixed effects. In this case, for jobs with high

wage growth, we observe an additional 4.5-percentage-points likelihood in rejecting an easy interview. Interview difficulty thus appears to serve as an information signal to workers of a position's opportunities for human capital appreciation—possibly through skill development or promotions, or both.

Table 6: Probability of Accepting a Job Offer and Likely Wage of Future Jobs

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

Notes: Table 6 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 likely 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%.

5 Interview Difficulty as a Precursor for Match Quality

If job seekers will reject offers because they experience easy interviews, it must be because the interview itself has predictive power—at least, in the eyes of the job seeker—for the quality of that potential match. If the interviews did not, workers would simply ignore any signals being cast by the interview experience and only focus on objective measures distinguishing vacancies, e.g., wages, hours, etc. Especially if workers learn about match quality over the duration of the match (Nagypál, 2007), having an informative ex ante signal can enable workers to sort away from obviously poor matches. One measure for gauging match quality is the length of tenure a worker spends in their job, as workers with poor match quality will voluntarily quit sooner (Akerlof *et al.*, 1988) and workers will pursue outside options if they believe them to be more appealing than their current match (Jäger *et al.*, 2024).

To test whether interview difficulty can serve as a precursor for eventual match quality, we study turnover behavior matching workers' interview experiences to their accepted offers

Table 7: Tenure from Workers' Resumes After Offer Acceptance

	Logarithm of firm tenure			1(Firm tenure ≥ 12 months)		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Easy interview)	-0.196***	-0.201***	-0.203***	-0.093***	-0.091***	-0.092**
	(0.022)	(0.022)	(0.059)	(0.013)	(0.013)	(0.039)
Estimated log wage of vacancy		-0.050			0.029	
		(0.033)			(0.019)	
Mean DV for not easy	2.475	2.475	2.349	0.671	0.671	0.646
Observations	7,510	7,510	1,867	6,668	6,668	1,478
Adjusted R^2	0.16	0.16	0.44	0.08	0.08	0.28
Industry-occupation FE	✓	✓		✓	✓	
Firm-job title FE			✓			✓

Notes: Table 7 relates the length of firm tenure for a job using workers' resumes to their interview experiences for that same employer. Each column additionally includes fixed effects for the calendar year-month the job began × the calendar year-month the interview was submitted to Glassdoor. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

using their resumes. To construct this dataset of interview-tenure pairs, we consider all of the jobs listed on a worker's resume and identify for which (if any) the worker disclosed their interview experience on Glassdoor. We match an interview to a job on a resume if the worker reported an interview for that firm within a year of the job beginning. For jobs with end dates listed on the resume, we can calculate tenure with the firm. Of course not all jobs have ended, so as to not overlook still ongoing employment spells, we create an indicator for the match has survived at least twelve months. We then study whether we observe differences in these two measures of firm tenure between workers who accepted offers after easy interviews and their counterparts who accepted offers after not-easy interviews. The results are recorded in Table 7.[28]

Each specification paints the same narrative: Workers separate earlier if they thought the interview they had *before* starting the job was easy. Even within the same industries and occupations, workers separate 18 percent faster after an easy interview (column 1) — a relationship that is orthogonal to the wage of the role (column 2). Even when looking within the same firm and job title, workers separate 15 percent earlier if they experienced an easy interview (column 3). When examining whether workers remain with their employer for at least one year, we observe a significantly lower probability after an easy interview. Even when considering the same firm and job title, workers who accepted after easy interviews are 9.2 percentage points (column 6) less likely to remain in the match for at least one year, a 14 percent reduction relative to the 64.6 percent share observed following not-easy interviews.

[28]Since we do not observe age for most respondents, we exclude age from our benchmark specification. That said, despite the thinner sample, the takeaways would be unchanged if we did (Appendix Table IA9).

Of course, tenure is an equilibrium object. Faster turnover may reflect an increased propensity of voluntary quits just as easily as it could reflect a greater probability of layoffs. Depending upon which one dominates, the implications are drastically different. Under the former, the utility of the match is insufficient to dissuade the worker from pursuing outside opportunities. Indeed, others have shown that improved amenities, such as hybrid work arrangements (Bloom *et al.*, 2022), can induce workers to remain attached to their firms. If, instead, faster turnover primarily reflects heightened probability of layoffs, an easy interview might be an accurate proxy for a less-productive worker who is ultimately let go because they under-perform. To disentangle these two channels, i.e., worker-initiated separations from employer-initiated ones, we test whether the workers exhibit signs of poor match quality after an easy interview. To this end, we turn to reported levels of job satisfaction after easy and not-easy interviews, which we capture through Glassdoor employer reviews.

The reviews dataset is comprised of job satisfaction ratings where we observe the worker, their firm, and their job title. Glassdoor ratings are on an integral scale from 1–5 stars, and workers are incentivized to contribute through the give-to-get-mechanism introduced in Section 2.[29] Sockin (2022) shows Glassdoor satisfaction ratings across industries and occupations are strongly correlated with satisfaction reported in the National Longitudinal Survey of Youth 1997. To examine whether interview difficulty predicts satisfaction on the job, we match interviews in which the worker accepted the job offer to their later-written Glassdoor review. We assign an employer review to an interview report if they are written by the same worker, they are for the same firm in the same metropolitan area, and the review is provided after the interview occurred.[30] We are able to match 57,000 employer reviews. With regard to this sample of employer reviews, one may be concerned that they are differently selected from Glassdoor reviews more broadly since the worker would have had to contribute at least two separate survey responses—an employer review and an interview 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 employer reviews (Appendix Figure IA12), there is little difference between them.

As is shown in Table 8, easy interviews precede *much worse* job satisfaction. Workers who accept offers after easy interviews are 0.72 stars less satisfied with their jobs (column 1). For context, the magnitude of this disparity is seismic. For one, it is equivalent to one half of a standard deviation (which is 1.41 stars). Moreover, this disparity is larger in magnitude than the effect from learning your employer engaged in corporate misconduct (Gadgil and Sockin, 2020) or received an Accounting and Auditing Enforcement Release from the U.S.

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

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

Securities and Exchange Commission (Zhou and Makridis, 2021). This satisfaction gap between jobs accepted after easy and not-easy interviews persists when we compare workers evaluating the same firm and job title (column 2). Even when we consider the *same* worker reporting their satisfaction for multiple jobs that differed in whether they followed easy or not-easy interviews (column 3), that same worker reports 0.54 stars lower satisfaction, or one third of a standard deviation, for the job that followed the easy interview. Since job dissatisfaction predicts turnover (Akerlof *et al.*, 1988; Card *et al.*, 2012), such evidence strongly supports the narrative of more rapid quitting over that of more rapid layoffs. That the interview process has predictive power for longer-term outcomes (e.g., job satisfaction and firm tenure) suggests interviews offer ex ante credible signals of match quality.

Table 8: Indicator of Match Quality from Glassdoor Reviews After Offer Acceptance

	Overall rating		
	(1)	(2)	(3)
1(Easy interview)	-0.716***	-0.476***	-0.539**
	(0.014)	(0.038)	(0.264)
Overall rating standard deviation	1.410	1.363	1.508
N	56,539	11,865	534
R^2	0.150	0.529	0.860
Industry-occupation FE	✓		✓
Firm-job title FE		✓	
Worker FE			✓

Notes: Table 8 relates job satisfaction from workers' Glassdoor reviews to their interview experiences for the same position. Glassdoor reviews are matched to interviews if they are submitted by the same worker for the same firm in the same metro, and the interview was conducted before the review was submitted. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

6 Conclusion

Interviews are a two-way dialogue, featuring interactions between hiring managers and workers. Yet, the (personnel) literature has almost exclusively adopted the perspective of *hiring managers*, exploring how interviews allow employers to screen workers (Benson and Shaw, 2024; Hoffman and Stanton, 2024). In this paper, we take the opposite, underappreciated perspective. Do workers form perceptions of candidate employers through job interviews? They do. What exactly do workers learn through the interview process? Aspects that determine match quality yet are hard to gauge otherwise, such as the quality of future peers and their own degree of substitutability.

While this paper uniquely links workers' perceptions of the interview experience to their own labor market outcomes, many questions remain. For one, we cannot speak to how work-

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

Other work could also study how employee screening could be structured and to what extent different screening devices, such as IQ examinations, coding assignments, or personality 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 such evaluation methods causally shift the likelihood a worker will accept an offer, or even simply choose to continue with the interview process. These questions take on heightened relevance as firms increasingly consider automating segments of their screening processes.

In light of these considerations, what are the broader implications of these findings for firms and society at large? That firms appear to benefit from high-wage workers perceiving interviews to be difficult—as difficult interviews are positively associated with offer acceptance, firm tenure, and job satisfaction—invites moral hazard, i.e., for firms to engage in strategic deception. If firms know workers rely on interviews to gauge the quality of valuable non-wage aspects of the job, they have the incentive to disingenuously convey difficulty. For instance, firms might rely on their most productive workers to conduct interviews (to signal the ability of colleagues) or include questions that are overly challenging (to offer the mirage of human capital development), when the role in reality promises neither.

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

While this study considers interviews over the last fifteen years, it is plausible the nature of hiring will change. The advent of new technologies and the decentralization of hiring have

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

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

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Appendix

I Comparison of Glassdoor with Onsites Database

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

As with Glassdoor, for each of these interviews, we observe the employer, job title, and perceived interview difficulty. We thus calculate the average difficulty level for each firm-job title pair we observe in Onsites. We then calculate the average difficulty level among Glassdoor interviews for the same firm-job title pairs, and compare. The relationship between the two, summarized in Table A1, is reaffirming. Greater interview difficulty on Glassdoor aligns with greater difficulty on Onsites.

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

Table A1: Average Interview Difficulty in Glassdoor and Onsites

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

Notes: Table A1 compares the average difficulty reported for interview reports submitted to Onsites.fyi and interview reports submitted to Glassdoor. Interview difficulty is measured on a 1-5 Likert scale in both datasets. Averages are calculated for firm-job title pairs. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

II Applying Large Language Model to Interview Narratives

In this section of the appendix, we detail the procedure used in analyzing the text narratives written in interview reports with a large language model (LLM).

II.1 Procedure

First, we clean the dataset to focus on observations with interpretable text. We remove observations without an interview narrative and exclude observations whose text was a duplicate of that of another observation. The list of duplicate texts was also used to identify suspicious phrases that appeared many times, possibly indicating the interview description may have not been from a job seeker; examples include 'writing a job description, posting a job, scheduling interviews, conducting preliminary interviews', 'introductions. one of the most important steps in the interview process' and 'committed to protecting our community from fraudulent submissions.' Interviews containing any of these phrases were dropped. We also exclude observations where the text contains fewer than eight words of length three letters or more. These steps slightly trim the dataset from 2,503,000 to 2,477,000 observations.

Second, we use a stratified sampling approach to select a sub-sample of the cleaned dataset to annotate with the LLM. For each unique combination of two-digit NAICS industry and Glassdoor interview difficulty (very easy, easy, average, difficult, and very difficult), we randomly select 500 observations. If there are fewer than 500 observations in the sample for any given combination of industry and interview difficulty level, we use all such observations. This produces a dataset of 33,752 interview descriptions.

Next, we use the LLM to analyze the content of the interview descriptions in the sub-

sample and annotate them across nine dimensions of interest. They are: colleague ability, colleague pleasantness, whether "they'd accept anybody," direct assessment, compensation, hours and scheduling, workplace amenities, interview engagement, and realistic job preview. The LLM used is GPT-4o-mini and the prompts are detailed in full in Section II.3.

Last, for each of the nine dimensions, we use the GPT-generated annotations to train an adapter for the RoBERTa model under 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) in order to maximize the precision score. We then use the trained models to scale up the binary annotations to the entire database (not just those that received offers or are for high-wage occupations) of 2.5 million interviews.

II.2 LLM Annotation Prompts

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

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

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

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

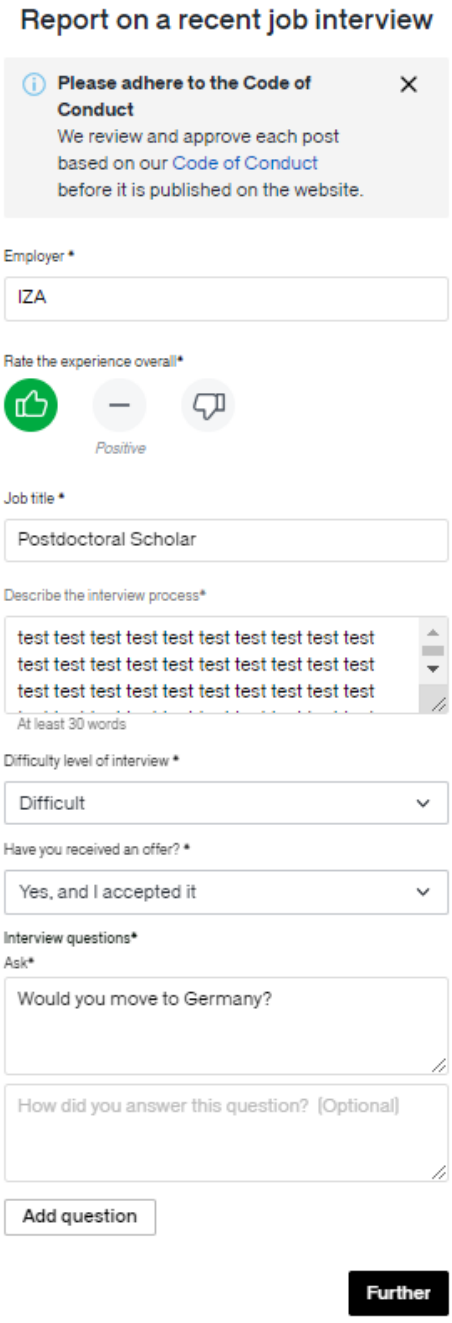
II.3 Validating LLM Annotations

To ensure that the LLM's annotations were of high quality, we hired two freelancers with experience of text annotation from the online freelancing platform Upwork. For each dimension, we provided the annotators with 100 interview descriptions, randomly sampled from the dataset that we had given to the LLM, and the same prompts that we had used to train the LLM. We then compare the two annotators' responses with those of the LLM. For each dimension, we observe an agreement score between the human annotations and those of the LLM of over 80%. We interpret the high agreement score as indicative of the LLM producing reliable interpretations for each prompt.

Internet Appendix

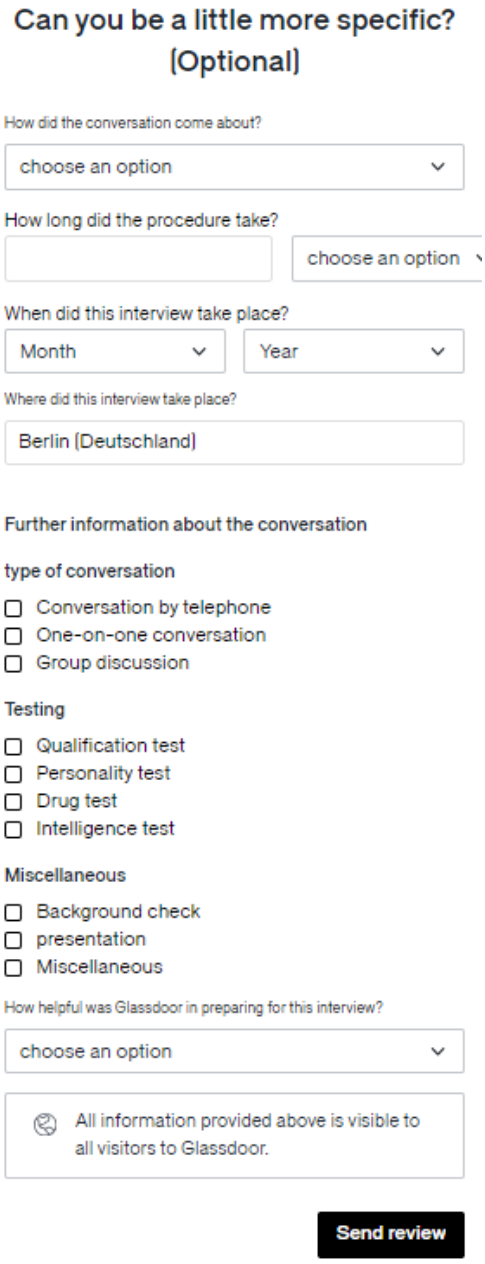
A Additional Summary Information

Figure IA1: Screenshot of Interview Submission Process



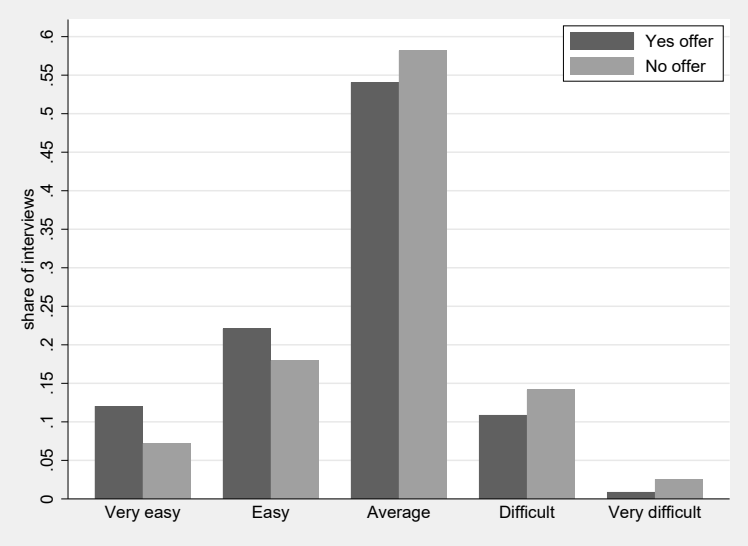
Notes: Figure IA1 provides a screenshot of the Glassdoor interview submission form from March 12, 2024.

Figure IA2: Screenshot of Additional, Optional Aspects of Interview Submission Process



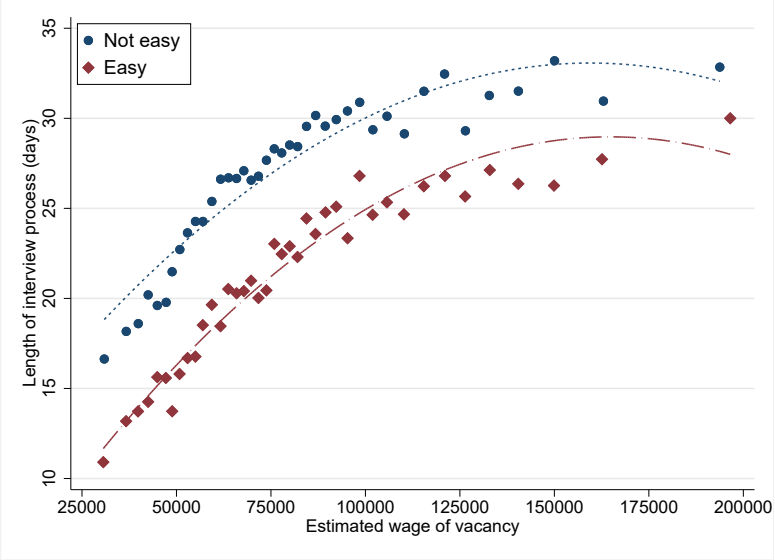
Notes: Figure IA2 provides a screenshot of the optional aspects of a Glassdoor interview submission form that a respondent can provide from March 12, 2024.

Figure IA3: Sample Distribution of Interview Difficulty, Including and Excluding Interviews That Did Not Result in Offers



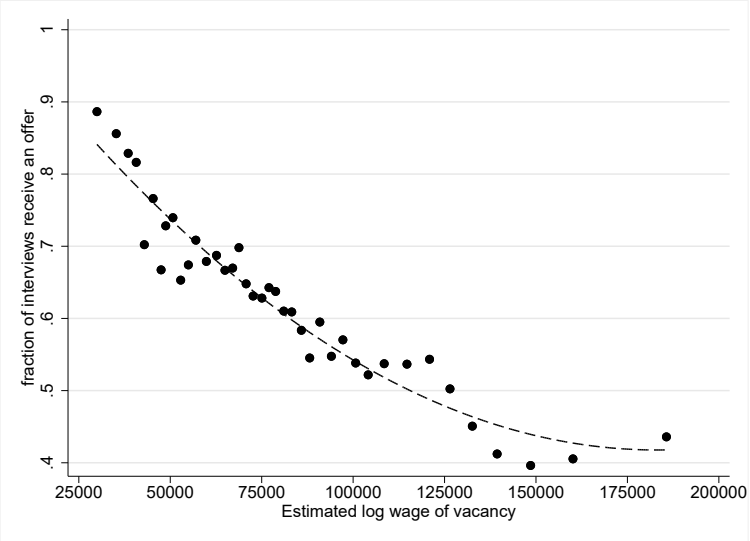
Notes: Figure IA3 plots the fraction of interviews in the sample reporting each level of interview difficulty, split by interviews that received an offer and those that did not.

Figure IA4: Interview Difficulty and Duration of the Entire Interview Process



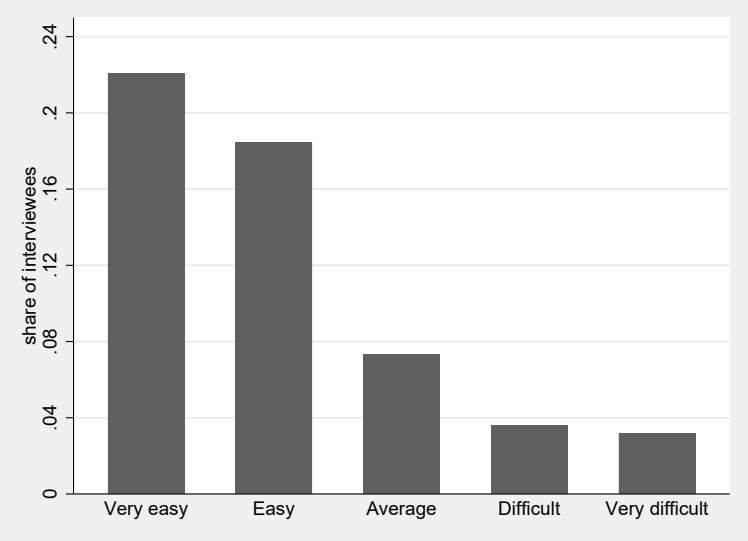
Notes: Figure IA4 presents a binscatter of the average length of the interview process (in days) against the estimated wage of the vacancy, with each series indicating the self-reported difficulty rating as easy ("very easy" or "easy") and not easy ("average," "difficult," or "very difficult").

Figure IA5: Offer Rate by Imputed Wage of the Vacancy



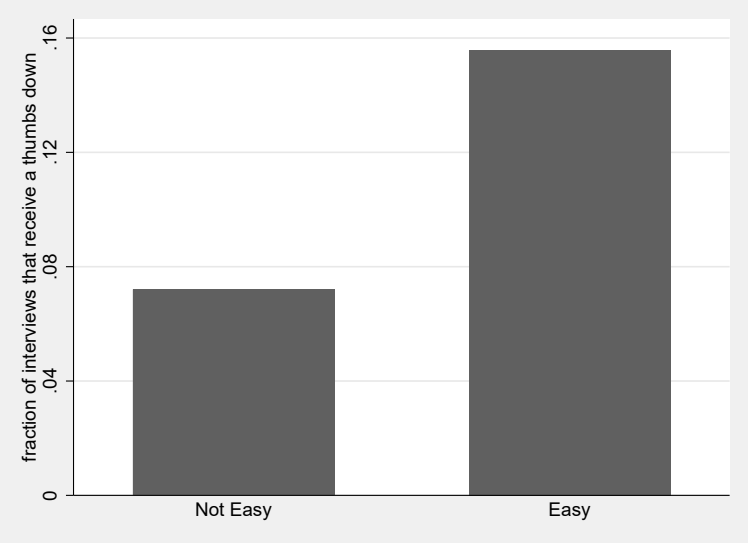
Notes: Figure IA5 is a binscatter of the fraction of Glassdoor interviews that led to an offer by the imputed wage of the vacancy. Imputed wage reflects the average pay among Glassdoor pay reports for the given firm and job title. Wages are inflation-adjusted to 2021 dollars. Sample is restricted to firm-job title pairs with at least five interviews.

Figure IA6: Fraction of Descriptions Mentioning "Easy" by Interview Difficulty



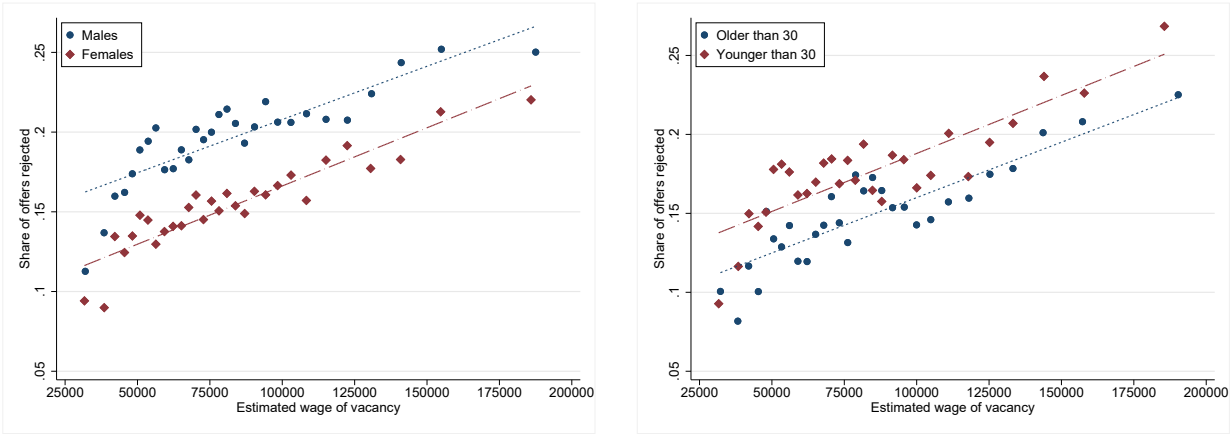
Notes: Figure IA6 plots the share of interviews for each difficulty level (rated on a 1-5 scale: 1-very easy, 2-easy, 3-average, 4-difficult, 5-very difficult) that mentioned the word "easy" in the free-response description workers provided about the interview.

Figure IA7: Fraction Report Interview was a Negative Experience by Interview Difficulty



Notes: Figure IA7 plots the share of interviews for each difficulty level (rated on a 1-5 scale: 1-very easy, 2-easy, 3-average, 4-difficult, 5-very difficult) that were characterized as negative experiences.

Figure IA8: Probability of Rejecting an Offer by Wage and Worker Demographics



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

Notes: Figure IA8 depicts a binscatter of the share of rejected job offers plotted against the estimated (log) wage of the vacancy. In panel (a), the sample is aggregated; panel (b) disaggregates by gender, and panel (c) by age group. The wage for each vacancy is *imputed* from Glassdoor pay reports for the same firm and job title, providing an approximate measure of what a hired worker would earn.

Table IA1: Iterative Procedure for Constructing Interviews Dataset

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

Notes: Table IA1 details the sample construction process, and the number of observations that are dropped with each step in the procedure.

Table IA2: Summary Statistics for Interviews Dataset

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

Notes: Table IA2 offers the mean, median, and standard deviation for each measure studied in our sample. Panel A pertains to aspects of the interview, Panel B to the demographics of the job seeker.

Table IA3: Firms with the Most Difficult Interviews

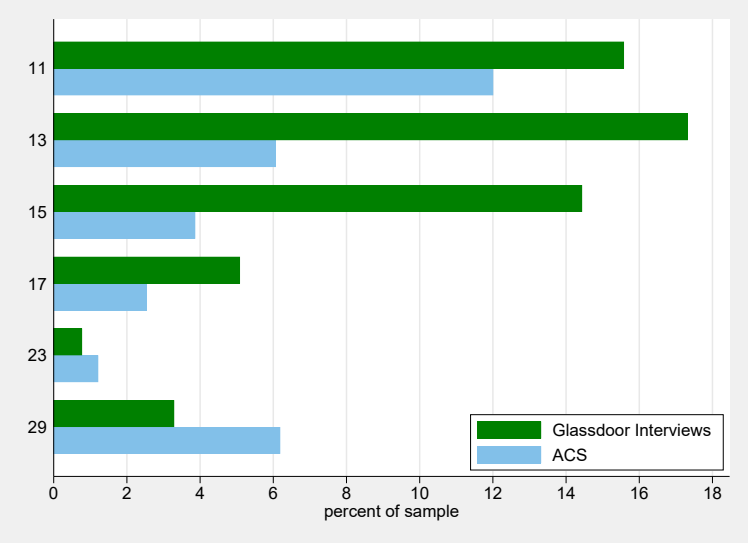
Ranking	Firm	Industry
1	McKinsey & Company	Management & Consulting
2	Kearney	Management & Consulting
3	Boston Consulting Group	Management & Consulting
4	YipitData	Information Technology
5	Bridgewater Associates	Financial Services
6	SpaceX	Aerospace & Defense
7	Amazon Web Services	Information Technology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

Notes: Table IA3 lists the 15 firms that offer the most difficult interviews. Ranking is based on the firm fixed effects from a regression on the full sample of interviews (offers and non-offers) that includes job title and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects.

B Selection into the Glassdoor Interviews Sample

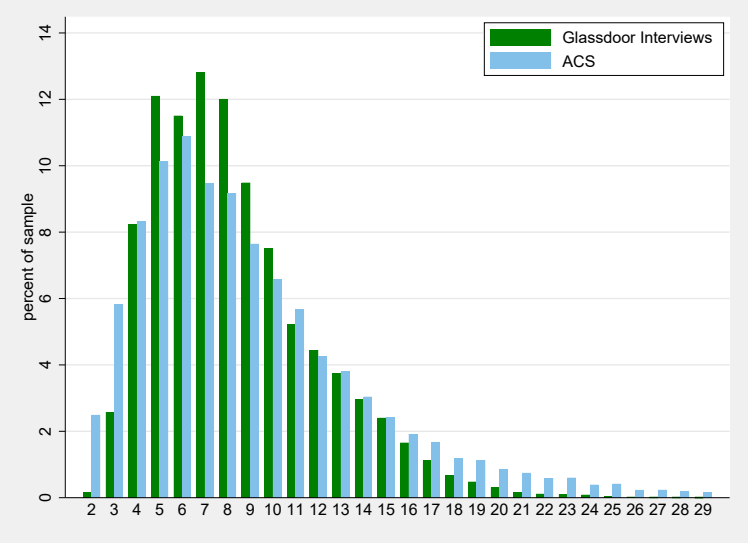
B.1 Comparison with the American Community Survey

Figure IA9: Distribution of Glassdoor Interviews Database by Two-Digit Occupation



Notes: Figure IA9 plots the fraction of interviews in the sample by each two-digit NAICS industry. Industries are assigned to each employer and come from a Glassdoor lookup table.

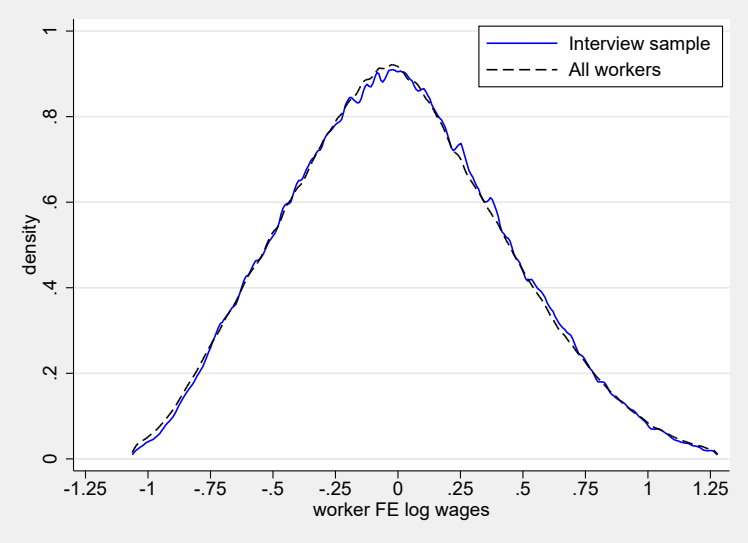
Figure IA10: Distribution of Interviews Sample by Imputed Wage of the Vacancy



Notes: Figure IA10 plots the fraction of interviews in the sample by the imputed wage of the vacancy within $10,000 bins. Imputed wage reflects the average pay among Glassdoor pay reports for the given firm and job title. Wages are inflation-adjusted to 2021 dollars.

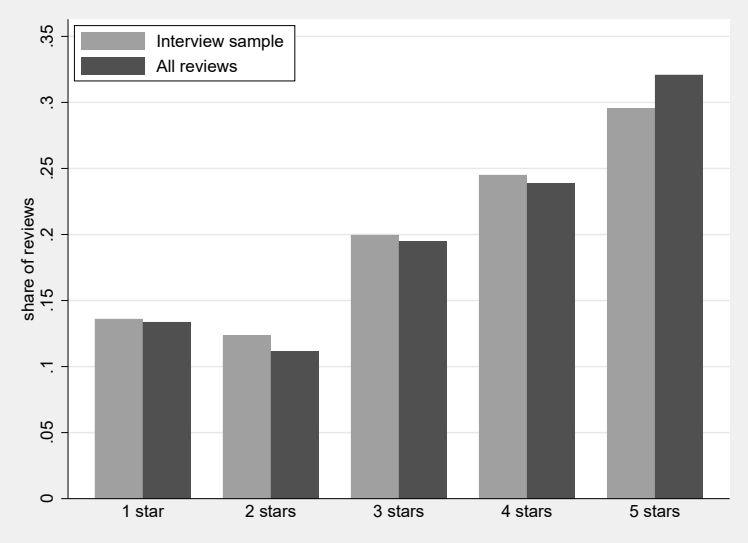
B.2 Comparison with the Entire Glassdoor Database

Figure IA11: Distribution of Worker AKM Fixed Effects in Interviews Sample Compared with the Full Sample of Glassdoor Pay Reports



Notes: Figure IA11 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 IA12: Distribution of Job Satisfaction Ratings in Interviews Sample Compared with the Full Sample of Glassdoor Reviews



Notes: Figure IA12 plots the distribution of the overall job satisfaction rating for the full sample of Glassdoor employer reviews and the distribution of those that could be matched to an interview report for analyzing match quality in Section 5.

C Interviews for Internships

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

Taking our sample of interview reports for internships, we re-estimate variations of Equation (1), the results of which are summarized in Table IA4. Looking at the cross-section of reviews, we observe that job seekers are 3–5 percentage points more likely to an offer if they perceived the interview to be easy. Compared with the average offer acceptance rates following not-easy interviews, this represents a 4–6 decline in the probability the offer is accepted. Even when we compare interview reports for the same role, i.e., job title at a firm in a metro area, easy interviews are more often rejected (Column 3). Although the sample is particularly thin, we observe a significant decline for easy interviews even for the same worker who made decisions over multiple internships (Column 4). Thus, for internships as well, interview difficulty is an important signal to workers of match fit.

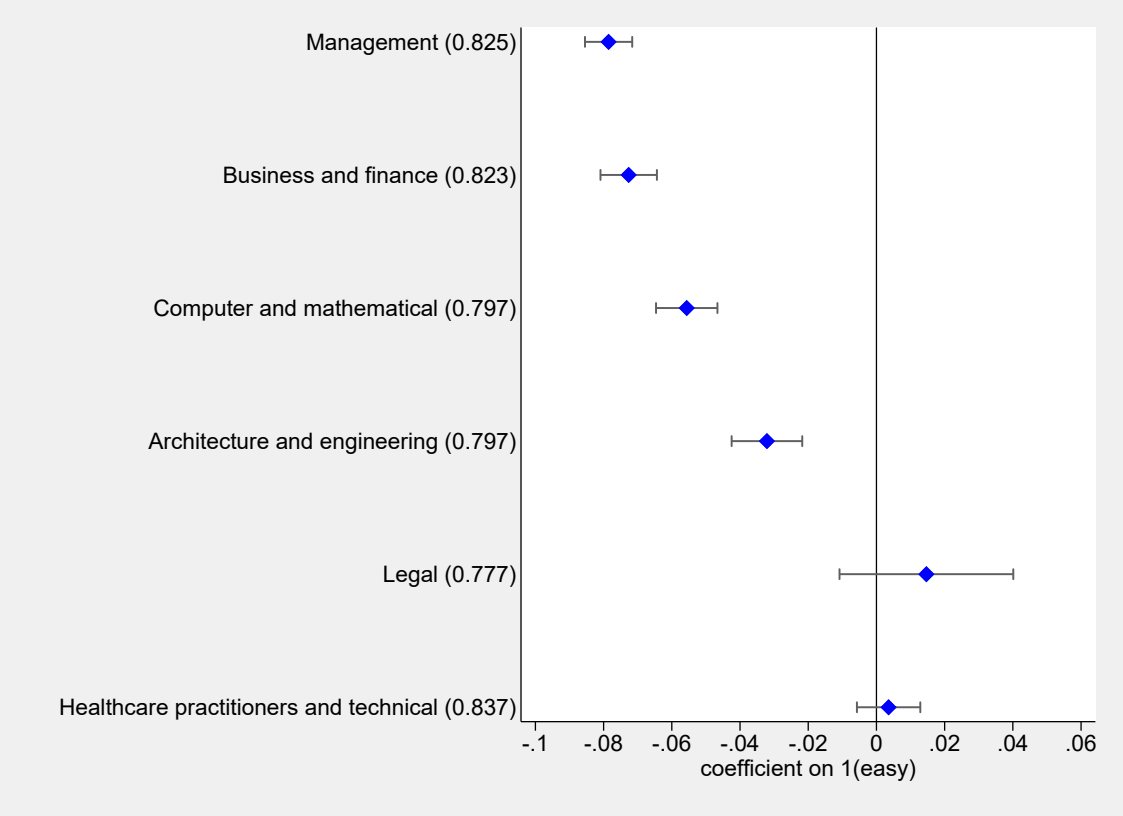
Table IA4: Probability of Accepting a Job Offer by Interview Difficulty for Internships

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

Notes: Table IA4 summarizes, for the relation between the probability an internship offer is accepted and the workers' perceived difficulty level of the interview process with the iterated addition of fixed effects for the firm, job title, and worker. Each specification includes year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

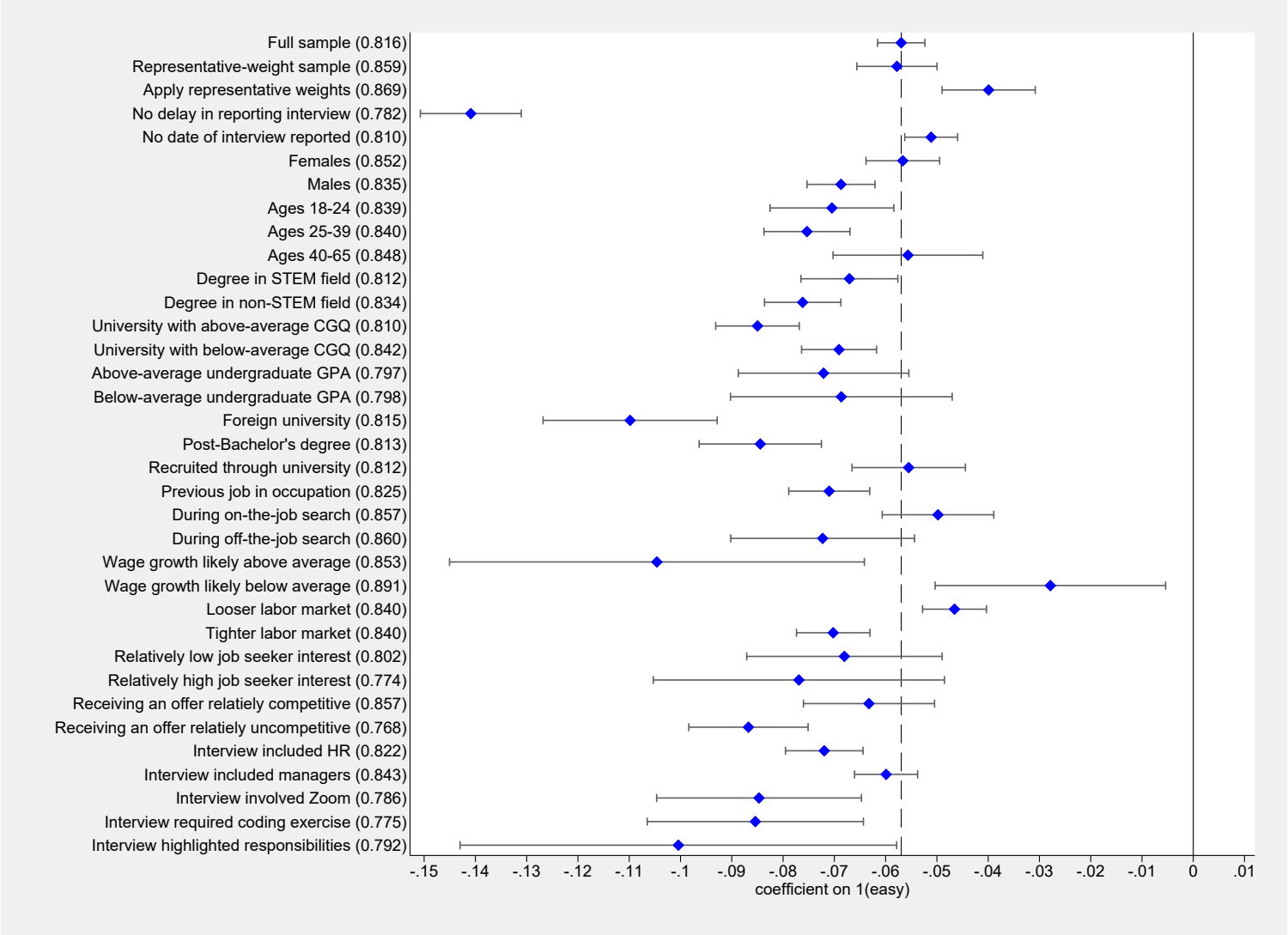
D Sensitivity Exercises

Figure IA13: Probability of Accepting an Easy Offer by Two-Digit Occupation



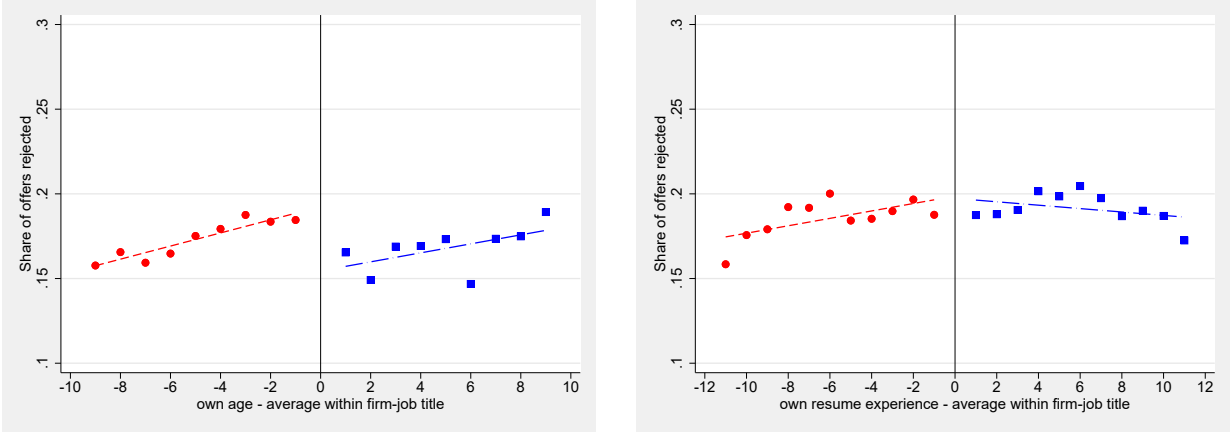
Notes: Figure IA13 reflects the coefficients on an indicator for the interview was considered easy for predicting acceptance rates separately for each two-digit SOC occupation. The mean offer acceptance rate among interviews not considered easy is recorded in parentheses. Blue horizontal bars indicate 95% confidence intervals around each point estimate. Standard errors are clustered by firm.

Figure IA14: Interview Difficulty and Offer Acceptance for Different Subsets of Workers



Notes: Figure IA14 summarizes the relation between an easy interview and whether an offer is accepted. Each row represents a separate regression in which the sample is restricted to the subgroup listed. Each specification includes industry-occupation and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Representative weights match annual employment in the American Community Survey by two-digit NAICS industry, two-digit SOC occupation, sex, metropolitan area, and earnings rounded to the nearest $10,000. College graduate quality (CGQ) is from Martellini *et al.* (2024). The mean offer acceptance rate among not-easy interviews in each subsample is recorded in parentheses. Horizontal bars indicate 95% confidence intervals around each point estimate. Standard errors are clustered by firm.

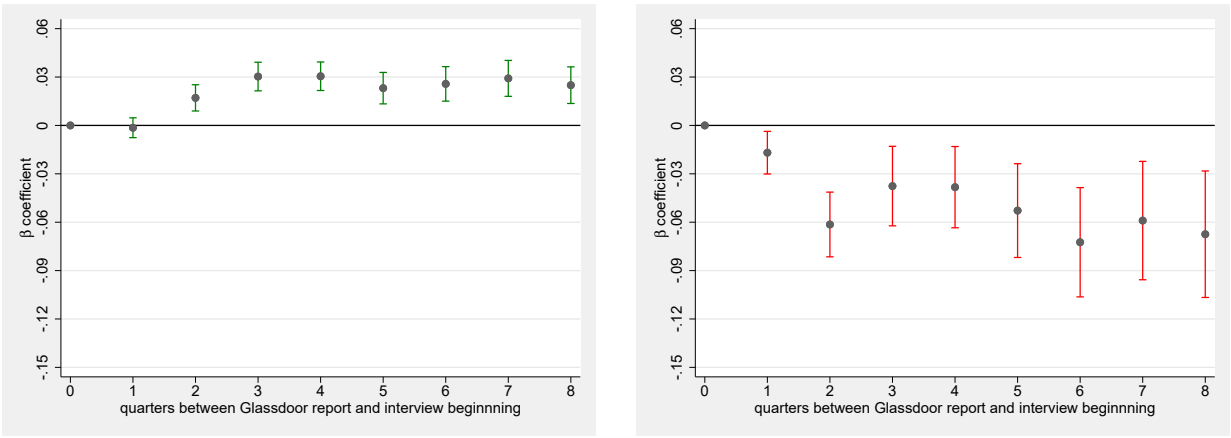
Figure IA15: Proxies for Under- or Over-Qualified and Offer Rejection Rate



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

Notes: Figure IA15 reflects the fraction of offers that are rejected by the relative age of the worker (panel a) and the relative years of prior experience on the worker's resume (panel b) to all others who received offers for the same firm and job title. Each dot represents a 0.20-rounded bin with at least 400 interviews.

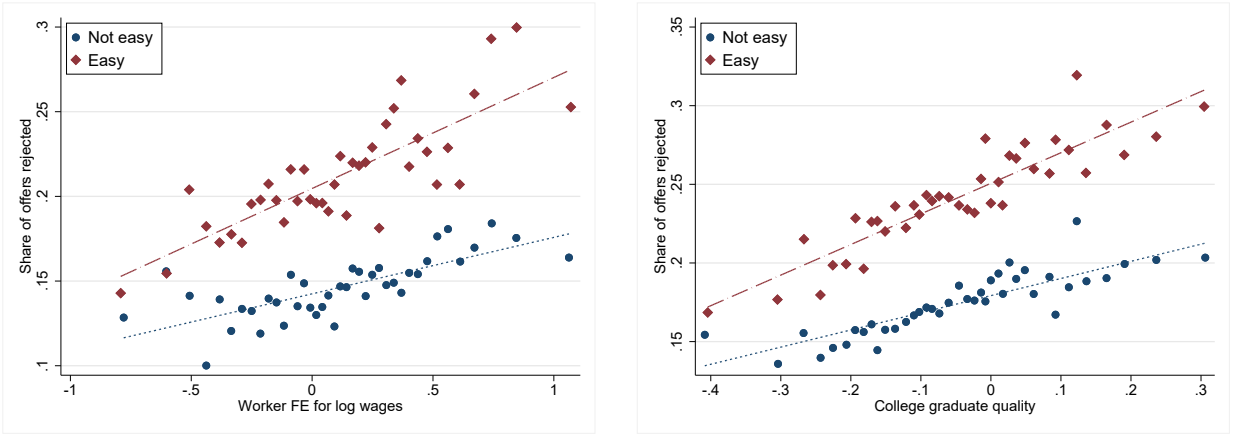
Figure IA16: Difference in Perceptions of Interview Difficulty by Time Since Interview



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

Notes: Figure IA16 reflects the difference in the probability of reporting an interview as very easy or easy based on the time elapsed between the interview start date and when it was reported to Glassdoor. Results are shown separately for workers who accepted (panel a) and rejected (panel b) the job offer. Low- and high-paying jobs are defined as having average pay below or above the sample mean, respectively.

Figure IA17: Probability of Rejecting a Job Offer by Interview Difficulty and Alternative Measures of Worker Productivity



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

Notes: Figure IA17 reflects a binscatter for the fraction of offers rejected, based on the worker's perception of interview difficulty and (a) the worker's AKM fixed effect on log pay or (b) the average graduate quality of the workerâs university. College graduate quality (CGQ), a measure of the average human capital of a university's graduates, is from Martellini *et al.* (2024).

Table IA5: Predictive Power of Imputed Wages for Actual Wages

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

Notes: Table IA5 summarizes the relationship between a worker's actual wage disclosed in a Glassdoor pay report and the imputed wage we assign the interview based on the firm and job title. To assign the actual wage, we merge pay reports to interviews if the year of the pay report is the same as the interview year, and if they are for the same worker, firm, and job title. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table IA6: Worker Demographics and Interview Difficulty within a Firm-Job Title

	1(Easy interview)		
	(1)	(2)	(3)
1(Female)	-0.004		0.002
	(0.006)		(0.013)
1(Employee referral)	-0.029***		-0.049***
	(0.008)		(0.017)
1(Age 18-30)	0.009		0.005
	(0.008)		(0.016)
1(STEM degree)		0.023***	-0.009
		(0.007)	(0.016)
College graduate quality		0.021***	0.012
		(0.003)	(0.007)
N	30,255	35,323	7,661
R^2	0.405	0.410	0.456
Firm-job title FE	✓	✓	✓

Notes: Table IA6 summarizes the relationship between worker demographic characteristics and whether the interview was rated as easy for the same firm and job title. College graduate quality reflects average human capital among a university's graduates from Martellini *et al.* (2024), standardized to have mean zero and standard deviation one. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table IA7: Interview Difficulty for the Same Worker Over Time

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

Notes: Table IA7 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 IA8: Perceived Interview Difficulty and Perceptions of the Firm for Same Worker

	High-ability colleagues	Pleasant colleagues	Would accept anybody	Engaging experience
	(1)	(2)	(3)	(4)
1(Easy interview)	-0.081***	-0.008	0.035***	-0.042***
	(0.012)	(0.015)	(0.008)	(0.014)
Mean DV for not easy	0.216	0.245	0.023	0.307
N	16,682	16,682	16,682	16,682
Adjusted R^2	0.14	0.13	0.10	0.15
Additional text covariates	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓

Notes: Table IA8 summarizes the relation between the interviewee's perceptions of the the employer and the perceived difficulty of the interview, incorporating worker fixed effects into the analysis. Each specification includes industry-occupation and year-quarter of interview x year-quarter submitted to Glassdoor fixed effects. Additional text covariates include indicators for the interview process illuminated compensation, illuminated hours or scheduling, illuminated desirable workplace amenities, and included a skills assessment. For details on constructing the text-based measures, see Appendix II. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table IA9: Tenure from Resumes After Offer Acceptance, Accounting for Worker's Age

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

Notes: Table IA9 examines the relationship between interview experiences and the length of firm tenure for a job using workers' resumes. The sample is restricted to workers whose age is recorded in the Glassdoor database. Each column includes fixed effects for the worker's age and the interaction of the calendar year-month when the job began with the year-month the interview was submitted to Glassdoor. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Supplementary References

Baert, B. S., Neyt, B., Siedler, T., Tobback, I. and Verhaest, D. (2021). Student internships and employment opportunities after graduation: A field experiment. *Economics of Education Review*, **83**, 102141.

Kuhnen, C. M. and Oyer, P. (2016). Exploration for human capital: Evidence from the mba labor market. *Journal of Labor Economics*, **34** (S2), S255–S286.

Margaryan, S., Saniter, N., Schumann, M. and Siedler, T. (2022). Do internships pay off? the effects of student internships on earnings. *Journal of Human Resources*, **57** (4), 1242–1275.

Martellini, P., Schoellman, T. and Sockin, J. (2024). The global distribution of college graduate quality. *Journal of Political Economy*, **132** (2), 434–483.