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A new era of voluntary disclosure? Empirical evidence on how employee postings on social media relate to future corporate disclosures

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ABSTRACT

With the advent of social media, individual public opinions about firms can be more easily accessed and aggregated, and recent research suggests that various platforms, such as Twitter, Seeking Alpha, and Estimize, provide information relevant in predicting future corporate disclosures. Rather than focusing on the general public's opinion, we examine a public platform designed to convey insider information - Glassdoor.com, where employees voluntarily share their opinions on a number of issues, including the company's near-term business outlook. Using a sample of approximately 150,000 employee reviews, we extract both employees' explicit assessments of outlook and a measure of their latent outlook derived from factor analysis. We then examine whether the opinions employees share on social media relate to future corporate disclosures. In particular, we find evidence that employee opinions are useful in predicting growth in key income statement information, transitory reporting items (e.g., restructuring charges), earnings surprises, and management forecast news. While voluntary disclosures about firm performance have traditionally come from executives, our evidence suggests that rank-and-file employees are chipping away at upper-level management's exclusive control over that channel.

1. Introduction

Voluntary disclosures represent one of the most widely studied topics in accounting research and, traditionally, this research has modeled disclosure decisions at the firm level, where a single manager considers the costs and benefits of disclosing their private information to the market place.[1] This approach is both intuitive and practical because upper-level management has largely controlled firm-level communications, such as press releases, earnings warnings, and other such announcements. Yet employees throughout an organization, especially when considered collectively, likely hold a wealth of information about the state of their company (e.g., Babenko & Sen, 2015; Huddart & Lang, 2003), but there have historically been few channels through which that information can be externally conveyed. As such, it has been up to firms to cultivate and disseminate much of the knowledge held by their employees (e.g., through internal processes of budgeting and forecasting). However, in recent years, advances in technology have resulted in social media platforms through which employee opinions can be directly shared and aggregated. In this paper, we assess how the opinions that rank-and-file employees voluntarily and anonymously submit on social media relate to information that will later be conveyed in their employers' voluntary disclosures and mandated accounting reports.

Glassdoor.com is a large recruiting website that, in addition to hosting information about job postings, also hosts a social media platform through which current and former employees can weigh in on a variety of firm characteristics, including internal CEO approval ratings, salary data, interview difficulty and questions, compensation and benefits assessments, and even office photos. By

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1 See Verrecchia (2001) for a broad review of research on disclosure.

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2017, Glassdoor reported hosting over 8 million individual employer reviews submitted by a current or former employee.[2] From this data, we construct a sample of 158,352 reviews representing 1265 of the S&P 1500 firms.

The structure of Glassdoor reviews allows current and former employees to provide quantitative (discrete) assessments of 9 different attributes. Most relevant to us, employees explicitly assess their opinion of the firm's outlook on a three-point scale (positive, neutral, negative). Employees rate six other attributes on a five-point scale: work-life balance, culture and values, career opportunities, compensation and benefits, senior management, and an overall rating, and CEO approval is assessed on a three-point scale (approve, neutral, disapprove). Finally, each review also includes a "yes/no" question about whether reviewers would recommend their employers to a friend.[3]

As mentioned, our primary focus is on the employee's opinion of firm outlook. However, since many of the employees' responses likely reflect the same latent constructs, we also use factor analysis, which collapses the nine attributes into a smaller set of variables, to identify which factor most likely reflects employees' opinions of the firm's future prospects. Our factor analysis suggests three basic dimensions. The most significant factor captures the employee's general feelings about the firm, which relates positively to all nine review attributes. While less significant than the first, the second factor indeed reflects the employee's latent beliefs about the firm's future, which relates most strongly to explicit outlook, recommendation to friend, and CEO approval. Finally, our analysis identifies a third significant factor that we interpret as opinions about job satisfaction and retention likelihood, which relates most strongly to the employee's assessment of career opportunities, opinion of compensation and benefits, and overall rating of the firm. In all our analyses, we utilize both the explicit measure of business outlook that employees provided and the latent measure of outlook we extracted from the factor analysis since each offers its own unique advantages.

Before exploring our primary research question, we first conduct a determinants analysis to assess the extent to which observable firm characteristics relate to employees' opinions and to develop a set of control variables to use in subsequent tests. We explore four sets of predictors: (1) basic firm characteristics, like firm size and age, (2) recent profitability and market performance, (3) employee growth and benefits, and (4) market risk and uncertainty. The results of this analysis indicate that firm size, though not age, relates positively to outlook. As expected, return volatility and the book-to-market ratio both relate negatively to outlook, consistent with uncertainty and limited growth opportunities yielding lower forecasts of future performance. Consistent with employees considering past performance when making an assessment of future prospects, we find that stock returns and return on assets both relate positively to outlook. Finally, measures of growth and spending (workforce growth and SG&A) also relate positively to outlook.

Our primary motivation is to explore the role that rank-and-file employees play in providing an alternative disclosure channel by utilizing social media platforms such as Glassdoor.com. In order to do so in a meaningful way, rank-and-file employees must both *hold* and *reveal* information about their firm's future prospects. The first part of this premise seems likely given employees' completion of job-related tasks and frequent interactions with others internal to the organization. In addition, research suggests that investment decisions made by employees imply that they have knowledge relevant to future stock performance (Babenko & Sen, 2015; Huddart & Lang, 2003). As such, publicly shared employee opinions about the future prospects of their employer could serve as an alternative disclosure channel about the firm, which is the focus of our empirical tests.

For our main analyses, we examine measures derived from news communicated by managers through future mandatory and voluntary disclosures. We begin by assessing whether employee outlook relates to core operating performance reflected in various income statement line items. We choose the income statement because most employees likely understand how their information relates to revenue generation or cost savings within a firm. We use multiple income statement line items because we expect employee opinions to be more informative about core performance benchmarks, like sales and gross margins, though we consider measures of income as well. Our results suggest that both explicit and latent employee outlook positively predict future sales, gross margins, operating income, and net income, controlling for current and past performance. We also assess whether outlook assessments predict other more transitory items, like goodwill impairments, other write-downs, and restructuring charges. Unlike other measures of financial health, transitory events like goodwill impairments are difficult for market participants to predict (Hayn & Hughes, 2006) and are not typically priced prior to the loss announcement (Li, Shroff, Venkataraman, & Zhang, 2011). However, our evidence suggests that explicit and latent employee outlook relates to these transitory events; periods where employees express more negative outlook coincide with larger goodwill impairments, other write-downs, and restructuring charges. Overall these two sets of analyses suggest employee opinions conveyed through social media appear to foreshadow information about firm performance that will be subsequently conveyed through mandatory disclosure channels.

We next examine whether information about future performance conveyed by employee outlook is incremental to other information available at the time of the review. Using analyst consensus as a proxy for information available to investors at the time of the reviews, we first examine whether measures of outlook predict the news in future earnings surprises. Specifically, we identify the quarterly earnings ending four to six months following the review and compute a measure of earnings surprise using the consensus estimates of earnings at the time of the review. Consistent with our prior results, both explicit and latent measures of outlook relate positively to earnings surprises, suggesting that employees' assessments of outlook are incremental to other earnings news (i.e., analysts' expectations) at the time of the review.

Second, as a sharper test of whether employee opinions can serve, not only as an alternative disclosure channel, but also as one that can precede (or front run) the more traditional voluntary disclosure channels controlled by firm management, we test whether employee opinions predict firms' voluntary disclosures following the review. To conduct this test, we identify quarterly and annual management forecasts occurring in the 90 days following the review and compute forecast news using the consensus estimate of earnings for the same forecast period available at the time of the review. We again find evidence that outlook reliably predicts the news in management forecasts. In sum, our evidence suggests that employees hold private information useful in predicting future

[2] See https://www.glassdoor.com/about/overview.htm (accessed March 30, 2017).

[3] Employees provide qualitative information as well. Specifically, employees have the option of separately writing about the pros and cons of working for the employer, advice to management, and an overall summary assessment. We largely exclude this information from our analyses for a number of reasons, including the considerable variation in length and language, which complicates objective classification of the content – especially as it relates to outlook. We leave a more detailed and rigorous analysis of the qualitative content of the reviews to future research.

firm performance and disclosure news.

While we posit that current employees' unique access to private information explains our results and attempt to control for the broader construct of employee sentiment in our models, we recognize that outlook may capture other dimensions of the workforce that relate to future performance. For example, as we have suggested, employees have an insider's view of the business, such that they can convey information about existing customer relations, pending sales orders, etc., by posting a positive review of their company. But that positive review might also reflect more stable characteristics, like employee optimism or firm culture, that could still translate into good or bad future firm performance without being closely tied to timely information about customer relations, future sales demand, or more general information that does not require employees' inside access to the company.

In light of these concerns, we perform two additional tests to provide more insight into whether employee opinions about their firm's outlook reflect private information about their firm. First, we examine whether *former* employees' outlook assessments similarly translate into accurate predictions of future disclosure news. We specifically exclude former employees from our main analyses since it is unclear on Glassdoor.com when former employees left the firm, and the longer they have been gone, the less informative we would expect their private information to be. When we analyze the opinions of these former employees, we find similar associations between outlook and future mandatory and voluntary firm disclosures as in our main tests, though the economic and statistical significance of these results are (as expected) weaker. This set of findings suggests that the informativeness of employee opinions about the firm's future outlook is more likely rooted in firm-specific knowledge that decays with time rather than more general knowledge. Second, we examine whether the informativeness of *current* employee opinions about future performance increases as they become more informed about the firms' activities, which we proxy for using employee tenure. Current employees self-report tenure from a list of options (e.g., "less than 1 year," "more than a year," "more than 3 years," etc.). We partition the sample and classify those with less (more) than 3 years of experience as short-tenure (long-tenure). In most of our analyses, the relation between outlook and our measures of future disclosure news appears stronger in the long-tenure partition, and this difference is statistically significant in several cases, again supporting our contention that employees' possession of private information explains our results.

In our final additional analysis, we consider whether explicit and latent outlook relate to future stock returns. While we believe metrics used in our main analyses best capture firm performance, changes in these metrics may also move subsequent stock prices, suggesting a second order positive relation between explicit and latent outlook and future stock returns. We find evidence that explicit outlook predicts returns over a 6-month horizon but fail to find statistically significant evidence that latent outlook predicts returns over a 6-month horizon.

Our study makes several contributions to the literature. First, the use of various websites and social media platforms as possible sources of company-specific information is of growing interest in accounting and finance (Miller & Skinner, 2015). Examples of research on this broad theme includes the role of Internet bulletin boards (Antweiler & Frank, 2004), Twitter (Bartov, Faurel, & Mohanram, 2018; Blankespoor, Miller, & White, 2014; Bollen, Mao, & Zeng, 2011; Jung, Naughton, Tahoun, & Wang, 2017; Lee, Hutton, & Shu, 2015; Tang, 2017), Seeking Alpha (Campbell, DeAngelis, & Moon, 2018; Chen, De, Hu, & Hwang, 2014), and Estimize (Da & Huang, 2017; Jame, Johnston, Markov, & Wolfe, 2016). Particularly, Bartov et al. (2018) and Tang (2017) investigate whether information disclosed through Twitter predicts a company's future performance, and Chen et al. (2014) and Campbell et al. (2018) link financial commentary on Seeking Alpha to current and future stock performance. This line of research provides evidence that "non-traditional" news outlets reflect information relevant in assessing firms' future prospects.

We also view our results as speaking to a much larger and more developed literature on voluntary disclosure. While this literature has largely modeled and analyzed voluntary disclosure as a firm-level decision, we add to this literature by exploring the potential for employee-dedicated, social media platforms, such as Glassdoor.com, to serve as an outlet through which rank-and-file employees can voluntarily communicate information about public and private firms, presumably without managers' consent. Miller and Skinner (2015, p. 226–227) observe that the advent of social media has led firms to lose "a certain amount of control of their information environments in ways that are difficult to predict and manage." Consistent with this view, our evidence suggests that rank-and-file employees are now chipping away at upper-level management's exclusive control over the firm's disclosure channels. Thus, while the choice to disclose is voluntary on the part of the employee posting the review, from the perspective of management, these reviews can be characterized as a type of *in*-voluntary (but not mandatory) disclosure on the part of the firm.

Consequently, our results also contribute to research examining the general question of whether employees' *own* interpretation of private information is reflected in future performance. Using option exercises and aggregate purchases of company stock by non-executives, prior research finds mixed results as to whether non-executives' decisions signal private information reflected in future returns (Babenko & Sen, 2015; Core & Guay, 2001; Huddart & Lang, 2003). An inherent limitation of these types of studies is that they rely on employee actions, such as stock option exercises, to proxy for employee opinions about the firm, even though the actions could be driven by factors unrelated to the firm (such as employee liquidity needs). We believe that social media platforms, such as Glassdoor.com, can serve as a good setting for examining whether rank-and-file employees hold private information about their firms because we can directly observe the opinions they have chosen to share rather than having to infer an opinion about the company from observing an action, like a stock purchase or option exercise.

Finally, we expect our results to be of interest to market intermediaries, like analysts or auditors. Our results suggest that employees' opinions expressed on Glassdoor.com provide insightful information about the future, which could be useful for analysts' recommendations. In addition, these informative reviews should be independent of management intervention suggesting that employee opinions expressed on Glassdoor.com could be used as corroborating third-party audit evidence.

The remainder of the paper is organized as follows. In Section 2, we discuss background literature and motivation related to our research question. Section 3 describes our data, sample selection, descriptive statistics, and results from our determinants analysis. We describe our research design and provide results in Section 4. Section 5 reports results from additional analyses and robustness tests, and Section 6 concludes.

2. Prior literature & research question

An extensive line of research examines how broad workforce characteristics, like employee sentiment, job satisfaction, or opinions of corporate culture, relate to outcomes measuring future performance (e.g. Edmans, 2011, 2012; Edmans, Li, & Zhang, 2014; Huang, Li, Meschke, & Guthrie, 2015; and; Green, Huang, Wen, & Zhou, 2017), audit risk (Huang, Masli, Meschke, & Guthrie, 2017), or reporting quality (Ji, Rozenbaum, & Welch, 2017).[4] In this study, we add to prior work by examining whether employee opinions, as expressed on social media platforms, are predictive of future mandatory and voluntary disclosures at the firms where they work. If employees both have informative opinions about the firms they work at and are willing to share those opinions, then social media platforms can serve as an alternative disclosure channel about firms.

Like those higher up in an organization, rank-and-file employees almost certainly have access to private information about the future of the firm, albeit at a much more granular level. While executives likely receive regular reports about firm-wide investments, contracts, and other relevant information, employees' gather their private information largely through completion of job-related tasks. For example, an accounts receivable clerk maintains constant communication with customers and, therefore, has intimate knowledge of past due invoices and so will likely have a sense of whether collections are improving or deteriorating, even before those changes are reflected in reported earnings.[5] Similarly, a sales representative may complete training on a new product still in development that the company hopes to bring to the market in the near future. Employees may also obtain private information through interaction with others internal to the organization, including both other rank-and-file employees and executives. Rank-and-file employees' "water-cooler" talk offers a venue for them to share private information about the firm with each other. Much of this information, whether current or forward-looking, will take time to make its way into and through the accounting and reporting cycle. In addition, companies often have department, division, or even company-wide meetings where individuals from the executive team review the past periods' results and propose goals and plans for the upcoming quarter or year. Both the tone and the content of the message delivered by the executive team provide rank-and-file employees with private information about their firm's future prospects.

To our knowledge, Glassdoor.com represents the first venue in which employees are encouraged to voluntarily convey their own opinions about their employers, including an explicit assessment of firm outlook. However, prior research has examined whether it is possible to *indirectly* infer employee opinions by examining observable actions and has found mixed results. On the one hand, Core and Guay (2001) fail to find evidence that option exercises by non-executives reflect private information about their firms. More recently, however, Babenko and Sen (2015) use data on employee stock purchase plans and find that firms in the top quartile of employee stock purchases earn 10 percent higher abnormal returns in the next 12 months than do firms in the bottom quartile. Similarly, using a sample of individual option exercises covering over 50 thousand employees across seven organizations, Huddart and Lang (2003) find that, when employees exercise fewer options, their employer's six-month stock return is 10% higher than when employees exercise many options.

To summarize, employees likely possess an information advantage over outsiders due simply to their status as insiders of the firm. Further, while research on employees' investment decisions implies that employees *may* convert their private information into decision-useful information, it is unclear exactly what triggers their investment decisions (i.e. why employees choose to buy stock or hold options). However, with the advent of social media, employees may now be able to more directly share their private information by posting opinions about their firm's future prospects.

Despite our aforementioned reasons that employee outlook may translate to accurate predictions of future disclosure news, we highlight several reasons why this may not be the case. Namely, while managers have market incentives to voluntarily disclose expectations about future earnings (e.g., Baginski & Rakow, 2012; Balakrishnan, Billings, Kelly, & Ljungqvist, 2014; Billings, Jennings, & Lev, 2015), it is less clear that these benefits extend to rank-and-file employees, given that completion of a review requires time and effort and yields no obvious direct benefit to the rank-and-file employee, as their opinion is neither compensated nor likely to move market prices on its own. Further, even if they hold substantial financial interests in the company and wish to accelerate price formation (Campbell et al., 2018; Pasquariello & Wang, 2018), employees could free ride off of the information dissemination of their fellow employees. Moreover, many rank-and-file employees may hold no equity stake in the firm at all, completely removing stock-based incentives to leave reviews. Finally, even with the best intentions, in aggregate employees may not possess sufficient private information or sophistication to make their assessment of outlook informative.

3. Glassdoor data

3.1. Data and descriptive statistics

Founded in 2007, Glassdoor is a social media company that collects and posts information about companies that is obtained directly from current and former employees, including information about salaries, interview experiences, and (the focus of our study) company reviews. Glassdoor claims to be "the fastest growing jobs and recruiting site" and now hosts over 8 million anonymous company reviews. In this study, we examine whether the employee opinions shared on this social media platform contain information that will later be revealed in mandatory and voluntary corporate disclosures.

Glassdoor's community guidelines state that "Glassdoor strives to be the most trusted and transparent place for today's candidate to search for jobs and research companies" (http://help.glassdoor.com/article/Community-Guidelines/en_US), and these guidelines also mandate that reviews be submitted voluntarily and without coercion by management (management may encourage employees to submit reviews, but should not offer incentives to leave positive feedback). Reviews are also completely anonymous, and Glassdoor encourages employees to write clear, balanced opinions of their employers. Additionally, Glassdoor reports using a rigorous, two-step moderation process to detect abuse or gaming, minimizing the likelihood that companies can unduly influence the information disclosed by employees. Thus, Glassdoor strives to provide useful information about firms and to prevent abuse or gaming by reviewers or employers.

When submitting a review, individuals are asked to provide several ratings, each measured on a five-point scale. In particular, Glassdoor collects the respondent's assessment of company culture and values, compensation and benefits, work/life balance, its senior management, and an overall rating. In addition to those ratings,

[4] Like us, Huang et al. (2015), Huang et al. (2017), Green et al. (2017), and Ji et al. (2017) use ratings from Glassdoor.com. However, none of these studies investigate whether employee outlook predicts future performance.

[5] Whether this perspective gives any one employee a distinct information advantage over anyone else in the firm is doubtful, given the relative size of firms compared to the purview of a typical rank-and-file employee. However, in aggregate, this information could accurately predict future corporate disclosures and events.

respondents are also asked to indicate whether they would recommend the company to a friend, to provide their opinion of the CEO, and, most relevant to our study, to give their assessment of the firm's outlook. We provide the full questionnaire in Appendix A.[6]

One concern with the Glassdoor data (or any voluntarily completed survey) is that the person providing the review and the timing of the review are non-random. Depending on the research question, this could create selection concerns that complicate inferences. We speculate (though we cannot verify) that many Glassdoor reviews are prompted by companies' encouraging employees to submit a review[7] and/or employment milestones. For example, a promotion or award might encourage an employee to be a steward of the firm and try to attract other high-quality individuals. Alternatively, a negative experience, like being passed over for promotion or receiving a poor performance review, might cause an employee to begin looking for a new job on Glassdoor. While the nature of these events likely correlates with the tone of the reviews, we feel selection concerns are somewhat mitigated in our setting for several reasons. First, we are primarily focused on whether social media platforms can serve as an alternative disclosure channel about firms. As such, we focus only on firms and periods with reviews, and we do not attempt to draw inferences about what employees in firms with no reviews might know, if they were to post something about their firm. Second, our models attempt to control for likely confounds. Specifically, we explicitly control for observable firm, industry, and market events in our models (e.g., past performance), as we discuss shortly, and we include time-period fixed effects in all models, which allows outlook (and other independent variables) to only explain *within*-time period variation. Finally, if the selection forces are internal to the firm, then they may reflect the variation we intend to capture—employees' inside view of their firms as revealed through Glassdoor reviews.[8]

We collect review data using a two-step procedure. First, Glassdoor hosts an application program interface (API) that allows us to programmatically access certain information within their databases. The API provides only summary information about reviews (e.g., average overall rating, percent approving of CEO, etc.), limiting its use for constructing a time series of review data. However, we use the API to obtain company-specific metadata that we then use to match review data with data from CRSP and Compustat. Specifically, we first identify the S&P 1500 as of 12/31/2013 in Compustat. We then utilize a Python Script to query Glassdoor's API by company name (Compustat "conm") for each firm in the S&P 1500.[9] For each record identified, we then obtain Glassdoor's firm identifier, which we use to access employee reviews. We then manually verify each link to avoid erroneously matching companies in Compustat to Glassdoor. This procedure allows us to successfully identify Glassdoor company profiles for 1,415 of the firms in the S&P 1500. Second, after matching Compustat identifiers to Glassdoor, we use two additional scripts to download and parse the individual reviews. The first script opens the website containing the reviews for a given company, extracts required information from the source code for the web page, and then cycles through each subsequent page in a similar fashion until all reviews for that company are collected. This process is repeated for the 1,415 firms in our original sample. A second script then parses individual pages of reviews into normalized data (described below). For each review, we also obtain the review's unique identifier, the date of the review, the employee's job title (if provided), status (current or former), and tenure (if provided).

Table 1
Sample attrition.

Total Reviews (May 2012-June 2015)	386,902
less: Reviews by former employees	(159,507)
less: Incomplete reviews (missing major rating components)	(69,043)
Maximum Sample	158,352
Unique Companies	1,265

Table 1 presents sample attrition.

From each review, we extract the following information (each on a five-point scale): the employee's overall rating (*Overall*) and subcomponent ratings capturing the employee's opinion of their employers' culture and values (*CultureValues*), work/life balance (*WorkLife*), senior management (*SeniorManagement*), career opportunities (*CareerOpps*), and compensation and benefits (*CompBenefits*). We also extract the respondent's assessment of the CEO (*CEOApproval*), coded as 1 (positive), 0 (neutral), or -1 (negative), whether he/she would recommend the company to a friend (*RecToFriend*, coded 1 for yes or 0 for no), and his/her opinion of the company's six-month business outlook (*Outlook*), coded as 1 (positive), 0 (neutral), or -1 (negative).[10] We are most interested in *Outlook*, as it is the variable most directly related to employees' opinions that might contain information that has not yet made its way into mandatory or voluntary corporate disclosures. However, while employees respond to nine discrete dimensions, we recognize that latent factors likely explain some covariation in their responses to the various questions. Therefore, we also utilize a factor analysis to identify latent factors that may serve as an alternative measure of outlook (discussed in the next subsection).

As discussed previously, our sample begins with employee reviews for the S&P 1500 available on Glassdoor. In total, we successfully download 386,902 reviews for these firms between May 2012 and June 2015. We start with May 2012 since *Outlook* was not collected prior to that date. For our main analyses, we remove 159,507 reviews completed by former employees and 69,043 incomplete reviews (i.e., missing at least one review component).[11]

[6] As noted in footnote 3, employees also provide qualitative information which we do not consider in this study.

[7] Glassdoor's Community Guidelines supports employers encouraging employees to share honest reviews on Glassdoor but discourages firms from offering incentives in exchange for reviews. In fact, Glassdoor will remove reviews with evidence that employees were compensated and/or coerced into leaving a review (http://help.glassdoor.com/article/Community-Guidelines/en_US).

[8] For future researchers interested in questions where selection issues might be more problematic, we note that our inspection of the data suggests that employees providing reviews appear to provide, on average, at least somewhat balanced reviews. For example, the mean number of words in the "pros" section is 23 words for reviews with a positive outlook versus 19 for reviews with a negative outlook (untabulated), implying favorable reviewers still consider negative aspects of their employer. In the "cons" section, word counts are significantly higher for negative outlook reviews than positive reviews. However, the mean number of words in the "cons" section for positive reviews (23) is nearly identical to the word count in the "pros" section for these reviewers, again suggesting employees try to offer a balanced view of their employers.

[9] We normalize company names before searching Glassdoor for a match by replacing uncommon acronyms like "HLDGS" with "HOLDINGS" and "SOLNS" with "SOLUTIONS." Common acronyms, like "COMP" and "INC" do not inhibit our searches.

[10] Specifically, employees are asked the following question: "In the next six months do you think your company will perform better, worse, or remain the same?"

[11] Like the opinions of current employees, the opinions of former employees may also reveal unique information because of their inside knowledge of the firm. However, we are unable to determine departure dates for the former employees making it difficult to compare them to current employees (or to each other). Although we remove them from our sample for our main analyses, we analyze these reviews in a supplemental analysis described in Section 5.

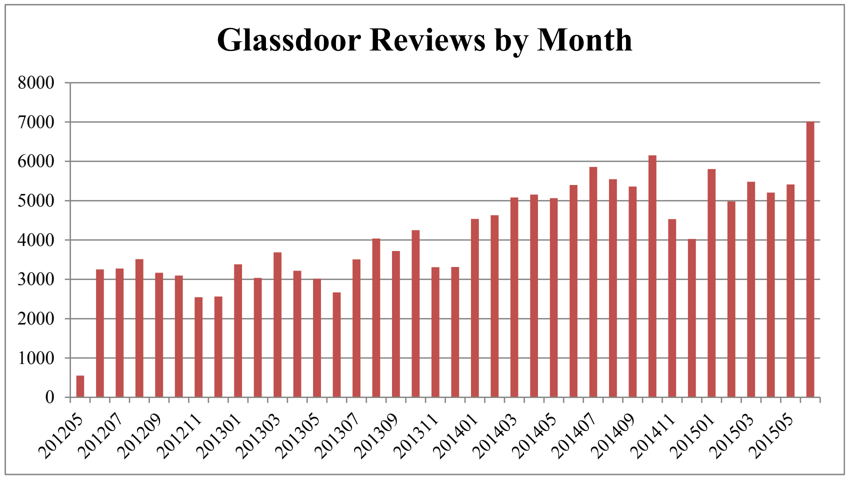

Fig. 1. Glassdoor reviews by month.
Figure 1 presents the number of reviews by month present in our final sample, described in Table 1.

This leaves a total of 158,352 reviews representing 1,265 companies. These reviews represent our starting sample for each of our main analyses. Table 1 describes this sample attrition.

Figure 1 graphs the number of reviews in our sample for each month between May 2012 and June 2015. Consistent with Glassdoor's self-described rapid growth, the number of reviews per month increases substantially over our sample period. With the exception of the first month in our sample, current employees completed more than 2,000 total reviews per month, and, in recent months, that number grows to approximately 7,000.

Table 2 presents descriptive statistics for the Glassdoor ratings data. Panel A describes the number of reviews per firm. The distribution of reviews is somewhat skewed, with a mean (median) number of reviews per firm of 549 (204). Panel B of Table 2 displays the sample distribution by industry designation using Fama-French 48-industry classifications. Except for Business Services (19 percent) and Retail (24 percent), most industries do not have a disproportionate number of reviews. Further, the fact that these industries have a higher number of reviews is consistent with companies in these industries relying heavily on large workforces. All of our empirical models include industry fixed effects, limiting the variance explained by our variables of interest to within-industry variation. However, in Section 5, we provide additional analyses to test whether these two industries unduly influence our main results.

Panel C of Table 2 presents descriptive statistics on review components. The mean value of *Outlook* of 0.272 suggests that the average employee posting a review has a positive opinion of the firm's near-term business prospects. In fact, almost 50 percent of respondents report a positive outlook, whereas fewer than 25 percent report a negative outlook. Similarly, the mean (median) value for *Overall* of 3.366 (4) on a 5.0 scale suggests that the average employee posting a review has a generally positive opinion of the firm. Indeed, four of the five subcomponents, *WorkLife*, *CultureValues*, *CareerOpps*, and *CompBenefits*, have mean (median) values above (above or equal to) the midpoint of three on a five-point scale. *SeniorManagement* is the only subcomponent rating with a mean (2.952) falling below the midpoint. Despite holding an ambivalent attitude toward senior management as a whole, employees posting a review appear to generally approve of the CEO (mean of 0.358 for *CEOApproval*), and approximately 65 percent would recommend their firm to a friend. Panel D of Table 2 presents Pearson and Spearman correlations between review measures. As expected, all components exhibit significantly positive correlations (ρ between 0.36 and 0.76). These significantly positive correlations suggest that a smaller number of latent dimensions may largely explain the reviewer's responses across the various parts of the review, which we discuss more in the next section.

3.2. Factor analysis

Our primary question is whether employee opinions contain information about future corporate disclosures and events, which would seem to be most directly captured by our *Outlook* variable. However, that one variable may be a noisy proxy for employee opinions about the near-term prospects of their firm, and it may be influenced by the employees' responses to preceding questions. In addition, employees' overall view of their firm's prospects is likely to partially influence other assessments they make in the review. Consistent with these notions, *Outlook* exhibits significant Pearson correlations ($\rho > 0.5$) with *Overall, RecToFriend, CEOApproval, CultureValues, CareerOpps,* and *SeniorManagement*.[12] Therefore, to better isolate the latent constructs that drive employees' assessments of outlook, we use a factor analysis to reduce these nine review dimensions to a smaller set of variables. A factor analysis provides several benefits. First, it uses common variance among review attributes to identify the latent constructs which drive the review responses. In addition, by focusing on a smaller set of latent constructs, we can isolate the construct that relates most strongly to employees' outlook assessments. From a practical perspective, it also replaces nine, highly correlated variables with a smaller set of less correlated measures. Note that we view this factor analysis as neither confirmatory (i.e., we make no *ex ante* prediction of *how* factors will load) nor purely exploratory (i.e., we expect *Outlook* to be the primary latent dimension of at least one factor).

We employ principal factor scoring with promax (oblique) rotation. We use an oblique rotation to allow extracted factors to be correlated, which we believe to be more theoretically valid.[13] For example, opinions of senior management are likely related to both

[12] The remaining two review questions, *Worklife* and *CompBenefits* exhibit positive correlations with *Outlook* of 0.38 and 0.40, respectively.

[13] We also conduct an analysis with unrotated factors, as reported later in Section 5.

Table 2
Distribution of reviews.

Panel A: Descriptive Statistics on Number of Reviews (n = 158,352)

	Mean	Std. Dev.	25%	50%	75%
Number of Reviews per firm	549.207	761.484	57	204	711

Panel B: Distribution of Reviews by Industry

Fama-French Industry (48-classification)	Total Reviews	% of Total Reviews	Average Reviews per Firm	Median Number of Reviews per Firm
Agriculture	151	0.10%	74	74
Food Products	1,369	0.86%	62	41
Candy & Soda	675	0.43%	228	211
Beer & Liquor	917	0.58%	386	382
Tobacco Products	276	0.17%	43	41
Recreation	151	0.10%	31	26
Entertainment	732	0.46%	61	45
Printing and Publishing	311	0.20%	37	30
Consumer Goods	1,908	1.20%	175	88
Apparel	1,896	1.20%	79	60
Healthcare	1,002	0.63%	57	42
Medical Equipment	1,608	1.02%	57	39
Pharmaceutical Products	2,923	1.85%	95	64
Chemicals	1,989	1.26%	168	96
Rubber and Plastic Products	47	0.03%	10	8
Textiles	102	0.06%	21	20
Construction Materials	326	0.21%	29	12
Construction	691	0.44%	69	42
Steel Works Etc	306	0.19%	19	12
Machinery	2,663	1.68%	79	53
Electrical Equipment	656	0.41%	82	63
Automobiles and Trucks	1,022	0.65%	121	82
Aircraft	1,356	0.86%	285	206
Shipbuilding, Railroad Equipment	33	0.02%	12	11
Defense	853	0.54%	349	343
Non-Metallic and Industrial Metal Mining	103	0.07%	16	10
Coal	47	0.03%	7	7
Petroleum and Natural Gas	2,395	1.51%	117	69
Utilities	1,130	0.71%	30	19
Communication	5,894	3.72%	540	275
Personal Services	832	0.53%	77	50
Business Services	29,979	18.93%	727	243
Computers	9,755	6.16%	890	406
Electronic Equipment	8,322	5.26%	348	182
Measuring and Control Equipment	1,752	1.11%	160	82
Business Supplies	870	0.55%	59	46
Shipping Containers	165	0.10%	22	18
Transportation	3,464	2.19%	248	131
Wholesale	2,169	1.37%	71	44
Retail	37,974	23.98%	829	505
Restaurants, Hotels, Motels	6,646	4.20%	531	266
Banking	12,196	7.70%	728	488
Insurance	5,205	3.29%	178	104
Real Estate	487	0.31%	90	79
Trading	3,465	2.19%	114	58
Other	1,483	0.94%	261	138
Missing SIC	56	0.04%	19	17
Total	**158,352**	**100.00%**	**185**	**60**

Panel C: Descriptive Statistics on Review Components (n = 158,352)

Variables	Mean	Std. Dev.	25%	50%	75%
Outlook	0.272	0.764	0	0	1
Overall	3.366	1.207	3	4	4
RecToFriend	0.650	0.477	0	1	1
CEOApproval	0.358	0.757	0	1	1
WorkLife	3.270	1.281	2	3	4
CultureValues	3.378	1.338	2	4	5
CareerOpps	3.195	1.246	2	3	4
CompBenefits	3.291	1.183	3	3	4
SeniorManagement	2.952	1.296	2	3	4

Panel D: Correlations on Review Components (Spearman Above/Pearson Below) (n = 158,352)

	Overall	Outlook	RecToFriend	CEOApproval	WorkLife	CultureValues	CareerOpps	CompBenefits	SeniorManagement
Overall		**0.600**	**0.725**	**0.576**	**0.572**	**0.748**	**0.717**	**0.595**	**0.756**
Outlook	**0.604**		**0.560**	**0.510**	**0.364**	**0.532**	**0.523**	**0.389**	**0.565**
RecToFriend	**0.732**	**0.568**		**0.546**	**0.475**	**0.635**	**0.593**	**0.462**	**0.637**

Table 2 (*continued*)

Panel D: Correlations on Review Components (Spearman Above/Pearson Below) (n = 158,352)									
	Overall	Outlook	RecToFriend	CEOApproval	WorkLife	CultureValues	CareerOpps	CompBenefits	SeniorManagement
CEOApproval	**0.588**	**0.516**	**0.553**		**0.366**	**0.553**	**0.478**	**0.396**	**0.565**
WorkLife	**0.587**	**0.376**	**0.490**	**0.378**		**0.541**	**0.427**	**0.389**	**0.542**
CultureValues	**0.760**	**0.541**	**0.654**	**0.566**	**0.553**		**0.615**	**0.472**	**0.722**
CareerOpps	**0.723**	**0.525**	**0.599**	**0.485**	**0.440**	**0.625**		**0.531**	**0.644**
CompBenefits	**0.601**	**0.396**	**0.475**	**0.403**	**0.401**	**0.483**	**0.542**		**0.488**
SeniorManagement	**0.758**	**0.567**	**0.639**	**0.570**	**0.551**	**0.726**	**0.650**	**0.497**	

Table 2 presents descriptive statistics and distributional data for the sample of reviews used in this study. Panel A presents descriptive statistics on number of reviews per firm. All untransformed continuous variables are winsorized at the 1st and 99th percentile of their distributions. Panel B presents distributions of the reviews by industry. Panel C presents descriptive statistics on review components and Panel D presents correlations among review components; correlations with significance levels <0.05 are in bold. All variable definitions appear in Appendix B.

Table 3
Factor analysis.

Variables	Employees' Overall Opinion of the Firm	Employees' Outlook of Future Firm Performance	Employees' Expectations about Personal Growth Opportunities
	(SentimentFactor)	(OutlookFactor)	(RetentionFactor)
Outlook	0.5190	0.4227	0.2103
Overall	0.7962	0.2664	0.3601
RecToFriend	0.6615	0.3649	0.2406
CEOApproval	0.5374	0.4068	0.1609
WorkLife	0.6377	0.0684	0.1305
CultureValues	0.7775	0.2628	0.1696
CareerOpps	0.6193	0.2500	0.4150
CompBenefits	0.5117	0.1345	0.3863
SeniorManagement	0.7647	0.2792	0.2072
Eigenvalue	5.1029	0.1229	0.0937
% Variance Explained	0.7876	0.1588	0.1359

Table 3 presents results from a factor analysis conducted on the nine review components. Reported factor loadings are based on principle factoring with promax (oblique) rotation. All variable definitions can be found in Appendix B.

job satisfaction and expectations about future performance. We use parallel analysis to determine the number of factors to retain (Horn, 1965; Humphreys & Ilgen, 1969; Humphreys & Montanelli, 1975; Montanelli & Humphreys, 1976). In parallel analysis, eigenvalues obtained from the factor analysis are compared to eigenvalues from simulated, random data with similar distributional properties. The rationale with parallel analysis is that nontrivial components from our data with valid underlying factor structure should have larger eigenvalues than parallel components derived from random data (Ford, MacCallum, & Tait, 1986; Hayton, Allen, & Scarpello, 2004; Lautenschlager, 1989). This analysis is repeated a number of times (in our case, 100), and the mean eigenvalue for each factor from the simulated data is compared to the eigenvalue from the factor analysis. Factors with eigenvalues greater than factors from simulated data are considered significant.[14] Thus, the critical value for factor "significance" varies by factor, with more (less) significant factors having higher (lower) eigenvalue "hurdles" from the simulated data.

This procedure results in three factors, and we present factor loadings in Table 3. When discussing factor loadings, we focus on loadings greater than 0.3 for brevity, though all loadings are used for estimating each of the three factors. As shown in column 1, the first principal factor, has an eigenvalue exceeding 5 and is, by far, the most significant factor in explaining review content. It relates positively to all nine review components, consistent with the employee's general opinion and feelings towards the company explaining a large portion of his or her review. We label this variable *SentimentFactor*. Our primary motivation for conducting this analysis is to identify a second measure that reflects employees' latent outlook, or their opinions about the firm's future prospects revealed in the complete review. The pattern of loadings in column 2 are consistent with this intent. Specifically, *Outlook*, *RecToFriend*, and *CEOApproval* are the main contributors to the second factor. Each of these factors logically relates to the company's future prospects. In contrast, *WorkLife* and *CompBenefits*, which reflects attributes that are costly for a firm to maintain, exhibit much smaller loadings (0.07 and 0.13, respectively). Thus, we label this variable *OutlookFactor* and note that, as expected, it is highly correlated with *Outlook* ($\rho = 0.83$). Finally, as reported in column 3, one additional factor has an eigenvalue that exceeds its randomly generated counterpart. *Overall*, *CareerOpps*, and *CompBenefits* contribute the most to this third factor. We interpret this third factor as relating to employees' view of personal growth

[14] Other common factor extraction methods are Kaiser's test and Catell's scree test. These tests are often selected due to their ease in implementation (Velicer, Eaton, & Fava, 2000) but have been criticized for both overestimating and underestimating the number of relevant factors (Cattell & Jaspers, 1967; Cattell & Vogelmann, 1977; Hakstian, Rogers, & Cattell, 1982; Hubbard & Allen, 1987; Linn, 1968; Tucker, Koopman, & Linn, 1969; Zwick & Velicer, 1982, 1986). Thus, more recent research suggests that parallel analysis, which is non-parametric and imposes no *ex ante* assumptions, produces a more accurate method for identifying the true number of factors (Lance, Butts, & Michels, 2006; Velicer et al., 2000, p. 67).

opportunities and their satisfaction with compensation. Since these views come from current employees, we label this variable *RetentionFactor*.

Note that while *SentimentFactor* is clearly the most significant factor in explaining the content of the reviews, this does not imply that the remaining factors are insignificant nor that they capture similar constructs to employee sentiment. Further, if *OutlookFactor* reflects a meaningless (insignificant) combination of review components, this biases against rejection of the null in our tests when using it as a measure of latent outlook.

3.3. Determinants analysis

Before moving to our primary research question, we consider firm and market characteristics associated with our two measures of employees' outlook assessments (*Outlook* and *OutlookFactor*). We conduct this analysis primarily to assess the extent to which observable firm characteristics relate to employees' opinions and to develop a set of control variables to use in future tests. We focus on four sets of attributes: 1) general firm characteristics, 2) recent profitability and market performance, 3) employee growth and well-being, and 4) market risk and uncertainty. Given *Outlook* and *OutlookFactor* are both measured at the review level (which occur sporadically over our sample period), whereas other data, like firm and analyst characteristics, are only available at fixed quarterly or monthly intervals, we collapse our data to the firm-quarter level by computing the mean of each measure by firm and quarter.[15] Using this firm-quarter dataset, we estimate the following model:

$$Outlook\ or\ OutlookFactor = a_0 + a_1 Size + a_2 Age + a_3 ROA + a_4 Returns + a_5 SGA + a_6 EmpGrowth + a_7 RetVol + a_8 \mathrm{BTM} + a_9 n + e \quad (1)$$

For firm characteristics, we include the natural log of assets (*Size*) and firm age (*Age*).[16] We make no predictions as to how employee outlook relates to these characteristics. For profitability and performance, we include return on assets (*ROA*) and market returns (*Returns*). We expect employees to lean, on average, toward momentum expectations and express a more (less) positive outlook for the firm when their firm has been performing better (worse). For employee growth and well-being, we include the ratio of SG&A expenses to sales (*SGA*), a rough proxy for wages and benefits paid to employees, and growth in the workforce (*EmpGrowth*). We expect both of these measures to also relate positively to employee outlook. We include return volatility (*RetVol*) to proxy for general uncertainty about the firm's prospects and *BTM* as an inverse proxy for perceived growth opportunities. We expect both measures to relate negatively to employee outlook. Finally, we control for the variation in the number of reviews across firm-quarters by including the natural log of the number of Glassdoor reviews per firm-quarter (n) and make no prediction as to how this variable relates to employee outlook.

We present descriptive statistics on our variables used in our determinants analysis and correlations between these variables in Panels A and B, respectively, of Table 4. Descriptive statistics suggest the average firm in our sample is large, with over 4 billion in assets (*exp(8.326)*), is well-capitalized (*BTM* of 0.433), and experiences positive growth in their workforce (*EmpGrowth* of 5.7 percent). Correlations between factors are significantly positive and range from 0.35 to 0.63. The significant correlations between our factors are a result of employing promax (oblique) rotation.

Results from estimating (1) are presented in Panel C of Table 4. Column 1 (2) presents results using *Outlook* (*OutlookFactor*) as the dependent variable. We find that firm size relates positively to both measures (t-statistics between 5.3 and 5.9). That is, employees of larger firms express a more positive outlook for their firms than do employees of smaller firms. We also find that measures of past performance (*ROA*, *Returns*) relate positively to both of our measures of outlook (t-statistics between 6.6 and 10.5). For employee growth and well-being, both proxies (*SGA* and *EmpGrowth*) exhibit significant, positive associations (t-statistics between 1.6 and 8.0) with the outlook measures. These results are consistent with growing workforces and higher wages leading to more favorable employee opinions and expectations of the firm. Conditioning on size, firm age does not exhibit a significant association with either outlook measure. *RetVol* relates negatively to outlook (t-statistics between −2.0 and −2.7), suggesting uncertainty depresses employee outlook. *BTM* also exhibits negative associations with the outlook measures (t-statistics between −6.0 and −7.0), suggesting that employee outlook is lower for firms that face fewer growth opportunities. Lastly, n relates negatively to outlook suggesting periods of higher (lower) review intensity correspond to less (more) favorable outlook.

Overall, employee outlook relates in predictable ways to observable indicators of how the firm will perform in future periods. However, we highlight that adjusted R^2 values in Panel C of Table 4 are relatively low (between 8 and 9 percent), suggesting that other, perhaps private, information likely explains a large portion of employees' opinion of outlook.

4. Empirical results

For our main analyses, we begin with mandatory reports and examine whether employee outlook is predictive of a company's subsequently reported accounting performance. We supplement these tests in Section 4.2 by examining whether employees' posted opinions about firm outlook are also informative about what *management* will subsequently say about future firm performance. Specifically, we examine whether employee outlook relates to earnings news in future voluntary disclosures. Note that we construct the sample used in each test slightly differently depending on the periodicity of the dependent variable (e.g., firm-quarter, firm-year). All regressions include time (e.g., quarter, month) and industry fixed effects and two-way standard error clustering consistent with the dependent variable's unit of measure (e.g., firm and calendar quarter, firm and calendar month, etc.).

4.1. Relation between employee outlook and information in mandatory reports

4.1.1. Relation between employee outlook and fundamental performance

We begin by assessing how employee outlook relates to measures of future fundamental performance appearing in the income statement. We expect employee outlook to be more strongly related to items "further up the income statement" because rank-and-file employees likely have more information about changes in sales or COGS than about variations in effective tax rates and interest agreements, but we consider a wide range of measures. For these tests, we utilize a firm-quarter unit of measure to correspond with firms' quarterly income statements. Specifically, we test whether *Outlook* relates to future firm performance using future sales (*Sale*), gross margin (*GM*), operating income (*OpInc*), and income before extraordinary items (*Income*). For each measure, we compute cumulative performance over the two quarters ending

[15] In all tests, we collapse reviews down to a firm-time level (e.g., firm-quarter, firm-month, firm-day). We discuss our rationale for selecting each unit of measure when describing our tests.

[16] We provide exact variable definitions in Appendix B.

Table 4
Determinants data and regression results.

Panel A: Descriptive Statistics for Review Data and Determinants (n = 9472)

Variable	Mean	Std. Dev.	25%	50%	75%
Outlook	0.2511	0.5305	0.0000	0.2727	0.6364
OutlookFactor	−0.0249	0.3619	−0.2402	0.0111	0.2274
SentimentFactor	−0.0586	0.6377	−0.4403	−0.0176	0.3714
RetentionFactor	−0.0399	0.3281	−0.2324	−0.0258	0.1673
Size	8.3262	1.5946	7.1391	8.2126	9.3734
Age	9.0021	0.8153	8.6197	9.0076	9.6166
ROA	0.0147	0.0195	0.0052	0.0137	0.0236
Returns	0.0412	0.1211	−0.0284	0.0395	0.1093
SGA	0.2636	0.1677	0.1263	0.2388	0.3694
EmpGrowth	0.0565	0.1396	−0.0122	0.0339	0.0983
RetVol	0.2754	0.1127	0.1970	0.2490	0.3239
BTM	0.4328	0.2928	0.2257	0.3715	0.5735
n	1.8861	1.0988	1.0986	1.6094	2.4849

Panel B: Correlations (Spearman Above/Pearson Below) (n = 9472)

Variable	Outlook	OutlookFactor	SentimentFactor	RetentionFactor	Size	Age	ROA	Returns	SGA	EmpGrowth	RetVol	BTM	n
Outlook		**0.839**	**0.649**	**0.450**	**0.047**	**−0.021**	**0.155**	**0.077**	0.011	**0.197**	**−0.064**	**−0.163**	**−0.041**
OutlookFactor	**0.839**		**0.627**	**0.377**	**0.055**	−0.013	**0.166**	**0.061**	−0.010	**0.196**	**−0.058**	**−0.157**	**−0.028**
SentimentFactor	**0.652**	**0.596**		**0.542**	**0.096**	0.003	**0.097**	−0.004	**0.049**	**0.073**	**−0.040**	**−0.090**	**0.028**
RetentionFactor	**0.451**	**0.352**	**0.566**		**0.167**	**0.026**	**0.063**	−0.012	**−0.023**	**0.068**	**−0.055**	**−0.094**	**0.061**
Size	**0.063**	**0.075**	**0.110**	**0.162**		**0.384**	**−0.050**	**0.027**	**−0.212**	**−0.118**	**−0.458**	**0.030**	**0.410**
Age	−0.011	0.005	0.012	0.019	**0.337**		0.008	0.002	**−0.123**	**−0.250**	**−0.315**	**0.053**	**0.134**
ROA	**0.155**	**0.172**	**0.082**	**0.049**	**−0.029**	−0.017		**0.056**	**−0.061**	**0.159**	**−0.185**	**−0.464**	**0.109**
Returns	**0.084**	**0.067**	−0.008	−0.016	0.009	−0.010	**0.061**		−0.009	−0.008	**−0.085**	**−0.080**	**0.032**
SGA	0.026	−0.005	**0.065**	−0.001	**−0.207**	**−0.123**	**−0.117**	−0.010		**0.043**	**0.122**	**−0.123**	**0.065**
EmpGrowth	**0.134**	**0.133**	**0.029**	**0.035**	**−0.090**	**−0.232**	**0.089**	−0.017	**0.050**		**0.111**	**−0.178**	**−0.040**
RetVol	**−0.099**	**−0.096**	**−0.050**	**−0.054**	**−0.394**	**−0.257**	**−0.205**	**−0.072**	**0.140**	**0.095**		**0.173**	**−0.198**
BTM	**−0.173**	**−0.161**	**−0.084**	**−0.087**	**0.068**	**0.050**	**−0.374**	**−0.093**	**−0.100**	**−0.132**	**0.193**		**−0.176**
n	0.014	**0.031**	**0.065**	**0.078**	**0.482**	**0.148**	**0.083**	0.016	**0.051**	**−0.055**	**−0.184**	**−0.142**	

Panel C: Determinants Regression

VARIABLES	(1) Outlook	(2) OutlookFactor
Size	0.039***	0.027***
	(5.87)	(5.35)
Age	−0.009	0.000
	(-0.79)	(0.03)
ROA	2.873***	2.232***
	(10.09)	(10.47)
Returns	0.340***	0.197***
	(7.20)	(6.66)
SGA	0.218***	0.072*
	(3.44)	(1.69)
EmpGrowth	0.394***	0.279***
	(7.95)	(7.45)
RetVol	−0.222***	−0.126**
	(−2.65)	(−2.09)
BTM	−0.223***	−0.142***
	(-6.97)	(-6.02)
n	−0.036***	−0.020***
	(−4.78)	(−3.50)
Observations	9,472	9,472
Adjusted R^2	0.091	0.085

Table 4 presents descriptive statistics, correlations, and results from a determinants analysis. All variable definitions appear in Appendix B, and all untransformed continuous variables are winsorized at the 1st and 99th percentile of their distributions. Panel A presents descriptive statistics for review factors and determinants. Panel B presents correlations among variables in Panel A; correlations with significance levels <0.05 are in bold. Panel C presents results from regressing outlook variables on determinants. Industry fixed effects, based on the Fama-French 48 classifications, and quarter-end fixed effects are included. Standards errors are robust to heteroskedasticity and clustering at the firm-and quarter-end level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level.

4–6 months after the review to coincide with the employee's assessments of performance over the next 6 months.[17] We scale all performance metrics by assets in period *t*. We regress each performance metric on employee outlook (*Outlook* or *OutlookFactor*), our set of determinants identified in Section 3.3, and firm performance over the four quarters preceding those used in the

[17] We elect to use future levels of performance and control for current and past performance. We find similar results if we instead use seasonally adjusted changes in performance as our dependent variable and control for current and recent past performance.

Table 5
Descriptive statistics for variables of interest and controls.

Variable	Measurement Base	n	Mean	Std. Dev.	25%	50%	75%
Sale	Firm-quarter	9,490	0.5315	0.3969	0.2749	0.4219	0.6748
GM	Firm-quarter	9,427	0.1945	0.1205	0.1131	0.1729	0.2514
OpInc	Firm-quarter	9,375	0.0537	0.0435	0.0273	0.0479	0.0729
Income	Firm-quarter	9,499	0.0293	0.0384	0.0104	0.0274	0.0474
GWImp	Firm-quarter	8,270	0.1391	0.7546	0.0000	0.0000	0.0000
Writedown	Firm-quarter	9,499	0.0449	0.2145	0.0000	0.0000	0.0000
Restructure	Firm-quarter	9,499	0.1849	0.3771	0.0000	0.0000	0.2007
Following	Firm-month	19,195	2.4832	0.6040	2.0794	2.5649	2.9444
FcstDisp	Firm-month	19,195	0.0509	0.0530	0.0200	0.0300	0.0600
EarningsSurprise	Firm-month	19,195	−0.1044	0.5705	−0.1854	−0.0151	0.0902
MgmtFcst_Horizon	Forecast (Firm-day)	5,821	4.9560	4.6616	1.9108	3.5478	6.2775
QTRInd	Forecast (Firm-day)	5,821	0.2271	0.4190	0.0000	0.0000	0.0000
MgmtFcstNews	Forecast (Firm-day)	5,821	−0.0010	0.0050	−0.0016	−0.0003	0.0004

Table 5 presents descriptive statistics for variables of interest and other control variables not previously presented. All variable definitions appear in Appendix B. All untransformed continuous variables are winsorized at the 1st and 99th percentile of their distributions.

dependent variable.[18] Because future performance is measured using quarterly data, we collapse all independent variables to the firm-quarter level. Descriptive statistics for our dependent variables are presented in Table 5.

Regression results from our future performance tests are reported in Table 6. Besides variables listed, we include firm-quarter and Fama French 48 industry fixed effects and cluster standard errors by firm and quarter. For each dependent variable (both here and in future analyses), we estimate three specifications: one using *Outlook* only, one using *Outlook* and controlling for other review responses (e.g., *Overall, RecToFriend*, etc.), and one using the factors derived from our factor analysis. Columns 1 through 3 (4 through 6, 7 through 9, 10 through 12) present results using *Sale* (*GM, OpInc, Income*) in the two quarters following the review to measure future performance. Focusing on the first column for each performance measure (columns 1, 4, 7, and 10), we find positive and highly significant coefficients (*t*-statistics between 5.6 and 8.3) on *Outlook* in all specifications. In the second column for each measure (columns 2, 5, 8, and 11), we introduce the other review components. As shown, we continue to observe highly significant coefficients on *Outlook* (*t*-statistics between 4.8 and 6.3) and the magnitudes of these coefficients actually increase after considering other components. The final column for each performance metric uses the factors derived from our factor analysis. Like *Outlook*, *OutlookFactor* exhibits similar positive and highly significant associations with each measure of future firm performance (*t*-statistics between 4.1 and 6.3). These effects represent economically significant improvements as well. For instance, moving from negative to positive outlook (−1 to 1) corresponds to an increase in *Sale* of up to 2.4 percent of assets, or 4.5 percent of the sample mean for *Sale*. Together, these results suggest that the opinions employees share on Glassdoor about the firm's business outlook reveal information about their firms' future prospects as measured on the income statement.

Turning to the other variables in the regressions, we see that other aspects of employee reviews fail to consistently translate to future performance. *CompBenefits* (*Overall*) exhibits a significantly positive (negative) association with *Sale* in column 2 but fails to load in any other specification. *SeniorManagement* also loads positively in column 11 but is insignificant in other models. In column 8, we actually observe *negative* (though only marginally significant) associations between *OpInc* and both *WorkLife* and *CareerOpps*. We observe a similar mixed pattern of results with the other factors derived in the factor analysis. Only *SentimentFactor* exhibits a significant association (column 6), relating *negatively* to *GM*. Thus, employee outlook, measured explicitly or through a latent factor analysis, represents the only review component that consistently translates to accurate predictions of future performance.

4.1.2. Relation between employee outlook and transitory expenses

While the prior section focuses on the relation between employee outlook and several fundamental income statement measures, including earnings, prior research suggests transitory, one-time expenses, like goodwill impairments, inventory write-downs, or restructuring charges, are difficult for investors to predict (Hayn & Hughes, 2006) and represent significant market news events (Ayres, Campbell, Chyz, & Shipman, 2017; Bens, Heltzer, & Segal, 2011; Li et al., 2011). To the extent that these transactions reflect lagged information about the condition of firm assets or expected losses related to reorganizations, rank-and-file employees might hold information about these events while also facing fewer direct incentives to withhold such information compared to upper-level management. We, therefore, test whether rank-and-file employees' assessments of outlook carry information about future one-time income statement charges.

For this test, we define three measures of transitory expenses. First, we consider goodwill impairments, *GWImp*, which equals the total goodwill impairment in Compustat scaled by assets and multiplied by −1 (so that larger values correspond to larger impairments); note *GWImp* is set to missing for firms with no goodwill on the balance sheet. Second, we consider write-downs of assets other than goodwill (*Writedown*), again scaled by assets and multiplied by −1. Finally, we examine restructuring charges (*Restructure*). Unlike the prior two measures, restructuring charges often capture expenses associated with planned organizational changes, such as plant closures or layoffs. Like *GWImp* and *Writedown*, *Restructure* is scaled by assets and multiplied by −1. As in the prior section, we collapse the review data to the firm-quarter level to correspond to the same measurement window as these events. We use the same time line as our fundamental performance tests and construct these measures over the two quarters following the review (see footnote 18 for illustration). Since these three variables

[18] To illustrate, for a calendar-year firm, we regress performance over Q1 and Q2 of 2014 on employee outlook from reviews submitted in December of 2013 through February of 2014, controlling for performance in Q1, Q2, Q3, and Q4 of 2013. This design ensures that earnings announcements for a given quarter occur well after the end of each review accumulation period. Note that our results are robust to using only the second quarter of this 6-month window (Q2 2014 in the previous example), which does not overlap at all with the review period, or to using only current period performance (Q1 2014 in this example).

Table 6
Future performance.

Variables	(1) Sale	(2) Sale	(3) Sale	(4) GM	(5) GM	(6) GM	(7) OpInc	(8) OpInc	(9) OpInc	(10) Income	(11) Income	(12) Income
Outlook	0.009***	0.012***		0.004***	0.006***		0.003***	0.004***		0.003***	0.005***	
	(5.63)	(4.87)		(8.30)	(5.50)		(8.18)	(6.32)		(6.20)	(5.83)	
OutlookFactor			0.012***			0.007***			0.004***			0.005***
			(4.08)			(6.26)			(5.90)			(5.52)
SentimentFactor			−0.002			−0.001**			−0.000			−0.000
			(−1.09)			(−2.09)			(−1.13)			(−0.48)
RetentionFactor			0.005			0.001			−0.001			−0.001
			(1.15)			(0.69)			(−0.81)			(−1.00)
Size	−0.007***	−0.008***	−0.007***	−0.003***	−0.003***	−0.003***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(−4.99)	(−5.15)	(−5.00)	(−6.19)	(−6.48)	(−6.40)	(−3.67)	(−3.70)	(−3.57)	(−2.96)	(−2.87)	(−2.82)
Age	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001
	(0.27)	(0.38)	(0.25)	(0.52)	(0.57)	(0.45)	(0.97)	(0.96)	(0.87)	(1.30)	(1.23)	(1.17)
ROA	−0.736***	−0.734***	−0.732***	−0.214***	−0.214***	−0.212***	0.010	0.009	0.009			
	(-6.97)	(-6.95)	(-6.94)	(-4.43)	(-4.41)	(-4.39)	(0.28)	(0.25)	(0.27)			
Returns	0.049***	0.049***	0.050***	0.032***	0.031***	0.032***	0.029***	0.029***	0.029***	0.027***	0.027***	0.028***
	(5.51)	(5.36)	(5.57)	(7.87)	(7.69)	(7.83)	(7.90)	(7.84)	(7.88)	(7.11)	(6.93)	(7.07)
SGA	−0.006	−0.006	−0.004	0.011*	0.012**	0.012**	−0.001	−0.001	−0.001	−0.005**	−0.004*	−0.005*
	(−0.61)	(−0.66)	(−0.47)	(1.91)	(2.02)	(2.11)	(−0.45)	(−0.32)	(−0.23)	(−2.03)	(−1.74)	(−1.72)
EmpGrowth	−0.045***	−0.046***	−0.045***	−0.015***	−0.016***	−0.015***	−0.008***	−0.008***	−0.008***	−0.006*	−0.007*	−0.006*
	(−3.89)	(−4.00)	(−3.94)	(−3.73)	(−3.83)	(−3.75)	(−3.21)	(−3.29)	(−3.14)	(−1.71)	(−1.85)	(−1.70)
RetVol	−0.040**	−0.041**	−0.041**	−0.021***	−0.020***	−0.021***	−0.020***	−0.019***	−0.020***	−0.022***	−0.022***	−0.022***
	(−2.42)	(−2.45)	(−2.43)	(−3.69)	(−3.72)	(−3.69)	(−4.67)	(−4.72)	(−4.66)	(−3.48)	(−3.47)	(−3.47)
BTM	−0.024***	−0.023***	−0.024***	−0.008***	−0.008***	−0.008***	−0.007***	−0.007***	−0.008***	−0.014***	−0.014***	−0.014***
	(−3.92)	(−3.81)	(−4.00)	(−4.36)	(−4.28)	(−4.45)	(−5.11)	(−5.07)	(−5.26)	(−8.21)	(−8.12)	(−8.27)
n	0.004***	0.004***	0.004***	0.002***	0.002***	0.002***	0.001**	0.001**	0.001**	0.001**	0.001***	0.001**
	(2.91)	(3.13)	(2.85)	(4.27)	(4.47)	(4.30)	(2.35)	(2.53)	(2.31)	(2.58)	(2.85)	(2.55)
$Performance_t$	0.605***	0.604***	0.604***	0.508***	0.507***	0.508***	0.314***	0.314***	0.315***	0.328***	0.326***	0.328***
	(6.87)	(6.86)	(6.85)	(5.27)	(5.26)	(5.26)	(4.56)	(4.58)	(4.57)	(5.33)	(5.30)	(5.32)
$Performance_{t-1}$	0.115**	0.116**	0.116**	0.026	0.026	0.027	−0.012	−0.013	−0.011	0.149***	0.150***	0.151***
	(2.42)	(2.43)	(2.44)	(0.51)	(0.51)	(0.54)	(−0.31)	(−0.33)	(−0.29)	(4.65)	(4.65)	(4.68)
$Performance_{t-2}$	0.712***	0.711***	0.712***	0.801***	0.800***	0.800***	0.827***	0.828***	0.827***	0.595***	0.595***	0.595***
	(11.45)	(11.43)	(11.44)	(13.70)	(13.69)	(13.69)	(18.60)	(18.69)	(18.58)	(11.97)	(11.88)	(11.95)
$Performance_{t-3}$	0.512***	0.513***	0.511***	0.567***	0.568***	0.566***	0.634***	0.634***	0.632***	0.496***	0.497***	0.496***
	(6.47)	(6.48)	(6.47)	(7.29)	(7.31)	(7.27)	(10.05)	(10.07)	(10.02)	(10.52)	(10.59)	(10.51)
Overall		−0.004*			−0.001			−0.000			−0.000	
		(−1.82)			(−0.98)			(−0.96)			(−0.57)	
RecToFriend		0.001			−0.001			−0.001			−0.001	
		(0.24)			(−0.33)			(−0.45)			(−1.11)	
CEOApproval		0.001			0.001			−0.000			0.000	
		(0.28)			(0.97)			(−0.14)			(0.35)	
WorkLife		−0.002			−0.001			−0.001*			−0.000	–
		(−1.23)			(−1.64)			(−1.65)			(−0.76)	
CultureValues		0.001			−0.000			0.000			−0.001	
		(0.72)			(−0.11)			(0.34)			(−1.48)	
CareerOpps		−0.002			−0.001			−0.001*			−0.001	
		(−0.82)			(−0.95)			(−1.95)			(−1.32)	
CompBenefits		0.004***			0.001			0.000			−0.000	
		(3.27)			(1.46)			(0.21)			(−0.64)	
SeniorManagement		−0.000			0.001			0.001			0.002**	
		(−0.22)			(1.07)			(1.30)			(2.48)	
Observations	9,490	9,490	9,490	9,427	9,427	9,427	9,375	9,375	9,375	9,499	9,499	9,499
Adjusted R^2	0.964	0.964	0.964	0.938	0.938	0.938	0.802	0.802	0.801	0.581	0.581	0.580

Table 6 presents results from regressing measures of fundamental performance on outlook and outlook determinants. Variable definitions appear in Appendix B. All untransformed continuous variables are winsorized at the 1st and 99th percentile of their distributions. Industry fixed effects, based on the Fama-French 48 classifications, and quarter-end fixed effects are included. Standards errors are robust to heteroskedasticity and clustering at the firm- and quarter-end-level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level.

Table 7
Transitory items.

Variables	(1) GWImp	(2) GWImp	(3) GWImp	(4) Writedown	(5) Writedown	(6) Writedown	(7) Restructure	(8) Restructure	(9) Restructure
Outlook	−0.093***	−0.122***		−0.015***	−0.016**		−0.048***	−0.066***	
	(−3.61)	(−3.70)		(−2.75)	(−2.17)		(−6.73)	(−9.54)	
OutlookFactor			−0.124***			−0.026***			−0.065***
			(−3.72)			(−3.20)			(−7.34)
SentimentFactor			0.007			−0.005			0.007
			(0.34)			(−1.02)			(1.06)
RetentionFactor			0.016			0.025***			0.000
			(0.52)			(3.01)			(0.04)
Size	0.009	0.005	0.008	−0.006**	−0.007***	−0.006***	−0.002	−0.003	−0.002
	(0.83)	(0.43)	(0.74)	(−2.54)	(-2.94)	(−2.78)	(−0.52)	(−0.83)	(−0.70)
Age	0.241***	0.246***	0.247***	0.021*	0.022*	0.022*	0.002	0.002	0.005
	(3.47)	(3.54)	(3.53)	(1.69)	(1.78)	(1.77)	(0.08)	(0.09)	(0.23)
ROA	−1.492**	−1.501**	−1.519**	−0.146	−0.128	−0.130	−1.100***	−1.102***	−1.111***
	(−2.44)	(−2.48)	(−2.53)	(−0.73)	(−0.65)	(−0.66)	(−3.42)	(−3.41)	(−3.44)
Returns	−0.059	−0.094	−0.076	0.012	0.008	0.009	0.101***	0.092***	0.091***
	(−0.52)	(−0.83)	(−0.66)	(0.54)	(0.35)	(0.40)	(3.07)	(2.78)	(2.77)
SGA	0.052	0.063	0.046	−0.022	−0.022	−0.022	−0.047	−0.043	−0.048
	(0.53)	(0.66)	(0.48)	(−0.91)	(−0.92)	(−0.93)	(−1.34)	(−1.26)	(−1.38)
EmpGrowth	−0.018	−0.015	−0.017	−0.004	−0.003	−0.003	0.008	0.009	0.009
	(−1.17)	(−1.01)	(−1.13)	(−0.72)	(−0.58)	(−0.61)	(1.17)	(1.23)	(1.24)
RetVol	−0.439***	−0.424***	−0.444***	−0.036	−0.033	−0.035	−0.176***	−0.170***	−0.178***
	(−4.81)	(−4.70)	(−4.82)	(−1.57)	(−1.44)	(−1.48)	(−6.61)	(−6.41)	(−6.71)
BTM	0.393**	0.378**	0.395**	0.061	0.059	0.061	0.043	0.038	0.044
	(2.39)	(2.25)	(2.38)	(1.45)	(1.41)	(1.44)	(0.86)	(0.77)	(0.88)
n	−0.018	−0.018	−0.018	0.004	0.004	0.003	0.017***	0.017***	0.017***
	(−1.07)	(−1.06)	(−1.06)	(1.21)	(1.37)	(1.12)	(2.99)	(2.97)	(3.12)
Transitory $_{t}$	0.012	0.008	0.013	0.205***	0.204***	0.204***	0.386***	0.383***	0.386***
	(0.23)	(0.16)	(0.24)	(3.11)	(3.07)	(3.08)	(10.90)	(10.80)	(11.05)
Transitory $_{t-1}$	0.099	0.097	0.097	0.091***	0.093***	0.091***	0.210***	0.209***	0.211***
	(1.35)	(1.31)	(1.32)	(2.68)	(2.76)	(2.68)	(13.77)	(13.97)	(14.16)
Transitory $_{t-2}$	0.178***	0.177***	0.179***	0.099**	0.097**	0.098**	0.254***	0.255***	0.255***
	(2.59)	(2.59)	(2.63)	(2.45)	(2.42)	(2.46)	(9.40)	(9.62)	(9.61)
Transitory $_{t-3}$	0.129**	0.129**	0.130**	0.106***	0.108***	0.108***	0.201***	0.202***	0.202***
	(1.97)	(1.99)	(1.98)	(3.01)	(3.06)	(3.04)	(6.51)	(6.57)	(6.58)
Overall		0.022			0.005			0.003	
		(0.82)			(1.47)			(0.32)	
RecToFriend		−0.002			0.004			0.005	
		(−0.04)			(0.34)			(0.34)	
CEOApproval		0.013			−0.012			−0.004	
		(0.49)			(−1.57)			(−0.48)	
WorkLife		0.003			−0.004			−0.001	
		(0.39)			(−1.06)			(−0.14)	
CultureValues		0.021			−0.010***			0.008	
		(0.84)			(-2.59)			(1.36)	
CareerOpps		−0.010			−0.004			0.001	
		(-0.59)			(-0.72)			(0.13)	
CompBenefits		0.040**			0.016***			0.008	
		(2.51)			(5.18)			(1.29)	
SeniorManagement		−0.039**			0.008**			0.000	
		(−2.54)			(2.13)			(0.03)	
Observations	8,270	8,270	8,270	9,499	9,499	9,499	9,499	9,499	9,499
Adjusted R^2	0.057	0.058	0.056	0.040	0.043	0.041	0.257	0.257	0.256

Table 7 presents results from regressing the likelihood and magnitude of goodwill impairments, inventory write-downs, and restructuring charges on outlook and outlook determinants. Variable definitions appear in Appendix B. All untransformed continuous variables are winsorized at the 1st and 99th percentile of their distributions. Industry fixed effects, based on the Fama-French 48 classifications, and quarter-end fixed effects are included. Standards errors are robust to heteroskedasticity and clustering at the firm-and quarter-end-level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level.

are constructed to measure disclosure news inversely (i.e., goodwill impairments or inventory write-downs are bad news), we expect employee outlook to relate negatively to these measures.

Results from this test are presented in Table 7. The structure of the table is very similar to Table 6. For each measure, we report results using *Outlook* both with and without other review components and *OutlookFactor*. We also include the same set of control variables and control for values of the transitory items (*Transitory*) in the four quarters preceding the window used in the dependent variable. For *GWImp* (columns 1 through 3), we find highly significant, negative coefficients on *Outlook* and *OutlookFactor* (*t*-statistics between 3.6 and 3.7), consistent with employees' understanding how private information relates to future goodwill impairments. In columns 4 through 6, we examine other asset write-downs (*Writedown*) and continue to find evidence consistent with our predictions. *Outlook* and *OutlookFactor* both exhibit significant, negative associations with *Writedown* (*t*-statistics between 2.1 and 3.2). Finally, columns 7 through 9 present results using *Restructure.* As in other specifications, both measures of employee outlook relate significantly negatively to restructuring charges (*t*-statistics between 6.7 and 9.5).

Regarding other review aspects, we again find little consistent evidence that these measures relate to future transitory items. We do observe some evidence that *RetentionFactor* relates positively to *Writedowns*, implying that firms investing more in employee retention efforts are less likely to experience asset writedowns. Similarly, *CompBenefits* relates positively to *GWImp* and *Writedown*. However, most evidence related to other review components is mixed or insignificant.

In sum, our evidence suggests that the opinions employees share on Glassdoor about their firm's business outlook contain information about their firm's future fundamental performance, including not only general income statement information, but also information about future transitory, one-time expenses.[19]

4.1.3. Relation between employee outlook and earnings surprises

Recall that, when assessing their company's business outlook, employees are asked "In the next six months do you think your company will perform better, worse, or remain the same?" Because we do not know precisely what benchmark employees might be using as their benchmark when assessing their company's business outlook, we next test an alternative measure of expected performance derived from a clear and publicly available benchmark – namely, earnings surprises. Specifically, we collapse our data to the firm-month level and match review data to the quarter ending four to 6 months following the review. We use a firm-month definition because consensus analyst estimates are updated once per month. We construct *EarningsSurprise* as the difference between earnings announced in this 4–6 month window and the consensus analyst estimate, according to the IBES Summary File, for that period in the month preceding the review.[20] Since reviews are submitted throughout the year, we use quarterly earnings announcements to avoid large fluctuations in the length of time between review and earnings announcement and in the scale of our earnings surprise measure. We target a 4–6 month time window to coincide with the 6 month horizon specified in the review criteria and to ensure that performance occurring contemporaneous to the review (which is reported in the 1–3 months following the review) does not contaminate our measure of earnings surprise.

We follow a similar research design to prior sections and regress *EarningsSurprise* on the two measures of employee outlook (*Outlook* and *OutlookFactor*) and the determinants discussed in Section 3.3. For these tests, we also control for analyst forecast following (*Following*) and dispersion (*FsctDisp*) to account for differences in coverage characteristics of our sample firms. Results of this analysis are presented in Table 8. Columns 1 and 2 (column 3) report(s) results using *Outlook* (*OutlookFactor*) to measure employees' assessments of the firms' future prospects. As in previous tests, we again find strong evidence that both *Outlook* (*t*-statistics between 3.8 and 4.8) and *OutlookFactor* ($t = 3.5$) relate positively to future earnings news. That is, firms whose employees report a more positive (negative) outlook are more likely to report more positive (negative) earnings surprises, conditioned on news available at the time of the review.[21] These results are economically meaningful as well. For instance, moving from negative to positive explicit outlook

Table 8
Earnings surprises.

Variables	(1) EarningsSurprise	(2) EarningsSurprise	(3) EarningsSurprise
Outlook	0.046***	0.050***	
	(4.80)	(3.84)	
OutlookFactor			0.047***
			(3.45)
SentimentFactor			0.009
			(0.78)
RetentionFactor			−0.003
			(−0.21)
Size	0.015	0.015	0.015
	(1.40)	(1.40)	(1.39)
Age	−0.015	−0.015	−0.015
	(−1.11)	(−1.10)	(−1.13)
ROA	2.688***	2.690***	2.700***
	(3.33)	(3.32)	(3.32)
Returns	0.647***	0.646***	0.654***
	(8.24)	(8.23)	(8.30)
SGA	−0.087	−0.086	−0.084
	(−1.14)	(−1.14)	(−1.10)
EmpGrowth	0.049	0.047	0.055
	(0.64)	(0.62)	(0.72)
RetVol	−0.610***	−0.609***	−0.614***
	(−4.35)	(−4.36)	(−4.36)
BTM	−0.039	−0.039	−0.041
	(−0.67)	(−0.66)	(−0.71)
n	−0.008	−0.007	−0.008
	(−0.64)	(−0.55)	(−0.66)
Following	0.004	0.004	0.004
	(0.17)	(0.18)	(0.17)
FcstDisp	−0.788***	−0.792***	−0.788***
	(−2.94)	(−2.95)	(−2.93)
Overall		−0.019**	
		(−2.41)	
RecToFriend		−0.025	
		(−1.13)	
CEOApproval		0.006	
		(0.59)	
WorkLife		0.002	
		(0.26)	
CultureValues		0.001	
		(0.13)	
CareerOpps		−0.002	
		(−0.40)	
CompBenefits		0.008	
		(1.11)	
SeniorManagement		0.016*	
		(1.76)	
Observations	19,195	19,195	19,195
Adjusted R^2	0.104	0.105	0.104

Table 8 presents results from regressing earnings surprises on outlook and outlook determinants. Variable definitions appear in Appendix B. All untransformed continuous variables are winsorized at the 1st and 99th percentile of their distributions. Industry fixed effects, based on the Fama-French 48 classifications, and year-month fixed effects are included. Standards errors are robust to heteroskedasticity and clustering at the firm-and year-month-level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level.

[19] In Tables 6 and 7, we focus on mandatory disclosures four to six months in the future. We use this horizon because the explicit assessment of employee outlook is for the next six months. In additional analyses, we consider a longer, twelve-month horizon, and our results are qualitatively similar with the exception of our writedown tests after controlling for other review components.

[20] To illustrate, for reviews submitted in December 2013, we construct earnings surprise as the difference between earnings in Q2 of 2014 and the consensus estimate for these earnings as of November 2013. Note that we would also construct *EarningsSurprise* using Q2 2014 earnings for reviews submitted in October and November of 2013, but we would use consensus estimates from September and October, respectively. Thus, while the same period's earnings may be used multiple times, *EarningsSurprise* will vary by month, consistent with our decision to use a firm-month level of analysis.

[21] As with our findings for transitory items, we see little evidence that other aspects of the employees' reviews relate to earnings surprises.

corresponds to an increase in *EarningsSurprise* of up to 10 percent of price.

4.2. Relation between employee outlook and voluntary disclosures

In our final set of tests, we examine whether employee reviews convey information that will later be provided by upper-level management through more traditional voluntary disclosure channels. In particular, we focus on management forecasts following the review. Unlike our previous analyses, management forecasts are themselves voluntary and thus occur sporadically over our sample period. Therefore, we design this analysis differently from our previous tests. Because upper-level management can voluntarily disclose information via management forecasts at any given time for future quarterly or annual earnings, we include both quarterly and annual guidance in our analyses, similar to Cheng, Luo, and Yue (2013). Specifically, for each review in our sample, we search for earnings guidance occurring in the 90 days following the review. If multiple forecasts exist in this window, we use the one closest to the review, and if a quarterly and annual forecast occur on the same day, we retain the annual forecast. We then compute the management guidance news (*MgmtFcstNews*) as the difference between the forecast and the consensus earnings estimate at the time of the review (i.e., in the most recent summary report). Finally, since each forecast can be linked to multiple reviews, we collapse the dataset down to the forecast level (or compute the mean of each independent variable by forecast "firm-day").[22,23]

We regress *MgmtFcstNews* on the same set of variables as in Table 8. We also include *MgmtFcst_Horizon*, the number of days between the forecast date and earnings announcement date, since research suggests long-range (short-range) forecasts are more positively (negatively) biased (i.e., "walkdown") and *QTRInd*, an indicator equaling 1 for quarterly guidance and 0 for annual guidance to control for the potential difference in forecast surprise between annual and quarterly forecasts.

Results from this regression are presented in Table 9. As in Table 8, columns 1 and 2 (column 3) use(s) *Outlook* (*OutlookFactor*) to measure employee assessments of firm outlook. As shown, in column 1 (2) we find a significantly (marginally significant) positive association between *Outlook* and *MgmtFcstNews* (t-statistics of 1.3 and 2.1, respectively) consistent with employees accurately predicting future management disclosures. Similarly, column 3 reports a significant association between *OutlookFactor* and news in management forecasts ($t = 2.4$). While not as significant as the associations between employee outlook and news in mandatory disclosures, these results provide some evidence that employee reviews preempt information in future management forecasts. In other words, employee outlook provides information about how management forecasts will relate to the current market consensus *before* management issues their forecast.[24]

4.3. Synthesis

Overall, our evidence suggests that the reviews employees voluntarily share on Glassdoor reveal information that will be disseminated in subsequent mandatory and voluntary corporate disclosures. Specifically, using both explicit and latent measures of employee outlook, we observe significantly positive relations between those measures and several measures of future performance and the news in voluntary disclosures and negative relations between employee outlook and future goodwill impairments, write-downs and restructuring charges. We view these findings as evidence that, while any one review is unlikely to reveal material inside information, the social media platform created by Glassdoor serves as a portal through which employees can, in aggregate, share their inside views of the company. These results not only provide evidence of an alternative disclosure channel, but also complement and extend prior research that has used stock-options as a lens into whether rank-and-file employees hold private information about their companies (Babenko & Sen, 2015; Huddart & Lang, 2003). In the next section, we provide a series of additional tests to provide further insight into our main results.

5. Additional analyses

5.1. Cross-sectional tests

While our prior findings are consistent with rank-and-file employees possessing inside information, one may question whether the informativeness of their outlook assessments results from unique access to private information, as we argue, rather than basic industry knowledge that could be disseminated by virtually anyone or simply signals overall employee sentiment, which prior research links to performance. We next perform two cross-sectional analyses to shed light on whether employee opinions about their firm's outlook reflect private information about their firm. First, we consider reviews from a group of individuals that no longer have the same type of unique access they once had – namely, former employees.[25] Second, we explore whether our results are stronger for long-tenured employees, or employees that should be better able to convert their private information to accurate assessments of future performance.

5.1.1. Current vs. former employees

In our main analyses, we exclude reviews by former employees. In this supplemental analysis, we instead use the reviews of former employees. Specifically, we project the factor loadings reported in Table 3 onto the subsample of former employees.[26] If the informativeness of current employees' outlook comes from their inside view of the company, rather than, say, industry-specific or other more general knowledge, then we should see weaker relations

[22] To illustrate, assume management issues quarterly earnings guidance on October 15, 2013 and February 15, 2014. Our sampling procedure would link any reviews submitted between October 16, 2013 and February 14, 2014 to the February 15, 2014 forecast (reviews prior to but within 90 days of October 16 are associated with that forecast). However, the value for *MgmtFcstNews* potentially varies by review since we use the consensus analyst estimate as of the review date. We use analysts' consensus estimate at the time of the review rather than at the time the guidance is issued ("mean_at_date" in IBES Guidance), which reflects the market's earnings expectations *after* the review, to ensure that *MgmtFcstNews* reflects disclosure news as measured using information at the time reviews are submitted to Glassdoor. For our regressions, we collapse the dataset down to the forecast-level (or firm-day level) and use the average value of our independent variables.

[23] Following prior research, we restrict the sample to point and range forecasts, and, for range forecasts, we use the midpoint of the range to compute *MgmtFcstNews*.

[24] As with most of our preceding findings, we see little evidence that other aspects of the employees' reviews relate to management forecasts.

[25] Note that employment status and tenure are self-reported. To our knowledge, Glassdoor cannot enforce the accuracy of these responses. However, since reviews are anonymous it is unclear what incentives an employee would have to misreport, and any misreporting would add noise to our partitioning process.

[26] We use the factor loadings from current employees to quantify information in the former employees' reviews so that we can compare *OutlookFactor* between the two employee groups. In an untabulated analysis, we repeat our factor analysis using only former employees and observe a different pattern of factor loadings, consistent with these employees responding differently to review questions (and also confirming our choice to use current employee factor loadings to estimate the common factors).

Table 9
Management forecasts.

Variables	(1) MgmtFcstNews	(2) MgmtFcstNews	(3) MgmtFcstNews
Outlook	0.037**	0.029	
	(2.14)	(1.33)	
OutlookFactor			0.068**
			(2.39)
SentimentFactor			0.007
			(0.38)
RetentionFactor			−0.035
			(−0.99)
Size	−0.002	−0.002	−0.002
	(−0.14)	(−0.11)	(−0.13)
Age	−0.027*	−0.028*	−0.028*
	(−1.80)	(−1.87)	(−1.87)
ROA	1.917	1.851	1.847
	(1.63)	(1.57)	(1.57)
Returns	0.593***	0.587***	0.591***
	(7.06)	(6.95)	(7.05)
SGA	−0.043	−0.037	−0.035
	(−0.46)	(−0.39)	(−0.37)
EmpGrowth	0.021	0.011	0.017
	(0.25)	(0.14)	(0.20)
RetVol	−0.249	−0.256	−0.254
	(−1.59)	(−1.63)	(−1.62)
BTM	−0.020	−0.020	−0.020
	(−0.23)	(−0.23)	(−0.23)
n	−0.021*	−0.021*	−0.021*
	(−1.86)	(−1.87)	(−1.83)
Following	0.032	0.032	0.032
	(0.83)	(0.83)	(0.83)
FcstDisp	−0.935***	−0.928***	−0.931***
	(−3.20)	(−3.19)	(−3.20)
MgmtFcst_Horizon	−0.012***	−0.012***	−0.012***
	(−2.97)	(−2.96)	(−2.98)
QTRInd	−0.143***	−0.143***	−0.143***
	(−4.54)	(−4.53)	(−4.56)
Overall		−0.031	
		(−1.38)	
RecToFriend		0.008	
		(0.18)	
CEOApproval		0.021	
		(0.91)	
WorkLife		−0.012	
		(−1.04)	
CultureValues		0.017	
		(1.20)	
CareerOpps		−0.003	
		(−0.17)	
CompBenefits		−0.006	
		(−0.33)	
SeniorManagement		0.018	
		(1.08)	
Observations	5,821	5,821	5,821
Adjusted R^2	0.157	0.158	0.158

Table 9 presents results from regressing management forecast news on outlook and outlook determinants. Variable definitions appear in Appendix B. All untransformed continuous variables are winsorized at the 1st and 99th percentile of their distributions. Industry fixed effects, based on the Fama-French 48 classifications, and forecast period end fixed effects are included. Standards errors are robust to heteroskedasticity and clustering at the firm-and forecast-period-end-level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level.

between our outlook variables and our disclosure measures for former employees. Of course, the strength of this test depends in large part on how much time has elapsed since the former employee was employed at their previous company. Given that Glassdoor is a recruiting platform, we suspect many reviews by former employees are likely posted during an employee's transition from the target company to another employer, making them relatively recent at the time they are posted (resulting in a potentially low-powered comparison test).

In untabulated tests, we repeat tests reported in Tables 6

Table 10
Future returns.

Variables	(1)	(2)	(3)
	MAR6	MAR6	MAR6
Outlook	0.005**	0.010**	
	(2.08)	(2.41)	
OutlookFactor			0.006
			(1.00)
Observations	20,219	20,219	20,219
Adjusted R^2	0.003	0.004	0.003

Table 10 presents results from regressing market adjusted returns over 6-month (*MAR6*) horizons on employee outlook. Column 1 (2, 3) report results using *Outlook* absent other review components (*Outlook* in addition to other review components, *OutlookFactor* and other review factors). Each regression includes control variables from Panel C of Table 4 (outlook "determinants") but coefficient estimates are suppressed for ease of exposition. Variable definitions appear in Appendix B. All untransformed continuous variables are winsorized at the 1st and 99th percentile of their distributions. Standards errors are robust to heteroskedasticity and clustered at the calendar month level. ***, **, and * indicate two-tailed significance at the 0.01, 0.05, and 0.10 level.

through 9 using only former employees. For results reported in Tables 6, 8, and 9 (7), coefficients on *Outlook* and *OutlookFactor* are almost universally smaller (larger) and less significant for former employees. Additionally, these differences in strength are often at least marginally significant. Specifically, for *Outlook* controlling for other review dimensions *(OutlookFactor)*, we observe significant ($p < 0.10$ or better, one-tailed) differences for *Sale, OpInc, Income, Restructure, EarningsSurprise,* and *MgmtFcstNews (OpInc, Write-down, EarningsSurprise* and *MgmtFcstNews)*. We interpret these findings as providing support for the notion that the informativeness of opinions shared by current employees comes from their inside view of their companies.

5.1.2. Employee tenure

Next, we consider whether longer-tenured employees better predict news in mandatory and voluntary disclosures. We posit that an employee's ability to convert private information to accurate assessments of future prospects increases with employee tenure. Alternatively, if outlook really captures a more general measure of workforce sentiment we do not expect our results to strengthen with tenure. In the online review template, Glassdoor includes a drop-down menu of tenure choices for reviewers. Options include "less than a year," "more than a year," "more than 3 years," and continue in similar increments up to "more than 10 years." We successfully identify a value for this item for approximately 79 percent of our sample (the field containing this response is blank in remaining reviews). Absent a normative benchmark for "long-tenure", we choose to partition at the three-year mark, which yields reasonably large samples in each partition (approximately 41% in the short-tenure partition and 59% in the long-tenure partition). In other words, employees responding they have been employed for less than 1 year and more than 1 year are included in the "short-tenure" group, while employees reporting any other value (more than three years, etc.) are considered "long-tenure." We then repeat our tests in Tables 6 through 9 for these two partitions (untabulated).

Consistent with our evidence for former employees, we observe coefficients larger (smaller) in magnitude and more statistically significant for the long-tenure group in Tables 6, 8, and 9 (7) in many cases. These differences are marginally significant or better ($p < 0.10$, one-tailed) in regressions using *Outlook* (*OutlookFactor*) for *GWImp, Restructure* and *EarningsSurprise* (*Restructure* and *EarningsSurprise*) specifications. As with our analysis of current vs. former employees, we interpret this pattern of results as consistent with our arguments that private information drives the informativeness of employee outlook.

5.2. Employee outlook and stock returns

In our main analyses, we chose to focus on the association between employee outlook and future disclosure news. We made this choice for several reasons. First, the measures of fundamental performance and corporate disclosure news that we use reflect concrete, tangible information that more strongly relate to employees' private information. While improvements in these metrics may themselves move stock prices, we view this as a second-order effect (i.e., the employee predicts a sales increase, and the subsequent increase in sales leads to an increase in share price). Second, prior research examines how factors like employee sentiment relates to stock performance (Edmans, 2011, 2012; Edmans et al., 2014), and other research links information in Glassdoor reviews other than outlook to future stock returns (Chamberlain, 2015, Green et al., 2017). Nevertheless, we conduct one final analysis to assess whether employee outlook relates to future stock returns.

To conduct this test, we compute market-adjusted buy-and-hold returns over the 6 month periods following the review (*MAR6*).[27] We then regress these returns on average *Outlook* (and other review components) or *OutlookFactor* in the calendar month preceding the beginning of the return window as well as the determinants discussed in Section 3.1 (which include common proxies for market risk, like firm size and the book-to-market ratio). Table 10 reports these results. For brevity, we only report coefficients on our variables of interest (*Outlook* and *OutlookFactor*). As shown, we find some evidence that firms where employees express more positive outlook experience more positive returns over the subsequent 6-month period. Specifically, *Outlook* relates positively to *MAR6* (*t*-statistics between 2.1 and 2.6) and this significance is unaffected by inclusion of other review components, but we fail to observe an association between *OutlookFactor* and *MAR6*.[28]

[27] Similar to our main tests, we focus on returns six months in the future, however, in untabulated analyses, we consider a longer twelve-month return window and our results are qualitatively similar.

[28] We interpret this result merely to suggest that stocks of firms with higher employee outlook tend to outperform the market, on average, but we do not suggest that this evidence implies an executable trading strategy which could yield significant risk-adjusted returns.

5.3. Robustness tests

5.3.1. Prominent industries

In our primary analyses, we include industry fixed effects to isolate variance attributable solely to industry membership. In this analysis, we also consider whether our two most highly represented industries, Business Services (19 percent) and Retail (24 percent), unduly influence our results. To do so, we drop observations in each industry (individually) from our sample and re-run our main analyses. Overall, we continue to find results similar to those reported in the primary analyses, with the exception of the following cases. Specifically, in our write-down tests, the relation between *Outlook* and *Writedown* weakens when Business Services firms are excluded. In our management forecast tests, we also observe weakened significance for *Outlook* when excluding Business Services or Retail, and *OutlookFactor* is no longer significant in these tests when excluding these industries. Nonetheless, it does not appear that our main inferences are exclusively driven by either of these two industries.

5.3.2. Unrotated (orthogonal) factors

As discussed in Section 3.2, we use principal factor scoring with promax (oblique) rotation to extract factors from the nine measures contained in each review and allow these factors to be correlated, consistent with the theoretical relations of the constructs. While we believe this design is more theoretically valid than requiring orthogonality in factors, in untabulated tests, we repeat all analyses using unrotated (orthogonal) factors. After doing so, we continue to find evidence that our latent measure of employee business outlook, *OutlookFactor*, is positively and significantly related to our measures of fundamental performance, earnings news, and voluntary disclosure news and that it is negatively related to transitory reporting items.

6. Conclusion

Rapid advancements in technology and media have the potential to greatly alter firms' information environments (Miller & Skinner, 2015). Our findings highlight how a new social media platform, Glassdoor.com, allows rank-and-file employees to convey an insider's view of their company to outsiders. In particular, we find evidence that the opinions employees share about their firm's outlook is predictive of future performance, earnings news, and significant corporate events. In light of our findings, we view the technological shift in the reporting environment as one that chips away at executives' sole control over disclosure of inside information to the public. We, therefore, see our results informing a very broad literature on corporate reporting.

Our results also contribute, more specifically, to research on whether rank-and-file employees hold private information about their firms. Prior research has provided indirect evidence that this may be the case (Babenko & Sen, 2015; Huddart & Lang, 2003), but this evidence has previously been based on the pattern of investment decisions made by employees. This is because, prior to the creation of a dedicated social media platform for rank-and-file employees, researchers lacked a large-scale dataset of employee opinions. Our results complement this research by examining the link between employees' explicit and latent outlook assessments of firm performance and future corporate disclosures. Finally, we note that, in this study, we found little evidence that anything in the reviews, other than measures of business outlook relate to the future mandatory or voluntary disclosures that we examine. However, we note at least two possibilities for this lack of results. First, factors like employee sentiment and the likelihood of employee retention might by more strongly related to other aspects of corporate performance, such as CEO turnover or aspects of executive compensation. Second, they may need to be aggregated over a longer window of time or related to performance over a longer time horizon. As such, we suspect there is much to yet be learned by listening to the myriad of voices echoing across social media platforms, such as Glassdoor.

While we believe our evidence provides interesting insights into employees' ability to predict future performance and opens new avenues for future research, we recognize two primary limitations of which readers should be aware. First, as we discuss in previous sections, reviews are voluntarily submitted for reasons unobservable to us. In our opinion, the primary concern with this issue is that our models suffer a correlated omitted variables problem, and we erroneously attribute our evidence to employee outlook rather than the event prompting the reviews. However, we highlight that we control for an array of outlook "determinants", many of which relate to the types of events that likely prompt employees to leave reviews. Additionally, if the events are internal to the firm (e.g., promotions, performance reviews), then we view them as the private information from which we expect employees base their outlook ratings. Second, we attribute our results to outlook rather than employee sentiment or job satisfaction. We believe this is appropriate since we make every effort to control for other responses in the reviews that relate to these factors. Nonetheless, we recognize that survey-evidence is inherently noisy and we cannot rule out other latent dimensions explaining employees' outlook assessments.

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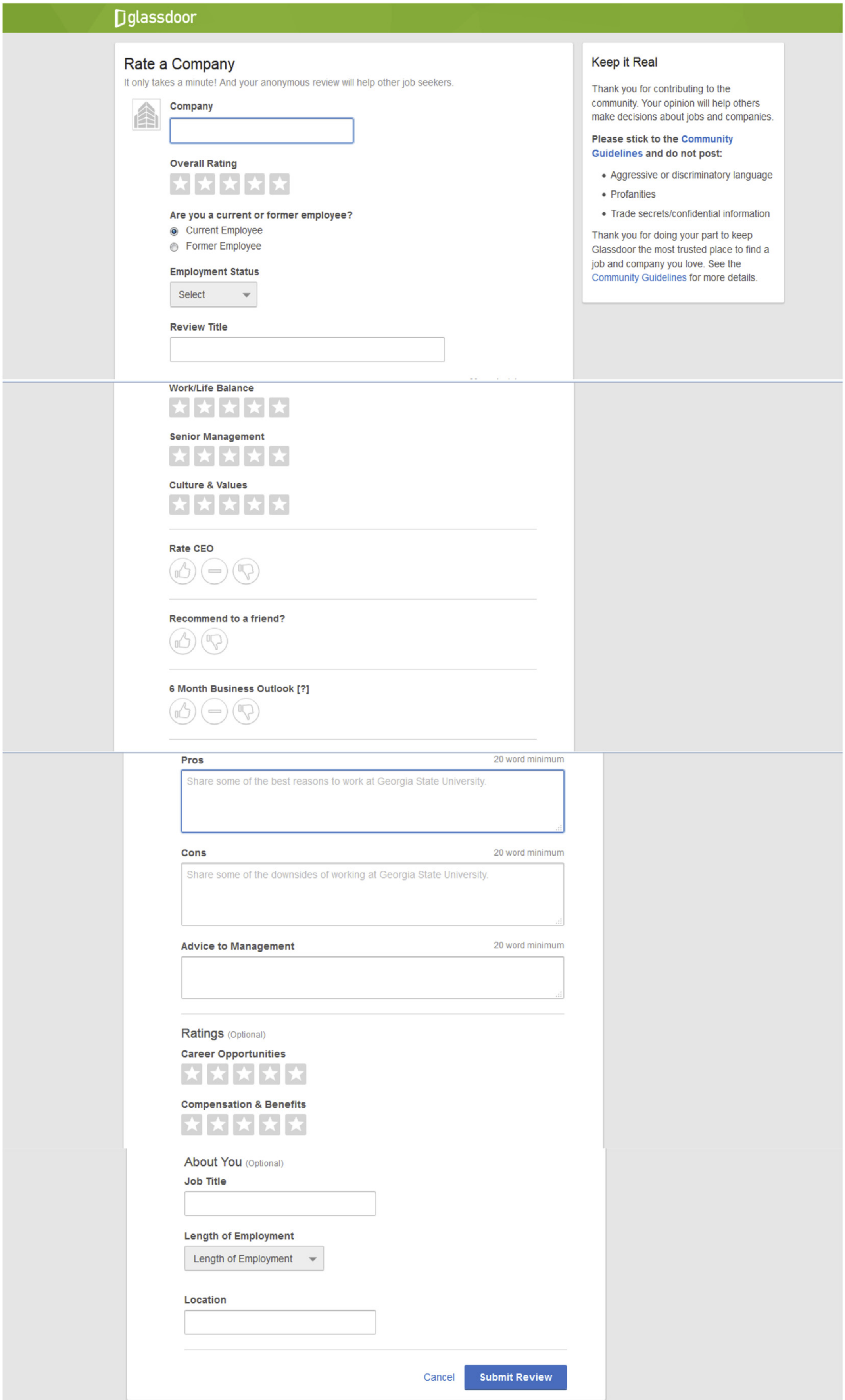
Appendix A

Glassdoor review form



glassdoor

Rate a Company

It only takes a minute! And your anonymous review will help other job seekers.

Company

Overall Rating

Are you a current or former employee?

- Current Employee
- Former Employee

Employment Status

Select

Review Title

Work/Life Balance

Senior Management

Culture & Values

Rate CEO

Recommend to a friend?

6 Month Business Outlook [?]

Pros 20 word minimum

Share some of the best reasons to work at Georgia State University.

Cons 20 word minimum

Share some of the downsides of working at Georgia State University.

Advice to Management 20 word minimum

Ratings (Optional)

Career Opportunities

Compensation & Benefits

About You (Optional)

Job Title

Length of Employment

Length of Employment

Location

Cancel **Submit Review**

Keep it Real

Thank you for contributing to the community. Your opinion will help others make decisions about jobs and companies.

Please stick to the Community Guidelines and do not post:

- Aggressive or discriminatory language
- Profanities
- Trade secrets/confidential information

Thank you for doing your part to keep Glassdoor the most trusted place to find a job and company you love. See the Community Guidelines for more details.

Appendix A presents screenshots describing the review format from Glassdoor.com. The review template was accessed on 10/20/2016.

Appendix B

Variable definitions

Data source is in brackets. All untransformed continuous variables are winsorized at the first and 99th percentiles.

Glassdoor Rating Components	
Overall	Employee's overall rating of employer ranked on a five point scale, with five (one) begin most favorable (unfavorable) [Glassdoor]
Outlook	Employee's assessment of firm's prospects. Equals 1 for reviews where employee assesses outlook as positive, 0 for reviews where employee assesses outlook as neutral, and −1 for reviews where employee assesses outlook as negative [Glassdoor]
RecToFriend	Indicator equaling 1 if employee responds that he or she would recommend employer to a friend [Glassdoor]
CEOApproval	Employee's opinion of CEO. Equals 1 (0, −1) if employee approves (remains neutral, disapproves) of the CEO. [Glassdoor]
WorkLife	Employee opinion of his or her work-life balance ranked on a five point scale, with five (one) begin most favorable (unfavorable) [Glassdoor]
CultureValues	Employee opinion of employer's culture and values ranked on a five point scale, with five (one) begin most favorable (unfavorable) [Glassdoor]
CareerOpps	Employee opinion of his or her opportunities for career advancement at their employer ranked on a five point scale, with five (one) begin most favorable (unfavorable) [Glassdoor]
CompBenefits	Employee opinion of his or her compensation and benefits package ranked on a five point scale, with five (one) begin most favorable (unfavorable) [Glassdoor]
SeniorManagement	Employee opinion of employer's senior management ranked on a five point scale, with five (one) begin most favorable (unfavorable) [Glassdoor]
OutlookFactor	Factor loading from review attributes factor analysis capturing employees' outlook of future firm performance
SentimentFactor	Factor loading from review attributes factor analysis capturing employees' overall opinion of the firm
RetentionFactor	Factor loading from review attributes factor analysis capturing employees' expectations about personal growth opportunities
Dependent Variables	
Sale	Cumulative 6-month net sales [saleq] scaled by assets [atq] ending 4–6 months after the date of the review [Compustat]
GM	Cumulative 6-month gross margin [saleq-cogsq] scaled by assets [atq] ending 4–6 months after the date of the review [Compustat]
OpInc	Cumulative 6-month operating income after depreciation [oiadpq] scaled by assets [atq] ending 4–6 months after the date of the review [Compustat]
Income	Cumulative 6-month income before extraordinary items [ibq] scaled by assets [atqq] ending 4–6 months after the date of the review [Compustat]
GWImp	Cumulative 6-month impairment of goodwill (pre-tax) [gdwlipq] scaled by assets [atq] ending 4–6 months after the date of the review, where missing values are assumed to be zero if goodwill exists as of the end of the fiscal quarter ending closest but prior to the date of the review. We then multiply this quotient by −1 so that higher (more positive) values correspond to larger impairments. [Compustat]
Writedown	Cumulative 6-month writedown of assets other than goodwill pre-tax [wdpq] scaled by assets [atq] ending 4–6 months after the date of the review, where missing values are assumed to be zero. We then multiply this quotient by −1 so that higher (more positive) values correspond to larger writedowns. [Compustat]
Restructure	Cumulative 6-month restructuring costs pre-tax [rcpq] scaled by assets [atq] ending 4–6 months after the date of the review, where missing values are assumed to be zero. We then multiply this quotient by −1 so that higher (more positive) values correspond to larger restructuring charges. [Compustat]
EarningsSurprise	The difference between the forecasted quarter's actual earnings per share for quarters ending (actual) 4–6 months after the date of the review and the consensus estimate available closest to but within thirty days before the date of the review scaled by stock price at the end of the month prior to the date of the review [IBES, CRSP]
MgmtFcstNews	The difference between the management's forecast of earnings per share (fcst) available closest to but within 90 days after the date of the review and the average consensus estimate available closest to but within thirty days before the date of the review scaled by stock price at the end of the month prior to the date of the review [IBES, CRSP]
MAR6	Market adjusted returns computed as the difference between the compounded return for firm *i* (ret) and the value-weighted market index (vwretd) over the 6-month period beginning the month following the calendar month of the employee review [CRSP]
MAR12	Market adjusted returns computed as the difference between the compounded return for firm *i* (ret) and the value-weighted market index (vwretd) over the 12-month period beginning the month following the calendar month of the employee review [CRSP]
Control Variables	
Size	The natural log of assets [atq] as of the end of the fiscal quarter ending closest but prior to the date of the review [Compustat]
Age	The natural log of the number of years with return history in CRSP as of the end of the month corresponding to the date of the review [CRSP]
ROA	Income before extraordinary items (ibq) divided by total assets (atq) as of the end of the fiscal quarter ending closest but prior to the date of the review [Compustat]
Returns	The abnormal stock return over the 30 days preceding the review. We use the market model to estimate abnormal returns. Betas are estimated from day −255 to day −46 [Eventus]
SGA	Selling, general, and administrative expenses (xsgaq) divided by net sales (saleq) as of the end of the fiscal quarter ending closest but prior to the date of the review [Compustat]
EmpGrowth	The percentage change in number of employees (emp) from the fiscal year containing the review to the previous fiscal year [Compustat]
RetVol	The standard deviation of logged returns [ret] over the 90 days preceding the review, annualized by multiplying by the square root of 252 [CRSP]
BTM	The ratio of the book value of equity [ceqq] to the market value of equity [prccq*cshoq] as of the end of the fiscal quarter ending closest but prior to the date of the review [Compustat]
n	The natural log of the number of Glassdoor reviews collapsed down to the respective analysis level.
Following	The natural log of the number of analysts (numest) providing quarterly earnings forecasts in the IBES monthly summary file dated closest to but within three months after the review [IBES]
FcstDisp	The standard deviation (stdev) of analyst forecasts providing quarterly earnings forecasts in the IBES summary report dated closest to but within three months after the review [IBES].
MgmtFcst_Horizon	The number of days between the earnings announcement date and the management forecast date, scaled by price [IBES, CRSP]
QTRInd	Indicator variable equal to one if management's forecast immediately following the date of the review and within 90 days of the date of the review is a quarterly earnings per share forecast (pdicity = "QTR"), zero if it is an annual earnings per share forecast (pdicity = "ANN") [IBES]

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