Employee-Generated Disclosures and Labor Market Outcomes*

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May 2025

Abstract:

Employees increasingly disclose detailed insights about their (former) workplaces on online platforms. Drawing on search theory, we study how these disclosures shape local labor markets by reducing search frictions through two mechanisms: (1) helping workers discover new employers; and (2) helping workers evaluate how well employer attributes align with their preferences. Using a large dataset that links employee-level data across a broad range of occupations to workplace ratings from Glassdoor aggregated at the metropolitan statistical area level for each employer-year, we find that employers with higher local ratings than their peers face lower employee turnover and attract larger, more qualified applicant pools—as evidenced by longer time-to-fill durations and higher wage offers in their job postings. Two complementary identification strategies support the roles of both search mechanisms. Our collective evidence provides insights into how voluntary, employee-generated disclosures influence a wide range of labor market outcomes by reducing search frictions.

JEL classification: D82, D83, J31, J63, J64

Keywords: labor market search theory, labor market transparency, workforce allocation, employee-generated disclosures, information processing costs, Glassdoor

* We thank Paul Fischer, Jeroen Suijs, Andrew Sutherland, Felix Vetter, and seminar participants at Fordham University, Massachusetts Institute of Technology, and The Wharton School for helpful discussion and comments. We also gratefully acknowledge financial support from the London School of Economics.

1. Introduction

In recent years, the factors that determine workers' job search and retention decisions have expanded beyond pay to include work-life balance, workplace culture, and other non-wage attributes. The Great Resignation and resignations driven by toxic workplace environments highlight this shift (Jorgensen, 2022; Sull et al., 2022a; Sull et al., 2022b). While workers benefit from understanding these workplace factors before committing to a position, limited access to information often hinders them from making fully informed decisions that align with their own preferences. The rise of employee-generated disclosures on online platforms, such as Glassdoor, provides a potential solution—offering real-time, decentralized insights into a wide array of workplace environments.[1]

In this paper, we study how these voluntary, employee-generated disclosures relate to local labor markets through employment decisions. Our study is motivated by the ubiquity and costs of job mismatches in the U.S. labor market: in 2024, preventable employee turnover accounted for 63% of all exits, representing an annual cost of nearly $1 trillion to U.S. employers (Work Institute, 2024, 2025). The growing significance of digital platforms such as Glassdoor—which facilitate detailed, voluntary employee disclosures about compensation, work-life balance, and workplace culture—underscores the contemporary relevance of this issue. Illustratively, within our dataset, the number of unique employers reviewed increased from 311 in 2008 to 1,498 in 2023, while the average annual number of reviews per employer rose markedly from 139 to 1,578 over the same period. Moreover, survey evidence shows that job seekers of diverse ages, income levels, and geographic locations increasingly rely on these disclosures when making employment decisions (Westfall, 2017).

Although employee-generated disclosures may help workers better align their job

[1] As Glassdoor notes, their mission is to "*[...] build a healthier, more transparent work community for all. Through the products we make and the communities we create, we're breaking down barriers that lead to discrimination, pay gaps and toxic work environments. Together, we're fostering a world where people have the support and resources they need to make the most of their worklife*" (Glassdoor, 2025e).

choices with their individual preferences, the very features that make these disclosures insightful—being decentralized and unfiltered—also raise concerns about reliability and representativeness. To evaluate the role of these disclosures, we therefore examine not only their consequences but also their underlying determinants. To guide our empirical analysis on the consequences side, we use a simple framework based on labor market search theory (introduced in Appendix A), which highlights incomplete information as a key friction in job matching. Our analysis centers on two mechanisms through which disclosures influence job search and retention decisions. First, an *awareness* mechanism: disclosures expand the set of employers known to workers and shift beliefs away from undifferentiated priors over employer quality. Second, an *evaluation* mechanism: disclosures provide comparative insights that help workers evaluate how well employer attributes match their individual preferences.

To examine the role of employee-generated disclosures in local labor markets, we combine labor market data from workers in a broad range of occupations with workplace ratings from Glassdoor. For each employer-year observation, we aggregate our dataset at the metropolitan statistical area level, which are geographically bounded labor markets where most job search and matching activity occurs (Moretti, 2011; Marinescu and Rathelot, 2018). We examine a variety of labor market outcomes—including employee-employer matches, job switches, employer-initiated job postings, and time-to-fill durations—by linking them to workplaces' relative attractiveness. We measure employer attractiveness using the employer's summary workplace rating at the metropolitan statistical area level, benchmarked against peers within that same area. We focus on summary ratings because these are the scores displayed prominently on an employer's local landing page, enabling straightforward comparisons (see Figure 1 for examples), and because they capture the fundamental trade-off workers face between pay and workplace quality (see Appendix B for examples). The focus on relative attractiveness follows from our prediction that the likelihood that a worker applies to another employer depends primarily on the relative utility offered by another employer compared to the worker's current employer.[2]

To address concerns about the direction of causality, we adopt several strategies.[3] First, our framework helps clarify the direction of causality flowing from ratings to employment decisions by providing structure around the hypothesized mechanisms. Second, in our analyses, we include firm-by-peer-by-year fixed effects, which ensure that we compare different locations of the same employer with varying exposure to local peer ratings—and thus control for a host of firm-specific and industry-wide factors like employer attractiveness, hiring trends, industry-wide labor competition, and macroeconomic shocks. We also include metropolitan statistical area-by-year and metropolitan statistical area-by-industry fixed effects to account for time-varying local labor conditions and time-invariant industry-specific factors within a local labor market. Third, we implement two complementary tests of the awareness and evaluation mechanisms (see details below). Since each test relies on a different set of identifying assumptions, their combined findings should assuage endogeneity concerns.

On the determinants side of our analysis, we show that employee-generated disclosures are related to various factors, including the economics of the firm, the local labor market, and the demographics of the local workforce. For instance, review activity is less common in metropolitan statistical areas with higher gross domestic product and higher average pay, but more common in those areas with more employers and workers. We also find that review activity is persistent within employers, while favorable prior ratings negatively impact review volume. Within employers, workforce composition also matters—engineering-heavy firms see

[2] This is consistent with existing evidence that workers increasingly evaluate potential employers relative to their labor market peers (deHaan et al., 2023; Li, 2024). A survey of over 4,500 respondents by HR platform SoftwareAdvice also supports this idea, finding that nearly half of the respondents use Glassdoor ratings primarily to identify top employers (Westfall, 2017).

[3] To address the possibility that Glassdoor ratings are strategically manipulated, we interviewed platform staff and reviewed moderation practices (see Section 2 for details). These conversations revealed several safeguards—such as pattern detection, review moderation, and user verification—that mitigate the threat of manipulation. Moreover, if some firms do manage to inflate ratings without genuine improvements, this would likely bias our estimates toward zero by diluting the informativeness of ratings.

more reviews, while finance and scientific employees contribute fewer reviews. Cross-sectionally, lower pay and layoffs predict unfavorable reviews, which points to dissatisfaction as a driver of unfavorable reviews.

On the consequences side of our analysis, we find that employers with higher ratings than their peers experience lower employee turnover, with fewer employees leaving and fewer new employees joining. This effect is strongest in low-growth and low-pay environments, where non-pecuniary factors (e.g., culture and work-life balance) likely play a greater role in job decisions. By contrast, ratings have a weaker impact in high-growth and high-pay settings, where workers are more likely to prioritize financial advancement and career mobility (Dutton et al., 1994; Adelino et al., 2017; Bennett and Levinthal, 2017). Analyzing approximately 50 million job postings, we further find that higher-rated employers post fewer job openings, consistent with greater workforce stability. However, when these employers do hire, they take longer to fill vacancies, consistent with larger applicant pools increasing screening time due to congestion (Roth and Xing, 1997; He and Magnac, 2022). Additionally, higher ratings are associated with higher posted wages, suggesting that employers attract stronger candidates and offer higher salaries to secure talent. These effects are most pronounced when employers have a high volume of Glassdoor reviews or a more balanced workforce, making ratings more precise and job matching more important but also more costly. These relations are also economically meaningful: a one within-fixed-effects standard deviation change in relative ratings is associated with a 4–11% change in the respective outcomes (see Section 5 for details).

Next, we try to substantiate our two proposed mechanisms with two complementary identification strategies. Regarding the awareness mechanism, we predict and find that the sensitivity between a focal employer's relative ratings and its own local labor market outcomes decreases when peers receive one of Glassdoor's annual *Best Places to Work* awards. This finding indicates that these awards shift worker attention away from non-award-winning employers toward those that receive attention. Regarding the evaluation mechanism, we predict and find that Colorado's *Equal Pay for Equal Work Act*—which mandates employers in Colorado to disclose pay ranges in job postings—increases the importance of non-wage workplace information on Glassdoor. This finding is consistent with Glassdoor providing insights into a broad array of workplace-related aspects that workers would otherwise lack. Together, these findings provide support for both mechanisms, suggesting that publicly available employee-generated disclosures not only make workers aware of peers' workplaces but also provide insights into these workplaces' relative attractiveness.

Our findings contribute to three streams of research. Our main contribution lies in formalizing the role of employee-generated disclosures within labor market search theory. (See, for instance, Rogerson et al. (2005) and Wright et al. (2021) for overviews of this literature.) We show *how* these disclosures reduce information frictions and enable workers to make more informed employment, namely by (1) raising awareness about available job opportunities and (2) informing workers about the relative attractiveness of these opportunities. We also provide supporting evidence on how these employee-generated disclosures relate in turn to labor market outcomes via workers' job search behavior and worker-employer job matching. These findings complement recent work that shows that centrally disclosed wage information influences workers' search behavior (Jäger et al., 2024). Our paper differs in that we bring in the perspective that employee-generated disclosures—which are decentralized—provide useful insights into multiple dimensions of workplaces. This distinction is relevant in light of evidence that workers respond strongly to non-wage information (Choi et al., 2023).

We also contribute to the growing literature on employee-generated disclosures (specifically Glassdoor reviews) by examining their effects on local labor markets (Hales et al., 2018; Huang et al., 2020; Dube and Zhu, 2021; Li, 2024). While anecdotal evidence indicates that workers frequently rely on Glassdoor reviews (Westfall, 2017), empirical evidence on their impact within labor markets is limited. Although these reviews may be endogenous, our findings indicate that they are related to local labor markets—affecting outcomes for both employers and workers. These findings therefore also add to the emerging accounting and labor market literature, specifically those studies linking disclosures to labor market outcomes (Bloomfield et al., 2017; Cascino et al., 2021; Barrios, 2022; Abramova, 2024; Sutherland et al., 2024).

Finally, our paper is related to the broader literature that focuses on firm-related disclosure. The unique nature of employee-generated disclosures fundamentally distinguishes them from traditional voluntary disclosures, such as those made by managers. Unlike firm-controlled voluntary disclosures—which are strategically timed and framed to highlight positive aspects—employee-generated reviews are not only decentralized and unfiltered but also self-selected. Not all workers within a firm participate in this voluntary "polling" process, and those who do often do so selectively. This means that reviews may disproportionately reflect the perspectives of workers with particularly strong—positive or negative—opinions rather than the broader workforce. Despite these unique features, our findings indicate that employee-generated disclosures provide valuable information to understand firms' workforce-related aspects such as worker retention and turnover.

2. Institutional background

We analyze employee-generated disclosures on *Glassdoor.com*, an online platform enabling workers to anonymously review employers and share their workplace experiences. Glassdoor offers an ideal setting because it specifically caters to workers by providing job listings, facilitating employer engagement, and encouraging structured, employment-focused discussions through reviews with ratings based on key workplace aspects. In contrast, broader online platforms such as X, Facebook, and Reddit include less structured discussion on employment topics and offer less easy access to actionable, job-related information. In addition, online job posting platforms such as *Monster.com* or *Indeed.com* do not provide workers with employee-generated workplace information.

Reviews on Glassdoor consist of an overall rating, ranging from one (lowest) to five (highest), accompanied by a mandatory review title and a descriptive text of at least six words. Reviewers also provide information about their job title, tenure, employment status, and workplace location. Furthermore, they can give subratings (out of five) for specific categories such as "compensation and benefits" and "work-life balance."[4] They may also indicate their likelihood of recommending the employer to a friend, their approval or disapproval of the CEO, and their personal business outlook. Appendix B provides examples of Glassdoor reviews.

Beyond the structure and nature of the disclosures, Glassdoor's platform is also specifically designed to streamline the job-search process by increasing awareness of employers and facilitating comparisons about the relative attractiveness of various workplaces. Both the homepage and individual employer landing pages provide suggestions of similar employers and employers frequently searched by other workers (Li, 2024). Additionally, Glassdoor provides industry-wide comparisons, displays ratings relative to peer employers, and annually highlights top-rated employers through awards and spotlights (Glassdoor, 2025c).

Glassdoor has become an increasingly prevalent tool in workers' job search processes over the past two decades.[5] Between 2008 and 2023, the number of unique employers rated on

[4] Glassdoor expanded its subratings at two points during our sample period. In 2012, it introduced the "culture and values" subrating and began asking contributors for their opinion on the firm's "business outlook." In 2020, it added the "diversity and inclusion" subrating.

[5] The core dynamics on Glassdoor share similarities with consumer review platforms like Amazon, Google Reviews, and Yelp. However, Glassdoor differs from these platforms in at least four key ways. First, workplace review platforms are inherently worker-focused, whereas consumer review platforms cater to customers. Second, product or restaurant reviews typically reflect one-time experiences, whereas workplace reviews capture long-term interactions between employers and workers. Third, Glassdoor requires users to disclose details like job title, location, and employment status, adding worker-relevant structure to reviews but potentially limiting participation due to anonymity concerns. Fourth, unlike consumer platforms—where firms can swiftly respond to feedback by adjusting prices, products, or services—employers have limited ability to immediately reshape workplace perceptions, as changes to work-life balance, culture, and management practices take time to implement.

Glassdoor in our sample grew from 311 to 1,498, with the average employer receiving 1,578 reviews per year in 2023—up from 139 in 2008. Additionally, Glassdoor attracts approximately 57 million unique visitors each month, ranking it as the third-largest job site in the United States (Glassdoor, 2025a). As such, a survey conducted by HR platform *SoftwareAdvice.com* found that the majority of 4,500 respondents used Glassdoor to evaluate potential employers (Westfall, 2017). Figure 2 visualizes the growth in the total number of reviews and the average rating over time, showing substantial increases in both metrics. This growth confirms the broader user engagement and widespread adoption of the platform but also indicates potential shifts in the nature or quality of rating information over this period.

To illustrate how Glassdoor facilitates workplaces' relative attractiveness, Figure 1 presents snapshots of several employers' location-specific ratings in two cities in the Boston (in Boston–Cambridge–Newton) and Philadelphia (in Philadelphia–Camden–Wilmington) metropolitan statistical areas. Panels A and B depict the Glassdoor pages for McDonald's Corporation and Starbucks Corporation, two labor market peers in our sample. While each rating offers limited information in isolation, together they reveal substantial geographic variation, indicating relative differences in workplace perceptions across cities. For example, McDonald's locations in Philadelphia are rated lower than those in Boston (3.2 versus 3.7 out of 5), yet still outrank Starbucks locations in Philadelphia (3.1). Similarly, while Starbucks is rated higher in Boston than in Philadelphia (3.3 versus 3.1), it remains lower-rated than McDonald's in both locations. These patterns suggest that workers perceive McDonald's as the more attractive employer in both markets, based on aggregate workplace characteristics.

Panels C and D present similar location rating comparisons for Jones Lang LaSalle Inc. and Cushman & Wakefield Inc., another pair of labor market peers. Here, JLL is consistently rated lower than Cushman & Wakefield across both cities. Another result that emerges when comparing Panels C and D to Panels A and B is that the JLL and Cushman & Wakefield locations are generally rated higher in Philadelphia, whereas the McDonald's and Starbucks locations are generally rated higher in Boston. As such, there is not necessarily a uniform "area fixed effect" in perceptions of workplace quality.

Regarding this information, Glassdoor's emphasis on anonymity and minimal content filtering allows workers to openly discuss sensitive workplace topics—such as compensation, organizational culture, and leadership—without fear of employer retaliation or backlash, which is less common on non-anonymous platforms like LinkedIn and Facebook. Glassdoor also uses several measures to enhance the credibility of its reviews (Glassdoor, 2025b). For instance, it explicitly encourages diverse perspectives, asserts that it neither edits nor filters reviews based on rating extremity or sentiment, and does not remove reviews upon employer request. Instead, Glassdoor's moderation policy is focused on enhancing the platform's reliability. For example, workers are required to authenticate their identities to Glassdoor through an email address or social media account. Interviews and discussions we conducted with Glassdoor indicate that comprehensive anti-abuse policies and tools are key to preserving trust and integrity on the platform. Rather than heavy-handed editing, the platform continuously refines its proprietary rating algorithm and bot- and spam-detection methods to outpace emerging manipulation tactics. For example, Glassdoor monitors reviewer IP addresses and posting patterns to flag suspicious activity.

3. Hypothesis development and related literature

3.1. Conceptual framework

Labor market search theory provides a framework for understanding the frictions that prevent instantaneous, fully efficient matching between workers and employers. Examples of these frictions are market power, bargaining, regulations, and worker preferences, all of which influence employment duration, turnover, and wages (Rogerson et al., 2005). Another key friction in labor markets—and the one we focus on—is incomplete information. A growing body of literature analyzes how such frictions increase the costs of searching for and targeting job opportunities and updating expectations about job features (McCall, 1970; Moen, 1997; Wright et al., 2021; Card, 2022).

To guide our empirical analysis and illustrate the main forces we have in mind, we use a simple framework that builds on this literature. To conserve space, Appendix A presents the model. While workers relied on word-of-mouth or firm-provided information historically, the emergence of online platforms featuring employee-generated disclosures now provide a more accessible, decentralized, timely, and detailed source of information about job opportunities and job characteristics. Such disclosures have the potential to reduce information frictions and influence labor market outcomes. Below, we discuss the two frictions we focus on: (1) *discovery costs*, which hinder workers in discovering new employers; and (2) *evaluation costs*, which hinder workers in evaluating how well employer attributes align with their preferences.

Discovery costs restrict workers' knowledge of available job opportunities. Initially, workers are aware of only a limited set of opportunities, prompting them to actively seek additional job options when they believe it will improve their choice set. However, the time and effort involved in searching impose costs that discourage continuous search activity (Rogerson et al., 2005). Consequently, workers cease searching when the marginal cost of identifying additional job opportunities exceeds the expected benefit, potentially leaving viable opportunities undiscovered. This unawareness induces labor market inefficiencies (Stigler, 1962; Stiglitz, 1989). Easily accessible information reduces discovery costs, expanding the set of employers known to workers. By reducing the time and effort associated with identifying available job opportunities, online platforms broaden the range of job opportunities workers can feasibly consider, resulting in improved labor market outcomes through enhanced and larger choice sets (Autor, 2001; Pallais, 2014).[6]

Evaluation costs hinder workers from making fully informed decisions. Even when workers are fully aware of available job opportunities, they may lack information about critical job characteristics, such as wages, working conditions, and organizational culture.[7] These information frictions generate evaluation costs related to acquiring and assessing information about job opportunities (Wright et al., 2021). As information frictions intensify, workers' ability to form accurate expectations about how well job opportunities align with their own preferences becomes increasingly impaired, thereby reducing labor market efficiency due to suboptimal worker-job matches (Carranza et al., 2022). Detailed information about prospective workplaces reduces evaluation costs, which improves job market efficiency. Easily accessible and credible workplace information reduces the need for workers to spend time and effort to gather it, enabling them to form clearer expectations and evaluate job opportunities in light of their preferences more efficiently (Farber and Gibbons, 1996; Altonji and Pierret, 2001; Manning, 2011; Pallais, 2014; Abebe et al., 2021).

3.2. Hypothesis development

We expect that employee-generated disclosures (i.e., employee-provided reviews) on Glassdoor influence labor market outcomes by lowering both discovery and evaluation costs. First, Glassdoor reviews enhance workers' awareness of available job opportunities by decreasing the time and effort required to locate suitable openings or potential employers. The initial rating displayed on employers' local landing pages shift worker beliefs away from undifferentiated priors over employer quality toward more specific beliefs. Second, Glassdoor

[6] This force is distinct from job websites, for example, which primarily influence the job search process by enabling workers to explore and identify more *vacancies* with less effort in less time (Kuhn and Skuterud, 2004).

[7] At the same time, employers typically lack perfect information regarding workers' skills and instead rely on imperfect signals—such as education credentials or previous job titles—or gradual learning over time. These approaches may fail to accurately capture a worker's true abilities, resulting in inefficient outcomes for both employers and workers (Farber and Gibbons, 1996; Altonji and Pierret, 2001). However, these frictions are beyond the scope of this paper.

reviews offer information that enables workers to carefully assess the match—or lack thereof—between location-specific job attributes and their own preferences for compensation, work-life balance, and workplace culture.

Appendix A outlines a simple model designed to formalize the intuition for how Glassdoor-provided ratings influence worker decisions in our empirical setting. We discuss the resulting testable predictions about key labor market outcomes below. Our primary outcome measures are chosen for their primary role in labor market research but also their practical relevance and significance (Beaumont, 1979).[8]

3.2.1. Worker turnover

We predict higher turnover at employers with lower relative online ratings. This is because online platforms reduce the discovery and evaluation costs for workers, making it more likely that they will become aware of, search for, and evaluate additional employers. This increase in job search activity raises the probability of workers encountering better opportunities. However, this effect is particularly pronounced for workers with low utility from their current job, as the benefit of discovering and evaluating new employers is more attractive to workers dissatisfied with their current employer. By contrast, workers with higher utility due to better wages and/or nonpecuniary job quality are less likely to engage in job search, as the perceived benefit of switching jobs is smaller. Thus, employers with lower ratings on online platforms tend to experience higher rates of employee turnover and less stable employment levels, as both more employees leave, and fewer new employees are hired. All these predictions are the opposite for employers with higher relative ratings on online platforms.

[8] Labor market search theory also makes predictions about pay and pay dispersion. However, we do not examine pay differences and pay dispersion due to the lack of accurate, large-sample data on pay. Revelio Labs, for instance, imputes pay based on job title descriptions (Revelio Labs, 2025), which means the resulting pay variable primarily reflects occupational composition rather than true variation in pay.

3.2.2. Job matching process

Our main prediction regarding the job matching process is that the time to fill positions is longer for employers with higher ratings on online platforms. This is because higher-rated employers attract a larger pool of applicants due to their perceived desirability as employers. As workers are more likely to apply to employers with higher relative ratings, the number of applicants increases. Any form of congestion—such as frictions arising from a lack of processing capacity or from the fact that new offers cannot be made until an outstanding offer is rejected—then lengthens the time to fill positions (Roth and Xing, 1997; He and Magnac, 2022).

We also have two other predictions regarding the job matching process. The first is that employers with higher ratings on online platforms offer higher wages in their job postings. The intuition behind this prediction is straightforward: it is more likely that employers with higher relative ratings have better wage-related attributes. The second is that employers with higher ratings post fewer job openings. This prediction follows from the earlier prediction that employers with better ratings face lower turnover, implying they need fewer new employees to replace those leaving. Both predictions are the opposite for employers with lower relative ratings on online platforms.

3.3. Related literature

An increasing number of studies focus on employee-generated disclosures as an alternative and/or complement to managerial disclosures. The unique nature of employee-generated disclosures fundamentally distinguishes them from traditional voluntary disclosures made by managers. That is, managers generally time and frame voluntary disclosures to highlight favorable outcomes while balancing the trade-offs of withholding potentially adverse information (Spence, 1973; Grossman, 1981; Milgrom, 1981; Verrecchia, 1983). In contrast, employee-generated disclosures often contain anonymous insights and unfiltered views about key firm characteristics. Online platforms such as Glassdoor thus shape how firm-related information is produced, shared, and used. Although individual employee-generated disclosures may be noisy due to idiosyncrasies, aggregating these insights filters out such noise, revealing shared perceptions and systematic patterns—consistent with the idea of the "wisdom of the crowd" (Surowiecki, 2004). Because the explicit and implicit costs of disclosure are relatively low for employees, these patterns capture a broad spectrum of opinions about workplace conditions, management practices, and organizational culture (Campbell and Shang, 2021; Graham et al., 2022; Briscoe-Tran, 2024).

Consequently, employee-generated disclosures on Glassdoor provide important context in many settings by providing forward-looking information about firms' workplaces. For instance, these disclosures are useful when combined with firms' financial information and help form expectations about the future (Hales et al., 2018; Huang et al., 2020). These disclosures also reveal misconduct (Dunham et al., 2023; Koenraadt et al., 2025), explain stock returns (Hales et al., 2018; Huang et al., 2020; Sheng, 2025), and explain the success of corporate transactions (Chemmanur et al., 2020; Lalova, 2025). Glassdoor reviews are also relevant to measure latent workplace characteristics, such as employee satisfaction (Green et al., 2023; Chiong and Xie, 2024) and management perception (Lee et al., 2021) and substitute for other, more formal employee-generated disclosure channels (Koenraadt et al., 2025). Combined, the evidence indicates that employee-generated disclosures provide incremental information beyond employer-controlled disclosures or that provided by other intermediaries (Fan et al., 2024).

At the same time, however, the voluntary aspect of employee-generated disclosures introduces concerns about reliability and representativeness. Since these disclosures are neither mandated nor randomly produced, certain factors increase the likelihood of disclosure. For instance, there was a surge in contributed reviews during the COVID-19 pandemic, the Great Resignation, and following the introduction of the "diversity and inclusion" subrating on Glassdoor in 2020—a change that spurred many employers to actively solicit feedback from their workforce. Moreover, employees tend to disclose their experiences during periods of organizational change, such as shifts in management, transformations in workplace culture, or changes in the employer's overall appeal (deHaan et al., 2023; Mkrtchyan et al., 2024). Regulatory changes that alter the perceived risks and costs of disclosure also influence disclosure behavior (Böke et al., 2025).

Several factors also influence the information employee-generated disclosures convey. Like reviews on platforms such as Google Reviews and Yelp, Glassdoor disclosures often display positive or negative tone in aggregate, as individuals with strong opinions and extreme experiences are more likely to share their opinions (Askalidis et al., 2017; Huang et al., 2020; Fan et al., 2024). Employee-generated disclosures may also contain outdated and/or inaccurate information when they are disclosed by former employees or intended to damage an employer's reputation.[9] Employers may also try to influence employee-generated disclosures to regain control over the presented narrative. For example, employers closely monitor employee reviews and views expressed on social media and respond to and address public scrutiny to mitigate reputational risks (Fuhrmans, 2017; Dube and Zhu, 2021). In addition, employers may encourage their employees to leave positive reviews (Bartov, 2022; Gong and Thomas, 2023) and several reports indicate that some employers target workers who leave negative reviews or seek to have unfavorable reviews removed.[10] There is also anecdotal evidence of individuals offering services promising "positive reviews for pay."[11]

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[9] For example, the lack of verification leaves firms open to "cyberbullying" or harassment (Sundberg, 2025).

[10] Social media provides ample anecdotal evidence of this practice. For example, several Reddit users in employee forums have reported that their employers request five-star reviews to inflate ratings or ask them to remove negative reviews (e.g., u/NotGonna_Lie2U, 2021; u/infpthoughts, 2022; u/TyrannicalKitty, 2023).

[11] u/ibsurvivors (2023)—Shikhar Sachdev, who curates a job-focused website and newsletter—explained the economics behind online review posting and how firms can recruit people to post positive reviews.

4. Variable measurement, sample selection, and summary statistics

4.1. Data sources and sample selection

Table 1 Panel A details the sample selection procedure. We construct our sample using data from Glassdoor, ISS Incentive Lab, Revelio Labs, and Compustat. The sample begins in 2008, with the introduction of Glassdoor, and ends in 2024. Following the labor economics literature, our unit of analysis is at the firm-peer-year-metropolitan area level (Moretti, 2011). We focus on these areas because they represent geographically bounded labor markets where most job search and matching activity occurs (Marinescu and Rathelot, 2018; Arnold, 2021).

Our final sample comprises 1,816,899 observations, including 2,224 unique employers and 95 unique metropolitan statistical areas. Our sample includes workers across a range of roles, with the largest groups in engineering, sales, and finance, followed by positions in administration, operations, marketing, and scientific research. The average employer has about seven local labor market peers and 307 workers in a given metropolitan statistical area. Appendix C details all variable descriptions. Throughout the paper, log(·) indicates a log(1 + ·) transformation to accommodate skewness and zeros.

4.2. Labor market information

We initially collect over 2.2 million reviews from more than 4,000 public firms on Glassdoor. This data spans from Glassdoor's launch in 2008 through 2024. After merging with other data sources, our final dataset includes 1,242,714 unique reviews. Appendix B provides examples of Glassdoor reviews.

We measure the attractiveness of a workplace using the overall workplace rating, which reflects an aggregate score based on employee reviews. These overall ratings reflect insights from a broad pool of (former) employees on key workplace factors, including compensation, benefits, work-life balance, culture and values—and thus capture the fundamental trade-off workers face between pay and workplace quality. Following the design of the Glassdoor platform, we carry forward an employer's most recent workplace rating in years with no new reviews because Glassdoor prominently displays the latest available rating, making it the most relevant and visible information to workers. Figure 1 presents snapshots of several employers' location-specific ratings across two cities in the Boston and Philadelphia metropolitan areas.

In most analyses, we concentrate on an employer's overall workplace rating relative to its local labor market peers. Specifically, our primary variable in these models, *Relative Rating*, captures the difference between the focal employer's overall workplace rating and that of each peer in the same metropolitan statistical area and year. This variable ranges between minus four and four and is unique to each firm-peer-year-metropolitan statistical area observation. A value of minus four indicates that the focal employer has the lowest possible rating (i.e., one) while its peer has the highest possible rating (i.e., five). Conversely, a value of four indicates that the focal employer has the highest rating, and its peer has the lowest rating.

4.3. Labor market peers

To identify local labor market peers, we combine data from ISS Incentive Lab and Revelio Labs. First, we obtain compensation-benchmarking peer data from ISS Incentive Lab. These benchmarking peers are designated by firms for the purpose of benchmarking incentive-compensation practices because of perceived similarities in labor market conditions and competition, particularly with respect to attracting and retaining talent (DiPrete et al., 2010; Faulkender and Yang, 2010; Cadman and Carter, 2013; Pittinsky and DiPrete, 2013; de Vaan et al., 2019). While firms must formally disclose these peers for executive purposes, these benchmarking networks are likely also relevant for the broader workforce. Indeed, in unreported analyses, we find that employee flows—both inflows and outflows—strongly comove with executive and director flows within these networks, indicating that the disclosed peers reflect meaningful labor market linkages for workers.[12]

There are three other advantages to using compensation-benchmarking peers to identify labor market peers for workers. First, U.S. publicly traded firms are required under Regulation S-K Item 402(k) to disclose a set of compensation-benchmarking peers, ensuring a large and systematically reported sample for the analysis. Second, unlike some peer networks (e.g., those based on industry membership), compensation-benchmarking relationships are not always reciprocal—one firm may select another as a peer without the relationship being mutual.[13] This reduces the likelihood that our employer-peer relationships reflect alternative firm characteristics, such as risk exposure commonality (Bloomfield et al., 2025). Third, these peers are relevant for labor market outcomes but do not have a mechanical relationship with job market dynamics and outcomes, unlike some alternative datasets on labor market peers (see, e.g., De la Parra and Glaeser, 2025).

Next, we obtain workforce data from Revelio Labs, which standardizes hundreds of millions of publicly available employment records to create a universal labor market database. This dataset includes detailed information on worker demographics, job titles, skills, seniority levels, compensation, and geographic locations. We aggregate this data at the employer-year-metropolitan statistical area level and match it to the employer-peer-year dataset from ISS Incentive Lab. The combined dataset allows us to identify whether a given employer operates in a specific metropolitan statistical area and whether it has a local peer in that region. If an employer has no recorded workers in a specific metropolitan statistical area, we treat the employer as having no active presence there. This approach aligns with standard practices for

[12] We estimate these flows in log-log regression specifications that include year, firm, or firm-by-peer fixed effects. In the specifications with year fixed effects, the estimated elasticity for flows over a three-year window is 0.482 for inflows and 0.393 for outflows. These coefficients imply that a 1% increase in executive flows is associated with a 0.48% to 0.39% increase in corresponding employee flows—indicating that compensation-benchmarking networks, though disclosed for executives, are highly relevant at the worker level.

[13] In our sample, we find that about 46% of the compensation-benchmarking peer connection are reciprocal.

defining labor market activity based on employment records.

4.4. Labor market outcomes

We examine a variety of labor market outcomes based on the predictions in Section 3. All data discussed in this section comes from Revelio Labs. First, we examine workers' employment decisions by analyzing worker mobility within each employer's location. We focus on overall employee movements as well as their two underlying components: the share of employees leaving the employer within a given location and the share of new employees joining the employer within a given location. *Overall Switches* is the total movement of employees in and out of an employer within a given location and year, divided by the total number of employees in that location at the beginning of the year. *Departing Employees* is the total number of employees leaving an employer within a given location and year, divided by the total number of employees in that location at the beginning of the year. *New Employees* is the total number of employees joining an employer within a given location and year, divided by the total number of employees in that location at the beginning of the year.

Second, we analyze characteristics of the job matching process, leveraging approximately 50 million job postings from Revelio Labs.[14] We focus on the number of employer-initiated job postings in a given location as well as the duration of the time-to-fill and the posted salaries. To determine whether a job posting is successfully filled, we match employer-initiated job postings at the most granular role level provided by Revelio Labs with new employee records. Specifically, we check whether there is a new employee with a starting date that follows the removal date of the job posting in the same employer-location. *Job Postings* is the total number of employer-initiated job postings in a given location. *Filled*

[14] The sample size for these variables differs from the other variables because job posting data is only available starting in 2019 for postings sourced from aggregators such as Indeed.com and from 2021 for postings sourced from LinkedIn.com.

Postings is the total number of employer-initiated job postings that are ultimately filled in a given location. *Time-to-Fill* is the average duration required to fill a job posting, calculated as the time between the removal date of the job posting and the starting date of the newly hired worker in the same employer-location in the role described in the job posting.[15] *Posted Salary* is the average salary reported in employer-initiated job postings in a given location. Due to skewness in the distribution of these variables, we use the natural logarithm of these variables in our regression specifications. In one of our cross-sectional tests, we divide the sample based on the average base salary of employees at a given employer-location-year (*Salary*).[16]

4.5. Summary statistics

Table 1 Panels B through E present a sample overview and summary statistics. Panel B highlights a steady increase in the number of employers, employer-MSA combinations, and total employment in our sample. Employee reviews and ratings also show an upward trend, with a sharp spike in reviews in 2020 and 2021, possibly due to the introduction of a new Glassdoor subrating ("diversity and inclusion") or labor market dynamics and increased online engagement during the COVID-19 pandemic and the Great Resignation. Figure 2 visually depicts this upward trend in the number of reviews and the average total rating over time.

Panel C indicates variation in employer presence and employment levels across industries in our sample consistent with broader economic trends. For instance, employers within consumer discretionary and financial industries have the largest employment bases.

[15] Posting time may be strategic or standardized (Sran, 2023), though this measure is intended to capture the length of the actual evaluation and screening part of the hiring process. Although it is possible that some postings may remain posted throughout this part of the hiring process, the typical duration of postings in our sample is relatively short, with mean, median, and 75th percentile values of 32, 30, and 44 days, respectively. As such, it is unlikely that postings remain posted long into the interview process or that our time-to-fill variable underestimates the actual time-to-fill duration.

[16] Since not all salaries are directly observable, Revelio Labs often imputes pay based on job title descriptions (Revelio Labs, 2025). As a result, this variable primarily reflects differences in job types (e.g., managers versus baristas), not differences in compensation for identical roles. While useful for splitting the sample into higher- versus lower-paying positions, this variable is not suitable as a dependent variable for examining pay disparities, as it conflates pay with occupational composition.

Employee ratings also vary by industry, with information technology and energy firms receiving the highest scores, while consumer staples and consumer discretionary firms have lower ratings. This may be consistent with industry-specific workplace environments and pay. Panel D further illustrates the metropolitan statistical areas in our sample, showing that major economic hubs like New York, Los Angeles, and San Francisco have the highest employer presence and employment. The differences in per-capita and per-employee income between Census and Revelio Labs data suggest that our sample consistently captures around 5% of employees in each metropolitan statistical area, tilted toward higher-paid positions due to these employees' presence on LinkedIn, an important source of Revelio Labs data (Karabarbounis and Pinto, 2018).

Panel E presents sample summary statistics. On average, employers in a given metropolitan statistical area receive a Glassdoor rating of 3.419 stars. In unreported analyses, we also find substantial within-employer variation across locations: the average standard deviation in ratings across areas within the same employer is 0.761, suggesting meaningful geographic differences in how workers evaluate the same firm. Regarding relative ratings, Figure 3 depicts distributions of *Relative Ratings*, with the two panels illustrating, respectively, the raw and the within-fixed-effects distributions (i.e., after removing firm-by-peer-by-year, area-by-year, and area-by-industry fixed effects) These plots indicate substantial between-employer variation in perceived workplace quality within a given location. Notably, the within-fixed-effects standard deviation of *Relative Rating* remains sizable relative to its raw variant (i.e., 1.273 versus 1.415), providing sufficient identifying variation for our empirical analysis.

5. Empirical analysis

5.1. When and why do workers choose to disclose?

We first examine why employees voluntarily disclose detailed insights about their workplaces. What drives them to contribute reviews, and how do employer and workforce characteristics shape the reviews and ratings? To do so, we examine overall reviews and overall absolute ratings, as well as reviews segmented by favorable versus unfavorable feedback. We estimate the following specification:

$$[Review_{imt}] = \mathbf{B} \cdot X_{imt} + \mathbf{\Omega} \cdot \mu_m + \mathbf{\Lambda} \cdot \eta_t + \mathbf{T} \cdot \varphi_i + \varepsilon_{imt}, \qquad (1)$$

where i indexes employers, m indexes metropolitan statistical area level, and t indexes years. [*Review*] is either the natural logarithm of one plus the total number of reviews (*Reviews*), the overall absolute score, continuously ranging between one to five stars (*Absolute Rating*), the total number of favorable reviews, defined as reviews accompanied by a rating of at least four stars (*Favorable Reviews*), the total number of unfavorable reviews, defined as reviews accompanied by a rating below four stars (*Unfavorable Reviews*). X is the vector of interest that contains geographical, workforce, and Glassdoor characteristics that all vary at the firm-area-year level (see Appendix C for details).

We include a variety of controls and fixed effects in Eq. (1) to ensure that our specification focuses on relevant within-group comparison. μ_m are metropolitan statistical area fixed effects that control for time-invariant features of the location's area, including those that are difficult to measure or observe such as local cultural norms. η_t are year fixed effects that control for general time trends in ratings as well as macroeconomic shocks, regulatory changes, or other temporal fluctuations that could systematically affect review activity across all employers. We also estimate Eq. (1) without and with φ_i, which are firm fixed effects. When we include them, the analysis relates variation in determinants to variation in ratings within a given employer across its different geographic locations. This allows us to isolate the effects of local determinants on review behavior while holding constant employer-specific characteristics, such as corporate culture, policies, and managerial style. We cluster standard errors by firm to address potential time-series dependence within firms (Abadie et al., 2023).

Table 2 presents results from estimating Eq. (1), with the two panels presenting, respectively, results for all reviews and ratings, and favorable versus unfavorable reviews. We present results both without and with firm fixed effects. Panel A shows that firms in metropolitan statistical areas with higher gross domestic product and those with higher pay receive fewer reviews, while those with more employers and employees attract more. Firms that offer higher pay to their employees also see more favorable ratings. Glassdoor-specific factors also play a significant role—prior reviews strongly predict new reviews, while prior ratings negatively impact review volume, indicating that employers with a history of reviews maintain engagement, but employers with higher prior ratings may receive fewer new reviews. Within employers, workforce composition also matters—engineering-heavy employers see more reviews, while finance and scientific workers contribute fewer reviews. Firms that increase admin staff see more favorable ratings, whereas firms that increase finance staff see more unfavorable ratings. Additionally, within a given employer, many reviews outside the focal metropolitan statistical area negatively predict local reviews, possibly indicating a dilution effect where national feedback substitutes for localized experiences. Panel B explores differences between favorable and unfavorable reviews. This panel shows that compensation (dis)satisfaction in reviews is evident, as pay is negatively related to within-employer variation in both favorable and unfavorable reviews. Moreover, prior ratings do not predict positive reviews within employers but significantly reduce negative ones, indicating asymmetric mean reversion.

These results support the idea that Glassdoor ratings vary predictably with economic conditions, workforce composition, and prior Glassdoor activity. This is consistent with prior studies that examine the determinants of Glassdoor rating contributions (deHaan et al., 2023; Gong and Thomas, 2023). While this evidence indicates that ratings reflect specific, relevant, and timely information, they may also be endogenous.[17]

5.2. How do employee-generated disclosures affect workers?

Next, we examine how employee-generated workplace disclosures influence worker behavior. We test whether an employer's relative workplace rating is associated with worker employment decisions, with higher relative ratings leading to lower employee turnover and more stable employment levels. To test this prediction, we analyze worker mobility within each employer's location, focusing on overall employee movements as well as its two underlying components: the share of employees leaving the employer within a given location and the share of new employees joining the employer within a given location.

Specifically, we estimate the following specification:

$$[Switches_{imt}] = \beta_1 \cdot Relative\ Ratings_{ijmt} + \beta_2 \cdot Employees_{imt} + \beta_3 \cdot Peer\ Employees_{jmt} + \mathbf{\Theta} \cdot \tau_{mt} + \mathbf{\Phi} \cdot \omega_{mg} + \mathbf{\Psi} \cdot \xi_{ijt} + \varepsilon_{imt}, \quad (2)$$

where i indexes employers, j indexes peers, g indexes four-digit GICS industries, m indexes metropolitan statistical area level, and t indexes years. [*Switches*] is either *Overall Switches*, *Departing Employees*, or *New Employees*. *Employees* and *Peer Employees* measure, respectively, the natural logarithm of one plus the number employees at the focal employer's local location and the number employees at the peer's local location. Our main variable of interest is *Relative Ratings*, which measures the difference in the focal employer's rating and the peer's ratings at the metropolitan statistical area-year level.

Because both labor market outcomes and relative ratings are available at the metropolitan statistical area level, we examine how peers' ratings influence labor market outcomes within the same employer, across different areas. To facilitate this comparison, we

[17] Because our dependent variables in these tests is a count variable, we assess the robustness of these findings by estimating Eq. (1) using a Poisson setup (Cohn et al., 2022). Results from these unreported analyses are similar in magnitude and statistical significance.

incorporate firm-by-peer-by-year fixed effects (ξ_{ijt}), which allow us to compare labor market outcomes across different locations of the same employer that face varying exposure to local peer ratings. This within-employer-within-time setup also accounts for all common but time-invariant characteristics shared by the focal employer and its peers, as well as time-varying employer- and peer-level factors that could affect employee-generated disclosures and labor market outcomes, such as employer attractiveness, hiring trends, industry-wide labor competition, and macroeconomic shocks.

To further help rule out potential alternative explanations, we include a variety of additional fixed effects, including area-by-year fixed effects (τ_{mt}) and area-by-industry fixed effects (ω_{mg}). Jointly, these fixed effects control for time-varying local labor market conditions that affect all employers in a local geographic location (e.g., regional wage shocks, labor laws, and economic cycles) and time-invariant factors that are specific to an industry within a given metropolitan statistical area (e.g., local industry-specific regulations and consumer demand). We cluster standard errors at the firm, peer, and metropolitan statistical area level to address potential time-series dependence within employers, their peers, and areas (Abadie et al., 2023).

Table 3 presents results from estimating Eq. (2), with the three panels presenting, respectively, results for all switches, departing employees, and new employees. We find that employers with higher ratings than their local peers experience fewer overall switches, which comes mainly from fewer employees leaving. Conversely, employers with lower relative ratings see more employees leaving. Taken together, these findings indicate that an employer's relative workplace ratings significantly influence workers' employment decisions, with higher relative ratings leading to lower employee turnover and more stable employment levels. This reduced turnover is consistent with the notion that employee-generated disclosures help workers find better workplaces and that favorable employee-generated disclosures enhance an employer's reputation, making it less likely for workers to leave and more challenging for peers to attract talent from highly rated employers.

To interpret the economic magnitude of these estimates, we compute the partial derivative of each outcome with respect to *Relative Rating*. Following Mummolo and Peterson (2018), Mitton (2024), and Breuer and deHaan (2024), we express these magnitudes using "within-fixed-effects standard deviations" that measure variation net of the fixed effects. Based on the estimates in Column (2) of each panel, a one within-fixed-effects standard deviation increase in *Relative Rating*—for the average employer-year with approximately seven local labor market peers—is associated with a 5.88%, 5.93%, and 3.59% decline in the within-fixed-effects value of *Overall Switches*, *Departing Employees*, and *New Employees*, respectively. Overall, these findings support our prediction that turnover rates are higher at employers with lower relative online ratings and lower at their counterparts with higher relative ratings.

5.3. How do employee-generated disclosures affect employers?

In this section, we examine how employee-generated disclosures affect employers. Specifically, we test the prediction that an employer's relative workplace ratings affects the job matching process. To test this prediction, we analyze measures of the job matching process: the number of employer-initiated job postings, duration of the time-to-fill, and posted salaries.

We estimate a modified version of Eq. (2) that has different dependent variables:

$$[\mathit{Outcome}_{imt}] = \beta_1 \cdot \mathit{Relative\ Ratings}_{ijmt} + \beta_2 \cdot \mathit{Employees}_{imt} + \beta_3 \cdot \mathit{Peer\ Employees}_{jmt} + \mathbf{\Theta} \cdot \tau_{mt} + \mathbf{\Phi} \cdot \omega_{mg} + \mathbf{\Psi} \cdot \xi_{ijt} + \varepsilon_{imt}, \tag{3}$$

where [*Outcome*] is either *Job Postings*, *Time-to-Fill*, or *Posted Salary*. As before, this equation includes firm-by-peer-by-year fixed effects (ξ_{ijt}), area-by-year fixed effects (τ_{mt}), and area-by-industry fixed effects (ω_{mg}).

In these analyses, the sample size differs from the preceding analyses because job posting data is only available starting in 2019 for postings sourced from aggregators such as

Indeed.com and from 2021 for postings sourced from LinkedIn.com. We further restrict the analysis of *Time-to-Fill* to observations with at least one filled job posting, ensuring that a meaningful time-to-fill duration is available. In this specification, we also additionally control for the overall hiring capacity and *filled* demand for workers by including the natural logarithm of one plus the number of postings that are ultimately filled (*Filled Postings*) (Sran, 2023).

Table 4 presents results from estimating Eq. (3), with the three panels presenting, respectively, results for the number of job postings, the duration of the time-to-fill, and the posted base salaries in the job posting. We find that employers with higher ratings than their local peers post fewer job openings. This finding is consistent with our earlier result that more favorable employee-generated disclosures contribute to greater workforce stability by reducing employee turnover. We also find that, conditional on a job being filled, employers with higher ratings than their peers take longer to fill these vacancies. This result aligns with our prediction that more favorable worker perceptions will attract a larger pool of applicants, thereby increasing the time required to evaluate and select candidates. Additionally, we find that these employers offer higher wages in job postings, further indicating that the applicant pool is of higher quality. Consistent with the argument presented above, a larger applicant pool enables higher-rated employers to be more selective, resulting in a more productive workforce. Higher productivity justifies increased compensation and aligns with the higher wage expectations of productive workers, which is reflected in job wage offers.

Taken together, these findings indicate that favorable employee-generated disclosures shape the job matching process—leading to fewer but more competitive job postings, longer recruitment timelines, and higher wages for new hires. Regarding the economic magnitude of these estimates, the estimates in Column (2) of each panel indicate that a one within-fixed-effects standard deviation increase in *Relative Rating*—for the average employer-year with approximately seven local labor market peers—is associated with an 11.00% decline in *Job*

Postings, and 8.52% and 10.55% increases in *Time-to-Fill* and *Posted Salary*, respectively (all measured within fixed effects). Overall, these patterns are consistent with our predictions: firms with higher online ratings post fewer job openings, take longer to fill them, and offer higher wages in their job postings.

5.4. Isolating the awareness and evaluation mechanisms

Our results so far indicate that employer relative ratings are related to worker employment decisions and the job matching process. We now try to isolate the two mechanisms—awareness and evaluation—using two different identification strategies.

The awareness mechanism implies that greater visibility of employers' ratings shifts worker attention toward these employers and away from less visible employer. To test this prediction, we leverage Glassdoor's annual *Best Places to Work* awards granted to peers (Glassdoor, 2025d). These awards serve as a signal—exclusively on the Glassdoor platform—that temporarily elevates a peer's visibility and, in turn, shift worker attention away from non-award-winning employers toward those that receive recognition.[18] We expect that when a peer receives an award, the sensitivity of a focal employer's relative rating to its local labor market outcomes weakens. We test this expectation by estimating the relation between Glassdoor reviews and workers' behavior in Eq. (2) using an event study design with a [–2, 2] window (in years) around the granting of a peer's *Best Places to Work* award on Glassdoor. We then test whether the coefficient on the focal employer's relative rating varies before and after the peer receives an award. We interact *Relative Ratings* with $\mathbb{1}$(*Post Peer Award*), which is an indicator equal to one in the period after the peer received the award, and zero otherwise. For this analysis, we replace the firm-by-peer-by-year fixed effects (ξ_{ijt}) with firm-by-peer fixed effects

[18] These awards are largely discretionary, are not limited to a single employer per region, category, or industry, and do not necessarily reflect recent reviews (Glassdoor, 2025d). In unreported analyses, we find that the correlation between an employer's *Overall Rating* and the likelihood of being awarded is only about 0.12.

to retain sufficient variation (Breuer and deHaan, 2024).

Table 5 presents results from testing the awareness mechanism. We find that the coefficient on the interaction term is positive and statistically significant across all specifications. This implies that the relation between a focal employer's relative ratings and its turnover outcomes weakens following a peer's award, consistent with job seekers' attention diverting toward award-winning firms. These findings support the awareness mechanism.

The evaluation mechanism implies that an employer's ratings inform workers about information they otherwise lack. To test this prediction, we leverage Colorado's 2021 *Equal Pay for Equal Work Act*, which mandates employers to disclose pay ranges in job postings (Colorado Department of Labor and Employment, 2025). We expect that this mandate increases the importance of non-wage workplace information on Glassdoor, because wage information is more broadly available.[19] We test this expectation by estimating the relation between Glassdoor reviews and workers' behavior in Eq. (2) using an event study design with a [–2, 2] window (in years) around the *Equal Pay for Equal Work Act* for employer locations in Colorado compared to employer locations in the seven neighboring states—Utah, Arizona, New Mexico, Oklahoma, Kansas, Nebraska, and Wyoming. Treated observations are those located in any metropolitan statistical area within Colorado, excluding those that extend into any control state. Control observations are those within the seven neighboring states, excluding those that extend into Colorado. We then test whether the coefficient on the focal employer's relative rating varies before and after the act for treated versus control locations. We do so by interacting *Relative Ratings* with $\mathbb{1}$(*Affected*), which is an indicator equal to one for locations in Colorado in the period after the act, and zero otherwise. For this analysis, we again replace the firm-by-peer-by-year fixed effects (ξ_{ijt}) with firm-by-peer fixed effects to retain sufficient variation

[19] Data from the Colorado Department of Labor and Employment's (2025) website indicates that the vast majority of firms comply with the act and, if not, comply when notified.

(Breuer and deHaan, 2024).

We focus on employers' overall relative ratings as well as their relative ratings along the work-life balance and compensation-benefit dimensions (*Relative Work–Life Rating* and *Relative Pay Rating*, respectively). We focus on the work-life balance dimension for two reasons. First, aside from pay, work-life balance is consistently ranked as the most important workplace characteristic (e.g., Morgan, 2023; Reuters, 2024; Partridge, 2025). Second, among the available ratings on Glassdoor, it is the most orthogonal to tangible workplace features such as career growth and compensation, while also being the most consistently available throughout our sample period.

Table 6 presents results from testing the evaluation mechanism, with the three panels presenting, respectively, results for the overall, work-life balance, and compensation-benefits dimensions. We find that the coefficient on the interaction term is negative and statistically significant across all specifications in Panels A and B, but not in Panel C. This implies that the relation between a focal employer's relative ratings and its turnover outcomes strengthens following the act, and that this is primarily related to non-compensation information on Glassdoor. This implies that the *Equal Pay for Equal Work Act* highlights the value of non-compensation information. These findings support the evaluation mechanism.

5.5. Cross-sectional analyses

In this section, we support our evidence by examining cross-sectional predictions via sample splits. We first discuss the auxiliary prediction arising from the predictions outlined in Section 3. Next, we estimate Eqs. (2) and (3) separately for different subsamples, allowing the coefficients on all variables and fixed effects to vary between them. We then test whether the differences in the coefficients between the subsamples align with our predictions.

5.5.1. Worker turnover and tangible job characteristics

The auxiliary prediction of our main turnover prediction is that wage-related job characteristics moderate the relation between ratings and worker turnover. Wage-related factors often weigh more heavily in workers' utility functions than nonpecuniary factors like work-life balance or company culture (Campbell et al., 2012; Adelino et al., 2017; Bennett and Levinthal, 2017; Jäger et al., 2024). Therefore, even if an employer's ratings are relatively low, favorable wage-related attributes may reduce the likelihood of turnover by making workers less likely to search for alternatives. This prediction is the opposite for employers with less favorable wage-related factors, in which case workers are more likely to apply elsewhere.

To test whether tangible job characteristics moderate worker behavior, we split the sample based on the employer's growth opportunities (*Market-to-Book*) and the average base salary of employees at a given employer-location-year (*Salary*). We expect that the influence of relative ratings is weaker in environments with more tangible benefits, such as strong growth prospects or high pay, and stronger in environments with fewer tangible benefits, where workers are more likely to rely on non-pecuniary aspects—such as workplace culture and work-life balance—when evaluating employers. Consistent with these predictions, Table 7 shows that the relations in Table 3 are most pronounced for employers with low growth opportunities and lower-paying positions. Interestingly, we find that departing turnover is more strongly associated with pay, whereas the arrival of new employees is more sensitive to growth opportunities. This suggests that compensation primarily influences retention decisions, while perceived future potential shapes job-seeking behavior.

5.5.2. Job matching process, signal precision, and employer workforce composition

We have two auxiliary predictions regarding the job matching process. The first is that the relation between relative ratings and the job matching process is moderated by the precision of relative ratings. Specifically, when a larger number of ratings are available, relative ratings become more precise and reliable, which reduces information frictions. As a result, more precise ratings are likely to have a stronger influence on workers' decisions to apply at a given employer, as they provide clearer signals of the employer's attractiveness. The second is that the relation between relative ratings and matching outcomes is moderated by the composition of the employer's workforce. Employers with more balanced workforces, particularly those that require diverse skill sets across departments or teams, must invest considerable resources in carefully evaluating each candidate's fit for specific roles. This increased effort to match workers with appropriate teams or departments leads to higher congestion in the matching process.

To test whether the impact of relative ratings on the job-matching process is moderated by the employer's ability to process and act on job applications, we split the sample by the number of focal employer reviews (*Reviews*) and the entropy of the employer's workforce composition (*Workforce Entropy*). We expect that when an employer has a larger number of reviews, the resulting workplace ratings are more precise and reliable, increasing their relevance to worker application decisions. Conversely, when available information is limited—such as a single five-star rating—workers are likely to rely less on this information. Similarly, we expect the impact of relative ratings to be stronger in employers with more diverse workforces, where hiring requires more careful candidate assessment and allocation across roles. By contrast, employers with concentrated workforces may require less intensive screening or have more experience screening applicants, reducing the role of rating-based perceptions in shaping job-matching outcomes. Consistent with these predictions, Table 8 shows that the relations in Table 4 are most pronounced in settings where employers have more reviews and more reviews and greater workforce heterogeneity. The exception is the relation between relative ratings and the number of employer-initiated reviews, suggesting that this outcome may be less sensitive to the precision of workplace information or the complexity of the employer's hiring needs.

6. Conclusion

Employees increasingly share detailed insights about their (former) workplaces on platforms like Glassdoor. Given the rising prevalence of employee-generated disclosures, we study their determinants and consequences for local labor markets. On the determinants side, we find that these disclosures are associated with a range of factors, including employer-specific economic conditions, local labor market dynamics, and the demographics of the local workforce. Our main result regarding the consequences of employee-generated disclosures for local labor markets is that employers with higher ratings relative to their peers experience lower worker turnover and attract a larger and higher-quality applicant pool, as evidenced by longer time-to-fill durations and higher wages in job postings. These findings indicate that stronger relative ratings enhance an employer's reputation—reducing turnover and enabling more selective hiring.

We formalize how employee-generated disclosures reduce search frictions within labor markets. We propose a simple model in which such disclosures reduce awareness and evaluation frictions in job search, providing structure for interpreting empirical patterns in a setting with many potential mechanisms. Using two complementary identification strategies, we find that online workplace reviews expand workers' awareness of alternative employers and provide insight into their relative attractiveness. We also add to the growing literature on Glassdoor by examining its impact on local labor markets, showing that it helps reduce information frictions that often hinder informed job decisions. More broadly, our findings highlight the economic importance of decentralized workplace information, particularly the role of relative ratings in retention, recruitment, and mobility.

Our findings also have broader implications for economic growth and productivity (Freeman, 1993; Nickell and Layard, 1999; Topel, 1999; Manning, 2003; Yeh et al., 2022). By reducing search frictions and enabling efficient job matching, employee-generated workplace disclosures enhance labor market fluidity. Our findings indicate that efficient job matching may minimize turnover costs, allowing firms to invest more in worker development. Moreover, by increasing labor market transparency, these disclosures help reduce information asymmetries that historically contribute to labor market inefficiencies. While our results indicate that favorable relative ratings may contribute to a more productive and stable workforce, they also point to potential costs for employers (e.g., Beaumont, 1979). Determining whether these outcomes ultimately improve employer efficiency or profitability (Zingales, 2000; Graham et al., 2022), however, is left for future research.

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Appendix A—Framework

This appendix outlines a simple model—including its timing and key assumptions—designed to formalize the intuition for how platform-provided ratings influence worker decisions in our empirical setting. The model captures two core mechanisms through which these ratings affect job search and retention decisions: (1) *awareness*: disclosures expand the set of employers known to workers and shift beliefs away from undifferentiated priors over employer quality; and (2) *evaluation*: disclosures provide comparative insights that help workers evaluate how well employer attributes match their individual preferences.

Below, we first describe the model's sequence of events, second solve it through backward induction from match outcomes to application decisions, and third analyze the resulting application rule to generate testable predictions.

A1. Environment

We model a finite-agent, discrete-time directed search environment in which workers choose which employers to target, employers differ in their underlying attributes, and search frictions influence matching outcomes, drawing on intuition from frameworks such as Moen (1997) and Moen and Rosén (2004) and overviews by Rogerson et al. (2005) and Wright et al. (2021). Matching is deterministic and capacity-constrained: once a worker is matched to an employer, they cannot be matched elsewhere. To allow for both voluntary and involuntary turnover, we incorporate the possibility that existing matches may dissolve exogenously. Affected workers re-enter the search process as unemployed and make application decisions under the same rules as employed workers, but with no incumbent utility to retain. In the spirit of Blankespoor et al. (2020), we operationalize search frictions as arising from limited awareness (discovery frictions) and misaligned or noisy employer evaluations (evaluation frictions).

The labor market consists of a finite set of workers $i \in \{1, \ldots, W\}$ and employers $j \in \{0, \ldots, F\}$, where each worker begins employed at an initial employer $j = 0$. Employers are heterogeneous in both their offered wages $w_j \in \mathbb{R}_+$ and a nonpecuniary job quality attributes $q_j \in \mathbb{R}$, drawn independently and identically across employers from a continuous joint distribution with support over $\mathbb{R}_+ \times \mathbb{R}$.[20] Workers are heterogeneous in two respects: skill s_i, which is observable upon application, and preferences (ω_i, φ_i), which determine how they value wage and nonpecuniary job quality.[21] A worker i's utility from a match with employer j is given by:

$$U_{ij} = \omega_i w_j + \varphi_i q_j.$$

Workers know their current employer's attributes and this setup implies that even workers initially employed at the same employer experience different utility levels due to differences in their preference weights. However, workers do not know the attributes of other employers. Instead, depending on the information environment, they may observe noisy platform-provided signals about other employers, which they use to form expectations. Based on these or their prior expectations, workers decide whether to apply to discovered employers, internalizing the

[20] This distribution may exhibit correlation between wage and quality—for example, jobs offering higher wages may also provide higher nonpecuniary quality on average.

[21] As a simplification, worker skill is independent of worker preferences and employer characteristics, though in practice high-skill workers may earn more in their current jobs and be less likely to switch. While this may modestly overstate their mobility in our model, it does not alter the core insights on preference alignment and information frictions.

possibility of rejection and any application cost or preference misalignment.

A2. Framework

0	1	2	3
Employer decides whether to post a vacancy or not	Worker decides whether to apply to employers or not	Matching unfolds over this period or not	Worker accepts best offer or stays with current employer

The timing of events is shown above. The job search process unfolds in four stages: (0) employers decide whether to post vacancies and offer compensation packages (or not); (1) workers decide which employers to apply to given search frictions (or not); (2) employers select among applicants based on observable skill (or not); and (3) workers choose whether to accept an offer or stay. We solve the model in line with backward induction, beginning from the acceptance stage when structuring decision rules.

A2.1. Time 3: Acceptance

At the final stage, each worker has applied to a subset of employers and may receive one or more offers. The worker then faces a simple discrete choice: accept the offer that yields the highest expected utility or remain at their current employer. For each employer $j \in \mathcal{O}_i$ that extends an offer, the worker forms expected utility based on their beliefs about the job's wage and nonpecuniary quality, denoted $\mu^*_{w_j}$, and $\mu^*_{q_j}$, respectively:

$$U_{ij} = \omega_i \mu^*_{w_j} + \varphi_i \mu^*_{q_j}.$$

The worker compares this to the utility from their current job:

$$U_{i0} = \omega_i w_0 + \varphi_i q_0.$$

The worker accepts the offer with the highest utility if and only if it exceeds U_{i0}; otherwise, they remain at their current employer.

A2.2. Time 2: Matching

At this stage, each employer receives applications and selects applicants to whom it extends offers, based on observable skill. Let $A_j \subseteq \{1, \ldots, W\}$ denote the set of workers who apply to employer j. Employer j ranks all applicants in A_j by skill s_i, in descending order, and selects the top $\min\{v_j, |A_j|\}$ applicants and extends offers to them.[22] Let $O_j \subseteq A_j$ denote this offer set. Formally:

$$O_j = \mathrm{Top}_{v_j}\left(\{(i, s_i) : i \in A_j\}\right),$$

where $\mathrm{Top}_{v_j}(\cdot)$ denotes the top $\min\{v_j, |A_j|\}$ applicants in terms of skills s_i.

[22] In the event of ties in skill, tie-breaking is resolved uniformly at random.

Each worker i then receives offers from all employers where $i \in O_j$. Let $\mathcal{O}_i = \{j \in A_i^* : i \in O_j\}$ denote the offer set for worker i.[23]

A2.3. Time 1: Application

At this stage, each worker i chooses which employers to apply to from a discrete subset $D_i \subseteq \{1, \ldots, F\}$ of employers, which depends on whether a platform such as Glassdoor is available.[24] With such a platform, workers observe all employers, capturing the role of platform-enabled reduced awareness frictions. Without such a platform, discovery is limited: each worker observes only a random subset of employers, capturing limited awareness through informal networks, local visibility, or incomplete information. Formally:

$$|D_i| = \begin{cases} F, & \text{if platform is available,} \\ d < F, & \text{otherwise.} \end{cases}$$

At the start of each period, existing matches dissolve exogenously with worker-specific probability $\lambda_i = \lambda_0 e^{-\beta U_{i0}}$, where $\lambda_0 \in (0, 1)$ is a baseline separation rate and $\beta > 0$ captures how higher current utility reduces involuntary turnover. Separated workers proceed through the application stage in the same way as employed workers, but with no incumbent utility, i.e., $U_{i0} = 0$.[25]

For each discovered employer $j \in D_i$, the worker evaluates whether to apply by weighing the expected utility gain against an application cost $\xi > 0$ for each application. Workers form beliefs about each employer's attributes based on the information environment:

- Without a platform, workers have no employer-specific signals. Instead, for each discovered employer $j \in D_i$, worker i's beliefs are centered around the average wage and nonpecuniary job quality across the discovered set, i.e., $\overline{w}$ and $\overline{q}$, with employer - specific deviations captured by independent and identically distributed mean-zero shocks drawn once per worker- employer pair. These weak priors introduce minimal differentiation in the absence of platform signals.
- With such a platform, workers observe noisy signals based on previous employee-generated disclosures, i.e., $\mu^*_{w_j}$, and $\mu^*_{q_j}$ (which deviate from employers' true wages w_j and nonpecuniary job quality q_j, in either direction, due to small idiosyncratic noise).

Thus, the net benefit of applying to employer $j \in D_i$ is therefore:

$$\Lambda_{ij} = \begin{cases} \omega_i \mu^*_{w_j} + \varphi_i \mu^*_{q_j} - U_{i0} - \xi, & \text{if platform is available,} \\ \omega_i \overline{w} + \varphi_i \overline{q} - U_{i0} - \xi, & \text{otherwise.} \end{cases}$$

[23] Employers with unfilled positions (i.e., $|O_j\} < v_j$) could enter a second substage, in which they extend offers to the next-highest-skill applicants in $(A_j \mid O_j)$, in descending order by skill s_i, until either all vacancies are filled or not applicants remain.

[24] We model platform access as a binary condition. In reality, access or adoption may be partial, and information quality may improve gradually over time.

[25] Alternatively, U_{i0} could take an epsilon value to capture the idea of unemployment insurance or the value of home leisure.

The worker applies to all employers in D_i for which $\Lambda_{ij} > 0$:

$$A_i^* = \{j \in D_i : \Lambda_{ij} > 0\}.$$

A2.4. Time 0: Job postings

At this stage, employers decide whether to participate in the labor market by posting a vacancy, and—if so—what compensation attributes to offer. Each employer j is endowed with a vacancy count $v_j \in \mathbb{R}_+$, a wage $w_j \in \mathbb{R}_+$, and a nonpecuniary job quality attribute $q_j \in \mathbb{R}$.

Employers face an implicit constraint: in order to attract applicants and successfully hire, they must offer combinations of wage and quality that yield utility improvements for at least some workers. However, employers cannot adjust these attributes freely—choices are subject to underlying productivity or profitability constraints. For example, an employer with limited resources may be unable to raise wages or improve working conditions without reducing its expected profits below sustainable levels.

We abstract away from a full employer optimization problem and take employers' offered attributes (w_j, q_j) as exogenously given, drawn jointly from a continuous distribution with support over $\mathbb{R}_+ \times \mathbb{R}$. These offerings reflect underlying heterogeneity in employers' capabilities and constraints.

A3. Analysis and predictions

In this section, we analyze the model to generate testable predictions about from the worker's application decision rule. We begin by deriving predictions for the worker's decision to apply. We then examine the employer-level implications of these application decisions, focusing on how platform-provided ratings affect the volume and distribution of applications received and the posted wages.

A3.1. Worker's decision to apply

The worker's decision to apply to an employer $j \in D_i$ depends on the net benefit of applying, given by Λ_{ij}. The worker applies to all employers for which $\Lambda_{ij} > 0$. From this expression, several predictions follow directly:

Proposition 1. *Workers with low current utility are more likely to apply to other employers, whereas workers with higher current utility are less likely to apply to other employers.*

Λ_{ij} is decreasing in U_{i0}. Therefore, all else equal, a lower utility from the current job (or zero utility if unemployed) makes it more likely that $\Lambda_{ij} > 0$, which increases the likelihood that the worker finds external opportunities attractive enough to justify applying. By contrast, a higher U_{i0} lowers Λ_{ij} across all employers. As a result, only employers with substantially higher expected utility can generate a positive net benefit, reducing the number of applications submitted by high-utility workers. In other words, a higher U_{i0} acts as a higher reservation utility, so only substantially better outside options yield Λ_{ij}.

Proposition 2. *When a platform such as Glassdoor is available, workers apply more selectively and are better able to match with employers that offer substantially higher expected utility relative to their current job.*

Platform access improves both discovery (by expanding the set of observable employers) and evaluation (by providing noisy but informative signals about employer-specific wage and quality attributes, $\mu^*_{w_j}$, and $\mu^*_{q_j}$). These signals help workers estimate how well a given employer aligns with their preferences and current job utility. As a result, the net benefit of applying Λ_{ij} is more likely to be positive for employers that are well-matched to the worker's preferences. High-utility workers—who are otherwise less inclined to apply—can now identify employers that exceed their reservation utility. Moreover, workers with strong preferences for specific job attributes (e.g., high pay or high quality) are more likely to find employers that cater to those preferences. As a result, workers become more selective as they target only the opportunities that offer a substantial expected utility gain and skip over marginal options. By contrast, without platform access, workers observe only average employer characteristics across the discovered set (i.e., $\overline{w}_j$ and $\overline{q}_j$ $\forall j \in D_i$), making it harder to distinguish between employers. This reduces the likelihood that $\Lambda_{ij} > 0$, particularly for workers whose current jobs already offer relatively high utility.

A3.2. Employer-level implications of worker application decisions

Each worker's application decision affects the distribution of applications across employers. Intuitively, the worker's decision to apply to an employer $j \in D_i$ has implications for employers. Several predictions follow.

Proposition 3. *Employers with higher platform-provided ratings are more likely to receive applications.*

With platform access, workers observe noisy signals about each employer's wage and nonpecuniary quality, i.e., $\mu^*_{w_j}$, and $\mu^*_{q_j}$. These signals enter directly into the worker's expected utility from applying to employer j and thus into the net benefit of applying Λ_{ij}. All else equal, higher $\mu^*_{w_j}$, and $\mu^*_{q_j}$ increase Λ_{ij}, making it more likely that the net benefit of applying is positive. This raises the probability that a worker chooses to apply to employer j. Aggregating across workers, this implies that, on average, employers with higher platform-provided ratings attract more applications.[26] Importantly, this effect does not arise without platform access, as workers then observe only average employer characteristics across the discovered set (i.e., $\overline{w}_j$ and $\overline{q}_j$ $\forall j \in D_i$)—making all employers observationally similar *ex ante* and limiting directed search.

Proposition 4. *Employers with higher platform-provided ratings tend to offer higher wages.*

In the model, each employer's wage and nonpecuniary job quality are drawn from a joint distribution. Workers with platform access observe noisy signals of these underlying attributes, and the platform-provided rating reflects a combination of perceived wage and quality. All else

[26] In our model, workers do not internalize the congestion at highly rated employers, which may reduce their private expected benefit from applying. This winner's curse-style externality could dampen the effect but does not reverse it: more highly rated employers remain more attractive. Even if workers did internalize congestion, applying would still be worthwhile when the expected benefit conditional on being hired exceeds the application cost.

equal, employers with higher true wages are more likely to generate higher observed ratings. Since platform ratings are a noisy function of underlying employer attributes, and wage enters linearly and positively into both worker utility and perceived employer attractiveness, there is a natural positive correlation between an employer's posted wage and its platform rating. Thus, even in the absence of strategic wage posting behavior, employers with higher ratings are more likely to be those that offer higher wages to begin with. Workers are more satisfied with (and thus rate more highly) jobs that pay better, all else equal, since $\omega_i > 0$. Alternatively, employers anticipating larger applicant pools may post higher wages to screen high-skill workers (see Moen (1997) and Proposition 3).[27]

[27] We remain agnostic and treat wages as exogenous but note the prediction is directionally identical. This assumption is plausible in the short run or a context where employers cannot easily change their compensation packages. In the long run or in a repeated game, one would expect some endogenous adjustment of job offers in response to persistent changes in application rates or worker preferences.

Appendix B—Examples of Glassdoor ratings

Panel A. Neutral Glassdoor review

3.0 ★★★☆☆ 8 Feb 2018 •••

Not great, but okay for some temporary $

Personal shopper

Former employee, less than 1 year | Onalaska, WI

Recommend ✗ CEO approval Business outlook

Pros
- training was quick and super easy to learn
- everyone was very helpful and kind
- most employees wore headphones in this department so it was chill in that sense and nice to listen to music all day. You didn't have to talk to many people other than if people asked you questions about where stuff was

Cons
- obviously you're just a number and they don't really care about you
- poor benefits, so many people working there you can tell are struggling with income
- working at least one day each weekend typically, can't avoid weekends often
- don't get to know coworkers super well, but to be fair I wasn't there very long
- Walking around during busy times to pick items is low key awful because you're always weaving through people and other carts

Panel B. Favorable Glassdoor review

5.0 ★★★★★ 30 May 2010 •••

Great place To Work! (Distribution Center)

Fork lift driver

Current employee | New Caney, TX

✓ Recommend — CEO approval Business outlook

Pros

I only work three days a week which allows for a second job. The hourly pay is great, in addition to getting a quarterly bonus. There's a real team atmosphere, everybody gets along pretty much and is happy to be there.

Cons

There are not too many negatives to working here. The job does get pretty repetitive, but it's only for three days a week, so not a big deal.

Advice to Management

There is not really any advice i can give about the leadership at this wal-mart distribution center without being too specific about the area i work in.

Panel C. Unfavorable Glassdoor review

1.0 ★☆☆☆☆ 24 Jan 2023 •••

Don't work here. Period

Sales associate

Former employee, less than 1 year | Pensacola, FL

✗ Recommend ✗ CEO approval ✗ Business outlook

Pros

The only thing I could think of was my co-workers who I will miss

Cons

- If you have any sort of hinderance whether it be physical or mental, they will pretty much write you off if you don't fit their core values which is: work like a robot. - Forget about asking for personal time for ANY reason. - Management doesn't give any care, pride, or responsibility for their employees. Period. - No work-life balance. - If you go to corporate, they will basically tell you since you don't fit the parameters of what they need, you're SOL. - There is no advocacy for employees rights whatsoever. -Their open door policy doesn't actually work since when I tried numerous times to contact upper management and they will ignore, berate, and belittle you. - Management is great at putting on a good face for the company when corporate is around.

This appendix presents three examples for Glassdoor reviews. Panels A through C depict, respectively, a neutral, favorable, and unfavorable review.

Appendix C—Variable definitions

See Table C1.

Table C1. Variable definitions

Variable	Description	Data source(s)
Population	Total number of inhabitants in a given metropolitan statistical area.	U.S. Bureau of Economic Analysis
Gross Domestic Product	Total gross domestic product in nominal terms in a given metropolitan statistical area.	U.S. Bureau of Economic Analysis
Per Capita Income	Total compensation divided by the total population in a given metropolitan statistical area.	U.S. Bureau of Economic Analysis
Firms	Total number of sample firms present in a given metropolitan statistical area.	Revelio Labs, U.S. Bureau of Labor Statistics
Labor Concentration	Herfindahl–Hirschman index of the share of employees per firm to the overall number of employees in a given metropolitan statistical area.	Revelio Labs, U.S. Bureau of Labor Statistics
Pay	Total compensation.	Revelio Labs
Employees	Total number of employees employed at a firm.	Revelio Labs
Employee Growth	Percentage change in total number of employees employed at a firm.	Revelio Labs
%Admin	Percentage of total number of employees classified as administrative.	Revelio Labs
%Engineer	Percentage of total number of employees classified as engineering.	Revelio Labs
%Finance	Percentage of total number of employees classified as financial.	Revelio Labs
%Marketing	Percentage of total number of employees classified as marketing.	Revelio Labs
%Operations	Percentage of total number of employees classified as operational.	Revelio Labs
%Scientific	Percentage of total number of employees classified as scientific.	Revelio Labs
Prior Rating	The average overall rating of all reviews in the prior year.	Glassdoor
Rating Outside MSA	The average overall rating of all reviews, except those in the metropolitan statistical area.	Glassdoor
Prior Reviews	The total number of reviews in the prior year.	Glassdoor
Reviews Outside MSA	The total number of reviews, except those in the metropolitan statistical area.	Glassdoor
Reviews	The total number of reviews.	Glassdoor

(continued on next page)

Table C1. Variable definitions (continued)

Variable	Description	Data source(s)
Absolute Rating	The focal firm's overall workplace rating in a given year-metropolitan statistical area.	Glassdoor
Favorable Reviews	The total number of favorable reviews, defined as reviews accompanied by a rating of at least four stars.	Glassdoor
Unfavorable Reviews	The total number of unfavorable reviews, defined as reviews accompanied by a rating below four stars.	Glassdoor
Relative Rating	The difference between the focal firm's overall workplace rating in a given year-metropolitan statistical area and its peers' overall workplace rating in that year-area. This variable is thus unique to each firm-peer-year-metropolitan statistical area observation.	Glassdoor
Relative Work–Life Rating	The difference between the focal firm's work–life balance rating in a given year-metropolitan statistical area and its peers' work–life balance rating in that year-area. This variable is thus unique to each firm-peer-year-metropolitan statistical area observation.	Glassdoor
Relative Pay Rating	The difference between the focal firm's compensation–benefits rating in a given year-metropolitan statistical area and its peers' compensation–benefits rating in that year-area. This variable is thus unique to each firm-peer-year-metropolitan statistical area observation.	Glassdoor
Overall Switches	The total movement of employees in and out of a firm within a given location and year, divided by the total number of employees.	Revelio Labs
Departing Employees	The total number of employees leaving a firm within a given location and year, divided by the total number of employees.	Revelio Labs
New Employees	The total number of employees joining a firm within a given location and year, divided by the total number of employees.	Revelio Labs
Salary	The average base salary of employees working for a firm in a given location-year.	Revelio Labs
Job Postings	The total number of firm-initiated job postings in a given location-year.	Revelio Labs
Filled Postings	The total number of firm-initiated job postings that are ultimately filled in a given location-year.	Revelio Labs

(continued on next page)

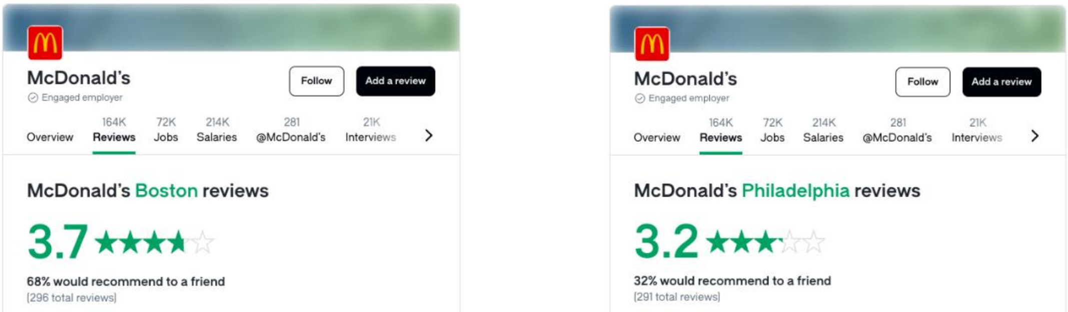
Table C1. Variable definitions (continued)

Variable	Description	Data source(s)
Time-to-Fill	The average duration required to fill a job posting, calculated as the time between the removal date of the job posting and the starting date of the newly hired employee in the same firm-location in the role described in the job posting.	Revelio Labs
Posted Salary	The average salary reported in firm-initiated job postings in a given location.	Revelio Labs
Workforce Entropy	The entropy of the workforce composition, calculating as: $$-\sum_{i=1}^{7} x_i log\,(1 + x_i),$$ where x is the proportion of employees in job category i, including administrative, engineering, financial, marketing, sales, operational, and scientific roles. A higher entropy value indicates a more balanced workforce distribution across these categories.	Revelio Labs

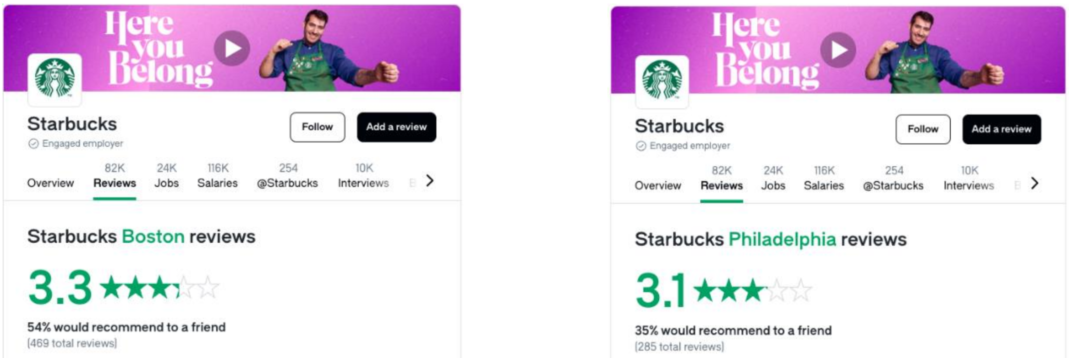
This table presents variable definitions.

Figure 1. Relative ratings

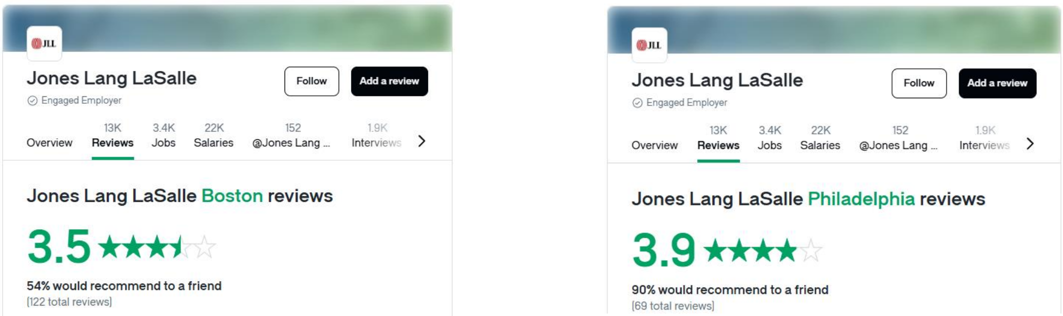
Panel A. Absolute ratings of McDonald's Corporation



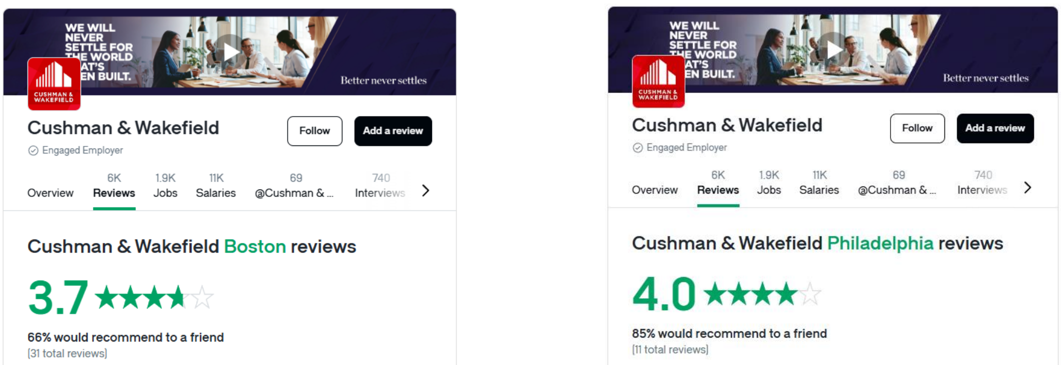
Panel B. Absolute ratings of Starbucks Corporation



Panel C. Absolute ratings of Jones Lang LaSalle Inc.

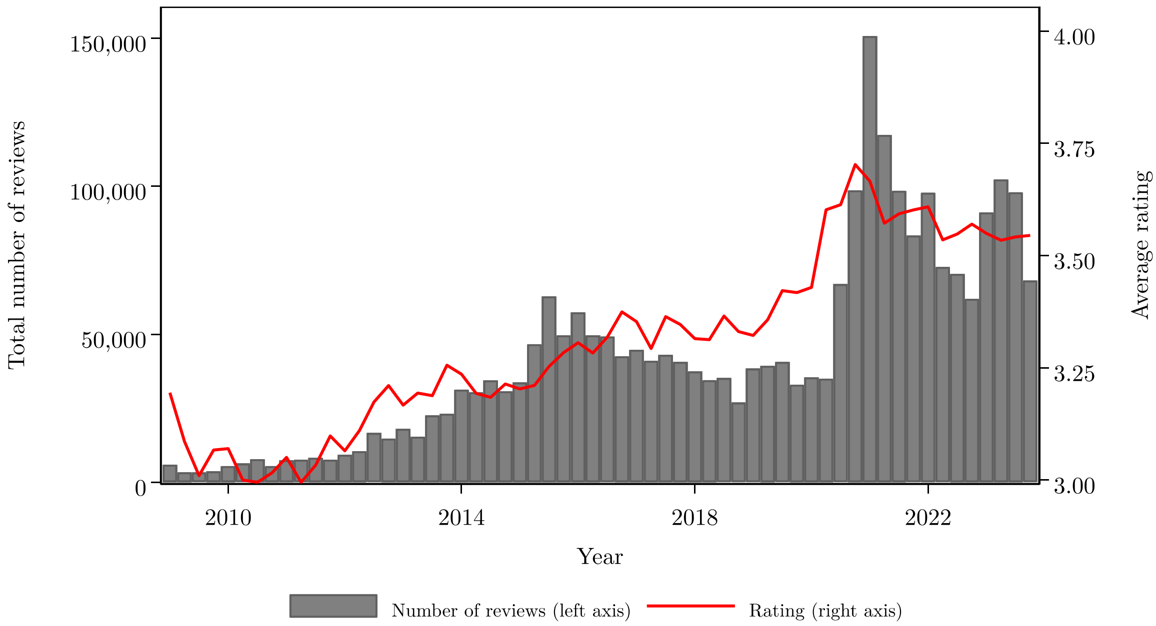


Panel D. Absolute ratings of Cushman & Wakefield Inc.



This figure depicts snapshots from Glassdoor and presents absolute ratings of firms across two metropolitan areas: Boston–Cambridge–Newton and Philadelphia–Camden–Wilmington.

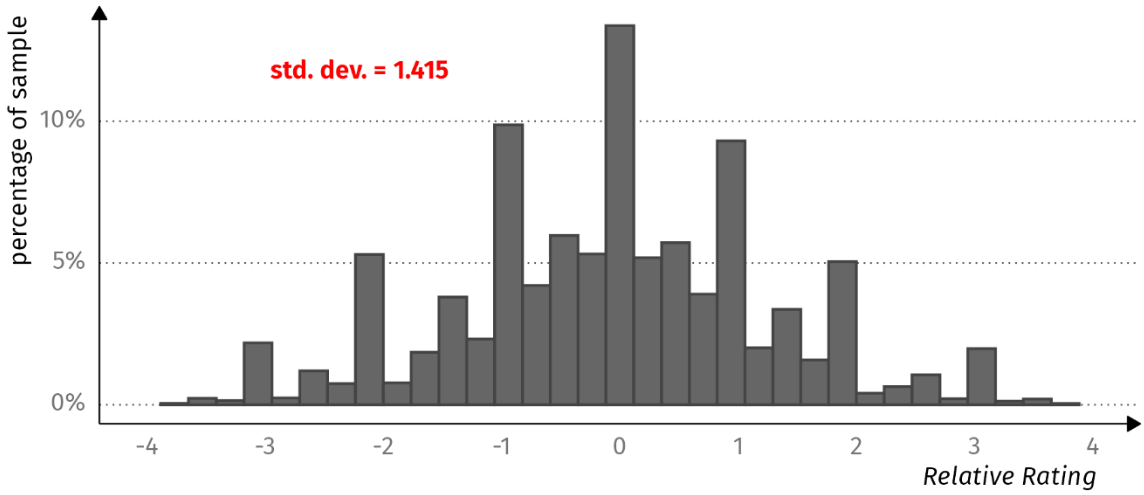
Figure 2. Sample composition



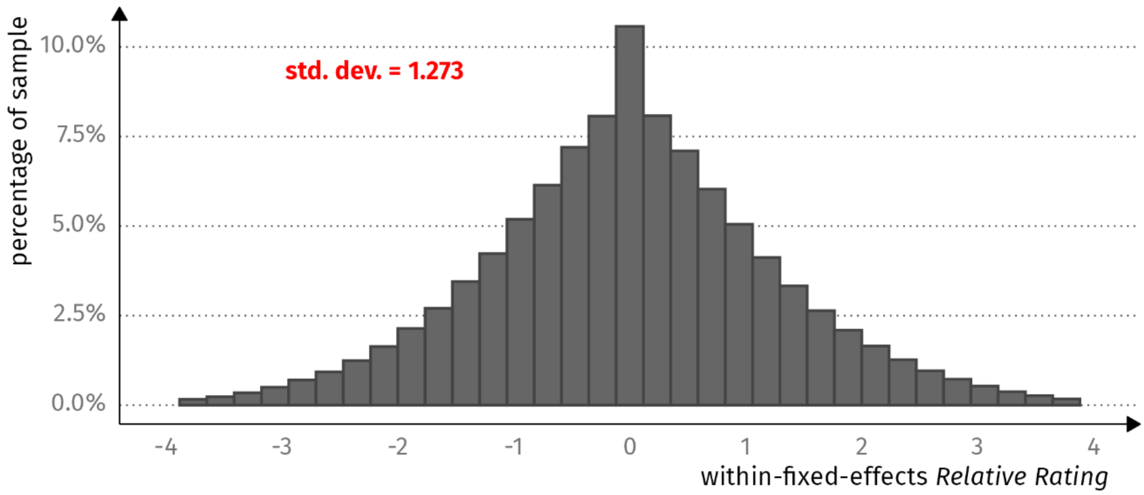
This figure depicts the total number of Glassdoor reviews and the average overall rating across time for all firms in our sample.

Figure 3. Distributions of *Relative Rating*

Panel A. Raw distribution



Panel B. Within-fixed-effects distribution



This figure depicts distributions of *Relative Rating*. Panels A and B illustrate, respectively, the raw and the within-fixed-effects distributions. The within-fixed-effects distribution plots the residuals from a specification that removes firm-by-peer-by-year, area-by-year, and area-by-industry fixed effects.

Table 1. Sample composition

Panel A. Sample selection

Step	Selection criteria	Change in observations	Total observations
(1)	Initial firm-peer-year pairs	+478,089	478,089
(2)	Add Glassdoor data at MSA level	+2,917,901	3,395,990
(3)	Remove firms without Revelio Labs data	–1,289,280	2,106,710
(4)	Remove peers without Revelio Labs data	–289,811	1,816,899

Panel B. Distribution by year

Year	Firms	MSAs	Firm-MSAs	Employment	Reviews	Rating
2008	311	82	1,615	4,641,847	7,313	3.161
2009	380	91	2,643	4,870,504	6,392	3.048
2010	464	94	3,940	5,220,213	9,743	2.999
2011	549	94	5,214	5,542,561	11,773	3.008
2012	593	94	6,668	5,832,075	19,969	3.143
2013	646	94	8,387	6,123,601	30,534	3.177
2014	988	94	12,071	6,443,850	52,598	3.174
2015	1,124	95	15,525	6,810,430	81,897	3.245
2016	1,192	95	17,719	7,071,539	84,141	3.314
2017	1,243	95	18,891	7,430,082	70,863	3.321
2018	1,301	95	19,653	7,868,770	56,005	3.295
2019	1,367	95	20,818	8,291,849	66,012	3.339
2020	1,439	95	22,644	8,495,288	110,611	3.637
2021	1,539	95	24,927	8,853,671	218,329	3.661
2022	1,542	95	22,649	9,143,106	149,747	3.599
2023	1,498	95	19,627	9,055,991	177,956	3.575

Panel C. Distribution by industry

Two-digit GICS sector	Firms	MSAs	Firm-MSAs	Employment	Reviews	Rating
10: Energy	82	75	557	1,782,252	15,615	3.552
15: Materials	85	93	1,116	923,743	12,950	3.439
20: Industrials	303	94	7,160	10,546,387	143,378	3.415
25: Consumer discretionary	275	95	9,837	15,935,808	359,332	3.313
30: Consumer staples	73	95	2,217	5,784,117	110,728	3.242
35: Health care	301	95	4,506	8,454,882	101,436	3.399
40: Financials	224	93	3,675	21,725,889	166,141	3.479
45: Information technology	291	94	4,763	10,912,939	152,303	3.718
50: Telecommunication	76	95	1,507	4,508,818	68,394	3.352
55: Utilities	41	57	247	830,111	5,776	3.655
60: Real estate	90	91	1,220	951,373	16,721	3.636

Table 1. Sample composition (continued)

Population rank	Name	Population	Gross Domestic Product ($)	Census Per Capita Income ($)	Census employees	Revelio employees	Sample firms
1	New York-Newark-Jersey City, NY-NJ	19,518,713	1,647,000,000	75,265	12,009,001	554,604	525
2	Los Angeles-Long Beach-Anaheim, CA	13,047,461	927,100,000	65,111	8,199,490	384,956	489
3	San Francisco-Oakland-Fremont, CA	9,388,796	648,000,000	60,181	5,796,406	338,226	463
4	Dallas-Fort Worth-Arlington, TX	7,098,708	477,400,000	59,057	4,668,037	344,245	442
5	Chicago-Naperville-Elgin, IL-IN	6,654,695	469,200,000	64,158	3,997,933	276,976	398
	…	…	…	…	…	…	…
91	Gainesville, FL	324,250	14,512,867	45,017	187,510	9,414	39
92	Lincoln, NE	323,905	18,748,915	42,882	224,337	7,794	35
93	Lafayette-West Lafayette, IN	220,158	10,835,285	47,063	124,996	940	19
94	Greenville, NC	170,746	9,093,288	43,690	99,626	1,853	25
95	Douglas, GA	51,278	1,926,985	36,496	26,881	584	5

Table 1. Sample composition (continued)

Panel E. Sample summary statistics

	Mean	Std. Dev.	25th	50th	75th
log(*Population*)	14.764	0.978	12.750	13.966	14.765
log(*Gross Domestic Product*)	18.968	1.123	16.625	18.092	18.967
log(*Per Capita Income*)	10.978	0.208	10.583	10.824	10.960
log(*Firms*)	5.475	0.804	3.091	4.898	5.635
Labor Concentration	0.011	0.014	0.002	0.003	0.006
log(*Pay*)	11.413	0.456	10.417	11.067	11.448
log(*Employees*)	4.532	1.712	0.693	3.401	4.500
Employee Growth	0.006	0.035	–0.121	–0.006	0.003
%Admin	0.068	0.083	0.000	0.018	0.049
%Engineer	0.218	0.239	0.000	0.026	0.113
%Finance	0.106	0.187	0.000	0.000	0.027
%Marketing	0.037	0.067	0.000	0.000	0.015
%Operations	0.079	0.107	0.000	0.011	0.044
%Scientific	0.037	0.107	0.000	0.000	0.000
Prior Rating	3.370	1.021	1.000	2.957	3.458
Rating Outside MSA	3.426	0.490	2.121	3.115	3.420
log(*Prior Reviews*)	0.984	0.997	0.000	0.000	0.693
log(*Reviews Outside MSA*)	4.714	1.527	0.693	3.738	4.762
log(*Reviews*)	1.011	0.971	0.000	0.000	0.693
Absolute Rating	3.419	1.049	3.000	3.500	4.000
log(*Favorable Reviews*)	0.853	0.925	0.000	0.000	0.693
log(*Unfavorable Reviews*)	0.393	0.628	0.000	0.000	0.000
Relative Rating	–0.054	1.415	–1.000	0.000	1.000
Relative Work–Life Rating	–0.051	1.514	–1.000	0.000	1.000
Relative Pay Rating	–0.047	1.387	–1.000	0.000	1.000
Overall Switches	42.750	27.860	25.000	38.878	55.556
Departing Employees	20.330	15.626	11.111	18.093	26.316
New Employees	22.414	16.576	11.667	20.000	29.787
log(*Salary*)	11.197	0.424	10.845	11.255	11.528
log(*Job Postings*)	4.342	2.078	2.773	4.344	5.808
log(*Filled Postings*)	2.833	2.600	0.000	2.565	4.804
log(*Time-to-Fill*)	5.244	0.768	4.788	5.279	5.765
log(*Posted Salary*)	10.978	0.484	10.566	10.973	11.376
Workforce Entropy	–0.388	0.139	–0.487	–0.363	–0.274

This table presents information on the sample. Panel A presents an overview of the sample selection procedure. Panels B through E present, respectively, mean statistics over time, mean statistics across industries, following the two-digit GICS sector codes, summary statistics on the largest and smallest metropolitan statistical areas, and sample summary statistics. log(·) indicates a log(1 + ·) transformation to accommodate skewness and zeros.

Table 2. Determinants of Glassdoor reviews and ratings

Panel A. All reviews and overall ratings

Variable:	(1)	(2)	(3)	(4)
	Dependent variable: log(*Reviews*)		Dependent variable: *Absolute Rating*	
MSA characteristics:				
log(*Population*)	0.113	0.093	0.103	–0.151
	(0.088)	(0.095)	(0.180)	(0.162)
log(*Gross Domestic Product*)	–0.154***	–0.159***	–0.112	–0.078
	(0.049)	(0.052)	(0.107)	(0.094)
log(*Per Capita Income*)	0.142*	0.109	0.119	0.121
	(0.081)	(0.087)	(0.159)	(0.139)
log(*Firms*)	0.083***	0.212***	0.025	–0.004
	(0.031)	(0.034)	(0.062)	(0.057)
Labor Concentration	0.664	3.167***	0.764	0.460
	(0.588)	(0.614)	(0.688)	(0.577)
Workforce characteristics:				
log(*Pay*)	–0.052**	–0.117***	0.135***	0.116***
	(0.022)	(0.019)	(0.023)	(0.024)
log(*Employees*)	0.132***	0.248***	0.015***	0.004
	(0.014)	(0.008)	(0.005)	(0.005)
Employee Growth	0.355***	–0.168***	0.404***	–0.038
	(0.094)	(0.062)	(0.112)	(0.109)
%Admin	0.106	–0.050	0.034	0.144*
	(0.070)	(0.056)	(0.065)	(0.078)
%Engineer	–0.026	0.079**	–0.024	–0.042
	(0.031)	(0.036)	(0.036)	(0.038)
%Finance	–0.076	–0.231***	–0.047	–0.103*
	(0.050)	(0.067)	(0.039)	(0.055)
%Marketing	0.133*	–0.055	0.193**	0.033
	(0.068)	(0.068)	(0.095)	(0.097)
%Operations	0.013	0.042	–0.124**	–0.078
	(0.070)	(0.057)	(0.053)	(0.067)
%Scientific	–0.087*	–0.150**	–0.192***	0.001
	(0.046)	(0.069)	(0.054)	(0.083)
Glassdoor characteristics:				
Prior Rating	–0.007***	–0.006***	0.088***	0.020***
	(0.002)	(0.002)	(0.005)	(0.004)
Rating Outside MSA	–0.002	0.052	0.601***	–7.003***
	(0.010)	(0.034)	(0.019)	(0.322)
log(*Prior Reviews*)	0.711***	0.494***	–0.032***	–0.021***
	(0.016)	(0.011)	(0.006)	(0.007)
log(*Reviews Outside MSA*)	0.038***	–0.779***	0.020***	–0.074
	(0.006)	(0.041)	(0.004)	(0.046)
Fixed effects	MSA, Year	Firm, MSA, Year	MSA, Year	Firm, MSA, Year
Observations	66,619	66,619	66,619	66,619
Adjusted R^2	76.100%	81.300%	15.500%	42.800%
Adjusted within-R^2	73.700%	70.700%	12.300%	28.200%

Table 2. Determinants of Glassdoor reviews and ratings (continued)

Panel B. Favorable versus unfavorable reviews

Variable:	(1)	(2)	(3)	(4)
	Dependent variable: log(*Favorable Reviews*)		Dependent variable: log(*Unfavorable Reviews*)	
MSA characteristics:				
log(*Population*)	0.180*	0.109	0.037	0.073
	(0.102)	(0.102)	(0.110)	(0.113)
log(*Gross Domestic Product*)	–0.174***	–0.167***	–0.051	–0.083
	(0.056)	(0.059)	(0.062)	(0.061)
log(*Per Capita Income*)	0.157*	0.161*	–0.085	–0.106
	(0.092)	(0.095)	(0.096)	(0.099)
log(*Firms*)	0.105***	0.215***	0.050	0.175***
	(0.036)	(0.037)	(0.040)	(0.043)
Labor Concentration	1.063	3.690***	0.245	1.858***
	(0.686)	(0.659)	(0.457)	(0.537)
Workforce characteristics:				
log(*Pay*)	–0.028	–0.074***	–0.065***	–0.078***
	(0.023)	(0.018)	(0.022)	(0.020)
log(*Employees*)	0.131***	0.237***	0.065***	0.118***
	(0.014)	(0.008)	(0.008)	(0.006)
Employee Growth	0.269***	–0.244***	0.355***	0.161***
	(0.096)	(0.072)	(0.082)	(0.059)
%Admin	0.043	–0.056	0.168***	0.006
	(0.066)	(0.057)	(0.063)	(0.056)
%Engineer	–0.027	0.063*	–0.020	0.110***
	(0.033)	(0.035)	(0.030)	(0.041)
%Finance	–0.084*	–0.272***	0.009	–0.107
	(0.049)	(0.069)	(0.039)	(0.068)
%Marketing	0.131*	–0.088	0.041	0.049
	(0.073)	(0.075)	(0.069)	(0.077)
%Operations	–0.010	0.013	0.069	0.041
	(0.068)	(0.057)	(0.084)	(0.058)
%Scientific	–0.144***	–0.103	0.039	–0.249***
	(0.051)	(0.068)	(0.040)	(0.078)
Glassdoor characteristics:				
Prior Rating	0.020***	0.002	–0.046***	–0.015***
	(0.003)	(0.002)	(0.003)	(0.002)
Rating Outside MSA	0.161***	–1.649***	–0.292***	2.169***
	(0.012)	(0.082)	(0.017)	(0.105)
log(*Prior Reviews*)	0.685***	0.482***	0.521***	0.389***
	(0.016)	(0.010)	(0.010)	(0.010)
log(*Reviews Outside MSA*)	0.047***	–0.754***	0.008	–0.574***
	(0.006)	(0.041)	(0.006)	(0.037)
Fixed effects	MSA, Year	Firm, MSA, Year	MSA, Year	Firm, MSA, Year
Observations	66,619	66,619	66,619	66,619
Adjusted R^2	72.300%	78.200%	54.200%	62.900%
Adjusted within-R^2	69.300%	65.600%	51.800%	49.400%

Table 2. Determinants of Glassdoor reviews and ratings (continued)

This table presents results from estimating determinants of Glassdoor reviews and ratings. Panels A and B present, respectively, results for all reviews and overall absolute ratings, and favorable versus unfavorable reviews. In both panels, we present results with metropolitan statistical area and year fixed effects. We also report results from adding firm fixed effects. For brevity, we do not report the coefficient estimates and standard errors of these fixed effects. Standard errors are in parentheses and are adjusted for within-cluster correlation at the firm level (Abadie et al., 2023). *, **, and *** denote that the coefficient is significantly different from zero at, respectively, two-tailed probability levels of 10%, 5%, and 1%. Appendix C defines all variables.

Table 3. Glassdoor reviews and employee turnover

Panel A. All employee switches

	(1)	(2)
	Dependent variable: *Overall Switches*	
Variable:		
Relative Rating	–0.133***	–0.112***
	(0.032)	(0.031)
log(*Employees*)	–0.511***	–0.723***
	(0.188)	(0.207)
log(*Peer Employees*)	0.115***	0.094**
	(0.042)	(0.038)
Fixed effects	MSA×Year, MSA×GICS4, Firm, Peer	MSA×Year, MSA×GICS4, Firm×Peer×Year
Observations	1,816,899	1,816,899
Adjusted R^2	42.635%	51.288%
Adjusted within-R^2	0.061%	0.127%

Panel B. Departing employees

	(1)	(2)
	Dependent variable: *Departing Employees*	
Variable:		
Relative Rating	–0.111***	–0.070***
	(0.021)	(0.020)
log(*Employees*)	–0.338***	–0.423***
	(0.097)	(0.105)
log(*Peer Employees*)	0.078***	0.060***
	(0.019)	(0.018)
Fixed effects	MSA×Year, MSA×GICS4, Firm, Peer	MSA×Year, MSA×GICS4, Firm×Peer×Year
Observations	1,816,899	1,816,899
Adjusted R^2	30.921%	40.442%
Adjusted within-R^2	0.076%	0.114%

Panel C. New employees

	(1)	(2)
	Dependent variable: *New Employees*	
Variable:		
Relative Rating	–0.022	–0.042**
	(0.019)	(0.018)
log(*Employees*)	–0.186*	–0.314***
	(0.106)	(0.115)
log(*Peer Employees*)	0.036	0.034
	(0.026)	(0.025)
Fixed effects	MSA×Year, MSA×GICS4, Firm, Peer	MSA×Year, MSA×GICS4, Firm×Peer×Year
Observations	1,816,899	1,816,899
Adjusted R^2	37.775%	47.546%
Adjusted within-R^2	0.019%	0.062%

Table 3. Glassdoor reviews and employee turnover (continued)

This table presents results from estimating the relation between Glassdoor reviews and employee turnover. Panels A through C present, respectively, results for all employee switches, departing employees, and new hires. In all panels, Column (1) presents results with metropolitan statistical area by year, metropolitan statistical area by industry, firm, and peer fixed effects. In Column (2), we replace the firm and peer fixed effects with firm by peer by year fixed effects. For brevity, we do not report the coefficient estimates and standard errors of these fixed effects. Standard errors are in parentheses and are adjusted for within-cluster correlation at the firm, peer, and metropolitan statistical area level (Abadie et al., 2023). *, **, and *** denote that the coefficient is significantly different from zero at, respectively, two-tailed probability levels of 10%, 5%, and 1%. Appendix C defines all variables.

Table 4. Glassdoor reviews and the job matching process

Panel A. Job postings

Variable:	(1)	(2)
	Dependent variable: log(*Job Postings*)	
Relative Rating	–0.760**	–1.017***
	(0.317)	(0.229)
log(*Employees*)	77.950***	81.307***
	(1.623)	(1.697)
log(*Peer Employees*)	0.852***	0.680**
	(0.278)	(0.277)
Fixed effects	MSA×Year, MSA×GICS4, Firm, Peer	MSA×Year, MSA×GICS4, Firm×Peer×Year
Observations	680,873	680,873
Adjusted R^2	73.761%	87.541%
Adjusted within-R^2	31.168%	50.796%

Panel B. Time-to-fill

Variable:	(1)	(2)
	Dependent variable: log(*Time-to-Fill*)	
Relative Rating	0.359	0.489*
	(0.272)	(0.283)
log(*Filled Postings*)	5.769***	6.942***
	(0.639)	(0.796)
log(*Employees*)	–13.268***	–14.969***
	(0.699)	(0.909)
log(*Peer Employees*)	0.164	0.088
	(0.146)	(0.164)
Fixed effects	MSA×Year, MSA×GICS4, Firm, Peer	MSA×Year, MSA×GICS4, Firm×Peer×Year
Observations	471,111	471,111
Adjusted R^2	26.396%	28.111%
Adjusted within-R^2	1.973%	1.966%

Table 4. Glassdoor reviews and the job matching process (continued)

Panel C. Salaries in job postings

	(1)	(2)
Variable:	Dependent variable: log(*Posted Salary*)	
Relative Rating	0.182***	0.171***
	(0.055)	(0.057)
log(*Employees*)	3.950***	3.790***
	(0.301)	(0.306)
log(*Peer Employees*)	0.303***	0.294***
	(0.075)	(0.073)
Fixed effects	MSA×Year, MSA×GICS4, Firm, Peer	MSA×Year, MSA×GICS4, Firm×Peer×Year
Observations	680,873	680,873
Adjusted R^2	83.239%	86.226%
Adjusted within-R^2	3.300%	3.663%

This table presents results from estimating the relation between Glassdoor reviews and outcomes related to the job matching process. Panels A through C present, respectively, results for the number of job postings, the duration of the time-to-fill, and the posted base salaries in the job posting. The sample size in these analyses differs from the preceding analyses because job posting data is only available starting in 2019 for postings sourced from aggregators such as Indeed.com and from 2021 for postings sourced from LinkedIn.com. The analysis in Panel B is further restricted to observations with at least one filled job posting, ensuring that time-to-fill duration is available. In all panels, Column (1) presents results with metropolitan statistical area by year, metropolitan statistical area by industry, firm, and peer fixed effects. In Column (2), we replace the firm and peer fixed effects with firm by peer by year fixed effects. For brevity, we do not report the coefficient estimates and standard errors of these fixed effects. Standard errors are in parentheses and are adjusted for within-cluster correlation at the firm, peer, and metropolitan statistical area level (Abadie et al., 2023). *, **, and *** denote that the coefficient is significantly different from zero at, respectively, two-tailed probability levels of 10%, 5%, and 1%. Appendix C defines all variables.

Table 5. Glassdoor reviews and labor market outcomes—awareness mechanism

	(1)	(2)	(3)
		Dependent variable:	
Variable:	*Overall Switches*	*Departing Employees*	*New Employees*
Relative Rating × 𝟙(*Post Peer Award*)	0.225***	0.083*	0.141***
	(0.081)	(0.049)	(0.042)
Relative Rating	–0.586***	–0.326***	–0.262***
	(0.133)	(0.084)	(0.073)
log(*Employees*)	–0.385	–0.204	–0.211
	(0.283)	(0.159)	(0.164)
log(*Peer Employees*)	–0.194*	–0.114**	–0.080
	(0.103)	(0.057)	(0.074)
Fixed effects	MSA×Year, MSA×GICS4, Firm×Peer	MSA×Year, MSA×GICS4, Firm×Peer	MSA×Year, MSA×GICS4, Firm×Peer
Observations	232,589	232,589	232,589
Adjusted R^2	52.279%	36.066%	51.980%
Adjusted within-R^2	0.135%	0.117%	0.072%

This table presents results from estimating the relation between Glassdoor reviews and the employee turnover outcomes using an event study design to test the awareness mechanism. We use a [–2, 2] year window around the granting of a peer's *Best Places to Work* award on Glassdoor. For brevity, we do not report the coefficient estimates and standard errors of the fixed effects. Standard errors are in parentheses and are adjusted for within-cluster correlation at the firm, peer, and metropolitan statistical area level (Abadie et al., 2023). *, **, and *** denote that the coefficient is significantly different from zero at, respectively, two-tailed probability levels of 10%, 5%, and 1%. Appendix C defines all variables.

Table 6. Glassdoor reviews and labor market outcomes—evaluation mechanism

Panel A. Overall ratings

	(1)	(2)	(3)
		Dependent variable:	
Variable:	*Overall Switches*	*Departing Employees*	*New Employees*
Relative Rating × 𝟙(*Affected*)	–0.598***	–0.328**	–0.270**
	(0.184)	(0.116)	(0.098)
Relative Rating	–0.218	–0.049	–0.170*
	(0.159)	(0.096)	(0.092)
log(*Employees*)	–1.462**	–0.792**	–0.681*
	(0.614)	(0.337)	(0.306)
log(*Peer Employees*)	–0.139	–0.041	–0.099
	(0.100)	(0.059)	(0.059)
Fixed effects	MSA×Year, MSA×GICS4, Firm×Peer	MSA×Year, MSA×GICS4, Firm×Peer	MSA×Year, MSA×GICS4, Firm×Peer
Observations	96,111	96,111	96,111
Adjusted R^2	45.870%	34.789%	42.848%
Adjusted within-R^2	0.282%	0.208%	0.177%

Panel B. Work–life balance ratings

	(1)	(2)	(3)
		Dependent variable:	
Variable:	*Overall Switches*	*Departing Employees*	*New Employees*
Relative Work–Life Rating × 𝟙(*Affected*)	–0.609**	–0.328*	–0.282**
	(0.224)	(0.167)	(0.117)
Relative Work–Life Rating	–0.124	–0.031	–0.094
	(0.103)	(0.061)	(0.063)
log(*Employees*)	–1.416*	–0.795**	–0.634*
	(0.649)	(0.345)	(0.333)
log(*Peer Employees*)	–0.144	–0.035	–0.110
	(0.109)	(0.063)	(0.068)
Fixed effects	MSA×Year, MSA×GICS4, Firm×Peer	MSA×Year, MSA×GICS4, Firm×Peer	MSA×Year, MSA×GICS4, Firm×Peer
Observations	91,856	91,856	91,856
Adjusted R^2	45.877%	34.658%	43.060%
Adjusted within-R^2	0.261%	0.209%	0.149%

Table 6. Glassdoor reviews and labor market outcomes—evaluation mechanism (continued)

Panel C. Compensation ratings

	(1)	(2)	(3)
		Dependent variable:	
Variable:	*Overall Switches*	*Departing Employees*	*New Employees*
Relative Pay Rating × 𝟙(*Affected*)	–0.502	–0.279	–0.224
	(0.289)	(0.182)	(0.146)
Relative Pay Rating	–0.096	–0.096	–0.000
	(0.204)	(0.086)	(0.137)
log(*Employees*)	–1.396*	–0.796**	–0.613*
	(0.655)	(0.350)	(0.334)
log(*Peer Employees*)	–0.149	–0.038	–0.112
	(0.108)	(0.062)	(0.070)
Fixed effects	MSA×Year, MSA×GICS4, Firm×Peer	MSA×Year, MSA×GICS4, Firm×Peer	MSA×Year, MSA×GICS4, Firm×Peer
Observations	91,775	91,775	91,775
Adjusted R^2	45.808%	34.790%	42.985%
Adjusted within-R^2	0.231%	0.212%	0.112%

This table presents results from estimating the relation between Glassdoor reviews and the employee turnover outcomes using an event study design to test the evaluation mechanism. Panels A through C present, respectively, results for the relative overall, work–life balance, and compensation ratings. We use a [–2, 2] year window around the 2021 Colorado's *Equal Pay for Equal Work Act*. Treated observations are those located in metropolitan statistical areas within Colorado, excluding those that extend into any control state. Control observations are those within Colorado's seven neighboring states—Utah, Arizona, New Mexico, Oklahoma, Kansas, Nebraska, and Wyoming—excluding those that extend into Colorado. In Panels B and C, the number of observations is slightly lower than in Panel A because not all firms have data available for the subcategory ratings. For brevity, we do not report the coefficient estimates and standard errors of the fixed effects. Standard errors are in parentheses and are adjusted for within-cluster correlation at the firm, peer, and metropolitan statistical area level (Abadie et al., 2023). *, **, and *** denote that the coefficient is significantly different from zero at, respectively, two-tailed probability levels of 10%, 5%, and 1%. Appendix C defines all variables.

Table 7. Glassdoor reviews and employee turnover—cross-sectional variation

Panel A. All employee switches

	(1)	(2)	(3)	(4)
Subsample:	*Market-to-Book*		*Salary*	
	Low	High	Low	High
	Dependent variable:			
Variable:	*Overall Switches*			
Relative Rating	–0.169***	–0.042	–0.153***	–0.042
	(0.046)	(0.045)	(0.042)	(0.046)
Controls	Yes	Yes	Yes	Yes
Fixed effects	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year
Observations	880,994	880,986	908,454	908,445
Adjusted R^2	50.816%	53.318%	56.503%	49.407%
Adjusted within-R^2	0.079%	0.236%	1.097%	0.016%
Δ in *Relative Rating*	0.127*		0.110*	

Panel B. Departing employees

	(1)	(2)	(3)	(4)
Subsample:	*Market-to-Book*		*Salary*	
	Low	High	Low	High
	Dependent variable:			
Variable:	*Departing Employees*			
Relative Rating	–0.088***	–0.038	–0.106***	–0.028
	(0.030)	(0.030)	(0.024)	(0.026)
Controls	Yes	Yes	Yes	Yes
Fixed effects	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year
Observations	880,994	880,986	908,454	908,445
Adjusted R^2	42.354%	40.552%	47.141%	38.072%
Adjusted within-R^2	0.087%	0.173%	0.670%	3.4e–05
Δ in *Relative Rating*	0.050		0.078**	

Table 7. Glassdoor reviews and employee turnover—cross-sectional variation (continued)

Panel C. New employees

	(1)	(2)	(3)	(4)
Subsample:	*Market-to-Book*		*Salary*	
	Low	High	Low	High
	Dependent variable:			
Variable:	*New Employees*			
Relative Rating	–0.081***	–0.005	–0.047	–0.015
	(0.025)	(0.026)	(0.028)	(0.027)
Controls	Yes	Yes	Yes	Yes
Fixed effects	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year
Observations	880,994	880,986	908,454	908,445
Adjusted R^2	44.531%	51.044%	50.931%	50.042%
Adjusted within-R^2	0.027%	0.149%	0.783%	0.035%
Δ in *Relative Rating*	0.076**		0.032	

This table presents results of examining whether the relations in Table 3 vary by firms' growth opportunities and salaries. Columns (1) and (2) present results split by *Market-to-Book*. Columns (3) and (4) present results split by *Salary*. We estimate the regression models separately for subsamples split at the yearly median, allowing all coefficients and fixed effects to vary across the two subsamples. We test for differences in coefficient estimates between the two subsamples using two-sided *Z*-tests and report the results at the bottom of each panel. All specifications include metropolitan statistical area by year, metropolitan statistical area by industry, and firm by peer by year fixed effects, consistent with the results in Column (2) of Table 3. For brevity, we do not report the coefficient estimates and standard errors of these fixed effects and the other controls, including *Employees* and *Peer Employees*. Standard errors are in parentheses and are adjusted for within-cluster correlation at the firm, peer, and metropolitan statistical area level (Abadie et al., 2023). *, **, and *** denote that the coefficient is significantly different from zero at, respectively, two-tailed probability levels of 10%, 5%, and 1%. Appendix C defines all variables.

Table 8. Glassdoor reviews and the job matching process—cross-sectional variation

Panel A. Job postings

	(1)	(2)	(3)	(4)
Subsample:	*Reviews*		*Workforce Entropy*	
	Low	High	Low	High
	Dependent variable: log(*Job Postings*)			
Variable:				
Relative Rating	–0.605**	–1.083***	–0.740***	–0.580
	(0.300)	(0.307)	(0.257)	(0.374)
Controls	Yes	Yes	Yes	Yes
Fixed effects	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year
Observations	340,439	340,434	340,439	340,434
Adjusted R^2	82.323%	90.758%	92.278%	84.619%
Adjusted within-R^2	27.592%	50.244%	43.695%	50.938%
Δ in *Relative Rating*	–0.478		0.160	

Panel B. Time-to-fill

	(1)	(2)	(3)	(4)
Subsample:	*Reviews*		*Workforce Entropy*	
	Low	High	Low	High
	Dependent variable: log(*Time-to-Fill*)			
Variable:				
Relative Rating	0.075	1.014***	–0.318	0.710*
	(0.367)	(0.286)	(0.352)	(0.396)
Controls	Yes	Yes	Yes	Yes
Fixed effects	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year
Observations	190,772	280,339	220,197	250,914
Adjusted R^2	29.445%	36.147%	34.425%	31.440%
Adjusted within-R^2	0.002%	2.481%	1.581%	1.071%
Δ in *Relative Rating*	0.940**		1.028*	

Table 8. Glassdoor reviews and the job matching process—cross-sectional variation (continued)

Panel C. Salaries in job postings

	(1)	(2)	(3)	(4)
Subsample:	*Reviews*		*Workforce Entropy*	
	Low	High	Low	High
	Dependent variable:			
Variable:	log(*Posted Salary*)			
Relative Rating	0.013	0.320***	0.004	0.242***
	(0.070)	(0.069)	(0.065)	(0.090)
Controls	Yes	Yes	Yes	Yes
Fixed effects	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year	MSA×Year, MSA×GICS4, Firm×Peer×Year
Observations	340,439	340,434	340,439	340,434
Adjusted R^2	85.673%	89.898%	90.868%	77.578%
Adjusted within-R^2	0.187%	8.293%	0.087%	4.305%
Δ in *Relative Rating*	0.307***		0.238**	

This table presents results of examining whether the relations in Table 4 vary by firms' number of reviews and workforce entropy. Columns (1) and (2) present results split by *Reviews*. Columns (3) and (4) present results split by *Workforce Entropy*. We estimate the regression models separately for subsamples split at the yearly median, allowing all coefficients and fixed effects to vary across the two subsamples. We test for differences in coefficient estimates between the two subsamples using two-sided *Z*-tests and report the results at the bottom of each panel. All specifications include metropolitan statistical area by year, metropolitan statistical area by industry, and firm by peer by year fixed effects, consistent with the results in Column (2) of Table 4. For brevity, we do not report the coefficient estimates and standard errors of these fixed effects and the other controls, including *Employees* and *Peer Employees*. Standard errors are in parentheses and are adjusted for within-cluster correlation at the firm, peer, and metropolitan statistical area level (Abadie et al., 2023). *, **, and *** denote that the coefficient is significantly different from zero at, respectively, two-tailed probability levels of 10%, 5%, and 1%. Appendix C defines all variables.