Exit through the Glassdoor: Employee-Generated Disclosures and Worker Flows[*]

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Abstract:

This paper examines why and when employee-generated disclosures about workplace experiences influence worker-employer matching, using data on Glassdoor ratings and matching outcomes within U.S. metropolitan areas. At this level, we find that broader employer coverage on Glassdoor is associated with outcomes indicative of improved matching between workers and employers. At a more granular level, we find that pairwise differences in ratings predict worker flows from lower- to higher-rated employers, consistent with a sorting mechanism. Additional analyses show that these flow patterns vary across employee, employer, and institutional factors. Overall, this paper provides evidence on the conditions under which employee-generated disclosures influence matching outcomes.

JEL classification: D82, D83, J62, J63, J64

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1. Introduction

Workers have long valued job attributes such as work-life balance, workplace culture, and opportunities for development in addition to wages when choosing employers. Yet historically, reliable information about these attributes was difficult to obtain before accepting a job offer. In recent years, platforms such as Glassdoor have emerged as among the most prominent sources of this information, providing a place where employees anonymously rate their workplace experiences (see Figure 1). These employee-generated disclosures broaden the scope of information available to workers about employers beyond traditional channels, thereby providing a mechanism that may reduce information frictions in labor markets.[1]

We predict that such reductions in information frictions: (1) influence matching between workers and employers; and (2) manifest in job-to-job flows, as workers redirect search toward employers with higher expected match quality, as predicted by competitive search theory (Moen, 1997). These two predictions, however, critically depend on whether employee-generated disclosures in practice reduce information frictions. It is hard to tell to what extent countervailing forces—such as voluntary and selective rating participation, uneven dissemination of information across employers, and employers' management of their online reputation—complicate the impact of these disclosures on matching outcomes. In addition, their influence likely varies across employee, employer, and institutional factors that influence the relevance and availability of this information (e.g., worker seniority and occupation, the completeness and credibility of the ratings, and the presence of alternative information). As such, there is value in empirical evidence on the conditions under which employee-generated disclosures influence matching outcomes.

To develop this evidence, we conduct an in-depth analysis of the relation between

[1] Throughout the paper, we use *firm* to refer to a corporation as a whole, *employer* to refer to the employing entity conceptually, and *establishment* to refer to a firm's establishments within a specific MSA. *Worker* refers to individuals in general, whereas *employee* refers to a worker employed by a specific employer.

Glassdoor ratings and worker-employer matching between 2008 and 2023 at the U.S. metropolitan statistical area (MSA) level—geographic areas that reflect the boundaries of most matching activities (Moretti, 2011; Marinescu and Rathelot, 2018). Because our conceptual interest lies in worker-employer matching, we focus the empirical analysis on observable outcomes that reflect realized matching: job-to-job flows, match duration, and promotion rates. This approach allows us to speak to actual matching outcomes that reflect joint decisions of workers and employers, rather than workers' search or application choices alone. The analysis is made possible by combining Glassdoor's location-specific granularity with Revelio Labs' worker-level data. Specifically, Glassdoor provides firm-MSA-level ratings that enable comparisons of workplace attributes across employers within an MSA as well as across MSAs for the same firm (see Figures 2 and 3). The richness of the Revelio Labs dataset further allows us to examine heterogeneity across employees, employers, and institutional environments.

We begin our empirical analysis by examining whether Glassdoor rating coverage is associated with improved matching outcomes at the labor market level. Because aggregate labor market outcomes reflect the accumulation of individual decisions, this analysis captures the macro implications of micro-level responses to employee-generated disclosures. We predict that if employee-generated disclosures reduce information frictions, then labor markets with a higher share of establishments rated on Glassdoor should exhibit more effective matching outcomes compared to those with lower coverage. To test this prediction, we construct local labor markets by grouping establishments that compete for similar workers within the same MSA and industry. Using worker-level employment histories, we examine three complementary outcomes that capture realized matching quality: (1) the incidence of job-to-job matches; (2) the duration of ongoing matches and (3) within-establishment promotion rates among current employees. We find that a higher share of establishments covered on Glassdoor is associated with more worker-establishment matches, longer match tenure, and higher promotion rates. Jointly, this evidence supports the idea that employee-generated disclosures influence matching between workers and firms in local labor markets across multiple economically meaningful indicators in local labor markets.

Next, we examine the mechanism that we predict drives this association, whereby workers move from establishments with less favorable signals toward those with more favorable ones. To test this prediction, we begin by constructing an establishment-peer-MSA-year panel that pairs all establishments within each local labor market and descriptively testing whether pairwise differences in Glassdoor ratings explain unidirectional flows between them. Specifically, we test whether workers at one establishment are more likely to move to another establishment in the same MSA when favorable information about the latter becomes available, using the same establishment pair in other MSAs as counterfactuals. We find that workers systematically and unidirectionally move from lower-rated establishments toward higher-rated peers. This pattern is robust to a wide range of fixed effects and persists even when comparing flows within the same establishment pair in the same MSA over time, suggesting that it is unlikely to be driven by persistent firm, peer, pair, or regional characteristics.[2]

In supplemental tests, we find that the effect is strongest when peers are rated moderately higher than the focal employer and attenuates when rating differences grow larger. This pattern is consistent with employee-generated disclosures operating through a reduction in information frictions rather than simply capturing mechanical quality differences. When rating gaps are small, relative employer quality is more difficult to infer *ex ante*, making incremental rating information particularly relevant for belief updating and job choice. As rating gaps widen and relative employer quality is easier to infer in the absence of explicit ratings, the marginal informational value of employee-generated disclosures diminishes.

[2] As shown in Appendix B, ratings and unfavorable reviews correlate with firm characteristics such as performance, size, and employee growth, motivating our use of rich fixed effects. In particular, firm-by-year fixed effects absorb these factors to the extent they are constant within a firm-year.

Furthermore, we find that worker flows respond most strongly to ratings related to "career opportunities" and "senior leadership," which the literature interprets as forward-looking dimensions that are particularly informative about future job prospects (Choi et al., 2023a).

To further strengthen the evidence for the predicted flow mechanism, we implement two complementary strategies that rely on distinct identifying assumptions and unique Glassdoor features. First, we examine job-to-job flows following peers' first-time Glassdoor ratings. Because the timing of these initial ratings is unlikely to coincide with changes in the focal establishment's characteristics, this design helps isolate the effect of new information disseminating through the labor market. Consistent with our prediction, we find that workers move toward newly rated peers when the focal establishment is unrated or rated lower than the peer, but not when the focal establishment is rated higher than the peer. Second, we exploit an institutional feature of the platform in that ratings are calculated with high precision but displayed rounded to one decimal. This introduces quasi-random variation in the presentation of ratings, because a true rating change from, for example, 3.449 to 3.451 results in a visible jump from 3.4 to 3.5, despite no meaningful shift in underlying conditions. Consistent with workers responding to the informational content of ratings, we find that workers are more likely to move toward peers whose displayed ratings are higher because of rounding.

Finally, we conduct cross-sectional analyses to examine under what conditions employee-generated disclosures are most strongly associated with job-to-job flows, focusing on a host of employee, employer, and institutional factors. We find that the sensitivity of flows to rating differences is strongest among employees in roles in finance, sales, and administration, those in more junior positions, and those in jobs with low remote suitability, consistent with these disclosures being most informative in settings where workplace attributes are more central to job choice. The documented effects are also stronger for flows from smaller to larger firms, when peers have a larger number of reviews, more complete reviews, or longer review text, suggesting that richer information more effectively reduces frictions.[3] Relative ratings also explain flows more strongly in competitive markets dominated by large employers, when peers have more job openings than the focal firm, and when the language in the review text that accompanies ratings can be used to corroborate peers' job-posting language. Finally, we find that institutional factors such as platform awards, pay-transparency mandates, and changes in the types of available workplace ratings all moderate the relation between relative ratings and job-to-job flows. We conclude that the relation between employee-generated disclosures and workers' job-to-job flows varies across contexts, being pronounced in some contexts and limited in others.

Overall, this paper studies employee-generated disclosures through the lens of labor market search theory and provides two main insights. At the labor market level, our first insight is that the dissemination of employee-generated disclosures is associated with outcomes that are indicative of improved matching between workers and employers (e.g., Rogerson et al., 2005; Wright et al., 2021). This evidence matters because it shows that employee-generated disclosures can reduce costly mismatches between workers and employers, which a large literature links to higher firm-level and aggregate productivity.[4] At the firm-peer level, our second insight is that these effects are, at least in part, driven by a sorting mechanism rather than bargaining within existing matches: pairwise differences in workplace ratings are associated with unidirectional flows from lower- to higher-rated employers. This finding implies that employee-generated disclosures actively facilitate the reallocation of workers toward employers perceived as being of higher quality. Importantly, this reallocation is not uniform: it is strongest where information frictions are arguably most severe.

[3] This finding provides suggestive evidence against review manipulation as a primary driver, because fabricated or strategically biased reviews tend to be shorter and less detailed, whereas we find that longer reviews amplify the effects (e.g., Hansen and Wänke, 2010; Sockin and Sojourner, 2023).

[4] See, for instance, Jovanovic (1979), Rosen (1986), Freeman (1993), Mortensen and Pissarides (1994), Nickell and Layard (1999), Topel (1999), Manning (2003), Hagedorn and Manovskii (2008), and Yeh et al. (2022).

Our paper builds on and extends prior experimental research that examines the mechanisms underlying worker flows (e.g., Van Hoye and Lievens, 2007; Walker et al., 2009; Yu et al., 2022; Zhang et al., 2022). We complement this work by connecting these mechanisms to their observable counterparts in real labor markets—individuals' realized job-to-job flows—with the added benefit that the richness of our data allows us to study heterogeneity across many employees, employers, and institutional environments. In doing so, our paper also builds on a growing body of field experiments that study how centralized or employer-provided information in controlled settings affects worker responses to, for example, wage transparency (Jäger et al., 2024), diversity practices (Choi et al., 2023c), and ESG policies (Colonnelli et al., 2025). We differ in that we focus on employee-generated disclosures, examining why and when such information influences realized matching outcomes, both on their own and in conjunction with firm-provided information. We believe that our analysis of actual matching outcomes is valuable because it moves beyond stated intentions and application behavior to capture outcomes that reflect equilibrium adjustments in the labor market jointly determined by workers and employers, thereby complementing recent work that examines workers' search and application decisions (Choi et al., 2023a; deHaan et al., 2023; Sockin and Sojourner, 2023).

2. What role can employee-generated disclosures play in labor markets?

2.1. The role of employee-generated disclosures in labor markets

As labor market search theory highlights, a variety of frictions may hinder matching between workers and employers. Examples include market power, bargaining constraints, regulations, and heterogeneity in worker preferences (e.g., McCall, 1970; Moen, 1997; Rogerson et al., 2005; Wright et al., 2021). Among these frictions, our main focus is on incomplete information frictions, which arise when workers lack reliable pre-employment information about workplace attributes such as work-life balance, organizational culture, opportunities for development, and compensation. Incomplete information makes it difficult and costly to identify, evaluate, and compare alternative job opportunities.

These search problems parallel the information problems faced by investors in capital markets. Analogous to how accounting disclosures can reduce investment information frictions by improving investors' ability to evaluate and compare firms (e.g., Badertscher et al., 2013; Shroff et al., 2017; Breuer et al., 2021), workplace information can reduce uncertainty in job choice by improving workers' ability to evaluate and compare employers.[5] Specifically, when job attributes are imperfectly observable, both discovery and evaluation of potential employers is costly. Discovery costs arise because workers must invest additional time and effort to identify potential opportunities (McCall, 1970). Evaluation costs arise because, even after identifying an employer, workers must interpret noisy signals and make decisions under uncertainty (Mortensen, 1986). Thus, the greater these frictions, the harder it becomes for workers to form accurate expectations about job fit, increasing the likelihood of mismatches and prolonged tenure in less suitable jobs.[6]

Historically, workers relied on word-of-mouth or firm-provided content, but the emergence of decentralized platforms like Glassdoor has fundamentally changed the information environment by providing a place where employees anonymously rate their workplace experiences. Unlike traditional or employer-controlled disclosure channels, these platforms aggregate experiences from current and former employees, thereby creating a novel and independent source of information.

The decision to provide such reviews can be understood through the framework of Bénabou and Vellodi (2025). In this model, individuals first choose actions to maximize their own utility (e.g., accepting a job) and then decide whether to disclose information about the

[5] Importantly, the information relevant for an investor's decision need not originate solely from the focal firm, but may also come from peer firms. Analogously, employee-generated disclosures at other firms can influence beliefs about relative workplace quality within a labor market.

[6] At the same time, employers typically lack perfect information about workers' skills and must also rely on imperfect signals. These signals may fail to accurately capture a worker's true ability, resulting in mismatches or suboptimal hiring and retention decisions for both employers and workers (Farber and Gibbons, 1996; Altonji and Pierret, 2001). These employer-related frictions, however, are beyond the scope of this paper.

resulting experience based on how doing so affects others' beliefs and subsequent actions in ways that feed back to the discloser's own welfare. Applied to the workplace, employees recognize that sharing their experiences affects how prospective workers evaluate the firm, which can influence future hiring, coworker quality, and organizational stability. Improvements along these dimensions benefit current employees directly through better matching with future coworkers, reduced turnover frictions, and a stronger external reputation. Given the low cost of posting a review, even modest expected benefits from these feedback effects can rationalize both positive and negative disclosures.

This logic aligns with "give-to-get" models of voluntary disclosure, in which individuals share information to improve the information environment they themselves rely on in the future (deHaan et al., 2023). Indeed, survey evidence and platform discussions indicate that reviewers are motivated not only by dissatisfaction but also by a desire to help others and contribute to a better-functioning market (e.g., Trustpilot, 2021; Glassdoor, 2023).

2.2. Testable predictions

Drawing on labor market search theory, we predict that employee-generated disclosures influence matching outcomes by reducing information frictions that hinder such matching. When workplace attributes are opaque, workers must form expectations about job attributes based on limited information before accepting a job offer. Employee-generated disclosures contain new information signals, which workers may use to update their beliefs, evaluate job opportunities more systematically, and make employment decisions more closely aligned with their preferences for certain job attributes (Moen, 1997).

Building on this mechanism, we develop two testable predictions. First, labor markets with greater access to employee-generated disclosures should exhibit better matching outcomes compared to those with less access. Intuitively, if more information is available, workers are more likely to leave their current employer when they discover superior alternatives. At the same time, those who choose to stay should also experience improved match outcomes as reflected in, for instance, longer tenures and stronger career progression.

Second, if these improvements arise in part through worker reallocation, they should be reflected in realized job-to-job flows. In competitive search models with directed search, reductions in information frictions lead workers to reallocate toward employers offering higher expected match quality, implying a comparative static in which improved information generates systematic flows from lower- to higher-quality firms (Moen, 1997). Accordingly, we predict that individual workers move from employers with less favorable signals toward those with more favorable ones.

We empirically examine these predictions in Sections 4 and 5, respectively, recognizing that the extent to which employee-generated disclosures are associated with matching outcomes is ultimately an empirical question. Although survey evidence suggests that employee-generated disclosures help workers during the job search process (Westfall, 2017), our predictions rest on a joint hypothesis: (1) employee-generated disclosures reduce information frictions in labor markets; and (2) reductions in these frictions affect workers' decisions. As such, their influence is unlikely to be uniform across settings. For instance, worker responsiveness to ratings may depend on individual characteristics such as occupation, seniority, or job type. Employer characteristics including labor market competition and hiring intensity may also interact with how workers act on new information. Likewise, institutional factors such as labor regulations may affect how widely and effectively employee-generated disclosures disseminate across labor markets. We empirically examine these boundary conditions in Section 6.

Barring likely observable differences in the cross section, several factors could dampen the relation between employee-generated disclosures and matching outcomes. For example, review participation is voluntary, so information may be selective or biased toward extreme experiences. The voluntary nature of disclosure could limit the informativeness of ratings, which may weaken the ability of disclosures to reduce information frictions. Moreover, operational frictions could offset informational gains. When highly rated employers attract disproportionate attention, congestion and intensive screening can constrain hiring, which reduces the reallocation of workers even when information improves.

Employers are also not passive observers. Some may respond to unfavorable reviews by improving workplace practices (Dube and Zhu, 2021), which blurs the interpretation of ratings as purely informational shocks. Others may attempt to influence perceptions by soliciting positive reviews, manipulating ratings, or suppressing negative content (Fuhrmans, 2017; Sockin and Sojourner, 2023; Zhang et al., 2025). To better understand how Glassdoor addresses these risks, we contacted Glassdoor employees to learn about the platform's internal review and moderation practices. They emphasized that reviews are not removed at employer request and that the platform continuously refines its algorithms to detect spam, bots, and coordinated manipulation using IP and posting pattern analysis. More broadly, Glassdoor (2025b) uses moderation tools focused on abuse detection rather than direct content control.[7]

In the spirit of Bénabou and Vellodi (2025), even when disclosures are noisy or subject to strategic manipulation, they can remain informative in equilibrium. In particular, a cheap-talk extension implies a partitioning outcome in which workers can distinguish large differences in workplace quality but not finer distinctions. Employer-induced manipulation may therefore affect the distribution of reviews within these partitions without fully eliminating their informational content. Importantly, if workers anticipate manipulation, they adjust their interpretation of ratings rationally—either by discounting biased signals (Stein, 1989) or by placing less weight on ratings altogether (Fischer and Verrecchia, 2000). Both responses would

[7] That said, social media posts offer anecdotal evidence of employers attempting to manipulate ratings. For instance, several Reddit users report being asked to leave five-star reviews or to delete negative feedback (e.g., u/NotGonna_Lie2U, 2021; u/infpthoughts, 2022; u/TyrannicalKitty, 2023).

attenuate, rather than generate, the empirical relation between ratings and matching outcomes that we study. Finally, to the extent that manipulation incentives are stable within a firm-year observation, our empirical analysis should absorb such behavior through fixed effects.

2.3. Related literature

Our paper builds on an extensive literature examining information frictions in labor markets. Recent field experiments document that introducing centralized or employer-provided information in controlled settings affects worker responses to wage transparency (Jäger et al., 2024), diversity practices (Choi et al., 2023c), and ESG policies (Colonnelli et al., 2025). Information provision can thus influence worker perceptions, but its effects depend on how the information is framed and by whom it is communicated. Another stream of work examines how workers incorporate firm-related disclosures into their employment decisions. For example, Choi et al. (2023c) and deHaan et al. (2023) show that earnings announcements trigger job search and application activity, whereas Choi et al. (2023b) find that poor financial reporting quality leads workers to demand a pay premium for employment risk. Our paper differs from this work by focusing on employee-generated disclosures posted on decentralized platforms. Rather than relying on controlled interventions or firm-initiated communication, we examine how naturally occurring workplace information influences worker flows in real labor markets, both on their own and in conjunction with employer-provided information.

Within the growing body of work examining employee-generated disclosures, several studies use Glassdoor data to examine worker responses at different stages of the job search process. For instance, Sockin and Sojourner (2023) study which Glassdoor content captures workers' attention in application decisions, and Li (2024) shows how workers use the "also viewed firms" feature to identify competing employers. Yu et al. (2022) use eye-tracking techniques to study how jobseekers assess Glassdoor content. Zhang et al. (2022) examine the relation between employee-generated ratings, awards, and application intentions. Van Hoye and

Lievens (2007) and Walker et al. (2009) show that online employee testimonials and word-of-mouth shape perceptions of prospective employers. Our paper complements these studies by shifting focus from application decisions to realized job-to-job flows. Whereas previous work primarily captures workers' stated intentions and application behavior, we examine outcomes that reflect equilibrium adjustments in the labor market jointly determined by workers and employers—decisions that incorporate job offers, switching costs, and uncertainty about match quality. Our archival design also connects the mechanisms identified in prior experimental work to their observable counterparts in real labor markets, with the added benefit that the richness of our data allows us to study heterogeneity across many employees, employers, and institutional settings that would be hard to capture in controlled environments.

Finally, our paper is related to the growing literature that shows that employee-generated disclosures provide decision-relevant, forward-looking information about firms' workplaces in a variety of contexts (see Zhou et al. (2024) and Booker et al. (2025) for overviews). For instance, employee-generated disclosures are useful when combined with firms' financial information to help form expectations about the future (Hales et al., 2018; Huang et al., 2020). They also reveal misconduct (Campbell and Shang, 2021; Dunham et al., 2023; Koenraadt et al., 2025), explain stock returns (Green et al., 2023; Sheng, 2025), explain the success of corporate transactions (Chemmanur et al., 2020; Lalova, 2025; Li and Pinto, 2025), and influence perceptions of diversity and workplace equity (deHaan et al., 2023; Mkrtchyan et al., 2024; Böke et al., 2025; Carter et al., 2025).

3. Data description

3.1. Data sources and samples

We construct our sample using data from three main sources: (1) Glassdoor; (2) Revelio Labs; and (3) Compustat. We use data from Glassdoor to identify employee-generated disclosures, data from Revelio Labs to measure matching outcomes, and data from Compustat to construct labor market peers using industry identifiers and measure variables for the cross-sectional analyses. The sample begins in 2008, with the introduction of Glassdoor, and ends in 2023, the last year for which we have complete data. Our data allow us to examine variation both across and within firms, including differences across establishments of the same firm. Our sample covers employees across a range of roles, with the largest groups in engineering, sales, and finance, followed by workers in administration, operations, marketing, and science.

We conduct our analyses at two complementary levels. First, to examine whether Glassdoor coverage explains aggregate matching outcomes, we aggregate observations at the labor market level, defined by MSA and eight-digit GICS industry membership (see Section 3.3 for details). Second, to examine whether Glassdoor rating differences predict job-to-job flows from lower- to higher-rated employers, we analyze data at the firm-peer-MSA-year level. Table 1 Panel A details our sample selection procedure for this second sample, which includes 2,246,437 observations across 3,026 unique firms.[8] Appendix A defines all variables.

3.2. Glassdoor

Our sample of employee-generated disclosures comes from Glassdoor, an online platform where workers anonymously review their employers and share detailed workplace experiences. We collect approximately 2.55 million reviews for more than 3,000 publicly listed firms on Glassdoor, covering all reviews posted between 2008 and 2023. Since its launch in 2008, Glassdoor has become a widely used tool in job search (Westfall, 2017), attracting over 50 million unique visitors each month (Glassdoor, 2025a). Figure 1 shows the expansion of Glassdoor coverage in our sample, highlighting its rapid adoption and growing user engagement. Between 2008 and 2023, for instance, the number of unique establishments rated on Glassdoor in our sample rose from 3,070 to 45,055, with the average firm receiving 88

[8] Our initial Compustat sample comprises 6,070 unique firms with non-missing total assets and net income during the sample period. Of these firms, 5,082 are successfully matched to the Glassdoor dataset, requiring at least one employee review that can be assigned to an MSA. Merging the Revelio Labs data further restricts the sample to 3,026 firms, yielding 2,246,437 firm-peer-MSA-year observations.

reviews per year in 2023—up from 14 in 2008.

Beyond its scale, Glassdoor offers an ideal setting for our analysis because it specifically caters to workers by providing job listings, facilitating employer engagement, and hosting structured, employment-focused discussions through reviews with ratings based on key workplace aspects.[9] 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. As Figure 2 illustrates, reviews vary in tone, ranging from favorable to unfavorable. Reviewers must authenticate their identities via email or a social media account and also disclose their job title, tenure, employment status, and workplace location. Optional subratings capture dimensions such as career opportunities, senior leadership, compensation and benefits, and work-life balance. Reviewers can further indicate whether they would recommend the employer to a friend, approve of the CEO, or hold a positive business outlook.

An important feature of Glassdoor that makes our empirical analysis possible is that reviewers specify their workplace location, allowing reviews and ratings to be linked to a specific MSA. This location-specific granularity enables workers (and researchers) to compare workplace perceptions across firms within an MSA as well as across MSAs for the same firm. Using this data, we construct two primary measures. In the aggregate labor market tests, we construct a measure of the percentage of firms within an MSA-industry cell that have at least one rating on Glassdoor (*%Glassdoor*). This measure captures the informational reach of Glassdoor within each labor market, which expanded unevenly across markets and industries (e.g., Dube and Zhu, 2021). Higher values indicate that workers can benchmark a larger share of employers based on employee-generated disclosures.

In the firm-peer tests, we focus on pairwise differences in workplace ratings. *Relative*

[9] By contrast, broader platforms such as X, Facebook, and Reddit include less structured discussion of employment topics and offer less direct access to actionable, job-related information. In addition, job posting platforms such as Monster.com or Indeed.com do not provide workers with employee-generated information.

Rating captures the difference between the focal firm's workplace rating and that of a peer operating in the same MSA and year. This variable ranges between negative four and positive four, where the value of negative four indicates that the focal establishment has the lowest possible rating (i.e., one) while its peer has the highest possible rating (i.e., five) and the value of positive four indicates the reverse. We focus on pairwise differences in Glassdoor's five-star workplace ratings, beginning with the overall rating that aggregates wage and non-wage job attributes into a single score, and subsequently examining differences across subrating types.

To illustrate Glassdoor's granularity and relative ratings, Figure 3 presents examples of establishment-specific ratings for several firms in two cities, Boston and Philadelphia (aggregated across locations within each MSA). Panels A and B compare McDonald's Corporation and Starbucks Corporation, two peers in our sample, showing substantial between-MSA variation in workplace ratings. McDonald's in Philadelphia is rated lower than in Boston (3.2 versus 3.7 out of 5) yet still outranks Starbucks in Philadelphia (3.1). Although Starbucks is rated higher in Boston than in Philadelphia (3.3 versus 3.1), it is lower rated than McDonald's in both MSAs. Panels C and D compare Jones Lang LaSalle Inc. (JLL) and Cushman & Wakefield Inc., another pair of peers. Here, JLL is consistently rated below Cushman & Wakefield in both MSAs. Notably, although JLL and Cushman & Wakefield receive higher ratings in Philadelphia, McDonald's and Starbucks are rated higher in Boston. Hence, perceptions of workplace quality vary across both firms and MSAs, suggesting variation both within- and between-MSAs in Glassdoor ratings.

3.3. Local labor markets

Because reviewers specify their workplace location, we can link firm-specific reviews and ratings to specific MSAs. A key variable in our analysis is thus the definition of local labor markets. Following previous work (e.g., Moretti, 2011; Marinescu and Rathelot, 2018), we focus on MSAs as our baseline definition because they represent geographically bounded labor markets where most job search and matching activity occurs.[10] Within each MSA, we define local labor markets as sets of firms that draw from similar pools of workers and compete for jobs requiring comparable skills, using eight-digit GICS industry membership to identify labor market peers. We use GICS because it offers two advantages over SIC or NAICS classifications. First, it updates annually to capture evolving industry structures, whereas SIC has remained static since 1987 and NAICS updates only every five years (Library of Congress, 2025; MSCI, 2025; U.S. Census Bureau, 2025). Second, GICS classifications better capture performance co-movements between firms (Bhojraj et al., 2003).[11]

Our labor market peer classification is reciprocal within a given MSA, because two firms are peers only in locations where they both operate. Thus, if one firm operates in multiple MSAs and another operates in only one, they are peers only in the overlapping MSA. This approach ensures that labor market peer networks reflect symmetric, geographically specific relationships.[12] This definition yields an average of 8 labor peers per firm within each MSA.

3.4. Matching outcomes

To measure matching outcomes, we obtain data from Revelio Labs, which provides high-frequency labor market data derived from online profiles and validated against official sources such as the Bureau of Labor Statistics. Revelio Labs offers broader and more consistent coverage compared to survey-based labor datasets such as the Current Population Survey or the Survey of Income and Program Participation. For example, for each employment spell, we have data on the start and end date, job title, hierarchy, worker, and employer, allowing us to observe both within-employer career progression for each employee and across-employer job-to-job

[10] In unreported analyses, we find that most job-to-job flows—approximately 70% to 80%—occur within MSAs, and this pattern is relatively stable over time.

[11] Nevertheless, we find similar results when using broader GICS industries or SIC-based industries (untabulated), suggesting that our findings are robust to the choice of labor market peers.

[12] Other labor market peer network measures, such as those based on job postings (De la Parra and Glaeser, 2025) or revealed worker interests (Li, 2024) are less suitable for our analysis because they are inherently related to worker job search: employers are identified as peers precisely because workers target or express interest in similar openings. Similarly, Glassdoor's own peer groupings are endogenous to platform activity, available only as a contemporaneous snapshot, and exclude firms that exit the platform—introducing survivorship bias.

flows. This worker-level structure of the Revelio Labs dataset is particularly suited for our analysis: unlike aggregate measures of separations or hires, we can measure individual workers' realized career progressions and flows within more granular, self-constructed labor markets.

Using these data, we construct several measures of worker-employer matching. In the aggregate tests, we focus on three indicators commonly associated with more effective matching (e.g., Rogerson et al., 2005; Wright et al., 2021). We first compute these variables at the establishment-year level and then aggregate them to the MSA-industry-year level. First, *Match Incidence* measures the log of the number of within-MSA-industry-year job-to-job flows with employment gaps shorter than 183 days, capturing how many new matches are formed. We chose this six-month cutoff to ensure that we distinguish between genuine job-to-job flows rather than temporary exits from the labor force or periods of unemployment.[13] Second, *Match Duration* measures the log of the average remaining tenure of current employees, capturing how long existing matches persist—a central implication of worker-employer alignment. Third, *Match Progression* measures the average future promotion rate among current employees within their current firm, capturing the degree of upward mobility within ongoing matches—a proxy for the quality of the match in terms of career advancement and internal reallocation. Together, these measures capture matching outcomes jointly determined by workers and employers, for both job switchers and stayers.

In the firm-peer tests, we focus on worker flows given their central role in labor market search theory and its practical relevance for understanding how individual workers respond to information (Hom et al., 2017). Specifically, *Focal → Peer Flows* measures the number of unidirectional job-to-job flows from a focal establishment to a peer establishment within the same MSA and industry with employment gaps shorter than 183 days. By linking *Focal →*

[13] The six-month cutoff corresponds to the Bureau of Labor Statistics' definition of long-term unemployment (i.e., more than 27 weeks) (e.g., Bureau of Labor Statistics, 2016, 2025), making it a natural threshold for separating direct job-to-job transitions from extended non-employment spells while mitigating measurement error from delayed or incomplete updates in online employment histories.

Peer Flows to *Relative Rating*, which measures pairwise differences in Glassdoor ratings at the firm-peer-MSA-year level, we are able to test whether employees at one establishment are more likely to move to another establishment in the same MSA when favorable information about the latter becomes available, using the same pair in other MSAs as counterfactuals. This design provides a direct link between employee-generated disclosures and worker flows by mapping the direction of realized flows to the content of the disclosures. Another advantage of this variable is that it is amendable and can be restricted to specific flow types (e.g., by employee or job type). We exploit this feature in cross-sectional tests in Section 6.

3.5. Summary statistics

Table 1 Panels B through D present a sample overview. Panel B highlights a steady increase in the number of actively rated firms and establishments in our sample over time. New workplace reviews and ratings also show an upward trend, with a sharp spike in reviews in 2020 and 2021, possibly because of the introduction of diversity and inclusion subrating or labor market dynamics and increased online engagement during the COVID-19 pandemic and the Great Resignation. Panel C shows variation in employer presence and review activity across industries in our sample, showing that workplace ratings vary by industry. Panel D further exemplifies the ten largest MSAs in our sample, showing that major economic hubs like New York, Los Angeles, and Chicago have the highest firm presence and employment. For interested readers, we provide an analysis of the determinants of review and rating activity in Appendix B, showing that ratings and unfavorable reviews correlate with firm characteristics such as performance, size, and employee growth. The insights from these analyses inform our subsequent fixed-effects specifications and identification choices, for example by absorbing most observable controls through firm-by-year, peer-by-year, and MSA-by-year fixed effects.

Table 2 presents sample summary statistics on the main variables included in our regression analysis and the variance reduction in these variables as a result of our fixed effects structure (Breuer and deHaan, 2024).[14] Overall, the substantial residual variation in matching outcomes, Glassdoor coverage, and relative ratings indicates that our key variables are not excessively persistent over time, supporting the feasibility of our fixed-effects identification strategy. For example, in the aggregate tests, roughly 77%, 93%, and 96% of the variation in *Match Incidence*, *Match Duration*, and *Match Progression* remain after including our main fixed effects, respectively; similarly, 72% of the variation in *%Glassdoor* persists. Furthermore, in the firm-peer tests, only 38% of observations have zero variation in *Focal → Peer Flows*, i.e., observations that never see an employee leave to a local peer, and after including our main fixed effects roughly 91% of the variation remains. Likewise, 99.8% of the observations have variation in *Relative Rating*, meaning that either their own or one of their peers' ratings changes, and roughly 87% of the variation remains after including our main fixed effects.

4. Does Glassdoor coverage explain aggregate matching outcomes?

The first question we seek to address is whether Glassdoor coverage has any impact on aggregate matching outcomes. If Glassdoor information reduces information frictions, we expect labor markets with greater access to employee-generated disclosures should exhibit better matching outcomes compared to those with less access. The intuition underlying this prediction is that as more information becomes available, workers are more likely to leave their current employer when they discover superior alternatives, whereas those who choose to stay should also experience improved match outcomes as reflected in, for instance, longer tenures and stronger career progression. To test this first prediction, we estimate variants of the following specification at the MSA-industry-year level:

$$[Match_{gmt}] = \beta_1 \cdot \%Glassdoor_{gmt} + \mathbf{\Omega} \cdot X_{gmt} + \mathbf{\Theta} \cdot \tau_g + \mathbf{\Phi} \cdot \omega_m + \mathbf{\Psi} \cdot \xi_t + \varepsilon_{gmt}, \qquad (1)$$

where g indexes eight-digit GICS industries, m indexes MSAs, and t indexes years. [*Match*] is

[14] For variables measured at the MSA-industry-year level, we compute within-FE-σ and after-FE-σ based on MSA, industry, and year fixed effects, except for *Google Search Index* where we only use MSA and industry fixed effects (see Table 3 Panel B for details). For variables measured at the firm-peer-MSA-year level, we compute within-FE-σ and after-FE-σ based on firm-by-year, peer-by-year, and MSA-by-year fixed effects.

either *Match Incidence*, *Match Duration*, or *Match Progression* (see Section 3.4 for details).

The main coefficient of interest is β_1, which captures the relation between Glassdoor coverage and local matching outcomes. In this setup, identification comes from variation in Glassdoor coverage across different labor markets and time. To help rule out potential alternative explanations, we control for labor market size and labor demand and supply (*Firms* and *Population*), labor market concentration (*Concentration*), and economic conditions (*GDP*). We also include industry, MSA, and year fixed effects, which absorb persistent regional differences, industry heterogeneity, and nationwide business-cycle fluctuations. We also estimate variants of Equation (1) that additionally include MSA-by-year and industry-by-year fixed effects to absorb time-varying regional and industry differences, respectively. We cluster standard errors by MSA and industry to address potential time-series dependence across observations (Abadie et al., 2023).

Table 3 Panel A presents results from estimating Equation (1). Across all specifications, we find that the coefficient on *%Glassdoor* is positive and statistically significant. These results are consistent with our first prediction and indicate that local labor markets with greater Glassdoor coverage have more worker-employer matches, longer expected match tenure, and higher promotion rates among current workers—patterns indicative of more effective matching between workers and employers (e.g., Rogerson et al., 2005; Wright et al., 2021). The economic magnitudes are also meaningful: a one within-fixed-effects standard deviation increase in *%Glassdoor* is associated with approximately 9.756%, 4.518%, and 3.206% within-fixed-effects standard deviation increases in within-market job-to-job flows, average match duration, and progression during the match, respectively.[15]

Overall, these results are consistent with the prediction that access to employee-

[15] To interpret the economic magnitude of these estimates, we follow Mummolo and Peterson (2018), Mitton (2024), and Breuer and deHaan (2024). Specifically, we compute the standard deviation of each variable's residuals after removing the relevant fixed effects. This approach expresses magnitudes as "within-fixed-effects standard deviations," i.e., variation net of regional, industry, and time effects.

generated disclosures facilitates worker-employer matching. A potential concern, however, is that certain labor market factors drive Glassdoor adoption. If those same factors drive matching outcomes, then our results may be spurious. For example, MSAs with higher turnover may attract more platform participation and exhibit more matching activity. We have addressed this problem in part by controlling for time-varying regional and industry differences, but to confront it directly we conduct an additional analysis using a two-stage least squares framework that is explicit about the source of variation used to assess the relation between Glassdoor coverage and matching outcomes.

Specifically, we instrument Glassdoor coverage using a state-level Google search index for the exact term *Glassdoor*. This index captures within-state variation over time in searches for the platform name, rather than national trends in search intensity, and is normalized by Google Trends such that the maximum search intensity within each state over the sample period is set to 100, with all other values scaled proportionally.

The Google search term activity instrument plausibly satisfies the testable relevance and untestable exclusion conditions (Roberts and Whited, 2013). State-level Google search activity is a relevant instrument for Glassdoor coverage, because search intensity for the platform name directly proxies for awareness, visitation, and usage of Glassdoor, all of which are likely to expand the volume of employee reviews and ratings available to workers in that state. In terms of exclusion, searches for the exact term *Glassdoor* are unlikely to be correlated with local matching outcomes except through the informational role of the Glassdoor platform itself. The search term index, by design, captures only exact searches for the platform name itself and excludes broader search topics that combine "Glassdoor" with employer names (e.g., "Glassdoor JLL") or generic employment-related terms (e.g., "jobs," "careers," or "salary"). As such, the instrument only captures attention to the Glassdoor platform rather than general job search intensity, firm-specific recruiting activity, or local labor demand. This instrument thus also functions as a channel test: if Glassdoor improves matching by helping workers evaluate outside options, then states with greater search interest in Glassdoor should show stronger indicators of improved worker-employer matching.

Table 3 Panel B presents results from estimating Equation (1) using two-stage least squares. In Column (1), the first-stage results show a positive association between *Google Search Index* and *%Glassdoor*. The weak instrument test statistics support the relevance of this instrument from an empirical perspective (Cragg and Donald, 1993; Kleibergen and Paap, 2006; Olea and Pflueger, 2013). Column (2) through (4) present the second-stage results, which identify a local average treatment effect for states with greater Glassdoor coverage that coincides with Google searches for Glassdoor. The results are consistent with those in Table 3 Panel A, reinforcing the conclusion that employee-generated disclosures can influence matching between workers and employers. The larger magnitude of the instrumental-variables coefficients relative to their ordinary-least-squares counterparts is consistent with attenuation bias in ordinary least squares arising from measurement error in platform coverage, as well as with the instrument identifying local average treatment effects for labor markets whose exposure to Glassdoor is more responsive to changes in platform-level attention. Given this local-average-treatment-effects interpretation of the instrumental-variables estimates, we focus on their sign and statistical significance rather than on direct magnitude comparisons.

5. Do Glassdoor rating differences predict worker flows?

5.1. How does Glassdoor information relate to individual matching outcomes?

The aggregate evidence in Section 4 supports our first prediction that access to employee-generated disclosures facilitates worker-employer matching. We now test our second prediction that if these improvements arise in part through worker reallocation, they should be reflected in realized job-to-job flows, as individual workers move from employers with less favorable signals toward those with more favorable ones. To test this sorting mechanism, we examine how granular pairwise differences in Glassdoor ratings between a firm and its local peer explain unidirectional flows between them. Specifically, we estimate variants of the following specification at the firm-peer-MSA-year level using ordinary least squares:

$$\begin{aligned} \textit{Focal} \rightarrow \textit{Peer Flows}_{ijmt} = \beta_1 \cdot \textit{Relative Rating}_{ijmt} \\ + \beta_2 \cdot \log(\textit{Employees}_{imt}) + \beta_3 \cdot \log(\textit{Peer Employees}_{jmt}) \\ + \mathbf{\Theta} \cdot \xi_{it} + \mathbf{\Omega} \cdot \nu_{jt} + \mathbf{\Phi} \cdot \omega_{mt} + \varepsilon_{ijmt}, \end{aligned} \quad (2)$$

where i indexes firms, j indexes peer firms, m indexes MSAs, and t indexes years.[16]

The main coefficient of interest is β_1, which captures the relation between pairwise rating differences between the focal establishment and its peer and unidirectional flows from the focal establishment to that same exact peer. To help rule out potential alternative explanations, we control for firm-MSA and peer-MSA size using *Employees* and *Peer Employees*. We also sequentially include firm-by-year, peer-by-year, and MSA-by-year fixed effects to control for time-varying characteristics and factors at the firm or peer firm level that could be correlated with both employee-generated disclosures and matching outcomes (e.g., employer attractiveness, hiring intensity, or employer-manipulation incentives). To further strengthen identification, we estimate variants of Equation (2) that include firm-by-peer or firm-by-peer-by-MSA fixed effects, which ensure that we compare worker flows from different focal establishments toward establishments of the same peer or the same establishment pair within a given MSA over time. We cluster standard errors by firm, peer, and MSA to address potential time-series dependence across observations (Abadie et al., 2023).

Table 4 presents results from estimating Equation (2). Across all specifications, we find that the coefficient on *Relative Rating* is negative and statistically significant. These results are consistent with our second prediction and indicate that workers move from employers with lower ratings toward those with higher ones. The effect remains robust, though somewhat attenuated, as we tighten the fixed effects. Notably, the effect persists in the tightest

[16] In unreported analyses, we estimate variants of Equation (2) using Poisson regression (Cohn et al., 2022) and obtain similar results.

specification in Column (6), which compares unidirectional flows within the same firm-peer pair in the same MSA over time. In terms of economic magnitudes, these estimates imply that for the average establishment-year with an average number of peers, a one within-fixed-effects standard deviation increase in *Relative Rating* is associated with a 1.309% to 5.374% within-fixed-effects standard deviation decline in unidirectional job-to-job flows toward peers, depending on the fixed effects specification.

Overall, these results suggest that the informational content of ratings help resolve uncertainty about employer attributes, rather than persistent employer, peer, pair, or regional characteristics. To further substantiate this conclusion, we partition the *Relative Rating* variable into bins and estimate regression specifications analogous to those in Table 4 Column (6), using observations with relative ratings in (–0.1, 0.1] as the baseline group. If rating differences indeed resolve uncertainty about employer attributes, we expect to observe systematically varying effects across rating differences. Intuitively, when differences are small, new information can update workers' beliefs, but when these differences are large, differences in employer attributes are likely common knowledge, attenuating the influence of ratings.

Figure 4 plots the corresponding coefficients. Consistent with our conjecture, Panel A shows that the effect peaks when peers are rated moderately higher—precisely where relative differences in workplace attributes are most informative for job choice—and diminishes when rating differences become large. When rating differences are modest, employer quality is harder to infer ex ante, making ratings especially informative for belief updating and job choice, whereas when differences are large and quality is more readily inferred, the marginal informational value of ratings diminishes. Panel B decomposes this relation across the six underlying rating dimensions to examine which dimensions most strongly predict worker flows, showing that 'career opportunities' and 'senior leadership' are the strongest predictors, consistent with workers placing greater weight on these forward-looking dimensions when assessing prospective job value (Choi et al., 2023a). We also find that, by and large, all rating types are informative about workers' staying decisions. That is, when these ratings exceed a given peer's ratings, the focal establishment experiences fewer employees moving to that specific peer.

5.2. Addressing identification concerns

The preceding analysis shows that relative ratings predict unidirectional flows from lower- to higher-rated establishments, especially when rating differences are small. Although our empirical design helps address some identification concerns—mainly because of the inclusion of dense fixed effects and within-pair comparisons—it does not rely on exogenous or random variation in ratings. To supplement our main findings, we implement two complementary strategies designed to help isolate the informational effect of ratings from confounding effects related to underlying workplace quality. The first strategy focuses on the introduction of workplace ratings about job attributes of peer employers. The second strategy focuses on plausibly random variation in peer ratings arising from rounding conventions on the Glassdoor platform. Because these two approaches rely on a different set of identifying assumptions, and thus distinct sources of identifying variation, their combined use should enhance the credibility of our inferences. Below we discuss each test in turn.

5.2.1. Do workers respond to peers' first-time ratings?

We adapt the framework of Dube and Zhu (2021) and use a continuous difference-in-differences setup to test whether the introduction of peer ratings facilitates job-to-job flows by providing workers with new information about outside options. Consistent with the literature on peer effects, using the timing of peers' first-time ratings should help address concerns about reverse causality stemming from the focal establishment's own workplace quality. Although a focal establishment's own conditions may influence both rating activity and worker departures, the timing of first-time ratings at peer establishments is unlikely to be driven by conditions at the focal establishment. This test also helps alleviate concerns about strategic managerial responses to ratings, as these are less likely to occur absent ratings.

Specifically, we estimate the following specification at the firm-MSA-event level:

$$\begin{aligned} \textit{Focal} \rightarrow \textit{Peer Flows}_{iet} = \beta_1 \cdot \mathbb{1}(\textit{Post}_t) \times \textit{Treatment Intensity}_e \\ + \mathbf{\Theta} \cdot \tau_e + \mathbf{\Phi} \cdot \omega_{tb} + \varepsilon_{iet}, \end{aligned} \tag{3}$$

where e indexes event, t indexes event time, and b indexes rating bins.

Each event in this stacked design corresponds to a focal establishment observation with one or more peers receiving their first Glassdoor rating. We examine unidirectional job-to-job flows from the focal establishment to those peers within a five-year window centered on the event year [–2, +2]. The continuous treatment variable, *Treatment Intensity*, measures the share of peer establishments that receive their first rating in a given year. Because multiple peers may become rated simultaneously, this measure reflects the gradual dissemination of workplace information across the local labor market and allows us to examine how incremental reductions in information frictions relate to worker movements.

We include event fixed effects and event-time-by-0.25 rating bin fixed effects to control for potential confounding factors and help isolate the effect of new information. The event fixed effects absorb time-invariant characteristics of each firm-MSA combination (e.g., industry composition or local amenities), whereas the event-time-by-rating-bin fixed effects control for time-varying patterns in worker flows across treated units at each event time (e.g., employer responses to peers' first-time ratings in the post period). Allowing these effects to vary by initial rating bins accounts for the possibility that establishments with lower starting ratings may respond more strongly to negative feedback. We cluster standard errors at the firm level to address potential time-series dependence across events of the same firm (Abadie et al., 2023).

Table 5 Panel A presents results estimating Equation (3), which tests whether workers move toward peer establishments that have just become rated on Glassdoor. Each column reflects a different control group: (1) focal establishments without a rating themselves; (2) focal establishments with a rating that is lower than peers' first-time rating; and (3) focal establishments with a rating that is higher than peers' first-time rating. In Columns (1) and (2), we find that the interaction between $\mathbb{1}(Post)$ and *Treatment Intensity* is positive and statistically significant. This finding indicates that when a larger share of peer establishments receives their first ratings, worker flows from the focal establishment to those specific peers increase—particularly when the focal establishment is unrated or rated below its newly rated peers. By contrast, Column (3) shows no significant effect when the focal establishment's rating exceeds that of newly rated peers, consistent with our earlier finding that workers reallocate toward higher-rated, but not lower-rated, peer employers.

Figure 5 Panel A further decomposes $\mathbb{1}(Post)$ into event-year-specific indicators and plots the estimated coefficients on $\mathbb{1}(Event\ Year)$ × *Treatment Intensity*, benchmarked to the year immediately prior to the first-rating period, i.e., period $t = -1$. This event-time specification allows us to examine the temporal pattern of worker responses and assess whether flow effects emerge sharply after peers receive their first ratings or evolve more gradually over time. The results reinforce the earlier evidence: worker reallocation toward newly rated peers occurs immediately after the first rating and is strongest for focal establishments whose ratings are lower than those of their peers. Importantly, we also find no evidence of differential pre-trends, with coefficients in the pre-treatment period statistically indistinguishable from zero. This sharp, contemporaneous response supports the prediction that the arrival of new, peer-generated information prompts belief updating and accelerates worker flows toward better-rated employers, rather than reflecting gradual or mechanical adjustments in labor demand.

5.2.2. Do workers respond to rating information?

As another step in sharpening our inferences about the informational value of ratings, we exploit a natural feature of Glassdoor's platform. Although ratings are internally computed with high precision, they are displayed to users rounded to one decimal place. This introduces quasi-random variation in the presentation of ratings. For example, a true rating change from 3.449 to 3.451 results in a visible jump from 3.4 to 3.5, despite no meaningful shift in underlying conditions. Following prior research that uses rounding-induced displayed ratings (e.g., Luca, 2016; Sockin and Sojourner, 2023), we compare rounded ratings to unrounded ratings. Specifically, we focus on cases with peer ratings within {±0.01, ±0.05} of a threshold, and compare unidirectional job-to-job flows when a peer's rating is rounded up versus when it is rounded down or unaffected by rounding.[17] Focusing on peer rounding-induced displayed ratings has two advantages. First, it creates variation in visible information while holding actual relative quality effectively constant. Second, by focusing on peer ratings, it minimizes concerns related to the focal establishment's own attributes, i.e., small rounding-based fluctuations in peer ratings are unlikely to coincide with meaningful changes at the focal establishment.

Table 5 Panel B presents results from re-estimating Equation (2) but replacing *Relative Rating* with $\mathbb{1}$(*Rounded Up*), which is an indicator variable equal to one when the peer's rating is rounded up, and zero otherwise.[18] Across all specifications, we find that the coefficient on $\mathbb{1}$(*Rounded Up*) is positive and statistically significant. These results indicate that workers are more likely to move toward peers whose displayed ratings are higher because of rounding. The accompanying Figure 5 Panel B examines heterogeneity across rating thresholds by cumulatively including thresholds up to a given star cutoff and plotting the corresponding estimated coefficients on $\mathbb{1}$(*Rounded Up*).[19] Both the regression and graphical evidence show

[17] Our design differs from a regression discontinuity design in that treatment arises from rounding behavior rather than from crossing a single threshold. Because rounding occurs at many points in the support of the running variable, a density test at a unique cutoff is not well defined. Moreover, unlike in a regression discontinuity design —where treatment effects are concentrated near the cutoff—the informational content of rounding in our setting increases with its magnitude. Accordingly, the key identification concern is whether rounding is systematically related to rating outcomes. In unreported analyses, we regress the rounding indicator on peer ratings and find a within-adjusted R^2 below 0.0001%, indicating that rounding is at most weakly related to ratings. Consistent with this, count-based binomial tests show symmetric observations around zero across narrow windows, providing no evidence of sorting or bunching around rounding points.

[18] Results are robust to also controlling for *Focal Absolute Rating* and *Peer Absolute Rating*.

[19] This figure follows the intuition of Sockin and Sojourner (2023), who examine application decisions across the firm size distribution.

that the effect strengthens at higher rating levels: estimated coefficients increase steadily across the rating distribution and flatten once ratings exceed roughly four stars. The estimated effect sizes are relatively large because, as shown in our earlier analyses, very small differences in displayed ratings, such as those induced by rounding, are particularly informative for workers' decisions. Overall, this pattern is consistent with workers responding to observable signals rather than underlying fundamentals. Small rounding-based rating differences are associated with flows when peer quality is moderate to good, where reputation gains are important, but have little influence when quality is low, where small differences carry limited value.

6. When do Glassdoor rating differences matter most?

The evidence developed in the previous section shows that relative ratings predict unidirectional flows from lower- to higher-rated employers. Although this evidence is, on average, consistent with our predictions, we next shed light on its boundary conditions. As conjectured in Section 2, the strength of the relation between ratings and worker flows is likely to vary across contexts. In the three subsections that follow, we therefore examine how employee-generated disclosures interact with employee, employer, and institutional factors. Appendix A provides detailed descriptions of the partitioning variables.

6.1. How do employee-generated disclosures interact with employee characteristics?

We examine whether the relation between relative ratings and unidirectional worker flows depends on employee characteristics. In this regard, labor market search theory predicts that worker responsiveness depends not only on the rating information itself, but also on how strongly workers value certain workplace aspects. Intuitively, not all information is equally decision-relevant to every worker. With this intuition in mind, we test whether flows toward higher-rated establishments are stronger for certain types of employees. We focus on three observable employee characteristics: (1) occupation; (2) seniority; and (3) job remote suitability. To implement a test, we re-estimate Equation (2) but restrict the dependent variable to flows segmented by these three characteristics (see Section 3.4 for details).

Table 6 Panel A presents results from examining cross-sectional variation in job categories. Here, we split the dependent variable into the seven categories provided by Revelio Labs. We find that worker flow effects are strongest for employees in sales, finance, administration, and operations, but statistically insignificant for employees in engineering, marketing, and scientific roles. This pattern suggests that employee-generated disclosures play a role in occupations with stronger relational aspects or where workplace success is more directly tied to job benefits, whereas workers in more technical or specialized roles may rely on other signals when making employment decisions.

Table 6 Panel B presents results from examining cross-sectional variation in job seniority. Here, we split the dependent variable into four groups based on the definitions provided by Revelio Labs. We find a monotonic pattern across seniority: the sensitivity of worker flows to relative ratings is largest for junior employees (e.g., interns, juniors, and associates) and for mid-level managers and directors but declines sharply for executives and senior executives. This pattern suggests that more junior workers rely more heavily on ratings to guide their employment decisions, consistent with their greater potential future prospects at the firm, whereas senior workers rely on other signals (Choi et al., 2023a).

Table 6 Panel C presents results from examining cross-sectional variation in job remote suitability. Here, we split the dependent variable into two groups based on the remote suitability score from Revelio Labs. We find that worker flows are concentrated among jobs with low remote suitability, but statistically insignificant for jobs with high remote suitability. This pattern suggests that employee-generated disclosures are most predictive for flows toward jobs where workers are more likely to experience the workplace environment directly.

6.2. How do employee-generated disclosures interact with employer characteristics?

We examine whether the relation between relative ratings and unidirectional worker flows depends on (peer) firm characteristics, both on the Glassdoor platform and in the labor market. On the platform side, we focus on three observable peer-year characteristics: (1) peer rating count; (2) peer review completeness; and (3) average peer review length. Holding all else constant, we predict that greater information availability reduces more frictions, thereby strengthening the link between relative ratings and worker flows.

On the labor market side, we consider two dimensions—firm-peer competition and peer recruitment attributes—each captured by two firm-peer-year pair or peer-year variables: (1) pairwise labor market concentration; (2) relative firm size; (3) relative number of job ads; and (4) similarity between peers' job-posting language and their Glassdoor reviews. We predict that relative ratings are stronger predictors of worker flows when competition is more intense and recruitment activity is higher, as workers have more available outside options. For language similarity, we make no directional prediction: workers may use Glassdoor either to seek new information not conveyed in employers' own communications or to validate employer-provided information. To implement a test, we re-estimate Equation (2) but partition the sample along each of these platform and labor market characteristics.

Table 7 Panel A presents results from examining cross-sectional variation in peer rating attributes. Across all specifications, we find that greater information availability strengthens the relation between relative ratings and worker flows. That is, when peer establishments have more ratings, a higher share of complete reviews, or longer average review text, the relation between relative ratings and unidirectional worker flows strengthens. This pattern highlights the importance of the overall rating information environment. It also provides suggestive evidence against review manipulation as a primary driver, because fabricated or strategically biased reviews tend to be shorter and less detailed, whereas we find that longer reviews amplify the effects (e.g., Hansen and Wänke, 2010; Sockin and Sojourner, 2023).

Table 7 Panel B presents results from examining cross-sectional variation in labor market competition. In Columns (1) and (2), we find that the relation between relative ratings and worker flows is concentrated in firm-peer pairs that jointly account for a large share of local employment. In Columns (3) and (4), we find that relative firm size also matters: the relation between relative ratings and worker flows is strongest in cases where the peer firm (i.e., destination firm) is larger than the focal firm (i.e., origin firm). This pattern suggests that worker reallocation is more pronounced in competitive markets dominated by large employers and tends to occur from smaller to larger employers.

Table 7 Panel C presents results from examining cross-sectional variation in peer recruitment attributes. We find that both recruitment activity and language moderate the relation between relative ratings and worker flows. Ratings predict flows toward peers more strongly when peers have more job openings than the focal establishment. Similarly, ratings are more important when the textual content of the reviews accompanying them is more similar to the language in the establishment's job advertisements, suggesting that employee-generated disclosures are most valuable when they can corroborate existing recruitment materials.

6.3. How do employee-generated disclosures interact with institutional factors?

We examine whether the relation between relative ratings and unidirectional worker flows depends on institutional factors. Our central prediction is that employee-generated disclosures influence worker-employer matching outcomes by reducing information frictions that hinder such matching. Intuitively, when alternative signals about workplace quality arise or already exist, the marginal informational value of employee-generated disclosures may diminish. To test this prediction, we examine three institutional settings that interact with Glassdoor ratings: (1) Glassdoor's own annual *Best Places to Work* awards; (2) Colorado's *Equal Pay for Equal Work Act* in 2021; and (3) the introduction of Glassdoor's business outlook rating in 2012. To implement a test, we examine whether relative ratings predict worker flows more strongly in periods before versus after these events.

Table 8 Panel A presents results from examining heterogeneity associated with Glassdoor's own annual *Best Places to Work* awards. These awards originate from the same platform but deliver a distinct, high-profile quality signal about peer workplaces that is unlikely to reflect changes at the focal establishment.[20] We merge the annual award lists with our firm-peer sample and interact *Relative Rating* in Equation (2) with an indicator for whether the peer firm receives an award in that year, and zero otherwise. The interaction term captures whether the relation between relative ratings and worker flows varies with the presence of this external quality signal. We find that the coefficient on the interaction term is positive, indicating that the sensitivity of worker flows to relative ratings weakens (and can reverse) once a peer receives institutional certification. This pattern suggests that workers are drawn toward award-winning peers even when those peers have lower ratings, consistent with certifications substituting for explicit platform ratings (Vatter, 2025).

Table 8 Panel B presents results from examining heterogeneity associated with Colorado's *Equal Pay for Equal Work Act* in 2021. This act mandates employers to disclose pay ranges in job postings (Colorado Department of Labor and Employment, 2025). This regulatory shock creates a natural experiment that allows us to test whether mandated compensation disclosures affect the extent to which workers rely on Glassdoor ratings when making employment decisions. We implement an event study design with a [–2, 2] window (in years) around the implementation of the act in 2021, comparing establishments in Colorado (treated) to those in seven neighboring states—Utah, Arizona, New Mexico, Oklahoma, Kansas, Nebraska, and Wyoming (control).[21] We then partition the sample along treated and

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

[21] Treated observations are those located in any MSA 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 use locations within neighboring states as controls for two reasons. First, they are likely to share similar regional economic conditions and labor market characteristics with those in Colorado, on average. Second, none of these states adopted pay transparency requirements during our sample period, providing a control group that is unaffected by similar regulatory changes.

control observations, and interact *Relative Rating* in Equation (2) with an indicator for the period after the act, zero otherwise. We find that the coefficient on the interaction term is negative in the treated subsample and insignificant in the control subsample, indicating that the sensitivity of worker flows to relative ratings increases once compensation information becomes publicly available. This pattern suggests that relative ratings become more valuable decision inputs when combined with outside information—potentially because the ratings gain credibility when one dimension of their content can be externally verified (Pooja and Upadhyaya, 2024) or because workers can now use these ratings as benchmarks for evaluating the full employment package (Liu et al., 2017).

Table 8 Panel C presents results from examining heterogeneity associated with the introduction of Glassdoor's business outlook rating in 2012. This institutional change expanded the platform's information set by adding a forward-looking measure of perceived firm prospects (Huang et al., 2020). It also creates a natural experiment that allows us to test whether this information piece affects workers' employment decisions. We implement an event study design with a [–2, 2] window (in years) around the implementation of the change in 2012, comparing firm-peer pairs in the same firm-level stock-return performance deciles before the change ("treated") with those in different deciles ("control"). Building on our main results (see, e.g., Figure 4), we predict that differences in the business outlook rating are most informative for firm-peer pairs with similar past performance, as differential outlook ratings in these cases provide decision-relevant forward-looking information. With this intuition in mind, we partition the sample along treated and control observations, replace *Relative Rating* with *Relative Business Outlook Rating* in Equation (2), and interact this variable with an indicator for the period after the change, zero otherwise. We find that the coefficient on the interaction term is negative in the treated subsample and insignificant in the control subsample, indicating that after the introduction of the subrating, workers are more likely to move toward peers with stronger outlook scores (but with comparable historical performance). This pattern suggests that the addition of a forward-looking rating provides new information that reduces frictions.

7. Conclusions and implications

We study why and when employee-generated disclosures about workplace experiences influence worker-employer matching, using data on Glassdoor ratings and matching outcomes within U.S. metropolitan areas from 2008 to 2023. Across a series of complementary tests, we develop evidence consistent with the prediction that employee-generated disclosures influence worker-employer matching outcomes by reducing information frictions that hinder such matching. This evidence matters because a large literature shows that better matching between workers and employers can reduce costly misallocations and enhance both firm-level and aggregate productivity.

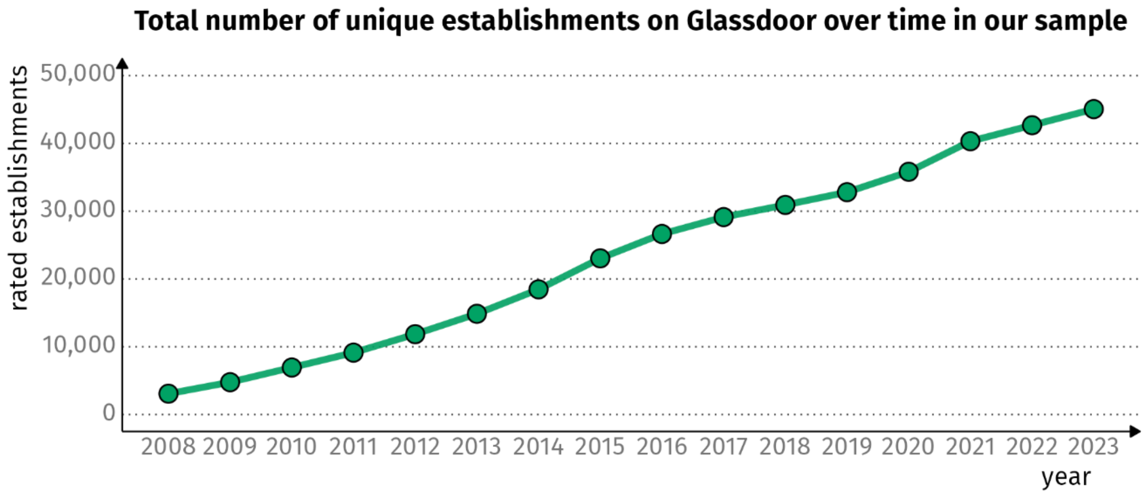
Our paper provides two key insights regarding worker-employer matching outcomes and dynamics. First, at the labor market level, we show that the dissemination of employee-generated disclosures is associated with outcomes indicative of improved matching between workers and employers. Specifically, a higher share of employers covered on Glassdoor is associated with more worker-establishment matches, longer match tenure, and higher promotion rates among current employees. The implication of these findings is that employee-generated disclosures can improve matching outcomes by helping workers assess employer quality. Second, at the firm-peer level, we show that these outcomes are partly driven by a sorting mechanism: pairwise differences in ratings predict unidirectional worker flows from lower- to higher-rated employers. These flow patterns persist across distinct empirical designs, reinforcing the interpretation that they reflect information effects. The implication of these findings is that employee-generated disclosures actively facilitate the reallocation of workers toward employers perceived as being of higher quality.

Importantly, this reallocation is not uniform: it is strongest where information frictions are arguably most severe. Their influence is also stronger for certain types of employees, varies with employer characteristics such as review informativeness, labor market competition, and recruitment language, and depends on institutional factors such as platform awards, pay-transparency mandates, and changes in the types of available workplace ratings. We conclude that employee-generated disclosures play an important role in helping workers assess employer quality in some contexts, whereas in others their influence is limited.

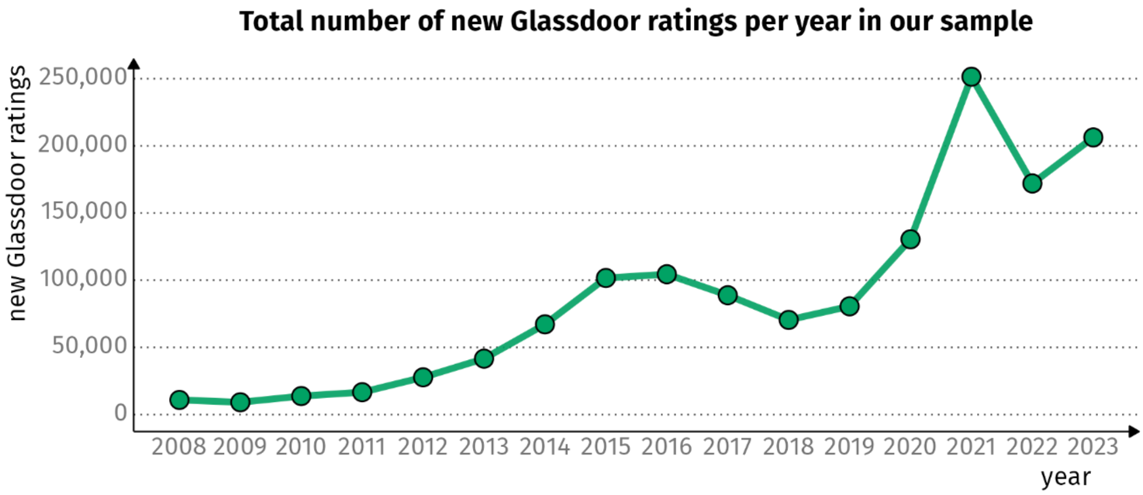
Taken together, our findings point to a meaningful role for employee-generated disclosures in worker-employer matching. At the same time, they should be interpreted in light of several limitations. First, although the Revelio Labs database is well suited for tracking job-to-job transitions at scale, coverage is concentrated among higher-paid and more digitally visible employees, potentially limiting generalizability to lower-wage or informal labor markets. Second, although our designs exploit rich fixed effects and quasi-random variation in ratings, we cannot fully rule out that Glassdoor coverage or ratings are correlated with unobserved firm (e.g., unobserved performance-related factors) or market characteristics (e.g., unobserved skill shortages) that independently affect matching outcomes. Third, although the anonymous nature of Glassdoor prevents us from linking individual reviews to subsequent separations, our use of directional firm-to-peer flow measures should mitigate concerns that relative ratings mechanically reflect employees' already-secured moves to specific peer firms; nevertheless, we cannot fully rule out this possibility. Finally, our results pertain to public firms in U.S. MSAs during a period of rapid growth in online workplace platforms and may not generalize to other firm types or time periods.

Figure 1. Growth of Glassdoor

Panel A. Unique establishments on Glassdoor



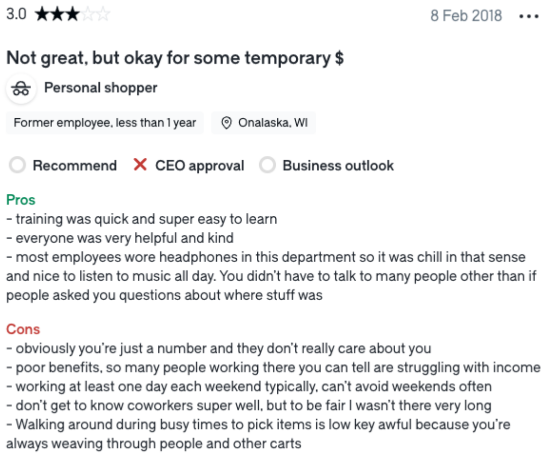
Panel B. New Glassdoor ratings per year



This figure depicts the expansion of Glassdoor coverage over time in our sample. Panels A and B depict, respectively, the total number of unique establishments on Glassdoor, and the total number of new Glassdoor ratings in each year.

Figure 2. Examples of Glassdoor ratings

Panel A. Neutral Glassdoor review


3.0 ★★★☆☆ 8 Feb 2018 ...

Not great, but okay for some temporary $

Personal shopper

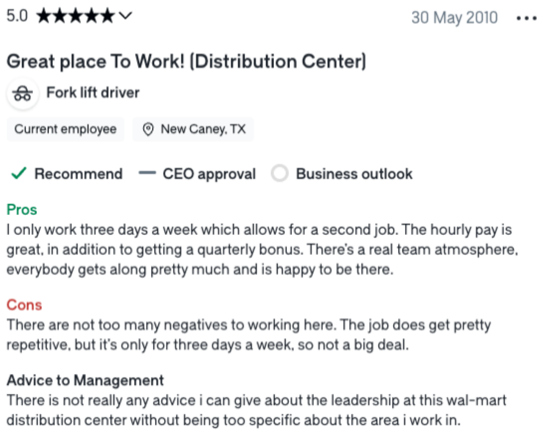
Former employee, less than 1 year | Onalaska, WI

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

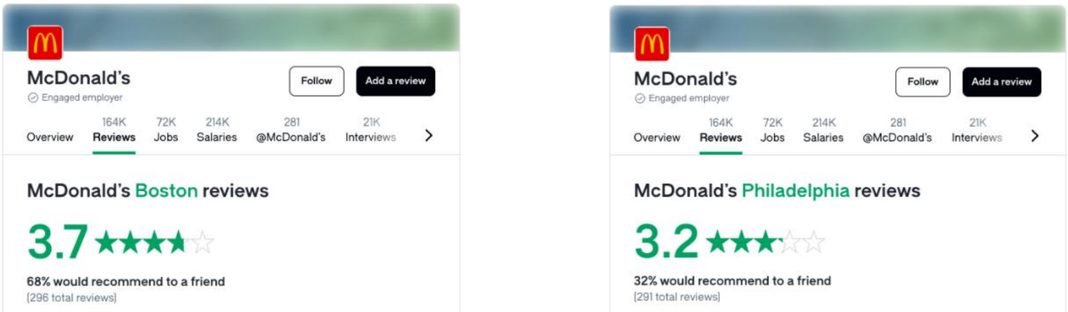
Pros
The only thing I could think of was my co-workers who I will miss

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.

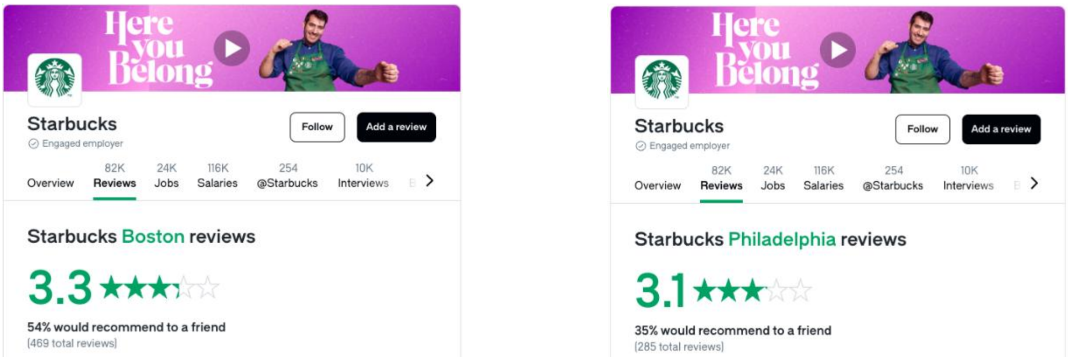
This figure depicts three examples of Glassdoor reviews. Panels A through C depict, respectively, a neutral, favorable, and unfavorable review.

Figure 3. Relative ratings

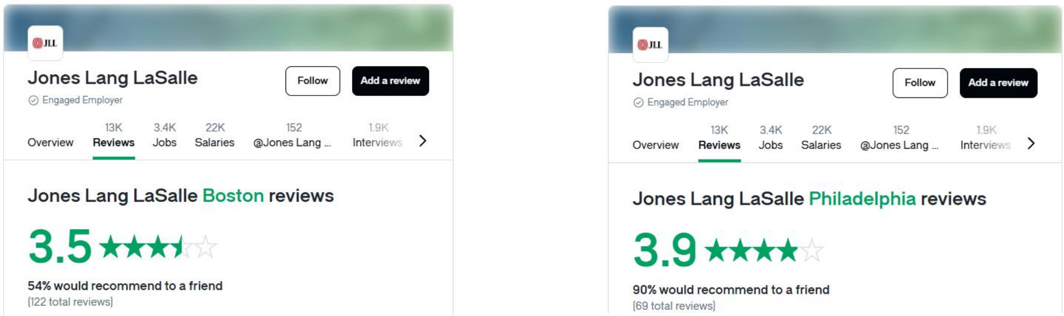
Panel A. Absolute ratings of McDonald's Corporation



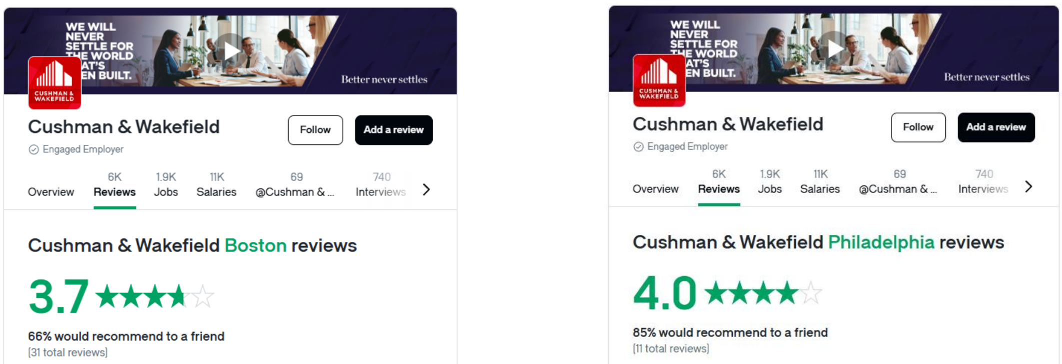
Panel B. Absolute ratings of Starbucks Corporation



Panel C. Absolute ratings of Jones Lang LaSalle Inc.



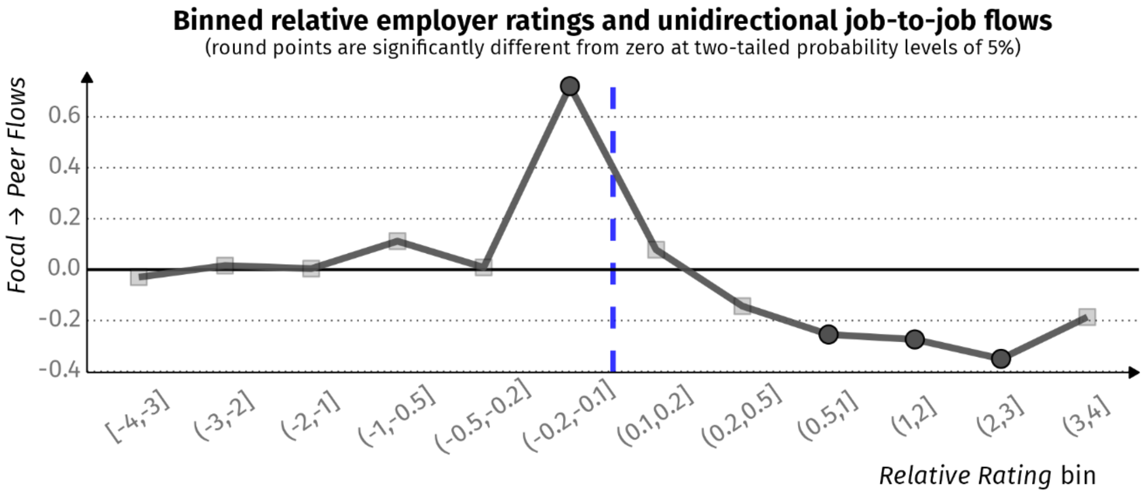
Panel D. Absolute ratings of Cushman & Wakefield Inc.



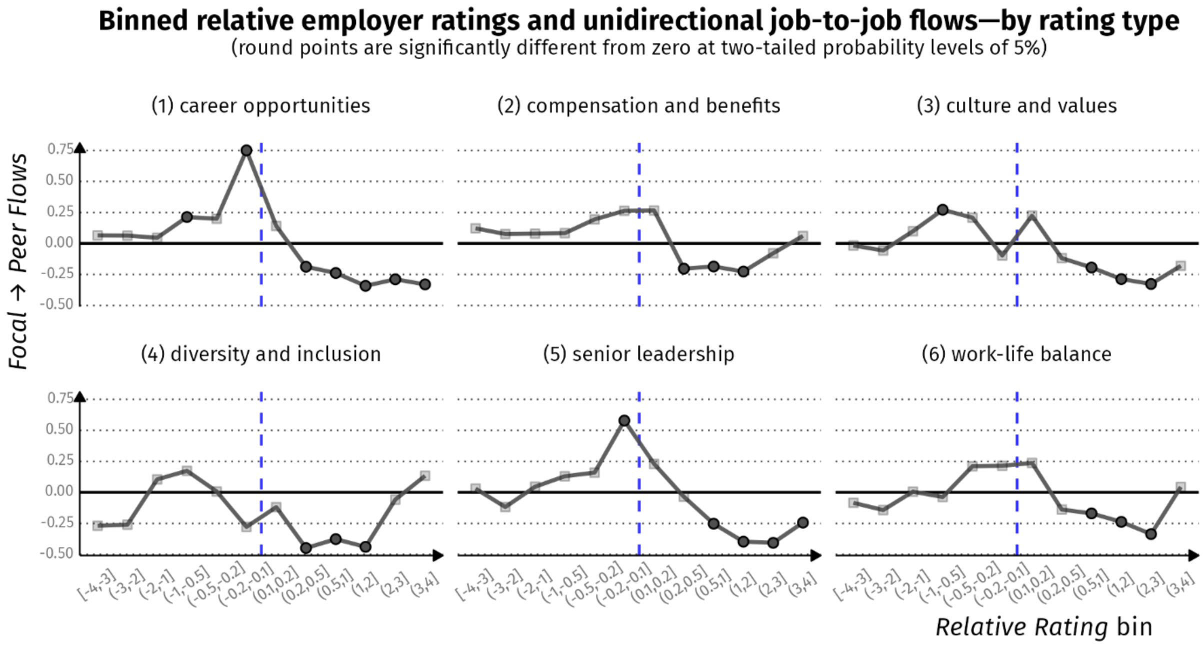
This figure depicts snapshots from Glassdoor and presents absolute ratings of firms across two MSAs: Boston-Cambridge-Newton and Philadelphia-Camden-Wilmington.

Figure 4. Relative Glassdoor ratings and unidirectional job-to-job flows

Panel A. Overall ratings and unidirectional job-to-job flows



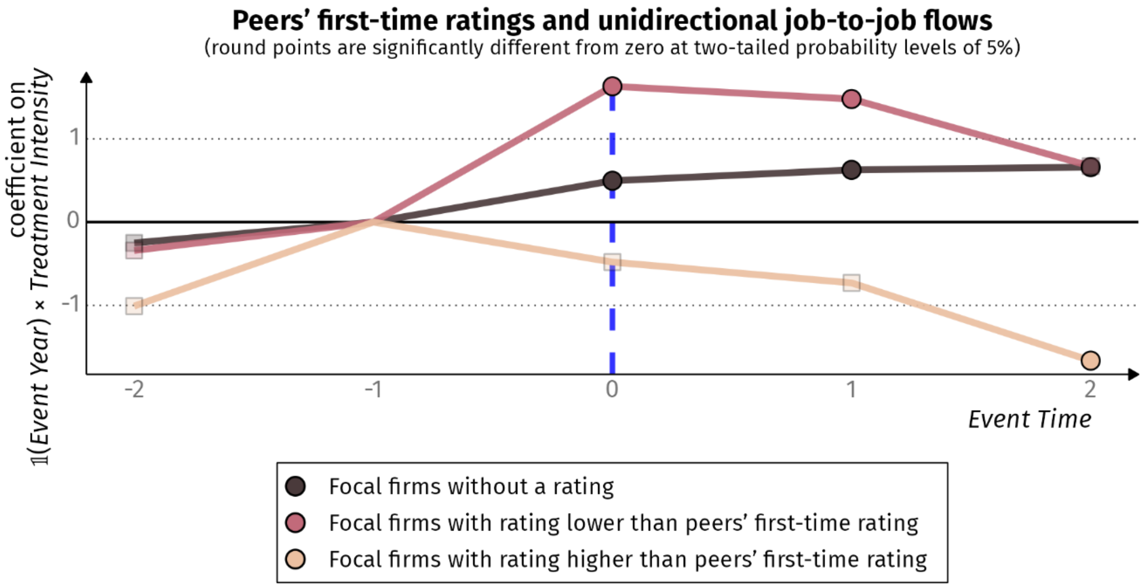
Panel B. Rating types and unidirectional job-to-job flows



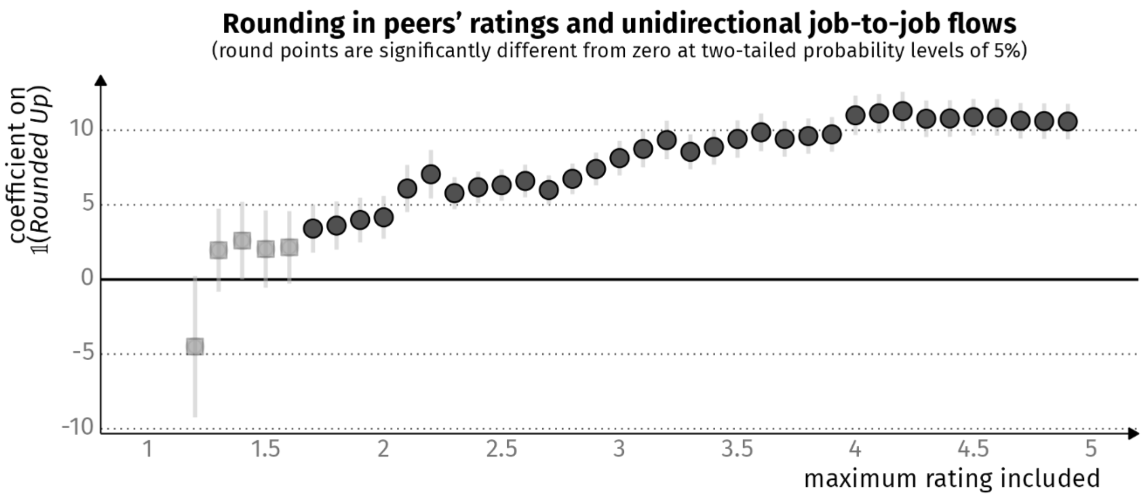
This figure, which accompanies Table 4, depicts the relation between relative Glassdoor ratings and unidirectional job-to-job flows from a focal establishment to a peer establishment within the same MSA and industry with employment gaps shorter than 183 days. Panel A depicts the relation across bins of the *Relative Rating* variable. Panel B depicts the relation across bins of the *Relative Rating* variable, constructed for the six different underlying rating dimensions. In both panels, we partition the *Relative Rating* variable into bins and estimate regression specifications analogous to those in Table 4 Column (6), using observations with relative ratings in (–0.1, 0.1] as the baseline group. Each panel plots the estimated coefficients on the relative rating bins, with round points significantly different from zero at two-tailed probability levels of 5%.

Figure 5. The information-facilitating role of Glassdoor ratings

Panel A. Peers' first-time ratings



Panel B. Rounding in peers' ratings



This figure depicts the relation between peer rating attributes and unidirectional job-to-job flows from a focal establishment to a peer establishment within the same MSA and industry with employment gaps shorter than 183 days. Panel A, which accompanies Table 5 Panel A, decomposes 𝟙(*Post*) into event-year-specific indicators and plots the estimated coefficients on 𝟙(*Event Year*) × *Treatment Intensity*, benchmarked to the year immediately prior to the first-rating period, i.e., period $t = -1$. Estimates are shown separately for: (1) focal firms without a rating themselves; (2) focal firms with a rating that is lower than peers' first-time rating; and (3) focal firms with a rating that is higher than peers' first-time rating. Panel B, which accompanies Table 5 Panel B, examines heterogeneity across rating thresholds by cumulatively including thresholds up to a given star cutoff and plotting the corresponding estimated coefficients on 𝟙(*Rounded Up*), with vertical bars indicating 95% confidence intervals. In both panels, round points are significantly different from zero at two-tailed probability levels of 5%.

Table 1. Sample composition

Panel A. Sample selection

Step	Selection criteria	Unique observations: Firm	Firm-peer-year	Firm-peer-MSA-year
(1)	Start with Compustat firm-peer-year pairs for which at least one firm has a Glassdoor presence at any point in the sample period	6,070	5,007,084	——
(2)	Require Glassdoor data at the firm-year-MSA level, restricting sample to years and MSAs in which both firms are rated	5,082	930,534	4,523,795
(3)	Require Revelio data at the firm-year-MSA level, restricting sample to observations for which we can observe matching outcomes	3,026	479,737	2,246,437
Average number of peers per firm-MSA-year:				8.214

Panel B. Distribution by year

Year	Firms	MSAs	Establishments	Number of ratings	Average rating
2008	534	70	1,688	7,563	3.118
2009	723	84	3,012	6,886	3.051
2010	933	92	4,800	11,107	2.997
2011	1,130	96	6,794	13,791	2.983
2012	1,303	96	9,192	23,796	3.080
2013	1,487	97	11,878	36,821	3.108
2014	1,708	97	15,184	60,693	3.148
2015	1,912	97	19,307	94,169	3.198
2016	2,025	97	21,964	97,621	3.268
2017	2,092	98	23,008	82,425	3.301
2018	2,185	98	23,975	65,628	3.300
2019	2,282	98	25,297	76,314	3.335
2020	2,356	98	27,096	123,624	3.532
2021	2,434	98	29,751	239,289	3.624
2022	2,331	98	26,447	163,946	3.591
2023	2,209	98	22,822	194,702	3.556

Table 1. Sample composition (continued)

Panel C. Distribution by two-digit GICS sector

Two-digit GICS sector	Firms	MSAs	Establishments	Number of ratings	Average rating
10: Energy	137	62	731	20,062	3.482
15: Materials	117	92	1,064	13,161	3.331
20: Industrials	468	96	8,782	174,958	3.342
25: Consumer discretionary	438	98	11,882	398,886	3.250
30: Consumer staples	122	98	2,414	115,423	3.244
35: Health care	529	96	5,678	112,787	3.359
40: Financials	378	95	4,605	184,825	3.454
45: Information technology	500	93	5,930	178,301	3.605
50: Telecommunication	150	97	1,859	75,020	3.271
55: Utilities	60	45	262	6,479	3.599
60: Real estate	106	84	1,074	18,473	3.625

Panel D. Largest MSAs, by population

MSA	Establishments	Number of ratings	Average rating	Revelio employees
1: New York-Newark-Jersey City	764	129,188	3.305	535,526
2: Los Angeles-Long Beach-Anaheim	676	59,381	3.285	407,792
3: Chicago-Naperville-Elgin	612	52,937	3.274	346,665
4: Dallas-Fort Worth-Arlington	578	51,278	3.289	329,026
5: Houston-Pasadena-The Woodlands	516	38,527	3.305	280,184
6: Philadelphia-Camden-Wilmington	369	15,066	3.222	158,748
7: Miami-Fort Lauderdale-West Palm Beach	388	20,294	3.358	151,507
8: Atlanta-Sandy Springs-Roswell	525	40,478	3.312	299,492
9: Boston-Cambridge-Newton	434	32,785	3.428	243,461
10: San Francisco-Oakland-Fremont	553	82,469	3.349	329,339

This table summarizes the sample. Panel A outlines the sample selection procedure. Panel B reports mean statistics over time. Panel C reports mean statistics by two-digit GICS sector. Panel D presents summary statistics for the ten largest MSAs.

Table 2. Summary statistics

MSA-industry-year-level variables	*N*	Mean	σ	Zero-σ MSAs	Zero-σ industries	Zero-σ years	Within-FE-σ	After-FE-σ
Match Incidence	214,908	0.219	0.616	1.030%	20.690%	0.000%	0.473	76.770%
Match Duration	214,908	7.553	0.632	0.000%	0.000%	0.000%	0.585	92.532%
Match Progression	214,908	0.078	0.109	0.000%	0.570%	0.000%	0.105	95.835%
%Glassdoor	214,908	0.207	0.282	0.000%	0.570%	0.000%	0.202	71.724%
Google Search Index	214,908	46.033	29.129	0.000%	0.000%	0.000%	28.814	98.918%
log(*Firms*)	214,908	1.741	0.777	0.000%	4.600%	0.000%	0.311	40.047%
Labor Concentration	214,908	0.538	0.292	0.000%	4.600%	0.000%	0.193	65.919%
log(*Population*)	214,908	14.074	1.007	0.000%	0.000%	0.000%	0.030	2.989%
log(*GDP*)	214,908	18.107	1.147	0.000%	0.000%	0.000%	0.055	4.809%

Firm-peer-MSA-year-level variables	*N*	Mean	σ	Zero-σ firms	Zero-σ MSAs	Zero-σ years	Within-FE-σ	After-FE-σ
Focal → Peer Flows	2,246,437	4.641	25.780	37.800%	3.100%	0.000%	23.524	91.249%
Relative Rating	2,246,437	0.016	1.532	0.200%	0.000%	0.000%	1.335	87.146%
Absolute Rating	2,246,437	3.448	1.107	9.100%	0.000%	0.000%	0.919	83.035%
log(*Employees*)	2,246,437	4.157	1.579	8.200%	0.000%	0.000%	0.960	60.777%

This table presents summary statistics on the main variables included in our regression analysis, including the percentage of observations with zero variation in specific groups, the within-group standard deviation that remains after applying relevant fixed effects, and the percentage of the total standard deviation that remains after controlling for these fixed effects. For variables measured at the MSA-industry-year level, we compute within-FE-σ and after-FE-σ based on MSA, industry, and year fixed effects, except for *Google Search Index* where we only use MSA and industry fixed effects. For variables measured at the firm-peer-MSA-year level, we compute within-FE-σ and after-FE-σ based on firm-by-year, peer-by-year, and MSA-by-year fixed effects.

Table 3. Aggregate effects of Glassdoor's presence in local labor markets

Panel A. Ordinary least squares

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable:					
	Match Incidence		*Match Duration*		*Match Progression*	
%Glassdoor	0.253***	0.240***	0.091***	0.137***	0.015***	0.018***
	(0.045)	(0.047)	(0.020)	(0.018)	(0.002)	(0.003)
log(*Firms*)	0.398***	0.373***	(0.021)	0.056***	0.006**	0.006**
	(0.062)	(0.063)	(0.018)	(0.018)	(0.002)	(0.003)
Labor Concentration	0.492***	0.492***	–0.238***	–0.232***	0.012***	0.011***
	(0.070)	(0.071)	(0.026)	(0.024)	(0.003)	(0.003)
log(*Population*)	–0.021	———	0.221*	———	–0.011	———
	(0.101)		(0.124)		(0.014)	
log(*GDP*)	0.194***	———	–0.125**	———	–0.001	———
	(0.052)		(0.061)		(0.009)	
Fixed effects	MSA Industry Year	MSA×Year Industry×Year	MSA Industry Year	MSA×Year Industry×Year	MSA Industry Year	MSA×Year Industry×Year
Observations	214,908	214,908	214,908	214,908	214,908	214,908
Adjusted R^2	45.249%	46.103%	14.929%	17.549%	8.151%	8.609%

Table 3. Aggregate effects of Glassdoor's presence in local labor markets (continued)

Panel B. Two-stage least squares

	(1)	(2)	(3)	(4)
Stage:	First		Second	
			Dependent variable:	
Variable:	*%Glassdoor*	*Match Incidence*	*Match Duration*	*Match Progression*
$\widehat{\%Glassdoor}$	———	0.424***	1.641***	0.073***
		(0.121)	(0.285)	(0.027)
Google Search Index	0.108***	———	———	———
	(0.012)			
log(*Firms*)	0.001	0.397***	0.014	0.005**
	(0.013)	(0.063)	(0.022)	(0.002)
Labor Concentration	0.079***	0.479***	–0.360***	0.007*
	(0.014)	(0.072)	(0.047)	(0.004)
log(*Population*)	–0.246*	0.285***	1.332***	0.094***
	(0.131)	(0.093)	(0.332)	(0.020)
log(*GDP*)	0.504***	–0.222***	–1.865***	–0.131***
	(0.033)	(0.064)	(0.155)	(0.016)
Fixed effects (in all specifications)			MSA, Industry	
Observations	214,908	214,908	214,908	214,908
Adjusted R^2	45.249%	———	———	———
First-stage strength test:				
(1) Kleibergen and Paap (2006)	214.900	———	———	———
Weak identification tests:				
(1) Cragg and Donald (1993)	2,640.400	———	———	———
(2) Olea and Pflueger (2013)	77.520	———	———	———
Endogeneity test:				
(1) Durbin (1954)-Wu (1973)-Hausman (1978)	———	16.400	773.900	34.600

Table 3. Aggregate effects of Glassdoor's presence in local labor markets (continued)

This table reports tests of the aggregate effects of Glassdoor's presence within a given MSA-industry-year observation, focusing on three outcomes: (1) match incidence, measured as the log of the number of within-MSA-industry-year job-to-job flows with employment gaps shorter than 183 days; (2) match duration, measured as the log of the average remaining tenure of current workers; and (3) match progression, measured as the average future promotion rate among current workers. Panel A presents ordinary least squares estimates. The independent variable of interest is *%Glassdoor*, defined as the percentage of firms within each MSA-industry-year cell that have at least one rating on Glassdoor. For each dependent variable, the two columns differ in the fixed-effects structure, which changes the set of comparisons underlying identification. Panel B presents two-stage least squares estimates. Column (1) presents the first-stage regression of *%Glassdoor* on the state-year Google search index for *Glassdoor*. Columns (2) through (4) present the second-stage regression of the three outcomes on the fitted value from the first stage. All specifications in Panel B include MSA and industry fixed effects. In both panels, we do not report the coefficient estimates and standard errors of the fixed effects for brevity. Standard errors are in parentheses and are adjusted for within-cluster correlation at the MSA and industry levels. *, **, and *** denote that the coefficient is significantly different from zero at, respectively, two-tailed probability levels of 10%, 5%, and 1%. In Panel B, we also report adjusted R^2 values, Kleibergen and Paap (2006) strength test statistics, and Cragg and Donald (1993) and Olea and Pflueger (2013) weak-instrument test statistics for the first stage, as well as Durbin (1954)-Wu (1973)-Hausman (1978) test statistics for endogeneity of the instrumented regressor in the second stage. For the second stage, we do not report R^2 values as they are not informative.

Table 4. Relative Glassdoor ratings and unidirectional job-to-job flows

	(1)	(2)	(3)	(4)	(5)	(6)
Variable:	Dependent variable: *Focal* → *Peer Flows*					
Relative Rating	–0.110***	–0.091***	–0.032***	–0.028***	–0.028**	–0.071***
	(0.029)	(0.023)	(0.011)	(0.011)	(0.012)	(0.015)
log(*Employees*)	3.249***	2.633***	2.838***	3.317***	3.493***	2.960***
	(0.252)	(0.172)	(0.194)	(0.188)	(0.214)	(0.242)
log(*Peer Employees*)	3.147***	3.055***	2.733***	3.199***	3.402***	4.295***
	(0.232)	(0.227)	(0.180)	(0.182)	(0.207)	(0.337)
Fixed effects	None	Firm×Year	Firm×Year Peer×Year	Firm×Year Peer×Year MSA×Year	Firm×Year Peer×Year Firm×Peer MSA×Year	Firm×Peer×MSA MSA×Year
Observations	2,246,437	2,246,437	2,246,437	2,246,437	2,246,437	2,246,437
Adjusted R^2	9.275%	14.785%	17.625%	18.026%	21.606%	33.823%

This table reports tests of the relation between relative Glassdoor ratings and worker flows, using a panel dataset at the firm-peer-MSA-year level. The dependent variable measures unidirectional job-to-job flows from a focal establishment to a peer employer within the same MSA and industry with employment gaps shorter than 183 days. The independent variable of interest is *Relative Rating*, defined as the difference between the focal establishment's overall workplace rating and that of a peer within the same MSA and year. Column (1) presents a specification without fixed effects, and each subsequent column alters the fixed-effects structure to change the set of comparisons underlying identification. We do not report the coefficient estimates and standard errors of the fixed effects for brevity. Standard errors are in parentheses and are adjusted for within-cluster correlation at the firm, peer, and MSA levels. *, **, and *** denote that the coefficient is significantly different from zero at, respectively, two-tailed probability levels of 10%, 5%, and 1%. Figure 4 accompanies this table by plotting the coefficient estimates from Column (6) across bins of the *Relative Rating* variable and across bins of the *Relative Rating* variable, constructed for different underlying rating dimensions, respectively.

Table 5. The information-facilitating role of Glassdoor ratings

Panel A. Peers' first-time ratings

	(1)	(2)	(3)
Control group:	Focal firms without a rating	Focal firms with rating lower than peers' first-time rating	Focal firms with rating higher than peers' first-time rating
Variable:	Dependent variable: *Focal → Peer Flows*		
𝟙(*Post*) × *Treatment Intensity*	0.719***	1.430***	–0.454
	(0.095)	(0.506)	(0.550)
Fixed effects (in all specifications)	Event, Event Time×Rating Bin		
Observations	1,286,325	154,335	160,225
Adjusted R^2	34.156%	38.807%	38.587%

Panel B. Rounding in peers' ratings

	(1)	(2)	(3)	(4)	(5)
Rounding thresholds:	All	Within [1, 2)	Within [2, 3)	Within [3, 4)	Within [4, 5]
Variable:	Dependent variable: *Focal → Peer Flows*				
𝟙(*Rounded Up*)	11.327***	3.990***	7.034***	10.007***	12.471***
	(0.639)	(0.765)	(0.583)	(0.625)	(0.761)
Fixed effects (in all specifications)	Firm, Peer, MSA, Year				
Observations	2,246,416	190,949	352,188	736,936	966,343
Adjusted R^2	12.923%	8.864%	13.436%	18.024%	8.847%

Table 5. The information-facilitating role of Glassdoor ratings (continued)

This table reports two tests of Glassdoor's information-facilitating role, both examining the relation between peer rating attributes and unidirectional job-to-job flows from a focal establishment to a peer establishment within the same MSA and industry with employment gaps shorter than 183 days. Panel A presents a peer spillover analysis focusing on peers' first-time Glassdoor ratings. The analysis uses a stacked event-study framework with a [–2, +2] year window around each peer's first rating, yielding five firm-year observations per event over the window. Every event involves at least one peer establishment receiving its first rating, but some events involve multiple peers, which generates the variation in *Treatment Intensity* (i.e., the number of peers receiving a first rating in the event year $t = 0$). The post-period indicator $\mathbb{1}(Post)$ equals one for years in [0, +2]. Each column reflects a different control group: (1) focal firms without a rating themselves; (2) focal firms with a rating that is lower than peers' first-time rating; and (3) focal firms with a rating that is higher than peers' first-time rating. All specifications include event and event-time-by-0.25 rating bin fixed effects, which absorb the main effects of *Treatment Intensity* and $\mathbb{1}(Post)$, respectively. Panel B presents an analysis that exploits plausibly exogenous variation in displayed peer ratings created by Glassdoor's rounding algorithm, which rounds ratings to the nearest tenth before displaying them on the platform (e.g., a true rating of 3.251 is displayed as 3.3, whereas a true rating of 3.249 is displayed as 3.2). This analysis focuses on cases with peer ratings within {±0.01, ±0.05} of a threshold, comparing unidirectional job-to-job flows when a peer's rating is rounded up versus when it is rounded down or unaffected by rounding. The treatment indicator $\mathbb{1}(Rounded\ Up)$ equals one when the peer's rating is rounded up. Each column reflects a different rounding threshold: (1) all thresholds pooled; (2) thresholds within displayed ratings in [1, 2); (3) thresholds within displayed ratings in [2, 3); (4) thresholds within displayed ratings in [3, 4); and (5) thresholds within displayed ratings in [4, 5]. All specifications include the running variable as well as firm, peer, MSA, and year fixed effects. In both panels, we do not report the coefficient estimates and standard errors of the fixed effects for brevity. Standard errors are in parentheses and are adjusted for within-cluster correlation at the firm level. *, **, and *** denote that the coefficient is significantly different from zero at, respectively, two-tailed probability levels of 10%, 5%, and 1%. Figure 5 accompanies this table by plotting the coefficient estimates from Panels A and B across event years and rating thresholds, respectively.

Table 6. Relative Glassdoor ratings and worker flows—by employee characteristics

Panel A. Heterogeneity in job categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable restricted to:	Admin	Engineer	Finance	Marketing	Operations	Sales	Scientist
Variable:	Dependent variable: *Focal* → *Peer Flows*						
Relative Rating	–0.006***	–0.007	–0.011***	–0.002	–0.005*	–0.022***	0.003
	(0.002)	(0.012)	(0.002)	(0.003)	(0.002)	(0.007)	(0.004)
log(*Employees*)	0.499***	2.777***	1.233***	0.401***	0.395***	1.270***	0.431***
	(0.074)	(0.420)	(0.395)	(0.043)	(0.042)	(0.121)	(0.099)
log(*Peer Employees*)	0.437***	2.629***	1.036***	0.358***	0.378***	1.150***	0.389***
	(0.057)	(0.398)	(0.316)	(0.035)	(0.038)	(0.114)	(0.093)
Fixed effects (in all specifications)	Firm×Year, Peer×Year, MSA×Year						
Observations	2,246,437	2,246,437	2,246,437	2,246,437	2,246,437	2,246,437	2,246,437
Adjusted R^2	1.300%	3.287%	12.580%	3.711%	3.742%	3.742%	7.903%

Panel B. Heterogeneity in job seniority

	(1)	(2)	(3)	(4)
Dependent variable restricted to:	Interns, Juniors, and Associates	Managers and Directors	Executives	Senior Executives
Variable:	Dependent variable: *Focal* → *Peer Flows*			
Relative Rating	–0.031**	–0.018**	–0.000	0.000
	(0.013)	(0.007)	(0.002)	(0.000)
log(*Employees*)	4.270***	2.321***	0.387***	0.028***
	(0.554)	(0.265)	(0.062)	(0.004)
log(*Peer Employees*)	4.069***	1.970***	0.316***	0.022***
	(0.498)	(0.211)	(0.045)	(0.003)
Fixed effects (in all specifications)	Firm×Year, Peer×Year, MSA×Year			
Observations	2,246,437	2,246,437	2,246,437	2,246,437
Adjusted R^2	7.109%	4.691%	1.163%	2.180%

Table 6. Relative Glassdoor ratings and worker flows—by employee characteristics (continued)

Panel C. Heterogeneity in remote job suitability

	(1)	(2)
Dependent variable restricted to:	Below	Above
	Median remote job suitability	
Variable:	Dependent variable: *Focal → Peer Flows*	
Relative Rating	–0.077***	–0.018
	(0.026)	(0.019)
log(*Employees*)	5.765***	6.036***
	(0.794)	(0.758)
log(*Peer Employees*)	5.451***	5.357***
	(0.717)	(0.636)
Fixed effects (in both specifications)	Firm×Year, Peer×Year, MSA×Year	
Observations	2,246,437	2,246,437
Adjusted R^2	8.869%	4.066%
Difference in *Relative Rating*	0.060*	

This table reports three cross-sectional tests of whether the relation between relative Glassdoor ratings and worker flows varies with employee characteristics. Panels A through C examine, respectively, heterogeneity in job categories, job seniority levels, and remote job suitability. In all panels, we restrict the dependent variable—unidirectional job-to-job flows from a focal establishment to a peer establishment within the same MSA and industry with employment gaps shorter than 183 days—to flows within a given job category, seniority level, or subsample of the remote job suitability score, as defined by Revelio Labs. All specifications include firm-by-year, peer-by-year, and MSA-by-year fixed effects. In all panels, we do not report the coefficient estimates and standard errors of the fixed effects for brevity. In Panel C, in order to test for differences in coefficient estimates between the two subsamples using two-sided *Z*-tests, we scale the dependent variables prior to estimation to have mean values of zero and standard deviation values of one. Standard errors are in parentheses and are adjusted for within-cluster correlation at the firm, peer, and MSA levels. *, **, and *** denote that the coefficient is significantly different from zero at, respectively, two-tailed probability levels of 10%, 5%, and 1%.

Table 7. Relative Glassdoor ratings and worker flows—by firm attributes

Panel A. Heterogeneity in peer rating attributes

	(1)	(2)	(3)	(4)	(5)	(6)
Sample partitioned by:	Below Median peer rating count	Above Median peer rating count	Peer review complete No	Peer review complete Yes	Below Median peer review length	Above Median peer review length
Variable:	Dependent variable: *Focal → Peer Flows*					
Relative Rating	–0.011	–0.095***	–0.012	–0.046***	–0.031	–0.150***
	(0.011)	(0.024)	(0.013)	(0.014)	(0.033)	(0.042)
log(*Employees*)	1.201***	5.258***	1.056***	4.067***	3.994***	6.233***
	(0.094)	(0.303)	(0.078)	(0.234)	(0.318)	(0.458)
log(*Peer Employees*)	1.441***	3.933***	1.200***	3.633***	4.193***	4.710***
	(0.117)	(0.211)	(0.096)	(0.204)	(0.386)	(0.334)
Fixed effects (in all specifications)	Firm×Year, Peer×Year, MSA×Year					
Observations	1,123,222	1,123,215	568,965	1,677,472	189,208	189,200
Adjusted R^2	11.912%	23.167%	11.912%	20.036%	18.715%	21.199%
Difference in *Relative Rating*	–0.084***		–0.033*		–0.119**	

Table 7. Relative Glassdoor ratings and worker flows—by firm attributes (continued)

Panel B. Heterogeneity in labor market competition attributes

	(1)	(2)	(3)	(4)
Sample partitioned by:	Below	Above	Peer is larger than focal	
	Median pairwise concentration		No	Yes
Variable:	Dependent variable: *Focal → Peer Flows*			
Relative Rating	–0.004	–0.063***	0.020	–0.081***
	(0.007)	(0.018)	(0.020)	(0.024)
log(*Employees*)	0.765***	5.758***	1.980***	5.219***
	(0.069)	(0.394)	(0.151)	(0.401)
log(*Peer Employees*)	0.728***	5.474***	5.284***	1.589***
	(0.061)	(0.358)	(0.392)	(0.149)
Fixed effects (in all specifications)	Firm×Year, Peer×Year, MSA×Year			
Observations	1,129,652	1,129,645	1,218,160	1,028,277
Adjusted R^2	9.355%	22.620%	22.289%	19.737%
Difference in *Relative Rating*	–0.059***		–0.101***	

Panel C. Heterogeneity in peer recruitment attributes

	(1)	(2)	(3)	(4)
Sample partitioned by:	Peer has more ads than focal		Below	Above
	No	Yes	Median peer Jensen-Shannon divergence	
Variable:	Dependent variable: *Focal → Peer Flows*			
Relative Rating	0.041	–0.099***	–0.183**	–0.016
	(0.035)	(0.036)	(0.073)	(0.032)
log(*Employees*)	3.141***	5.237***	7.366***	2.557***
	(0.260)	(0.493)	(0.585)	(0.255)
log(*Peer Employees*)	5.204***	2.756***	5.373***	2.466***
	(0.450)	(0.238)	(0.415)	(0.258)
Fixed effects (in all specifications)	Firm×Year, Peer×Year, MSA×Year			
Observations	289,549	327,180	189,208	189,200
Adjusted R^2	20.929%	19.159%	24.756%	15.101%
Difference in *Relative Rating*	–0.140***		0.167**	

This table reports six cross-sectional tests of whether the relation between relative Glassdoor ratings and worker flows varies with firm attributes. Panels A through C examine, respectively, heterogeneity in peer rating attributes, labor market competition attributes, and peer recruitment attributes. In Panel A, we split the sample based on peer rating count (low versus high), peer review completeness (incomplete versus complete reviews), and average peer review length (low versus high). In Panel B, we split the sample based on pairwise labor concentration (low versus high) and relative firm size (smaller versus larger peers). In Panel C, we split the sample based on relative job ads (fewer versus more peer ads) and the Jensen-Shannon divergence between peers' job-posting language and their Glassdoor reviews (low versus high). All specifications include firm-by-year, peer-by-year, and MSA-by-year fixed effects. In all panels, we do not report the coefficient estimates and standard errors of the fixed effects for brevity. We test for differences in coefficient estimates between the two subsamples using two-sided Z-tests. Standard errors are in parentheses and are adjusted for within-cluster correlation at the firm, peer, and MSA levels. *, **, and *** denote that the coefficient is significantly different from zero at, respectively, two-tailed probability levels of 10%, 5%, and 1%.

Table 8. Relative Glassdoor ratings and worker flows—by institutional features

Panel A. Best Places to Work awards

Variable:	(1) Dependent variable: *Focal → Peer Flows*
Relative Rating × 𝟙(*Peer Award*)	0.321**
	(0.151)
Relative Rating	–0.035***
	(0.011)
𝟙(*Peer Award*)	0.719
	(0.877)
log(*Employees*)	3.317***
	(0.188)
log(*Peer Employees*)	3.197***
	(0.182)
Fixed effects	Firm×Year, Peer×Year, MSA×Year
Observations	2,246,437
Adjusted R^2	18.027%

Panel B. Colorado's Equal Pay for Equal Work Act

	(1)	(2)
Subsample:	Treated	Control
Variable:	Dependent variable: *Focal → Peer Flows*	
Relative Rating × 𝟙(*Post*)	–0.884**	–0.203
	(0.395)	(0.157)
Relative Rating	0.093	0.112
	(0.271)	(0.100)
log(*Employees*)	4.899***	3.407***
	(1.232)	(0.608)
log(*Peer Employees*)	4.632***	3.352***
	(0.756)	(0.520)
Fixed effects (in both specifications)	Firm×Year, Peer×Year, MSA×Year	
Observations	33,663	51,615
Adjusted R^2	22.143%	14.285%

Table 8. Relative Glassdoor ratings and worker flows—by institutional features (continued)

Panel C. Introduction of Business Outlook ratings

	(1)	(2)
Subsample:	Treated	Control
	Dependent variable:	
Variable:	*Focal → Peer Flows*	
Relative Business Outlook Rating × 𝟙(*Post*)	–0.914**	–0.203
	(0.368)	(0.201)
log(*Employees*)	7.884***	5.989***
	(0.931)	(0.573)
log(*Peer Employees*)	8.251***	6.562***
	(0.886)	(0.582)
Fixed effects (in both specifications)	Firm×Year, Peer×Year, MSA×Year	
Observations	24,396	129,314
Adjusted R^2	29.881%	27.023%

This table reports three cross-sectional tests of whether the relation between relative Glassdoor ratings and worker flows varies with institutional features. Panels A through C examine, respectively, heterogeneity associated with peers' *Best Places to Work* awards on Glassdoor, the introduction of Colorado's *Equal Pay for Equal Work Act* in 2021, and the introduction of Glassdoor's Business Outlook rating in 2012. In Panel A, we interact *Relative Rating* with 𝟙(*Peer Award*), which is an indicator equal to one if the peer received the award, and zero otherwise. In Panel B, we implement a [–2, 2] year event-study design around the 2021 Act, classifying observations as treated if they are located in MSAs entirely within Colorado, and as controls if they are located in one of Colorado's seven neighboring states (i.e., Utah, Arizona, New Mexico, Oklahoma, Kansas, Nebraska, or Wyoming), excluding any MSAs that cross into Colorado. 𝟙(*Post*) is an indicator equal to one for the period after the Act, and zero otherwise. In Panel C, we implement a [–2, 2] year event-study design around the 2012 introduction, classifying observations as treated if the focal and peer firm fall into the same stock-return decile in the first year of the event period, and as controls otherwise. *Relative Business Outlook Rating* measures the difference between the focal establishment's business outlook rating and that of a peer within the same MSA and year, which we set to zero in the period before its introduction. 𝟙(*Post*) is an indicator equal to one for the period after the introduction, and zero otherwise. All specifications include firm-by-year, peer-by-year, and MSA-by-year fixed effects. In all panels, we do not report the coefficient estimates and standard errors of the fixed effects for brevity. Standard errors are in parentheses and are adjusted for within-cluster correlation at the firm, peer, and MSA levels. *, **, and *** denote that the coefficient is significantly different from zero at, respectively, two-tailed probability levels of 10%, 5%, and 1%.

Appendix A. Variable definitions

Panel A. Variables used in aggregate tests

Variable	Description and data source(s)
Match Incidence	Natural log of the number of within-MSA-industry job-to-job matches formed in a given year, defined as transitions between firms with an employment gap shorter than 183 days, aggregated to the MSA-industry-year level. Data come from Revelio Labs.
Match Duration	Natural log of the average remaining tenure (in years) of current employees within an MSA-industry-year cell, measured as expected future duration of ongoing employment spells. Data come from Revelio Labs.
Match Progression	Average future promotion rate among current employees within an MSA-industry-year cell, measured as the fraction of employees who experience an internal promotion within their current firm in any subsequent period. Data come from Revelio Labs.
%Glassdoor	Share of firms within an MSA-industry-year cell that have at least one Glassdoor rating by that year. Data come from Glassdoor and Revelio Labs.
Google Search Index	State-level Google Trends index for the exact search term *Glassdoor*, normalized within state over time by Google. Data come from Google Trends.
Firms	Total number of sample firms present in a given MSA. Data come from Revelio Labs and U.S. Bureau of Labor Statistics.
Labor Concentration	Herfindahl-Hirschman index of the share of employees per firms to the overall number of employees in a given MSA. Data come from Revelio Labs and U.S. Bureau of Labor Statistics.
Population	Total number of inhabitants in a given MSA. Data come from U.S. Bureau of Labor Statistics.
GDP	Total gross domestic product in nominal terms in a given MSA. Data come from U.S. Bureau of Labor Statistics.

Panel B. Variables used in firm-peer tests

Variable	Description and data source(s)
Focal → Peer Flows	Number of unidirectional job-to-job flows from the focal establishment to a specific peer establishment within the year, defined as transitions with employment gaps shorter than 183 days. In cross-sectional analyses, we restrict flows by *Occupation*, *Seniority*, and *Remote Suitability* (see details below). Data come from Glassdoor, Revelio Labs, and Compustat.
Relative Rating	Difference between the focal establishment and a specific peer establishment's Glassdoor rating within the same year, defined as focal rating minus peer rating (ranging from –4 to 4). In our main analysis, we compute *Relative Ratings* based on the overall Glassdoor rating. In cross-sectional analyses, we also compute variants based on subratings. Data come from Glassdoor, Revelio Labs, and Compustat.
(Peer) Employees	Natural log of the number of employees at the firm's (or peer's) establishment. Data come from Revelio Labs and Compustat.

(continued on next page)

Panel B. Variables used in firm-peer tests (continued)

Variable	Description and data source(s)
Peer Rating Count	Total number of Glassdoor ratings posted for a specific peer establishment within the year. Data come from Glassdoor.
Peer Review Complete	Share of peer establishment ratings within the year that contain non-missing entries for all six subratings: “career opportunities,” “compensation and benefits,” “culture and values,” “diversity and inclusion,” “senior management,” and “work-life balance.” Data come from Glassdoor.
Peer Review Length	Average number of words in the textual review component accompanying Glassdoor ratings for the peer establishment within the year. Data come from Glassdoor.
Pairwise Concentration	Combined employment share of the focal-peer establishment pair relative to total employment in the MSA-industry-year. Data come from Glassdoor, Revelio Labs, and Compustat.
Peer Ads	Number of active job advertisements posted by the peer establishment within the year. Data come from Lightcast.
Peer Jensen-Shannon	Jensen-Shannon divergence between the textual content of the peer establishment’s in the review component accompanying Glassdoor ratings and the textual content of the peer’s job advertisements. Data come from Glassdoor and Lightcast.
Occupation	Categorical classification of an employee’s primary job function, based on Revelio Labs standardized occupation taxonomy. Occupations are grouped into the following categories: “administration,” “engineering,” “finance,” “marketing,” “operations,” “sales,” and “scientific.” We use these categories to partition job-to-job flows in cross-sectional analyses. Data come from Revelio Labs.
Seniority	Categorical measure of an employee’s hierarchical position within the firm at the time of the job-to-job transition, based on Revelio Labs’ seniority classification. Seniority levels are grouped into the following categories: “interns/juniors,” “associates,” “managers/directors,” and “executives/senior executives.” We use these categories to partition job-to-job flows in cross-sectional analyses. Data come from Revelio Labs.
Remote Suitability	Measure of an employee’s job remote suitability, based on Revelio Labs’ occupation-level remote suitability score. We use this score to partition job-to-job flows in cross-sectional analyses. Data come from Revelio Labs.
Peer Award	Indicator equal to one if the peer firm receives a Glassdoor *Best Places to Work* award in the year, and zero otherwise. Data come from Glassdoor.

This appendix defines the variables used in the empirical analyses and describes their data sources. Variables are organized by unit of analysis. Peer establishments are firms that operate in the same eight-digit GICS industry with active employment in the same MSA as the focal firm.

Appendix B. Determinants of Glassdoor reviews

In this appendix, we 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:

$$[Review_{imt}] = \mathbf{B} \cdot X_{imt} + \mathbf{\Omega} \cdot \mu_m + \mathbf{\Lambda} \cdot \eta_t + \mathbf{T} \cdot \varphi_i + \varepsilon_{imt}, \tag{B1}$$

where i indexes firms, m indexes MSA 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-year-MSA level. Table B1 presents variable descriptions.

We include a variety of controls and fixed effects in Equation (B1) to ensure that our specification focuses on relevant within-group comparison. μ_m are MSA fixed effects that control for time-invariant features of the MSA, 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 establishments. We also estimate Equation (B1) 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 firm across its different MSA-establishments. This helps us 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 B2 presents results from estimating Equation (B1), 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 MSAs with higher gross domestic product and those with higher pay receive fewer reviews, whereas those with more employers and employees attract more. Firms that are more profitable and that offer higher pay to their employees also see more favorable ratings. Glassdoor-specific factors also play a significant role, as prior reviews predict new reviews, whereas 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 a given establishment, many reviews outside the focal MSA 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 between- and within-employer variation in unfavorable reviews. We also find that firms that are more profitable receive fewer unfavorable reviews. Prior ratings also predict positive reviews within employers and significantly reduce negative ones.

Consistent with prior studies on the determinants of ratings (deHaan et al., 2023), these results support the idea that Glassdoor ratings vary predictably with economic conditions, workforce composition, and prior Glassdoor activity. Although this evidence indicates that ratings reflect specific, relevant, and timely information, they may also be endogenous.

Table B1. Variable definitions

Variable	Description and data source(s)
Reviews	The total number of reviews. Data come from Glassdoor.
Absolute Rating	The focal employer's overall workplace rating in a given year-MSA. Data come from Glassdoor.
Favorable Reviews	The total number of favorable reviews, defined as reviews accompanied by a rating of at least four stars. Data come from Glassdoor.
Unfavorable Reviews	The total number of unfavorable reviews, defined as reviews accompanied by a rating below four stars. Data come from Glassdoor.
Population	Total number of inhabitants in a given MSA. Data come from U.S. Bureau of Economic Analysis.
GDP	Total gross domestic product in nominal terms in a given MSA. Data come from U.S. Bureau of Economic Analysis.
Per Capita Income	Total compensation divided by the total population in a given MSA. Data come from U.S. Bureau of Economic Analysis.
Firms	Total number of sample employers present in a given MSA. Data come from Revelio Labs and U.S. Bureau of Economic Analysis.
Labor Concentration	Herfindahl-Hirschman index of the share of employees per employer to the overall number of employees in a given MSA. Data come from Revelio Labs and U.S. Bureau of Economic Analysis.
ROA	The firm's annual return on assets. Data come from Compustat.
Return	The firm's annual stock return. Data come from Compustat.
Pay	Total (imputed) compensation of employees employed at an employer. Data come from Revelio Labs.
Employees	Total number of employees employed at an employer. Data come from Revelio Labs.
Employee Growth	Percentage change in total number of employees employed at a firm. Data come from Revelio Labs.
%Admin	Percentage of total number of employees classified as administrative. Data come from Revelio Labs.
%Engineer	Percentage of total number of employees classified as engineering. Data come from Revelio Labs.
%Finance	Percentage of total number of employees classified as financial. Data come from Revelio Labs.
%Marketing	Percentage of total number of employees classified as marketing. Data come from Revelio Labs.
%Operations	Percentage of total number of employees classified as operational. Data come from Revelio Labs.
%Scientific	Percentage of total number of employees classified as scientific. Data come from Revelio Labs.
Prior Rating	The average overall rating of all reviews in the prior year. Data come from Glassdoor.
Rating Outside MSA	The average overall rating of all reviews, except those in the MSA. Data come from Glassdoor.
Prior Reviews	The total number of reviews in the prior year. Data come from Glassdoor.
Reviews Outside MSA	The total number of reviews, except those in the MSA. Data come from Glassdoor.

This table presents variable definitions on the variables used in this appendix.

Table B2. Determinants of Glassdoor reviews and ratings

Panel A. All reviews and overall ratings

	(1)	(2)	(3)	(4)
	Dependent variable:		Dependent variable:	
Variable:	log(*Reviews*)		*Absolute Rating*	
MSA characteristics:				
log(*Population*)	0.118	0.131	–0.026	–0.002
	(0.091)	(0.101)	(0.049)	(0.039)
log(*GDP*)	–0.158***	–0.163***	0.034	0.012
	(0.051)	(0.055)	(0.028)	(0.022)
log(*Per Capita Income*)	0.136*	0.072	0.020	0.023
	(0.083)	(0.090)	(0.038)	(0.030)
log(*Firms*)	0.089***	0.159***	0.013	0.011
	(0.032)	(0.036)	(0.013)	(0.011)
Labor Concentration	0.776	0.940	0.314	0.544***
	(0.606)	(0.773)	(0.207)	(0.174)
Firm and workforce characteristics:				
ROA	–0.048	–0.070	0.123***	0.189***
	(0.055)	(0.057)	(0.043)	(0.044)
Return	0.003	–0.003	0.010	0.008
	(0.011)	(0.008)	(0.007)	(0.005)
log(*Pay*)	–0.053**	–0.070***	0.013	0.014***
	(0.023)	(0.017)	(0.010)	(0.004)
log(*Employees*)	0.130***	0.288***	0.003	0.005***
	(0.015)	(0.008)	(0.003)	(0.001)
Employee Growth	0.348***	–0.262***	0.141***	0.129***
	(0.100)	(0.066)	(0.041)	(0.030)
%Admin	0.090	–0.053	0.036	–0.019
	(0.072)	(0.053)	(0.044)	(0.014)
%Engineer	–0.031	0.009	0.017	–0.006
	(0.032)	(0.032)	(0.022)	(0.008)
%Finance	–0.084*	–0.262***	0.066***	–0.010
	(0.050)	(0.056)	(0.021)	(0.010)
%Marketing	0.115	0.065	0.068	–0.018
	(0.071)	(0.068)	(0.047)	(0.020)
%Operations	0.007	–0.006	0.034	0.007
	(0.072)	(0.055)	(0.031)	(0.010)
%Scientific	–0.094**	–0.146**	–0.066	–0.002
	(0.046)	(0.059)	(0.041)	(0.018)
Glassdoor characteristics:				
Prior Rating	–0.007***	–0.008***	0.028***	0.006***
	(0.002)	(0.002)	(0.002)	(0.001)
Rating Outside MSA	–0.004	0.000	0.784***	0.587***
	(0.011)	(0.011)	(0.011)	(0.012)
log(*Prior Reviews*)	0.716***	0.545***	–0.009***	–0.005***
	(0.017)	(0.009)	(0.003)	(0.002)
log(*Reviews Outside MSA*)	0.038***	0.104***	0.011***	0.014
	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects	MSA, Year	Firm, MSA, Year	MSA, Year	Firm, MSA, Year
Observations	66,755	66,755	66,755	66,755
Adjusted R^2	76.300%	79.100%	82.300%	89.100%

Table B2. 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*)	0.203*	0.225*	0.027	0.037
	(0.106)	(0.115)	(0.112)	(0.117)
log(*GDP*)	–0.192***	–0.195***	–0.037	–0.054
	(0.058)	(0.062)	(0.065)	(0.064)
log(*Per Capita Income*)	0.152	0.097	–0.104	–0.162
	(0.094)	(0.102)	(0.099)	(0.103)
log(*Firms*)	0.113***	0.177***	0.048	0.096**
	(0.036)	(0.039)	(0.042)	(0.047)
Labor Concentration	1.246*	1.513*	0.118	–0.215
	(0.701)	(0.827)	(0.456)	(0.745)
Firm and workforce characteristics:				
ROA	0.067	–0.003	–0.289***	–0.180***
	(0.056)	(0.054)	(0.068)	(0.068)
Return	0.001	0.000	0.014	–0.001
	(0.011)	(0.009)	(0.011)	(0.009)
log(*Pay*)	–0.028	–0.004	–0.069***	–0.088***
	(0.024)	(0.017)	(0.022)	(0.020)
log(*Employees*)	0.129***	0.278***	0.064***	0.143***
	(0.015)	(0.007)	(0.008)	(0.006)
Employee Growth	0.237**	–0.287***	0.398***	–0.015
	(0.102)	(0.074)	(0.087)	(0.060)
%Admin	0.033	–0.079	0.149**	0.040
	(0.067)	(0.055)	(0.065)	(0.055)
%Engineer	–0.029	–0.011	–0.030	0.069*
	(0.034)	(0.032)	(0.030)	(0.037)
%Finance	–0.085*	–0.303***	–0.015	–0.136**
	(0.048)	(0.060)	(0.039)	(0.060)
%Marketing	0.135*	0.043	–0.016	0.109
	(0.077)	(0.076)	(0.071)	(0.078)
%Operations	–0.010	–0.038	0.060	0.029
	(0.070)	(0.057)	(0.086)	(0.057)
%Scientific	–0.148***	–0.077	0.025	–0.277***
	(0.053)	(0.062)	(0.041)	(0.072)
Glassdoor characteristics:				
Prior Rating	0.020***	0.006**	–0.045***	–0.025***
	(0.003)	(0.003)	(0.003)	(0.002)
Rating Outside MSA	0.157***	0.042***	–0.291***	–0.083***
	(0.012)	(0.012)	(0.017)	(0.013)
log(*Prior Reviews*)	0.690***	0.526***	0.523***	0.430***
	(0.017)	(0.010)	(0.010)	(0.009)
log(*Reviews Outside MSA*)	0.046***	0.097***	0.011*	0.044***
	(0.000)	(0.000)	(0.000)	(0.015)
Fixed effects	MSA, Year	Firm, MSA, Year	MSA, Year	Firm, MSA, Year
Observations	66,755	66,755	66,755	66,755
Adjusted R^2	72.500%	75.200%	54.800%	57.800%

Table B2. 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 MSA 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. *, **, and *** denote that the coefficient is significantly different from zero at, respectively, two-tailed probability levels of 10%, 5%, and 1%.

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