Asset Pricing in the Information Age: Employee Expectations and Stock Returns*

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Abstract

This paper studies the investment value of non-professional forecasts in financial markets, using a unique dataset of nearly one million employee reviews. Employee beliefs about their employers' business prospects predict future returns at one- to five-month horizons, delivering an annualized abnormal return of 7% to 9%. The abnormal returns do not reverse during a 12-month holding period. Employee reviews also predict future earnings, and this channel explains about 50% of the return predictability. In addition, the reviews predict future trading activity by hedge funds, suggesting some sophisticated investors exploit this information or its underlying sources. There are information hierarchies within firms in the sense that the return predictability of forecasts increases with employee rank. Overall, this paper highlights the role of non-experts in forecasting firms' fundamentals through online platforms, which is beyond traditional information intermediaries such as equity analysts.

Keywords: Employee expectations, return predictability, machine learning, information hierarchies

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1 Introduction

The arrival of the information age has significantly changed the landscape of financial markets. Investors can access more information than ever. Not only has the amount of information that investors face increased, the composition of information producers has also changed dramatically. In the past, investors relied on professionals, such as sell-side analysts, to acquire value-relevant information regarding the future performance of firms.[1] The rise of the internet and social media has greatly facilitated the generation and dissemination of information by non-professionals, including retail investors, consumers, and employees. Yet, little is known about the value of non-professional forecasts to the stock market. I address this question using a unique dataset of nearly one million online employee reviews.

Whether employee forecasts are valuable to the stock market is not clear *ex ante*. On the one hand, prior research finds that employees do not seem to have superior information about their firms' future returns, in the context of investments in stocks of their own companies in 401(k) accounts (Benartzi, 2001; Cohen, 2009). Also, employees are not experts in forecasting firms' fundamentals and their information is limited to their own occupations, and may be influenced by their own experiences.[2] On the other hand, employees as insiders may possess a wealth of information about their firms. Upper-level management often knows more about the performance of their firms than outsiders. Even non-executive employees can possess information relevant to a firm's future prospects through their day-to-day jobs (Babenko and Sen, 2015). Information from employees helps financial analysts make accurate forecasts (Malloy, 2005) and investment managers achieve good performance (Coval and Moskowitz, 1999, 2001).[3] Thus, even if employees post only a subset of their information online, it may

[1]There were about 6000 sell-side analysts at the world's 12 largest investment banks in 2016 (Financial Times, 2017, "Sell-side research would be little missed").

[2]For example, Kuchler and Zafar (2017) show that individuals extrapolate from recent personal experiences when forming expectations about aggregate economic outcomes. Extrapolation in expectation formation is also found in an experimental setting (Landier, Ma, and Thesmar, 2017).

[3]These studies find that local investment managers and analysts possess an information advantage, and this advantage translates into better performance. One major source of their information advantage is access to private information from top executives and employees. For example, Coval and Moskowitz (2001) argue that "Investors located near a firm can visit the firm's operations, talk to suppliers and employees, as well

be valuable to the stock market. Moreover, despite potential bias and errors in individual forecasts, the aggregation process may help to filter out noise, thereby resulting in high quality information.

To examine the role of non-expert forecasts, I extract employee reviews of companies from Glassdoor, the largest job review website in the world. As of June 2017, Glassdoor had 45 million unique visitors per month (Glassdoor, 2017). Glassdoor is a website where current and former employees anonymously review companies and their management. The reviews evaluate companies on certain criteria, including company reviews, compensation and benefits, and interview experiences. Although Glassdoor reviews are not directly related to investment opinions, they provide a variety of unique information.[4] Most importantly, one component of Glassdoor reviews focuses on the employee's opinion about the firm's business outlook (hereafter employee outlook).[5] I measure employee forecasts using this outlook variable.

Anecdotal evidence suggests that employee outlook contains value-relevant information to the stock market. For instance, Sears, the famous 130-year-old retailer, has been struggling since 2010. The fraction of reviews that had positive employee outlook dropped 6.3% in November 2013 compared to the previous three months, with employee comments such as: "Not enough customers and not competitively priced enough for sales," "Online shopping from within store very frustrating - products weren't available and customers were disappointed," and "My store didn't see a lot of customers (like many Sears stores these days)." The stock price of Sears dropped from $64 in November 2013 to $49 in December 2013 (i.e., -23% in returns), and never since recovered to the $64 level. The decline in positive outlook also coincided with a negative earnings surprise for the last quarter of 2013. Employees as a group can therefore hold valuable information about a firm's fundamentals and stock prices.

as assess the local market conditions in which the firm operates" (p. 839). Similarly, Malloy (2005) claims that "The ability of local analysts to make house calls rather than conference calls, during which time they can meet CEOs face to face and survey the firm's operations directly, provides them with an opportunity to obtain valuable private information" (p. 721).

[4]Job seekers, investors, and corporations use information from Glassdoor for important decisions. For instance, a news article in the Wall Street Journal reports that Zillow's CEO Mr.Rascoff and leaders at other companies look at information from Glassdoor of acquisition candidates. Mr Rascoff says "we walked away from dozens of acquisitions that looked good on paper and made strategic sense."

[5]The specific question Glassdoor asks is: "In the next six months, do you believe your company's business will perform better, worse or remain the same?"

While anecdotal evidence is appealing, it is not necessarily the case that this pattern holds systemically across all firms. Using review data from Glassdoor for S&P 1500 firms from 2012 to 2016, I provide a comprehensive study of employee outlook. Information embedded in employee outlook is novel and different from known information from financial statements and media coverage. I find evidence that employee outlook contains value-relevant information. Higher abnormal positive outlook predicts increased future stock returns. A long-short portfolio trading strategy delivers an abnormal return of 0.61% to 0.78% per month for a one-month holding period. The return predictability of employees' information is robust to controlling for firm characteristics such as size, market beta, book-to-market, media coverage, profitability, and employee satisfaction. The return predictability of employee outlook is strongest over one to four weeks, and declines gradually over five months. The abnormal returns do not reverse during a 12-month holding period. This alpha decay pattern holds for weekly and daily results as well, suggesting that this information is incorporated into stock prices over time.

To understand the information contained in employee outlook, I investigate the relation between employee outlook and firms' future earnings. I find that employee outlook positively predicts subsequent earnings surprises and changes in profitability. The results are robust to controlling for other variables that affect earnings, such as analyst coverage and past stock returns. The economic magnitude is significant. For instance, one standard deviation change of abnormal positive outlook is associated with an increase of 29% of the mean of earnings surprises. I further examine the extent to which the predictive power of employee outlook for future stock returns can be explained by future earnings. I find that the return predictability declines 48% after controlling for future earnings surprises, suggesting that future earnings can account for about half of the return predictability. These findings suggest that employee outlook contains novel information about firms' fundamentals.

Because employee outlook contains value-relevant information about stocks, an interesting question is whether sophisticated investors exploit this information from Glassdoor or its underlying sources. I examine this question by looking at the trading activities of various types of institutional investors. Anecdotal evidence suggests that hedge funds exploit Glassdoor data and, indeed, I find that abnormal positive outlook predicts the net purchases by hedge funds. In contrast, abnormal positive outlook does not predict net purchases by mutual funds or other non-hedge-fund institutions. My results show that abnormal positive outlook also predicts a decrease in short selling quantity and costs. Both findings indicate that sophisticated investors trade on the information from employee outlook or its underlying sources.

Several recent studies point out the importance of looking at the heterogeneity in analyst forecasts (Chiang et al., 2016; Michaely et al., 2017). Motivated by these studies, I examine whether significant quality differences exist in online forecasts by different levels of employees. Are high-level employees' outlooks better than low-level employees' outlooks? The answer to this question is not clear *ex ante*. While some theories of organization hierarchies predict that high-level employees have better information (Garicano, 2000), other theoretical evidence stresses the benefits of having a different structure where low-level employees possess important information (Landier, Sraer, and Thesmar, 2009). To examine the heterogeneity in employee outlook, I classify employee job titles into three groups (high-, middle-, and low-level) within a firm based on wages, and examine the return predictability of outlook by different levels of employees. I find that, on average, the return predictability of employee outlook increases with employee rank, suggesting the presence of information hierarchies within firms.

Interestingly, a firm's information hierarchy depends on its complexity. I use three proxies to measure a firm's complexity: organization hierarchy, size, and whether the firm is a conglomerate. For complex firms, high-level employees' outlooks tend to have better return predictability, and middle- and low-level employees' outlooks do not predict future stock returns. However, for simple firms, middle- and low-level employees' outlooks also predict future returns. The return predictability among high-, middle-, and low-level employees' outlooks is statistically indistinguishable. These findings are consistent with theoretical evidence and economic intuition that the information structure is flatter among simple firms because the communication cost among different levels of employees is smaller.

Why are high-level employees' outlooks better in predicting future returns? I address this question by examining whether high-level employees' reviews convey different information compared to those from low-level employees. Using machine learning to detect latent topics in review texts, I compare the topics from reviews by different levels of employees. High-level employees' reviews are often about business growth, which is more related to a firm's fundamentals. Low-level employees' reviews focus on work hours and personnel development, which are less related to a firm's fundamentals. Although employees' opinions on work hours and personnel development may affect a firm's valuation in the long run, they are slow-moving variables and thus less important in predicting short-run earnings and stock returns.

This paper makes four main contributions to the finance and economic literature. First, this study is the first to test the investment value of online non-professional forecasts of firms' fundamentals. While several studies examine the impact of social media on stock returns (e.g., Tumarkin and Whitelaw, 2001; Antweiler and Frank, 2004; Chen et al., 2014)[6], their results are based on investment opinions and stress the importance of peer-effect among investors[7]. Different from these studies, this paper focuses on online forecasts that are directly about firms' fundamentals. This unique feature allows me to distinguish between a fundamental story (where employee outlook contains relevant information about firms' fundamentals) and a behavioral story (where investors just react to employee outlook for behavioral reasons and the outlook does not provide valuable information about firms' fundamentals). Also, previous studies often use a relatively small sample of firms or have a small number of reviews for each firm. My study utilizes a comprehensive sample of S&P 1500 firms where an average firm has about 700 reviews. Because the power of online data arises from the aggregation of a large amount of data, my large sample allows for reliable statistical inferences. Thus, this paper not only extends earlier results to another category of social media, but also sheds light on the underlying reasons why social media matters for stock markets.

Second, by studying non-professional forecasts, this paper highlights a new type of infor-

[6] Other studies of social media include Da, Engelberg, and Gao (2011), Jame et al. (2016), and Huang (2017). In general, this paper fits into the literature on the impact of media on stock returns (e.g., Tetlock, 2007; Tetlock et al., 2008; Fang and Peress, 2009; Dougal et al., 2012; Gurun and Butler, 2012; Fisher, Martineau, and Sheng, 2017; Manela and Moreira, 2017). For survey papers in this literature, see Tetlock (2014), Loughran and McDonald (2016), and Gentzkow, Kelly and Taddy (2017). Several papers use employee review data, but they focus on corporate culture and do not provide evidence for return predictability (Popadak, 2013; Huang et al,. 2015).

[7] Campbell et al. (2017) show that 36% of investment platform users are financial professionals.

mation intermediary that is different from traditional types such as sell-side analysts (e.g., Womack, 1996; Jegadeesh et al., 2004). Although financial analysts are experts in producing earnings forecasts, employees' forecasts may contain novel information for several reasons. First, employee outlook is based on first-hand information from day-to-day jobs. This type of information, called "serendipitous information" by Subrahmanyam and Titman (1999), is diffuse but genuine. Second, social media is unique in the sense that it allows a large number of people to produce information at a very low cost. Although individual employee's forecasts may not be precise about a firm's future prospects, employee forecasts in aggregate may contain information that is not fully incorporated into earnings forecasts. Third, prior studies find that financial analysts tend to behave strategically and do not always reveal their true opinions due to conflicts of interest (e.g., Michaely and Womack, 1999; Kadan et al., 2009). In contrast, employees are more likely to provide genuine opinions, because their forecasts are anonymous.[8] Moreover, an individual employee has little incentive to intentionally spread false information and mislead investors because a single forecast is not likely to exert significant influence on stock prices. This study contributes to this literature by showing that non-professional forecasts can provide value-relevant information that is beyond analyst forecasts, which is a novel phenomenon in the information age.

Third, my findings shed new light on the debate over whether rank-and-file employees possess value-relevant information. Prior studies report contradicting findings based on indirect evidence from employees' investment decisions (Benartzi, 2001; Cohen, 2009; Babenko and Sen, 2014, 2015). While inferring employees' information from their stock purchases is useful, it is not direct. Even if employees' stock purchases do not predict firms' future returns, this does not necessarily mean that employees do not have valuable information about their firms. Employees might not exploit their information due to a lack of financial literacy or significant fixed costs of participation. Using a direct measure of employee information from their online reviews, I show that employees do possess valuable information.

Fourth, this paper shows the first direct empirical evidence of the existence and magnitude of information hierarchies within firms. While various theories of organization hierar-

[8] This does not mean that online anonymous reviews are unbiased. Online reviews often suffer from response bias. I find response bias is not severe in Glassdoor data due to their policy to encourage more balanced reviews (see Section 2).

chies study information structure within firms (Garicano, 2000), direct empirical evidence is limited. Empirical testing of information hierarchies is challenging because measuring employees' information is extremely hard, and it is difficult to evaluate the value of information. I use employees' online reviews as a proxy for their information and use the stock market as a laboratory to evaluate the value of information. If one group of employees' information can better predict future returns, then their information is better. This study complements the literature on organization hierarchies by explicitly examining the information structure within firms.

2 Data

2.1 Employee review data

I retrieve employee reviews from Glassdoor, the largest website for employee reviews. Launched in June 2008, Glassdoor provides information about companies that is posted by current and former employees, including company reviews, compensation and benefits, and interview experiences. Since then, hundreds of thousands of users have posted over 33 million reviews and insights for approximately 700,000 companies around the world. The website is widely used and had 45 million global users visit in July 2017 (Glassdoor, 2017).

Each company review contains numerous components: an overall rating as well as ratings on compensation and benefits, work-life balance, company culture and values, and senior management, all of which are measured on a five-point scale. Each company review also reveals whether the reviewer would recommend the company to a friend, and whether they approve of the CEO. Most importantly, it contains an assessment of a firm's 6-month business outlook (see Figure A1 in the Appendix for the full questionnaire). Other important information in a review includes reviewer's job title and location. Reviewer's job title is crucial to analyze information distribution within the firm. For each job title, I collect its average salary from the same website (see Figure A2 in the Appendix for an example). The outlook information only became available since March 2012, and thus my main analysis focuses on the sample period of 2012-2016. I also use machine learning to backfill the outlook variable to 2008 and the results are robust.

A common concern about online review data is response bias. Glassdoor uses a "Give to get" policy as an incentive to encourage more neutral and balanced company ratings. Under this policy, users must share their opinions of their own employer to access information on Glassdoor. In a report released in October 2017, Glassdoor shows that the polarization bias on its website is less severe than other online review sites, such as Amazon and Yelp.[9] Nevertheless, I check whether there is serious bias in the data. Luca and Zervas (2016) find that suspect reviews tend to have a bimodal distribution of either very low or very high scores. As such, bimodally distributed employee reviews would indicate a serious response bias in the sample. Figure A3 in the Appendix shows that star ratings are approximately normally distributed rather than bimodally distributed. Although this evidence does not fully eliminate the possibility of response bias, it makes bias a less serious concern. In a robustness test, I also remove firms with less than 5 reviews per month during the sample period because these firms are more likely to be affected by extreme responses.

2.2 Summary statistics

In this paper, I focus on S&P 1500 firms and collect firm returns and volume data from CRSP, accounting variables from Compustat, and analyst forecasts from I/B/E/S. After matching CRSP and Compustat to employee reviews data, the final sample consists of 1422 firms with about one million reviews. I also remove stocks that have less than 20 reviews in total during the sample period.[10] Table 1 Panel A presents the distribution of reviews and firms over Fama-French 12 industries. The top three industries in terms of the number of employee reviews are wholesale, business equipment, and finance. In a robustness test, I exclude financial firms and find similar results. On average, a firm has about 700 reviews from 2012 to 2016.

To construct the monthly panel sample, I aggregate daily reviews to monthly frequency. For outlook, I calculate the fraction of reviews that have positive outlook (*Positive outlook*).

[9] See the Appendix for further discussion of "Give to get" policy and the Glassdoor report on this policy.

[10] This is to address the concern that the results might be driven by firms with very few reviews, which are biased. These firms tend to be small firms, for which the return predictability is stronger. Thus, removing these firms is conservative and results in a lower bound. The results are robust when including these firms.

Similarly, I calculate the fraction of reviews that state "recommend to a friend" (*Recommend*). For the star rating variables, I calculate the monthly average of the overall rating (*Overall*), culture and values rating (*Culture*), work-life balance rating (*WorkLife*), senior management rating (*Management*), compensation and benefits (*Compensation*), and career opportunities (*Career*). To measure the new information conveyed by employee outlook (i.e., surprises in employee outlook), I use average positive outlook over the prior three months as a benchmark for employees' expectations of a firm's future prospects. I thus measure the abnormal positive outlook (*AbnOutlook*) as the difference between the *Positive outlook* and its mean over the prior three months. By using this measure, I difference out time-invariant biases in employee outlook. In a robustness test, I use the means over the prior six months as benchmarks to calculate *AbnOutlook*, and get similar results.

Table 1 Panel B reports the summary statistics on these review variables. The mean value of *Positive outlook* suggests that, on average, 41.7% of employees who post a review have a positive opinion of their firm's near-term business prospects. The mean *AbnOutlook* is 0.35%, which is not statistically different from zero. On average, about 56.01% of employees said that they would recommend their company to a friend. The average *Overall* rating is 3.18 (out of 5), indicating that the average employee posting a review has a generally positive view about the firm. The five subcomponents have similar means, with *Management* having a slightly lower value. Table 1 Panel B also reports the descriptive statistics of firm characteristics. The summary statistics of firm characteristics are comparable to the literature for the S&P 1500 sample.

Does employee outlook convey novel information or just reflect stale news from existing financial statements and media reports? To examine this question, I regress employee outlook on lagged positive media coverage and firm characteristics including size, book-to-market, market beta, institutional ownership, analyst coverage, profitability, and trading volume.[11] The results, presented in Table 2, show that none of these variables can predict abnormal positive outlook. This finding suggests that abnormal positive outlook is largely independent of the information contained in accounting statements, analyst coverage, and media coverage.

[11] RavenPack provides a sentiment score (out of 100) for each news article. A news article for a firm is positive if the score is above 50.

2.3 Employee outlook

I examine the nature of employee outlook by looking at other components of an employee review: star ratings, employee characteristics, and texts. Specifically, I run the following regression:

$$Outlook_{it} = \gamma_0 + \gamma_1 X_{it} + \varepsilon_{it} \tag{1}$$

where $Outlook_{it}$ is a dummy variable that is equal to one if outlook is positive, and zero otherwise; and X_{it} includes three sets of variables: (i) employee characteristics: current vs. former, work in headquarter states vs. non-headquarter states; (ii) star ratings as discussed in Section 2.2; and (iii) text characteristics: number of words in title, pros, cons, and advice to management sections, and number of words of the whole review.[12]

First, I examine what type of employees are more likely to have positive outlook. Table A3 Panel A in the Appendix presents the results. Current employees are more likely to have positive outlook than former ones (Column (1)), and employees who work in the headquarter state do not have a more optimistic outlook than others (Column (2)). Second, I also look at the recommendation variable and the star ratings and find that employees who state "recommend to a friend" or give high star ratings are more likely to have positive outlook (Columns (3)-(4)).

Finally, I investigate the differences in review texts among reviews with positive and negative outlook along two dimensions: length and meaning of text. A review text has four parts: review title, pros, cons, and advice to management. I count the number of words in each part. If business outlook indeed reflects employees' opinions of the firm's future prospects, it might be related to the length of discussion in pros, cons, and advice parts of the review. Table A3 Panel B in the Appendix shows that employees who have a positive outlook tend to write a shorter title, say less in cons and advice to management sections, and say more in pros section (Column (1)). In general, employees with a positive outlook tend to write a shorter review than those who do not (Column (2)).

I examine the relationship between outlook and meaning of review text by finding the

[12] I also use logit and probit regression methods to conduct this test and get similar results.

top words in reviews. If employee outlook is indeed related to the business operation of the firm, employees who have positive outlook may also tend to say something good about the firm in the text. I use the bag-of-words method to convert raw reviews into words, and remove stop words (i.e., meaningless words such as the, an, and). I then convert the words into numeric vectors. To account for the relative importance of a word in each review, a term-frequency-inverse document frequency (tf-idf) method is used in the transformation process. After transformation, each review is represented as distributions of words with their weights. Finally, I run a logistic regression where the dependent variable is a dummy variable that is equal to one if employee outlook is positive, and zero otherwise, and the independent variables are distributions of words. The regression coefficients give the relative importance of each word.

Figure 1 reports the results of such a test and shows the top 10 words associated with both positive and negative outlook. The blue bars are words that are the most important for a review with a positive outlook. These words include great, awesome, love, growing, amazing, excellent, continue, fantastic, superb, and incredible, all of which are positive words. The red bars are words that are the most important for a review with a negative outlook. These words include horrible, downhill, sinking, worst, unstable, uncertain, layoffs, declining, poor, and terrible, all of which are negative words. Overall, the list of top words from textual analysis seems to be consistent with the opinion of outlook.

3 Employee outlook: is it valuable to the stock market?

There is no systemic evidence of the existence and magnitude of the value of employee outlook to the stock market. I examine this question by looking at whether employees' positive outlook can predict a significant increase in future stock returns, controlling other factors affecting stock returns. I use both portfolio sorting and panel regression approaches, followed by a battery of robustness tests. To understand the underlying information sources of employee outlook, I test whether it is linked to future fundamental information.

3.1 Employee outlook and stock return predictability

I use a portfolio approach to examine the investment value of employee opinions about the prospects of firms. In each month from June 2012 through December 2016, I sort sample stocks into tercile portfolios based on *AbnOutlook*. That is, stocks with a high (low) *AbnOutlook* are assigned into the top (bottom) portfolio, and the rest are assigned into the middle portfolio. I then track the performance of the three portfolios over the following month. I employ two weighting methods across firms, equal weighting and value weighting. I also use a weighting method based on the number of reviews in each month in a robustness test.

Figure 2 graphically presents the stock performance of high- and low-*AbnOutlook* firms. It shows the cumulative return of the high-*AbnOutlook* and low-*AbnOutlook* portfolios that are formed at the end of June 2012, rebalanced at the end of each month, and held to December 2016. Over my sample period, the equal-weighted (value-weighted) high-*AbnOutlook* portfolio has cumulative returns that are 73% (45%) higher than the low-*AbnOutlook* portfolio.

To formally test the investment value of employee outlook, I first examine whether it can predict excess returns adjusted by risk-free rate. Table 3 Panel A shows that portfolio returns monotonically increase with positive outlook value. For stocks with low abnormal positive outlook (Portfolio 1), their average excess return is 0.71% (equal weighting). On the other hand, the average excess return of stocks with high positive outlook (Portfolio 3) is 1.57%. The difference (0.86%) between the two portfolios is statistically significant at the 1% level. The pattern is similar for value-weighted portfolios. This evidence suggests that firms with more positive outlook tend to have higher future stock returns after adjusting the risk-free rate.

While the evidence from excess returns is significant, it is possible that stocks in Portfolio 3 are different from Portfolio 1 in systematic ways. For example, stocks in Portfolio 3 may have more exposure to risk factors than stocks in Portfolio 1. To ensure the outperformance based on abnormal positive outlook does not result from risk, I use the Fama-French-Carhart four-factor model (Fama and French 1993; Carhart, 1997) to adjust returns. I compute a four-factor alpha by regressing monthly portfolio excess returns on the monthly returns from the risk factors:

$$R_{it} = \alpha + \beta_{MKT} MKTRF_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \varepsilon_{it} \qquad (2)$$

where R_{it} is the excess return adjusted by the risk-free rate from portfolio i at time t. For the long-short portfolio, R_{it} is the return difference between portfolio 1 and portfolio 3. $MKTRF_t$, SMB_t, HML_t, and MOM_t are market, size, value, and momentum risk factor returns, respectively.[13]

Table 3 Panel B reports the alphas and factor loadings from this regression for both equal-weighted and value-weighted portfolios. Stocks with high *AbnOutlook* outperform the four-factor benchmark by 0.51% to 0.56% per month. On the other hand, stocks with low *AbnOutlook* underperform by 0.05% to 0.26% per month. A long-short portfolio that buys stocks in the top tercile of positive outlook and sells stocks in the bottom tercile outperforms the benchmark by 0.61% to 0.78% per month, or about 7% to 9% annually, which is significant at the 1% level. While the magnitude of alpha is sizable, it is not unusually large for investment strategies based on information that is not from traditional sources. It is comparable to abnormal returns of long-short strategies based on managerial ownership (4%-10% in Lilienfeld-Toal and Ruenzi, 2014), employee stock purchases (10% in Babenko and Sen, 2015), and firm complexity (11.8% in Cohen and Lou, 2012).

To understand the sources of the predictability of future stock returns based on employee outlook, I conduct various subsample analyses. First, prior literature has established that the information environment of firms can affect the processing of information. Firms with a more opaque information environment will have stronger return predictability because their information gets less attention, resulting in slower incorporation of news. I use firm size and analyst coverage as proxies for the information environment. Information about small firms and firms with lower analyst coverage is more likely to be ignored by investors. If a worse information environment slows the incorporation of the information embedded in employee outlook, the predictability should be concentrated among small firms and firms

[13] These risk factor returns are downloaded from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

with low analyst coverage. I partition the sample into two subsamples based on their market capitalization.[14] Small firms are firms with a market cap below the median, and large firms are those with a market cap above the median. Similarly, I partition the sample based on the median of analyst coverage. Table 4 Panels A and B show that the return predictability is stronger among small firms, and comes mainly from firms with fewer analysts.

Second, because the information is from employees, the relative importance of employees within firms may also affect the return predictability. Prior literature finds that the level of human capital or organization capital in a firm affects its stock returns (Eisfeldt and Papanikolaou, 2013; Boguth, Newton, and Simutin, 2017). Moreover, for firms with more employees, the information quality from Glassdoor is better because these firms tend to have more reviews. I use labor intensity at the industry level to proxy for the importance of employees in a firm. Employees' outlook for firms with high labor intensity may have greater impact on their stock returns, and the return predictability will be stronger for these firms. I partition firms into two groups based on their labor intensity at the industry level. Firms in industry with labor intensity above the median are high labor intensity firms, while the rest are low labor intensity firms. Table 4 Panel C shows that the return predictability of employee outlook is much greater among firms in higher labor intensity industries.

Third, the information quality of employee outlook also depends on employees' characteristics. Current employees and employees who work near the headquarters are more likely to have better information about their firms. Former employees do not work in the company anymore and therefore their information may be stale. Employees who work far away from headquarters may only have limited information about their division. Thus, the outlook of current employees and employees who work near headquarters likely has stronger return predictability. To test this conjecture, I partition the sample based on employee status and employee location.[15] Table 4 Panel D shows that the return predictability is mainly driven by current employees. Table 4 Panel E shows that, although the return predictability of employees who work in the headquarter state is greater than that of other employees, in-

[14]I use the market capitalization from previous year to avoid forward-looking bias.

[15]About 60% of reviews are posted by current employees, and the remaining 40% are by former employees. About 20% of reviews are posted by employees who work in the headquarter state, while the remaining 80% are by employees in other states.

formation from employees in a non-headquarter state is still valuable in predicting future performance.

3.2 Fama-MacBeth regressions

The results so far show that employee outlook contains value-relevant information. Is this information new, or does it simply capture return predictability from contemporaneous accounting variables? To address this concern, I conduct Fama-MacBeth regressions by explicitly controlling for accounting variables and other known predictors in the cross-section of stock returns. Fama-MacBeth regressions are performed in two steps (Fama and MacBeth, 1973). For the first step, in each month, I run the following cross-sectional regression:

$$R_{j,t+1} = \eta_0 + \eta_1 AbnOutlook_{j,t} + \eta_2 BC_{j,t} + \boldsymbol{\theta} Z_{j,t} + \epsilon_{j,t} \tag{3}$$

where $R_{i,t+1}$ is the excess return adjusted by the risk-free rate of stock j in month $t+1$; *AbnOutlook* is the abnormal positive outlook of stock j in month t; and BC is a dummy variable that is equal to one if the firm is on Fortune's list of the "100 Best Companies to Work for" in that year, and zero otherwise. $Z_{j,t}$ is a vector of firm characteristics for firm j in month t. I include the following firm characteristics as controls: exposure to market risk (Beta), market capitalization (Size), cumulative stock returns in the prior 12 months, institutional ownership, analyst coverage, gross profitability of Novy-Marx (2013), and dollar trading volume. Media coverage, which is the number of news articles that mentioned the firm in the Dow Jones News Archives (from RavenPack), is also included as a control variable.

For the second step, I estimate the time-series averages of the cross-sectional regression coefficients. Table 5 reports the results of the second step. Column (1) shows the results of a univariate regression. The coefficient on employee outlook is positive and significant at the 1% level, suggesting that employee outlook can predict future stock returns. Edmans (2011) finds that firms on the "100 Best Companies to Work for" list tend to have higher future long-term returns. Column (2) reports the results of a univariate regression of BC on future returns. The coefficient is negative and insignificant, suggesting that employee satisfaction cannot predict short-run returns. In Column (3), I regress both *AbnOutlook* and BC on future returns and find that the coefficient on employee outlook remains similar at both statistical and economic levels. Column (4) reports the results of multivariate regressions with a battery of additional controls and shows that change in employee outlook continues to predict future stock return after adding these controls. The economic magnitude is significant. For instance, the coefficient estimate on *AbnOutlook* in Column (4) indicates that one standard deviation change of *AbnOutlook* is associated with an increase of about 0.84% in the one-month-ahead excess returns. Overall, these results suggest that the information from employee outlook is likely new information, which is different from other sources such as accounting statements, past returns, media coverage, and employee satisfaction.

3.3 Employee outlook and earnings

The fact that employee outlook predicts future stock returns suggests that it may contain new information about a firm's earnings. If this is the case, then employee outlook may predict a firm's earnings news. To test this conjecture, I use earnings surprises to capture new information in earnings and examine whether employee outlook can predict earnings surprises. Because earnings are released at a quarterly frequency, I calculate the employee outlook at a quarterly frequency as the fraction of reviews with positive outlook during a quarter. *AbnOutlook* is then defined as the quarterly positive outlook minus its mean over the prior three quarters. Following the literature, I run the following panel regression:

$$SUE_{i,q} = \gamma_0 + \gamma_1 AbnOutlook_{i,q} + \gamma_2 SUE_{i,q-1} + \theta Z_{i,q-1} + \varepsilon_{i,q} \tag{4}$$

where SUE is earnings surprises for firm i in quarter q (as defined in Section 2); $AbnOutlook_{i,q}$ is the abnormal positive outlook for firm i in quarter q; and $Z_{i,q-1}$ is a vector of firm characteristics of firm i in quarter $q-1$, including lagged earnings surprises, size, market beta, book-to-market, profitability, stock returns in the past 12 months, media coverage, institutional ownership, analyst coverage, and trade volume. I also add time and firm fixed effects in some specifications. Note that abnormal positive outlook is measured *before* the release of quarterly earnings news, which typically occurs about 30 days after a quarter-end.

Table 6 Panel A reports the regression results. Abnormal employee outlook positively predicts earnings surprises regardless of the specifications. The economic magnitude is significant. For instance, in Column (3) the coefficient on *AbnOutlook* indicates that one standard deviation change of *AbnOutlook* is associated with an increase of 0.02 % in *SUE*, which is about 29% of the mean of *SUE*.

I also use cumulative abnormal returns (*CAR*) around the earnings announcement window to proxy for earnings surprises. Specifically, I use the *CAR[-1,1]* where returns are measured by using a three-day window centered on the announcement date and adjusted using the market model. I use the same regression as in Equation (4), except replace the *SUE* with *CAR[-1,1]*. The regression results with *CAR* as the measure of earnings surprises are reported in Columns (4)-(6) of Table 6 Panel A. The coefficient on *AbnOutlook* is positive and significant regardless of specifications. The economic magnitude is also significant. One standard deviation change of *AbnOutlook* is associated with an increase of 0.44% in *CAR*.

Moreover, I investigate whether employee outlook predicts firms' future performance. I use two measures of performance: change in return on asset (ΔROA) and change in operating profitability (Δ*Profitability*). I regress these two measures on lagged *AbnOutlook* with some controls and time and firm fixed effects. Table 6 Panel B reports the results. The coefficient on *AbnOutlook* is positive and significant for all specifications, suggesting employee outlook positively predicts a firm's future performance for both measures.

To further examine the extent to which the predictive power of employee outlook for future stock returns can be explained by future earnings, I use Fama-MacBeth regression as in Equation (3) and add subsequent earnings surprises as an additional control variable. I find that the coefficient on *AbnOutlook* declines from 0.93 to 0.48, suggesting the return predictability declines 48% after controlling for future earnings surprises. This finding indicates that firms' future earnings can account for about half of the return predictability from employee outlook.

Overall, the results regarding employee outlook and subsequent earnings surprises and firm performance suggest information embedded in employee outlook contains novel information about firms' fundamentals.[16] Information regarding earnings, ROA, and profitability

[16]This evidence is further confirmed by abnormal returns over long holding periods in Section 4.1. If employee outlook just captures sentiments, the predictability should eventually reverse. If employee outlook indeed conveys valuable information about firms' fundamentals, the return predictability should not sub-

is released at a quarterly frequency, while information conveyed from employee outlook is analyzed at a monthly frequency. Employees who work in a firm with strong earnings, ROA, and profitability may know that their firm is doing well and express their confidence about the firm's prospect on Glassdoor, which predicts the subsequent release of earnings, ROA, and profitability. It also indicates that the average analyst does not fully incorporate the information from employee reviews in their forecasts.

3.4 Robustness

I conduct a battery of tests to assess the robustness of the main results. First, these review components are not independent of each other. As discussed in Section 2, employees who have a positive outlook of the company tend to give a high rating for Culture, WorkLife, Management, Compensation, and Career as well. This suggests that a set of latent variables may explain reviewers' responses across various components of the reviews. My main focus is whether employee reviews contain information about firms' future performance, which may be most directly captured by the outlook variable. But, it is possible that other variables also contain valuable information about the near-term prospects of the firm. To further understand this, I conduct a Principal Component Analysis (PCA) and extract the top three components out of eight variables. Table A4 Panel B in the Appendix shows that the first and most important component is mainly loaded by outlook variable. The other two components are mainly about work-life balance and compensation and benefits. I construct an expected positive outlook variable, which is a linear combination of employee outlook, recommendation dummy, and star ratings based on the weights from PCA. The *expected AbnOutlook* is calculated as expected positive outlook minus its mean over the prior three months. Table 7 Panel A shows that a long-short portfolio that buys stocks in the top tercile of *expected AbnOutlook* and sells stocks in the bottom tercile outperforms the Fama-French-Carhart four-factor benchmark by 0.30% to 0.63% per month. Notice that the magnitude of alpha based on *expected AbnOutlook* is smaller than alpha based on actual AbnOutlook, suggesting the outlook variable contains more value-relevant information.

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sequently reverse. As shown in Section 4.1, there is no reversal for the long-short portfolio even after 12 months.

Second, I use several alternative risk benchmarks to adjust the returns, including the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model, the Fama-French-Carhart six-factor model, the Hou, Xue, and Zhang (2015) four-factor model, and the Fama-French-Carhart four-factor model augmented with a liquidity factor (Pastor and Stambaugh, 2003).[17] Table 7 Panel A shows that the results are similar to those obtained from the main specification in terms of statistical significance and economic magnitude.

Third, I construct an abnormal positive outlook using the mean of positive outlook over the prior six months, rather than three months, as a benchmark. The *AbnOutlook* is measured by positive outlook minus its mean over the prior six months. The results, reported in Table 7 Panel A, show that the four-factor alphas on the long-short portfolio continue to be positive and significant at the 1% level.

Fourth, one may also be concerned that the sample period of 2012-2016 is too short to draw any reliable conclusion. In fact, it is normal to use a relatively short sample period due to the availability of online data.[18] Nevertheless, I use rating variables and text to backfill outlook values from June 2008 to February 2012 with machine learning methods. Specifically, I use ratings variables and text of all reviews from March 2012 to December 2016 as training and test samples to find the relationship between these variables and outlook, and then predict outlook based on the training samples. I use various machine learning methods: KNN, logistic regression, linear SVC, decision tree, random forest, gradient boosted regression trees, and deep learning.[19] Table A5 in the Appendix presents the out-of-sample accuracy of these methods. While KNN and other machine learning methods provide decent accuracy, deep learning outperforms all of them with an accuracy score of 91% (see the Appendix for more details). Thus, I use the predicted outlook from a deep learning method in the end. With a reliable predicted outlook back to 2008, I then sort portfolios based on predicted *AbnOutlook* and calculate the Fama-French-Carhart four-factor alphas. Table 7

[17] The liquidity factor returns data are from Lubos Pastor's website: http://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2016.txt.

[18] For instance, Antweiler and Frank (2004) use Yahoo! message board data in 2000 to examine its influence in financial markets. Da, Engelberg, and Gao (2011) use Google trend data from 2004-2008 to measure investor attention and study their impact on stock returns.

[19] See Friedman, Hastie, and Tibshirani (2001) for a detailed discussion on machine learning. See LeCun, Bengio, and Hinton (2015) for a review on deep learning.

Panel B shows that firms with high *AbnOutlook* outperform firms with low *AbnOutlook* by 0.39% to 0.53% per month.

I also use several alternative samples to assess the robustness of the return predictability. While the sample of S&P 1500 firms is already large and accounts for more than 90% of the market capitalization of the US stock market, I also extend the sample to all Compustat-CRSP firms. I then use the final matched sample of 2108 firms with employee reviews to form long-short portfolios and calculate the Fama-French-Carhart four-factor alphas. To address concerns on financial firms, I remove them from the sample and construct the portfolios with non-financial firms. To address the concern that the information is noisy and the quality of data is not high for firms with very few reviews, I remove stocks with less than 5 reviews per month and redo the tests as in the main specification. For a similar reason, I remove reviews from outside of the US, and then conduct portfolio regression tests. The results for these alternative samples, reported in Table 7 Panel B, are similar to the main results in terms of both statistical significance and economic magnitude.

Finally, I use an alternative weighting scheme, weighting by the number of reviews. This weighting method lessens the possibility that the portfolios are dominated by firms with a relatively small number of reviews that may contain more noise. Table 7 Panel C reports the results of review-weighted portfolio returns using the same regression specification as in Equation (2). The results are similar to those of equal-weighted portfolio returns in the main specification.

4 Information processing: alpha decay and trading

4.1 Return predictability over different holding horizons

To understand the processing of information in employee outlook, I examine the performance of long-short portfolios over one to 12 months after portfolio formation. Again, a long-short portfolio buys stocks in the top tercile of abnormal positive outlook and sells stocks in the bottom tercile.

Figure 3 Panel A reports the results of portfolios constructed over different holding periods. There is clearly a decay pattern of alpha over the holding horizon. Although the four-factor alpha of the long-short portfolios with a two-month horizon is statistically significant, the economic magnitude (0.20%) is just one-third of the alpha of portfolios with a one-month horizon. The alphas are still significant up to a five-month holding horizon.[20] These results indicate that the return predictability of employee outlook works in the short run, which is consistent with evidence that managers are unable to forecast returns past 100 days (Jenter, Lewellen, and Warner, 2011). Together with results from Fama-MacBeth regression in Section 3, these finding suggests the underlying mechanism of the return predictability of employee outlook is likely different from that of employee satisfaction, which predicts long-run returns (Edmans, 2011).

To further understand the information processing and address the concern that most of the monthly alpha may come from the first week after portfolio formation, I conduct a similar exercise at a weekly frequency. I sort stocks into tercile portfolios based on *AbnOutlook* in each month. I then track the performance of the three portfolios over one to four weeks after portfolio formation. The results, reported in Figure 3 Panel B, show a decay pattern in alphas over different holding weeks that is consistent with the notion that information is incorporated into stock prices gradually and the return predictability of this information weakens over time. But, the abnormal return (0.14%) of the long-short portfolios for the fourth week after portfolio formation is still statistically and economically significant (t-statistic is 3.24).

Moreover, I track how stock prices react to this information at a daily frequency, using a 30-day rolling window to aggregate employee outlook. Specifically, for each firm I calculate the fraction of positive outlook over the past 30 days, and determine abnormal positive outlook by comparing to its mean over the past 120 days. Daily portfolio is noisy due to market microstructure issues. Instead, I use a regression approach where the dependent variable is abnormal return adjusted by the market model and the independent variables are daily abnormal positive outlook based on a rolling window and controls (size, turnover, trading volume, and past month returns). Figure 3 Panel C reports the coefficient on abnormal

[20] Di Mascio, Lines, and Naik (2016) use institutional investors' trading to infer their private information and document an alpha decay pattern over 12 months.

positive outlook for up to 20 trading days. Again, there is a decay pattern in the impact of employee outlook on stock returns and the impact is still significant on day 20.

4.2 Institutional trading

Having demonstrated the return predictability of employee outlook, one might wonder whether investors exploit this information. Also, the alpha decay pattern indicates that the information from employee outlook is incorporated into stock prices over time, which suggests that investors may trade on this information. I investigate this question by looking at trading activities by institutional investors.

Anecdotal evidence suggests that some hedge funds trade on information from Glassdoor[21], and I perform a systematic test. Using a list of 1274 hedge funds from Agarwal, Jiang, Tang, and Yang (2013), I collect their holdings from Thomson Reuters' 13f filings data. For each stock, I calculate net purchases by hedge funds as the difference in hedge-fund ownership between this quarter and the last quarter. If hedge funds exploit this information, they should trade in the same direction as the employee outlook signal. To test this conjecture, I regress net purchases on the lagged abnormal positive outlook and controls including stock returns, firm characteristics, and media coverage.

Table 8 presents the results of this regression. The coefficient on abnormal positive outlook is positive and significant, suggesting that hedge fund managers are trading in the same direction as abnormal positive outlook. In terms of economic magnitude, one standard deviation change of abnormal positive outlook is associated with a 0.01% increase in hedge funds' net purchases, which is about 4% of the mean of net purchases. I also do similar tests for non-hedge funds and mutual funds. The results, reported in Columns (3)-(6), show that abnormal positive outlook does not predict net purchases by mutual funds or non-hedge funds in general. This is consistent with the fact that hedge funds are more active in trading on online information.

Another way to examine whether sophisticated investors exploit this information is to look at short sellers. Although there is big overlap between short sellers and hedge funds, the short selling data is more detailed and available at a high frequency. If short sellers exploit

[21] Financial Times, January 21, 2017, "Hedge funds and private equity tap Glassdoor for investment tips."

this information, we would expect to see less short selling when a firm has high abnormal positive outlook. I test this conjecture by using detailed short selling data where I can observe each short selling transaction and associated fees. I first aggregate the short selling transactions to a monthly frequency and scale them with the number of shares outstanding for each firm. Abnormal short selling is calculated by demeaning its average over the prior three months. I then regress the abnormal short selling on lagged abnormal positive outlook and controls.

Table 9 presents the results for the short selling test. The first set of results is for the fraction of shares that is shorted (Columns (1)-(3)). The coefficient on abnormal positive outlook is negative and significant for all three specifications, suggesting that positive employee outlook predicts a decrease in short selling. Not only does the short selling quantity decline following positive employee outlook, but short selling cost also decreases. Results in Columns (4)-(6) show that positive employee outlook predicts a reduction in short selling cost.

Notice that these findings do not exclude the possibility that sophisticated investors have their own sources of private information about firms' fundamentals. If their private information is correlated with employee outlook from Glassdoor, their trading activities can reflect either their own information or employee outlook signal. One way to disentangle the underlying sources is to examine whether trading activities can predict abnormal positive outlook. In untabulated results, I show that neither hedge funds' nor short sellers' trading activities can predict abnormal positive outlook. Although this finding does not completely rule out that sophisticated investors have their own information sources, it suggests that employee outlook is at least one type of information that they exploit. Moreover, the fact that abnormal returns of trading strategy based on employee outlook decline over the holding horizon indicates that investors trade on this information.

5 Information hierarchies: Employee rank and the value of employee outlook

The results so far show that employee outlook contains value-relevant information to the stock market. Recent studies on analysts forecasts show that it is important to examine the heterogeneity in analyst forecasts rather than just look at forecast concensus (Chiang et al., 2016; Michaely et al., 2017). Thus, an interesting question is whether there are significant quality differences in online forecasts across different levels of employees. Are high-level employees' outlooks better than low-level employees' outlooks? Another motivation is related to the literature on theories of organization hierarchies within firms. If a firm has a "top-down" structure (Garicano, 2000), high-level employees may possess better information than low-level employees. However, if a firm has a "bottom-up" structure, low-level employees as a group may hold better information than high-level employees. Even for a firm with a "top-down" structure, low-level employees may hold a wealth of information that is useful to predict future performance. Thus, it is an empirical question whether high-level employees have better information than low-level employees.[22] In fact, whether low-level employees have valuable information is not even clear. Prior studies use indirect evidence from employees' portfolio choices and find mixed results. Benartzi (2001) and Cohen (2009) show that employees seem not to have superior information based on investments in stocks through 401(k) accounts. However, Babenko and Sen (2015) find that non-executive employees do have valuable information by examining employee stock purchase plans.

I define the difference of information quality across employee ranks as "information hierarchies." A direct empirical test for information hierarchies is challenging for two reasons. First, it is hard to measure employees' information. Second, it is difficult to evaluate whose information is better or whether their information is different. In this section, I use employees' online reviews as a proxy for their information, and use the return predictability as a tool to gauge the value of information. If high-level employees' outlooks are better than low-level employees, then one would expect that the return predictability of high-level

[22] Several papers study the empirical side of organization hierarchy (e.g., Caliendo, Monte, and Rossi-Hansberg, 2015; Skrastins and Vig, 2017), but direct testing from an information perspective is limited.

employees' information to be better than low-level employees' information.

5.1 Rank hierarchies within firms

Although the employee review data contains a job title for each review, it is hard to classify hierarchies just based on job titles. For example, is a senior engineer at Google a high-level employee or middle-level one? In the literature of firm organization hierarchies, some studies use international data that come with hierarchy classifications (Caliendo, Monte, and Rossi-Hansberg, 2015; Muller, Quimet, and Simintzi, 2017). Although the hierarchy code is not available for US firms, prior studies often use occupation title to define hierarchies (Bloom, Sadun, and Van Reenen, 2012). Because employee rank is positively associated with wage (Caliendo, Monte, and Rossi-Hansberg, 2015), I rank employees' job titles based on the average wage of each title within a firm.[23] For each firm, I then assign all job titles into three layers: high, middle, and low. Although having a large number of layers is appealing and allows us to explore rich dynamics, a relatively small number of three is conservative. If I find information hierarchies within three layers, I would expect to see an even larger spread of information quality difference when there are more than three layers. Thus, the estimated magnitude of information hierarchies from three layers provides a lower bound.[24]

5.2 Information hierarchies: return predictability

To show information hierarchies, I test whether high-level employees' outlooks can better predict future stock returns than middle-level employees' outlooks, and whether middle-level employees' outlooks can better predict stock returns than low-level employees' outlooks. I first match the employee review data with wage based on the reviewer's job title and then assign all reviews into three groups based on wage within each firm. I then form portfolios based on reviews by a certain level of employees. Specifically, in each month, I construct abnormal positive outlook based on outlooks by high-level employees, assign stocks into three

[23]Liu et al. (2017) find that distributions of wages on Glassdoor are representative and comparable to that of the American Community Survey.

[24]Studying the optimal number of layers is important and interesting, but it is outside the scope of this paper.

portfolios, and track the performance of each portfolio in the next month. I run a Fama-French-Carhart four-factor regression test as in Equation (2) for the long-short portfolio. I repeat the steps for middle- and low-level employees. For simplicity, I only report results based on value-weighted returns. The results, reported in Table 10, show that high-level employees' outlooks have strong return predictability (Column (1)). *AbnOutlook* of middle-level employees can predict future return, but only at the 10% level. *AbnOutlook* of low-level employees does not predict increase in future stock returns. This finding provides evidence of information hierarchies within firms in the sense that high-level employees' outlooks have better return predictability than that of middle- and low-level employees.

In theories of firm organization hierarchies, the degree of information hierarchy depends on a firm's organization structure. Also, it is possible that information hierarchies may only be concentrated among certain types of firms. To investigate this conjecture, I partition the sample of firms into two groups based on their organization structure. Specifically, I label a firm as complex (simple) if its number of occupation titles is greater (smaller) than the median. For both complex and simple firms, I then repeat the same exercise as above to calculate the four-factor alphas based on high-, middle-, and low-level employees' outlooks. The results are reported in Columns (2)-(3) of Table 10. Interestingly, for complex firms, only high-level employees' outlooks can predict returns (Column (2)) and the economic magnitude of the four-factor alpha (1.70 % per month) is twice the alpha in Table 3. However, for simple firms, employees' outlooks at all levels can predict returns (Column (3)). In terms of economic magnitude, the four-factor alpha based on high-level employees' outlooks is about 0.29% greater than that for low-level employee outlooks. This difference is statistically insignificant (the p-value of the F-test is around 0.5). These results suggest that information hierarchies are more pronounced among complex firms. Only if the number of job titles is large enough is the information of high-level employees significantly better than that of middle- and low-level employees. For firms with relatively fewer job titles, employees at all levels possess valuable information about the firm and their outlooks can predict returns at almost the same magnitude.

Another way to look at the heterogeneity of information hierarchies is by firm size. Large firms tend to have more complex hierarchies. Thus, it is possible that information hierarchies only exist among large firms. To test this conjecture, I partition the sample of firms into two groups based on their size. For both large and small firms, I then repeat the same exercise as above to calculate the four-factor alphas based on high-, middle-, and low-level employees' outlooks. The results, presented in Columns (4)-(5) of Table 10, show that high-level employees' outlooks have stronger return predictability than middle- and low-level employees' outlooks among large firms. However, this is not the case for small firms where employees at all levels have valuable information. In terms of economic magnitude, middle-level employees' outlooks are as good as high-level employees' outlooks for predicting future returns.

The heterogeneity of information hierarchies also depends on whether a firm is a conglomerate or a standalone firm. Conglomerates tend to have more complex organization structures than standalone firms. Following the literature (Cohen and Lou, 2012; Boguth, Duchin, and Simutin, 2016), I define a firm as a conglomerate if it operates in two or more industries.[25] For both conglomerates and standalone firms, I then repeat the same exercise as above to calculate the four-factor alphas based on high-, middle-, and low-level employees' outlooks. The last two columns in Table 10 show the results. While high-level employees' outlooks are better than middle- and low-level employees' outlooks among conglomerates, this is not the case for standalone firms where employees at all levels have valuable information. This finding is consistent with Cohen and Lou (2012), who find that the complicated structure of conglomerates leads to slow incorporation of information. Overall, there is evidence that information hierarchies are prevalent among firms. This pattern is more pronounced among firms with complex organizational forms, large firms, and conglomerates.

5.3 Information hierarchies: textual analysis

Why do high-level employees' outlooks have better return predictability? Do their reviews contain different information compared to low-level employees'? I examine information hierarchies from another perspective: review texts. One popular method in the literature is to use word count, where researchers count the number of words of interest in a text and

[25] Industries are defined by Fama-French 49-industry classifications. The results are robust to using alternative classifications such as 3-digit SIC or 4-digit SIC code.

then divide by the total number of words in that text. While this method has its merits, it requires researchers to have good prior knowledge about what type of words they are looking for in the texts. Researchers without prior knowledge about what they should expect from texts require more advanced methods, such as machine learning and deep learning.[26]

Similar to other textual analysis methods, machine learning methods involve a first step to remove useless information (i.e., stop words) and then represent the text as data. The representation process converts text data to vectors of numbers by detecting latent patterns in transformed data (Gentzkow, Kelly, and Taddy, 2017). I use Latent Dirichlet Allocation (LDA), which is a popular method in the finance and economic literature to detect latent topics among employee reviews (e.g., Hansen, McMahon and Prat, 2017). Specifically, I use LDA to analyze potential topics in employees' reviews for three samples of firms: all firms, complex firms, and simple firms. The definitions of complex and simple firms are the same as noted above. For each sample, I use LDA to find ten topics in the review texts (see the Appendix for details). After transforming each review into a distribution of ten topics, I calculate the average weight of each topic among high-, middle-, and low-level employees (defined the same way as in Section 5.2). The two most important topics are reported.

The outputs of machine learning are summarized in Table 11. Column (1) shows different topics across employee levels for all firms. There is clearly a difference between topics of high-, middle-, and low-level employees. High-level employee reviews focus more on business growth and career opportunities, middle-level employees focus on salary and culture of the company, and low-level employees care most about personnel development and work hours. Although it is hard to compare the importance of these topics, it is clear that some topics, such as business growth, are more related to a firm's fundamentals, while other topics, such as work hours, are less directly linked to a firm's fundamentals.

Column (2) presents the results for complex firms. Again, high-level employees' reviews are about business growth and career opportunities, while low-level employees' reviews focus on benefits and work hours. However, the results for simple firms, reported in Column (3), display a different pattern: high-, middle-, and low-level employees tend to have more overlap

[26]A fast growing body of literature uses machine learning methods (Antweiler and Frank, 2004; Li, 2010; Routledge et al., 2016; Abis, 2017; Buehlmaier and Whited, 2017).

in LDA topics, such as leadership. This finding suggests that information contained in high-, middle-, and low-level employees' reviews for firms with relatively simple organization structures tend to focus on similar topics. Overall, the textual analysis indicates a large dispersion among latent topics in reviews by different levels of employees. The dispersion of topics in texts is further evidence of information hierarchies within firms.

6 Conclusion

The relation between information and stock prices is one of the most fundamental questions in finance. Increasing access to information has made the problem of how non-traditional information is incorporated into stock prices ever more relevant. I use a novel dataset of one million online employee reviews to understand the value and processing of a new type of information, online forecasts, in stock markets. I first show that employee outlook contains value-relevant information and predicts future stock returns. The information embedded in employee outlook is different from accounting information, past returns, media coverage, and employee satisfaction. The return predictability of employee outlook decays over five months. Employee outlook predicts trading activities by hedge funds and short sellers, suggesting that sophisticated investors exploit this information or its underlying sources.

These findings highlight the role of non-experts in forecasting firms' fundamentals through online platforms, which is beyond traditional information intermediaries such as sell-side analysts. Employees as a group can potentially provide both more timely and better quality information on firms' performance than analysts.

The results in this paper also have important implications with respect to the efficient market hypothesis (Fama, 1970). The strong-form efficient market hypothesis, where stock prices should reflect all public and private information, is often violated (e.g., Schwert, 2003). Private information, and even some public information, is not fully incorporated into stock prices. This study shows that some new public information from employees is valuable to the stock market and is incorporated into stock prices within a relatively short period. My results also echo the argument that the improvements in financial market efficiency in past decades is related to greater information production (Bai, Philippon, and Savov, 2016).

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Figure 1: Top words in reviews with positive and negative outlook

This figure presents the top 10 words in reviews with positive or negative outlook. Starting from the raw texts of review title, pros, cons, and advice to management, I remove stop words and transform the remaining words to numeric vectors. To account for the relative importance of a word in each review, a term-frequency-inverse document frequency (tf-idf) method is used in the transformation process. After transformation, each review is represented as a distribution of words with their weights. I then run a logistic regression where the dependent variable is a dummy variable that is equal to one if employee outlook is positive, and zero otherwise, and the independent variables are weights of words. The regression coefficients give the relative importance of each word and are reported on the y-axis. The blue bars are for positive outlook, and red bars are for negative outlook.

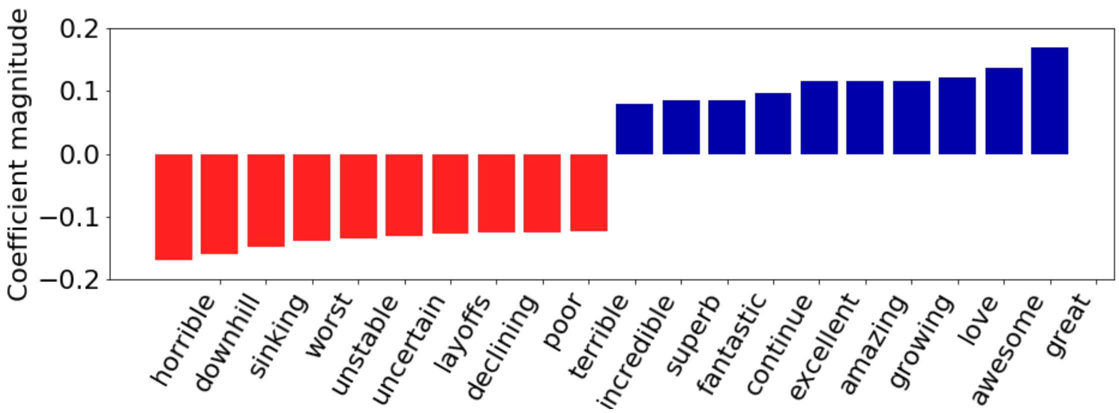
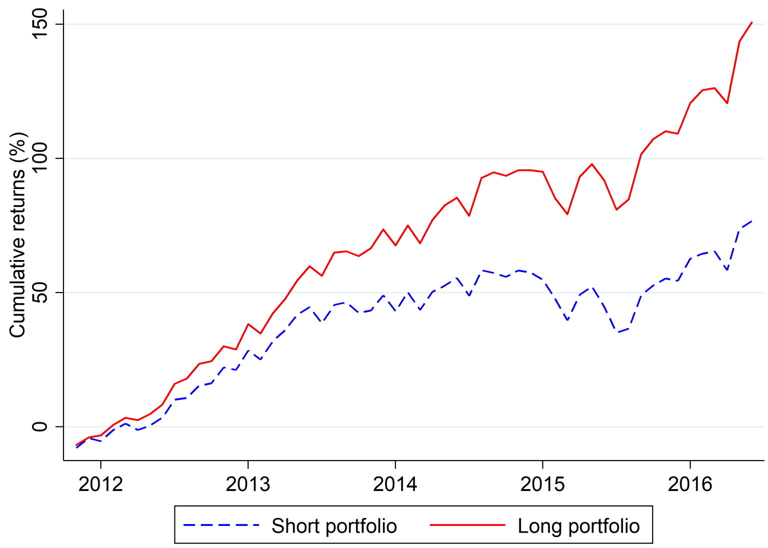


Figure 2: Cumulative returns

This figure shows the cumulative portfolio returns over the sample period for a high AbnOutlook and low AbnOutlook portfolio. Portfolios are formed at the end of June 2012, rebalanced each month, and then held to December 2016. The solid red line is the long portfolio and the dashed blue line is the short portfolio. Panel A shows the equal-weighted results and Panel B shows the value-weighted results.

Panel A. Equal weighted returns



Panel B. Value weighted returns

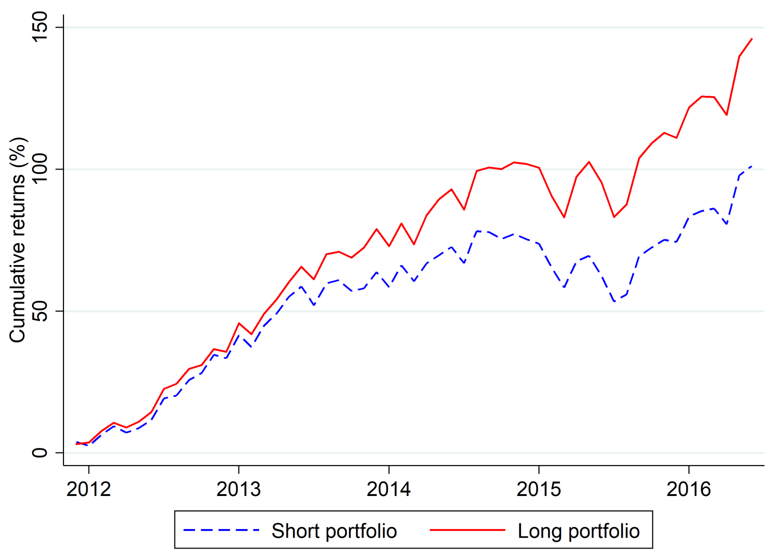
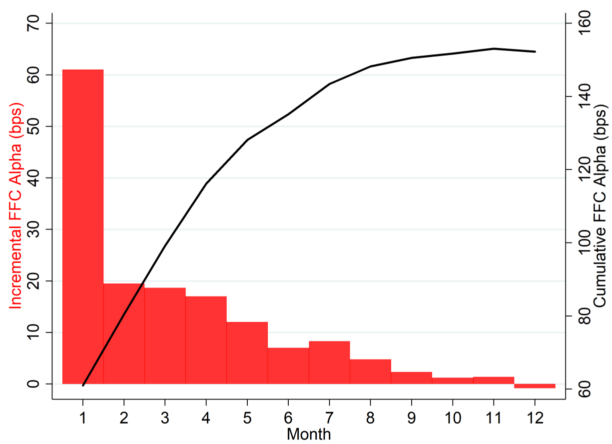


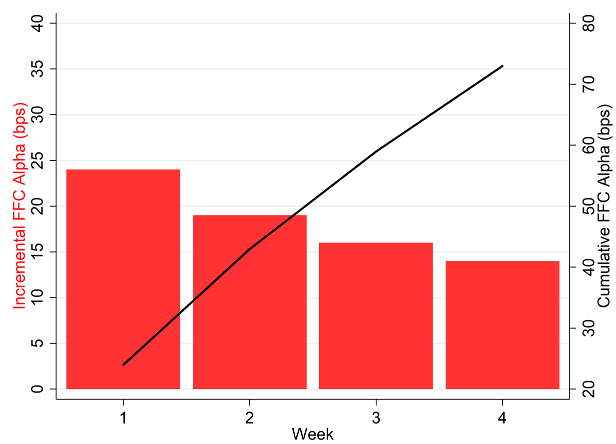
Figure 3: Return predictability over different horizons

This figure plots the impact of employee outlook on stock returns over different horizons. In Panel A, I sort stocks into tercile portfolios based on abnormal positive outlook in each month. I then track the performance of the three portfolios two to 12 months after portfolio formation. In Panel B, I sort stocks into tercile portfolios based on abnormal positive outlook in each month. I then track the performance of the three portfolios over one to four weeks after portfolio formation. Portfolio returns are calculated using a value weighting method. All alphas are calculated using the Fama-French-Carhart four-factor model. In Panel C, I use a regression approach where the dependent variable is abnormal return adjusted by the market model and the independent variables include daily abnormal positive outlook and controls (size, turnover, trading volume, and past 30-day returns). Abnormal positive outlook is calculated for a 30-day rolling window with its mean over the past 120 days as a benchmark. The regression coefficient on abnormal positive outlook is reported in the figure.

Panel A. Monthly portfolio returns



Panel B. Weekly portfolio returns



Panel C. Daily regression coefficient

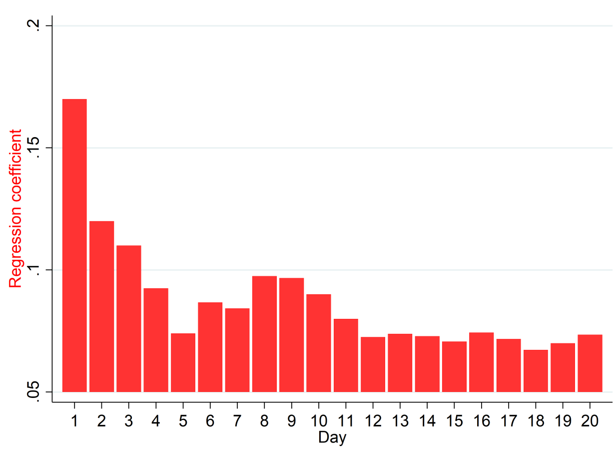


Table 1: Summary statistics

This table reports summary statistics for the sample of employee reviews for S&P 1500 firms from June 2012 to December 2016. Panel A reports the number of reviews and firms for 12 Fama-French industries. Panel B reports summary statistics of employee reviews at the firm level and related firm characteristics. *Positive outlook* is the number of reviews with positive outlook divided by the total number reviews in each month for each firm. *Abnormal positive outlook* is *Positive outlook* minus its mean over the prior three months. *Recommend* is the fraction of reviews that state "recommend to a friend" divided by the total number of reviews in each month for each firm. *Overall* is the average overall star rating (on a scale of 1 to 5) in each month for each firm. The monthly average of culture and values rating (Culture), work-life balance rating (WorkLife), senior management rating (Management), compensation and benefits (Compensation), and career opportunities (Career) are calculated in the same way. *Market cap* is market capitalization of the firm, calculated as the number of shares outstanding multiplied by the stock price. *Market beta* is a firm's exposure to market risk, calculated from a 3-year rolling regression of monthly excess stock returns of the firm on market returns. *Stock returns 12 months* is the cumulative stock returns over the past 12 months. *Dollar volume* is trading volume multiplied by stock price. *Profitability* is gross profitability, calculated as the ratio of income before extraordinary items to book value of assets. *Institutional ownership* is the fraction of shares owned by institutional investors. *Analyst coverage* is the number of analysts that cover a firm.

Panel A. Summary statistics on employee reviews

Fama-French 12 industries	# of reviews	# of firms
Consumer NonDurables	29,537	96
Consumer Durables	10,669	36
Manufacturing	52,368	151
Oil, Gas, and Coal Extraction and Products	10,424	47
Chemicals and Allied Products	16,600	40
Business Equipment	235,885	261
Telephone and Television Transmission	46,356	37
Utilities	7,712	46
Wholesale, Retail, and Some Services	295,272	188
Healthcare, Medical Equipment, and Drugs	39,227	117
Finance	143,637	205
Other	85,330	198
Total	973,017	1,422

Panel B. Summary statistics at firm-month level

	Mean	StdDev	25th	Median	75th
Employee reviews					
Positive outlook (%)	41.70	32.98	10.71	40.00	63.16
Abnormal positive outlook (%)	0.35	32.81	-16.67	0.00	16.67
Recommend (%)	56.01	33.05	33.33	57.89	81.25
Overall	3.18	0.89	2.67	3.22	3.77
Culture	3.15	0.97	2.57	3.17	3.83
WorkLife	3.18	0.90	2.67	3.18	3.80
Management	2.78	0.93	2.17	2.83	3.33
Compensation	3.25	0.84	2.79	3.27	3.88
Career	2.96	0.86	2.50	3.00	3.50
Firm characteristics					
Market cap ($ mil)	17297.06	42043.39	1476.84	4340.63	14087.20
Market Beta	1.22	0.57	0.84	1.17	1.53
Stock returns 12 months (%)	14.01	34.50	-5.14	11.97	29.78
Dollar volume	2524.75	6522.59	247.45	910.87	2711.98
Profitability	0.20	0.14	0.10	0.17	0.27
Institutional ownership	0.74	0.17	0.65	0.74	0.84
Analyst coverage	13.84	8.69	7.00	13.00	20.00

Table 2: Employee expectations and firm characteristics

This table reports determinants regression of abnormal positive outlook and lagged firm characteristics from June 2012 to December 2016. *Abnormal Positive outlook* is the fraction of reviews with positive outlook in each month for each firm minus its mean over the prior three months. *Size* is the logarithm of market capitalization of the firm, calculated as the number of shares outstanding multiplied by the stock price. *Book-to-market* is a firm's book value divided by its market value. *Beta* is a firm's exposure to market risk, calculated from a rolling regression of monthly excess stock returns of the firm on market returns. *Stock returns 12 months* is the cumulative stock returns over the past 12 months. *Positive Media coverage* is the number of positive news articles that mentioned a firm in the Dow Jones News Archives, provided by RavenPack. *Institutional ownership* is the fraction of shares owned by institutional investors. *Analyst coverage* is the number of analysts that cover a firm. *Profitability* is gross profitability, calculated as the ratio of income before extraordinary items to book value of assets. *Dollar volume* is trading volume multiplied by stock price. Firm and time fixed effects are included. Numbers in parentheses are t-statistics that are adjusted for heteroscedasticity and clustered by industry and time. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
VARIABLES	Abnormal positive outlook		
Size	0.00		0.01
	(0.16)		(1.08)
Book-to-market	-0.00		-0.01
	(-0.01)		(-0.66)
Beta	-0.00		-0.01
	(-0.37)		(-0.57)
Stock returns 12 months	-0.00		-0.00
	(-0.24)		(-0.61)
ΔPositive media coverage	-0.00		-0.00
	(-0.58)		(-0.33)
Instititional ownership		-0.03	-0.04
		(-1.09)	(-1.16)
Analyst coverage		-0.00	-0.00
		(-0.18)	(-0.29)
Profitability		-0.07	-0.08
		(-1.54)	(-1.64)
Log(Dollar volume)		-0.00	-0.01
		(-0.93)	(-1.18)
Observations	26,534	26,534	26,534
Adjusted R-squared	0.012	0.012	0.012
Firm, Time FEs	Y	Y	Y

Table 3: Employee expectations and stock returns

This table reports portfolio returns results. In each month from June 2012 to December 2016, I sort sample stocks into tercile portfolios based on *AbnOutlook*, which is the fraction of reviews with positive outlook minus its mean over the prior three months. I then track the performance of the three portfolios over the following month. The portfolio returns are calculated by two weighting schemes: equal- and value-weighting. Portfolio returns are adjusted by risk-free rate. Long-short portfolio buys the top tercile portfolio and sells the bottom tercile portfolio. The regression results in Panel B are based on Equation (2). Numbers in parentheses are t-statistics calculated using Newey-West standard errors with four lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Portfolio excess returns

	Equal-weighting	Value-weighting
Portfolio 1 (Low positive outlook)	0.71	1.10
Portfolio 2	0.99	1.03
Portfolio 3 (High positive outlook)	1.57	1.72
Long-short (High-Low)	0.86***	0.62***

Panel B. Portfolio alphas

	(1)	(2)	(3)	(4)	(5)	(6)
	Equal-weighting			Value-weighting		
VARIABLES	Portfolio 1	Portfolio 3	Long-short	Portfolio 1	Portfolio 3	Long-short
Alpha	-0.26**	0.51***	0.78***	-0.05	0.56***	0.61***
	(-2.09)	(3.23)	(3.79)	(-0.49)	(2.93)	(3.62)
MktRF	1.03***	1.02***	-0.00	0.95***	1.00**	0.05
	(3.52)	(3.25)	(-0.03)	(2.93)	(2.23)	(0.90)
SMB	0.54***	0.42**	-0.11***	0.03	-0.09**	-0.12
	(2.93)	(2.60)	(-2.87)	(0.75)	(-2.57)	(-1.64)
HML	0.07**	0.10	0.03	-0.07	0.02	0.09
	(2.19)	(1.63)	(0.51)	(-1.17)	(0.40)	(0.80)
MOM	-0.10***	-0.04	0.06	-0.15***	-0.11***	0.05
	(-3.15)	(-1.22)	(1.56)	(-3.78)	(-2.98)	(0.80)

Table 4: Employee expectations and stock returns: subsample

This table reports the Fama-French-Carhart four-factor alphas on a monthly long-short portfolio based on abnormal positive outlook for various subsamples. In Panel A, I partition the sample of stocks into a large firm group and a small firm group based on the median of market cap in the past year. In Panel B, I partition the sample of stocks into a high-analyst-coverage group and a low-analyst-coverage group based on the median of analyst coverage in the past quarter. In Panel C, I partition the sample of stocks based on industry labor intensity, which is the number of employees divided by Property Plant and Equipment. Stocks that belong to an industry with labor intensity higher than the median are assigned to the high labor intensity group, while the rest are assigned to the low labor intensity group. In Panel D, I partition the sample based on employee status: current vs. former employees. In Panel E, I partition the sample based on whether an employee works in the headquarter state or not. Within each group of stocks in each month, I form a long-short portfolio that buys the top tercile stocks and sells the bottom tercile stocks based on abnormal employee outlook and calculate the four-factor alphas. Numbers in parentheses are t-statistics calculated using Newey-West standard errors with four lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Equal-weighting	Value-weighting
Panel A: Firm size		
Small firms	1.03***	0.68***
	(3.09)	(3.53)
Large firms	0.40**	0.32**
	(2.17)	(2.61)
Panel B: Analyst coverage		
Low analyst coverage	0.88***	0.69***
	(2.90)	(3.34)
High analyst coverage	0.47**	0.20
	(2.11)	(0.70)
Panel C: Industry labor intensity		
Low labor intensity	0.61**	0.35*
	(2.37)	(1.83)
High labor intensity	0.99***	0.66***
	(3.05)	(3.51)
Panel D. Employee status		
Current employee	0.78***	0.63***
	(3.69)	(3.48)
Former employee	0.28**	0.29
	(2.65)	(1.38)
Panel E. Employee Location		
Headquarter state	0.83***	0.82***
	(3.01)	(2.85)
Non-headquarter state	0.48**	0.32**
	(2.42)	(2.31)

Table 5: Fama-MacBeth regressions

This table reports the coefficient estimates of Fama-MacBeth regressions of one-month-ahead excess stock returns on abnormal positive outlook and other cross-sectional predictors of stock returns as in Equation (3). *Abnormal positive outlook* is the fraction of reviews with positive outlook in each month for each firm minus its mean over the prior three months. *100 Best companies* is a dummy variable that is equal to one if a firm is on Fortune's list of the "100 Best Companies to Work for" in that year, and zero otherwise. *Size* is the logarithm of market capitalization of the firm, calculated as the number of shares outstanding multiplied by the stock price. *Book-to-market* is a firm's book value divided by its market value. *Beta* is a firm's exposure to market risk, calculated from a rolling regression of monthly excess stock returns of the firm on market returns. *Stock returns 12 months* is the cumulative stock returns over the prior 12 months. *Positive media coverage* is the number of positive news articles that mentioned the firm in the Dow Jones News Archives in each month, provided by RavenPack. *Institutional ownership* is the fraction of shares owned by institutional investors. *Analyst coverage* is the number of analysts covering the firm. *Profitability* is the gross profitability, calculated as the ratio of income before extraordinary items to book value of assets. *Dollar volume* is trading volume multiplied by stock price. Numbers in parentheses are t-statistics calculated using Newey-West standard errors with four lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	One-month-ahead excess returns			
Abnormal positive outlook	0.93***		0.93***	0.84***
	(2.82)		(2.83)	(2.81)
100 Best companies		-0.14	-0.13	-0.11
		(-0.60)	(-0.56)	(-0.49)
Size				-0.25*
				(-1.84)
Book-to-market				0.78**
				(2.43)
Beta				-0.32
				(-1.54)
Stock returns 12 months				0.00
				(0.00)
ΔPositive media coverage				0.02***
				(2.95)
Institutional ownership				-0.96*
				(-1.69)
Analyst coverage				0.00
				(0.25)
Profitability				0.99
				(1.53)
Log(Dollar volume)				-0.07
				(-0.50)
Observations	27,023	27,023	27,023	27,023
R2	0.004	0.002	0.006	0.175

Table 6: Employee expectations and firms' earnings

This table reports regressions of earnings surprises and profitability on employee outlook and controls as in Equation (3) in the paper. *Abnormal positive outlook* is the fraction of reviews with positive outlook in each quarter for each firm minus its mean over the past three quarters. *Size* is the logarithm of market capitalization of the firm, calculated as the number of shares outstanding multiplied by the stock price. *Book-to-market* is a firm's book value divided by its market value. *Beta* is a firm's exposure to market risk, calculated from a rolling regression of monthly excess stock returns of the firm on market returns. *Stock returns 12 months* is the cumulative stock returns over the prior 12 months. *Positive media coverage* is the number of positive news articles that mentioned the firm in the Dow Jones News Archives in each quarter, provided by RavenPack. *Institutional ownership* is the fraction of shares owned by institutional investors. *Analyst coverage* is the number of analysts that cover the firm. *Profitability* is gross profitability, calculated as the ratio of income before extraordinary items to book value of assets. *Dollar volume* is trading volume multiplied by stock price. *SUE* is standardized unexpected earnings, calculated as the difference between realized quarterly earnings and consensus of earnings by analyst forecasts divided by stock price at the end of that quarter. Cumulative abnormal returns (CAR) are returns measured using a three-day window centered on the announcement date and adjusted using the market model. Return on asset (ROA) is income before extraordinary items divided by total assets. Numbers in parentheses are t-statistics that are adjusted for heteroscedasticity and clustered by industry and time. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Earnings surprises

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Earnings surprises (SUE)			CAR		
Abnormal positive outlook	0.037***	0.032**	0.028**	0.437**	0.443**	0.473**
	(2.97)	(2.46)	(2.04)	(2.11)	(2.10)	(2.16)
SUE_lag		0.059***	0.044***		0.091	0.071
		(3.91)	(2.78)		(1.29)	(0.86)
Size		-0.024**	-0.025*		-0.069	-0.063
		(-2.27)	(-1.68)		(-0.52)	(-0.40)
Book-to-market		0.066***	0.077**		-0.015	0.202
		(2.89)	(2.21)		(-0.07)	(0.66)
Beta		0.013	0.007		0.004	-0.136
		(1.20)	(0.39)		(0.03)	(-0.62)
Stock returns 12 months		0.011	0.011		0.689***	0.574*
		(0.72)	(0.57)		(2.69)	(1.66)
ΔPositive media coverage		0.001	0.002		0.048***	0.062***
		(0.81)	(1.16)		(2.69)	(2.71)
Instititional ownership		-0.038	-0.078		-0.018	0.519
		(-0.93)	(-1.10)		(-0.04)	(0.97)
Analyst coverage		0.001	0.002		0.004	0.015
		(1.10)	(1.53)		(0.41)	(1.15)
Profitability		-0.067*	-0.085		-1.163***	-2.488***
		(-1.69)	(-1.28)		(-3.27)	(-3.82)
Log(Dollar volume)		0.023**	0.022		0.030	0.037
		(2.02)	(1.45)		(0.23)	(0.23)
Time, Firm FEs	N	N	Y	N	N	Y
Observations	13,947	13,947	13,947	13,905	13,905	13,905
Adjusted R2	0.000	0.009	0.146	0.000	0.001	0.105

Panel B. Profitability

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		△ROA			△Profitability	
Abnormal positive outlook	0.083***	0.076***	0.060***	0.066***	0.075**	0.046*
	(3.02)	(3.61)	(3.81)	(3.67)	(2.51)	(1.79)
Size		0.291	1.743		7.061***	26.778***
		(0.24)	(1.06)		(3.84)	(4.94)
Book-to-market		-2.844***	-1.683***		1.261	-2.444***
		(-3.86)	(-3.08)		(0.49)	(-2.62)
Beta		-3.020***	-2.919**		-2.360	-0.238
		(-3.20)	(-2.03)		(-1.57)	(-0.08)
Stock returns 12 months		0.072***	0.056***		0.033	-0.012
		(4.57)	(3.60)		(1.48)	(-0.46)
ΔPositive media coverage		-0.006	-0.009		0.016	0.021
		(-0.47)	(-0.62)		(0.80)	(0.87)
Instititional ownership		6.486*	-0.949		-1.645	22.733***
		(1.89)	(-0.24)		(-0.30)	(2.68)
Analyst coverage		-0.158	-0.199**		0.017	-0.781*
		(-1.33)	(-2.04)		(0.10)	(-1.95)
Log(Dollar volume)		1.530	0.968		-1.800	-2.462
		(1.48)	(0.84)		(-1.32)	(-0.78)
Time, Firm FEs	N	N	Y	N	N	Y
Observations	17,608	17,608	17,608	17,608	17,608	17,608
Adjusted R2	0.015	0.130	0.207	0.011	0.719	0.809

Table 7: Employee expectations and stock returns: robustness

This table reports robustness tests of portfolio regression. Panel A presents results with various alternative methods to calculate alphas. The HXZ four-factor alpha is calculated during the sample period of June 2012 to December 2015 due to the availability of the HXZ factor data. Panel B presents results with a variety of alternative samples and all alphas are calculated using the Fama-French-Carhart four-factor model. Panel C presents results with review-weighted portfolio returns returns with the alpha calculated using the Fama-French-Carhart four-factor model. Numbers in parentheses are t-statistics calculated using Newey-West standard errors with four lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Equal-weighting	Value-weighting
Panel A: Alternative methods		
Using estimated outlook by PCA	0.63***	0.30***
	(3.14)	(2.75)
Fama-French three-factor model	0.88***	0.64***
	(3.53)	(3.27)
Fama-French five-factor model	0.89***	0.64***
	(3.69)	(3.16)
Fama-French-Carhart six-factor model	0.87***	0.61***
	(3.43)	(2.74)
Hou-Xue-Zhang four-factor model	0.90***	0.65***
	(3.09)	(3.41)
Fama-French-Carhart with the liquidity factor	0.85**	0.61***
	(2.28)	(2.77)
AbnOutlook based on the mean over the prior 6 months	0.94***	0.81***
	(3.94)	(2.96)
Panel B: Alternative samples		
Extended sample 2008-2016	0.53***	0.39***
	(3.10)	(3.39)
Sample with all CRSP-Compustat firms	1.08***	0.64***
	(3.45)	(2.78)
Sample with more than 5 reviews per month	0.96***	0.83***
	(3.24)	(2.89)
Sample excluding financial firms	0.68***	0.53***
	(3.59)	(2.98)
Sample excluding non-US reviews	0.71***	0.55***
	(2.88)	(3.47)
Panel C: Alternative weighting method		
Review-weighted portfolios	0.71***	
	(2.76)	

Table 8: Employee expectations and institutional trading

This table reports the results of regressions of one-quarter-ahead institutional trading on employee outlook. *Hedge fund netbuy* is the change in hedge fund ownership compared to the past quarter. Similar definitions are applied to *Non-hedge fund netbuy* and *mutual fund netbuy*. *Abnormal positive outlook* is the fraction of reviews with positive outlook in each quarter for each firm minus its mean over the past three quarters. *Stock returns* is the stock returns at the end of that quarter. *Stock returns 12 months* is the cumulative stock returns over the past 12 months. *Size* is the logarithm of market capitalization of the firm, calculated as the number of shares outstanding multiplied by the stock price. *Book-to-market* is a firm's book value divided by its market value. *Beta* is a firm's exposure to market risk, calculated from a rolling regression of monthly excess stock returns of the firm on market returns. *Positive media coverage* is the number of positive news articles that mentioned the firm in the Dow Jones News Archives, provided by RavenPack. *Analyst coverage* is the number of analysts that cover a firm. *Profitability* is gross profitability, calculated as the ratio of income before extraordinary items to book value of assets. *Dollar volume* is trading volume multiplied by stock price. Numbers in parentheses are t-statistics that are adjusted for heteroscedasticity and clustered by industry and time. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Hedge fund netbuy		Non-Hedge fund netbuy		Mutual fund netbuy	
Abnormal positive outlook	0.012***	0.011***	0.001	0.003	0.003	-0.007
	(4.38)	(3.87)	(0.49)	(0.90)	(0.59)	(-1.37)
Stock returns		0.215***		-0.126***		0.345***
		(13.29)		(-6.95)		(11.27)
Stock returns 12 months		-0.010*		-0.012**		0.029***
		(-1.83)		(-2.22)		(7.45)
Size		-0.756		0.216		-4.516***
		(-1.16)		(0.34)		(-6.59)
Book-to-market		-0.244		0.379*		-0.243
		(-1.24)		(1.67)		(-1.09)
Beta		0.477		-0.523		0.746
		(0.80)		(-0.86)		(1.46)
ΔPositive media coverage		0.140		-0.170		0.243
		(1.32)		(-1.37)		(1.24)
Analyst coverage		-0.007		0.005		0.104**
		(-0.16)		(0.11)		(2.19)
Profitability		0.256		1.649		2.398
		(0.12)		(0.72)		(1.15)
Log(Dollar volume)		-0.000*		0.000*		-0.000
		(-1.85)		(1.65)		(-0.71)
Time, Firm FEs	N	Y	N	Y	N	Y
Observations	16,102	16,102	16,102	16,102	16,102	16,102
Adjusted R2	0.059	0.138	0.058	0.105	0.064	0.154

Table 9: Employee expectations and short selling

This table reports the results of regressions of one-month-ahead short selling on employee outlook. *Short selling* is the number of shares shorted in each month divided by shares outstanding. *Shorting cost* is the fee associated with short selling. *Abnormal Positive outlook* is the fraction of reviews with positive outlook in each month for each firm minus its mean over the past three months. *Stock returns* is the stock returns in that month. *Stock returns 12 months* is the cumulative stock returns over the past 12 months. *Size* is the logarithm of market capitalization of the firm, calculated as the number of shares outstanding multiplied by the stock price. *Book-to-market* is a firm's book value divided by its market value. *Beta* is a firm's exposure to market risk, calculated from a rolling regression of monthly excess stock returns of the firm on market returns. *Positive media coverage* is the number of positive news articles that mentioned the firm in the Dow Jones News Archives, provided by RavenPack. *Institutional ownership* is the fraction of shares owned by institutional investors. *Analyst coverage* is the number of analysts that cover a firm. *Profitability* is gross profitability, calculated as the ratio of income before extraordinary items to book value of assets. *Dollar volume* is trading volume multiplied by stock price. Numbers in parentheses are t-statistics that are adjusted for heteroscedasticity and clustered by industry and time. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	one-month-ahead short selling			one-month-ahead shorting cost		
Abnormal positive outlook	-0.06**	-0.05**	-0.05**	-0.13***	-0.05**	-0.09***
	(-2.65)	(-2.54)	(-2.38)	(-3.86)	(-2.44)	(-4.29)
Stock returns		0.42***	0.23		0.10	-0.08
		(2.89)	(1.04)		(0.44)	(-0.45)
Stock returns 12 months		0.12*	0.14		0.02	-0.17***
		(2.02)	(1.06)		(0.34)	(-5.07)
Size		-0.51	16.79		-6.75***	-4.15***
		(-0.23)	(0.68)		(-6.89)	(-4.98)
Book-to-market		5.03	17.27		5.02	-3.03
		(1.22)	(1.58)		(1.57)	(-0.92)
Beta		-1.61	14.39		6.58***	7.46***
		(-0.85)	(1.46)		(3.76)	(4.52)
Media coverage		0.06	0.15		0.43***	-0.00
		(0.77)	(1.10)		(5.13)	(-0.08)
Analyst coverage		0.01	-0.23		0.53***	0.05
		(0.03)	(-0.44)		(5.15)	(0.55)
Institutional ownership		8.85	12.96		5.74	-44.90***
		(0.77)	(0.71)		(0.59)	(-6.20)
Profitability		-5.70	5.22		-4.39	-3.94
		(-0.84)	(0.20)		(-0.91)	(-0.83)
Log(Dollar volume)		-0.00	-0.00**		0.00	0.00***
		(-0.38)	(-2.25)		(0.75)	(5.99)
Time, Firm FEs	N	N	Y	N	N	Y
Observations	27,189	27,189	27,189	27,189	27,189	27,189
Adjusted R2	0.000	0.001	0.019	0.001	0.011	0.068

Table 10: Information hierarchies within firms—evidence from returns

This table reports information hierarchy within firms. I first match the employee reviews data with wage based on reviewer's job title and then assign all reviews into three groups based on wage within each firm. I then form portfolios based on reviews by a given level of employees. Specifically, in each month, I construct portfolios based on abnormal positive outlook among high-level employees, assign stocks into three portfolios, and track the performance of each portfolio in the following month. I run a four-factor regression test as in Equation (2) for the long-short portfolio. I repeat the steps for middle- and low-level employees. For simplicity, I only report results based on value-weighted returns. In Columns (2)-(3), I partition the sample of firms into two groups based on number of job titles. A firm with a number of job titles that is greater (less) than the median is labeled a complex (simple) firm. Within each group of firms, I then repeat the tests described above based on reviews by high-, middle-, and low-level employees. Similarly, I partition the sample of firms based on the median of firm size in Columns (4)-(5). In Columns (6)-(7), a conglomerate is defined as a firm that operates in two separate industries, while a standalone is a firm that only operates in one industry. Numbers in parentheses are t-statistics calculated using Newey-West standard errors with four lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	All firms	Hierarchy		Firm size		Organization	
		Complex	Simple	Large	Small	Conglomerates	Standalone
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High-level employees	0.84***	1.70**	0.69***	0.93***	0.88**	0.85***	0.84***
	(3.73)	(2.21)	(3.89)	(2.89)	(2.03)	(2.87)	(3.63)
Middle-level employees	0.37*	0.42	0.56**	0.48	0.83**	0.35	0.70***
	(1.74)	(0.50)	(2.56)	(1.64)	(2.15)	(1.25)	(4.06)
Low-level employees	0.33	0.35	0.38***	0.33	0.68**	0.37	0.48***
	(1.48)	(0.51)	(2.69)	(1.57)	(2.15)	(1.58)	(2.80)

Table 11: Information hierarchies within firms—evidence from textual analysis

This table reports information hierarchies within firms by analyzing latent topics in employee reviews. Using Latent Dirichlet Allocation (LDA), I first find ten topics in review texts and transform each review as a distribution of topics with a weight for each topic. I then calculate the average weight of each topic among high-, middle-, and low-level employees and report the two most important topics. In Columns (2) and (3), I partition the sample of firms into two groups based on number of job titles. A firm with a number of job titles that is greater (less) than the median is labeled a complex (simple) firm. Within each group of firms, I repeat the LDA analysis and find the two most important topics.

	(1)	(2)	(3)
	All firms	Complex firms	Simple firms
High-level employees	business growth	business growth	business growth
	career opportunities	career opportunities	leadership
Middle-level employees	salary	flexibility	leadership
	culture	personnel development	flexibility
Low-level employees	personnel development	work hours	salary
	work hours	benefits	leadership

Appendix

A. Information about Glassdoor

In this appendix, I provide detailed background information about Glassdoor. Compared to other employee review websites such as Indeed, Vault, and CareerBliss, Glassdoor is not only the largest website for employee reviews but also has the most diverse set of users (Table A1), as discussed in Popadak (2013).

Give to get policy: Glassdoor uses a "Give to get" policy to encourage users to post information. A report by Glassdoor released in October 2017 shows that the "Give to get" policy helps reduce polarization bias and encourages more neutral and balanced company ratings on Glassdoor.[27]

Here is the full text of the "Give to get" policy: "Glassdoor's give to get policy requires that you submit a contribution in order to receive unlimited access to other content on our website. It ensures that we have enough salaries, company reviews, interview reviews, & benefits reviews to share with the community. It only takes a minute to submit, and your contribution is anonymous. Your contribution will also help others, as their contributions will help you. When you contribute a review, salary, interview, or benefit review you will be granted 12 months of unlimited access to our content. After that period you may be asked to contribute another salary, review, interview or benefit review to extend your unlimited access for another 12 months. If you are not ready to contribute, you can create a Glassdoor account without posting. You will have full access to salary, review, interview, and benefit content for 10 days."[28]

Seasonality. One may be concerned about seasonality in the reviews. In particular, Glassdoor runs Employees' Choice Awards: "Best Places to Work" in each year. To be considered for the awards, several minimum requirements for eligibility must be met. For instance, the Glassdoor 2017 Employees' Choice Awards: "Best Places to Work" uses company reviews and ratings from current and former employees between November 2, 2015 and October 30, 2016. It requires a firm to have at least 75 reviews/ratings, an overall rating of at least 3.51, workplace factor ratings of at least 2.85 during the eligibility period, and at least 1000 employees at the end of the eligibility timeframe. These awards have been in place for several years and the timeframe is similar from year to year. Thus, it is possible that companies give employees incentives to write more good reviews so as to reach these requirements before the timeframe ends. If this is the case, then one

[27] https://www.glassdoor.com/research/studies/give-to-get/

[28] See http://help.glassdoor.com/article/Give-to-get-policy/en_US

would expect to see more reviews close to the deadline.

I first check whether there is seasonality in the number of reviews. Figure A4 plots the fraction of reviews in each month. The number of reviews is relatively greater in August, September, and October, which is consistent with the idea that employees tend to post more reviews leading up to the deadline for the Awards. However, the difference between months is not statistically significant. Even the difference between October (most reviews submitted) and December (least reviews submitted) is not statistically different from zero (the t-value is 1.00). Even if the number of reviews is not statistically different, is it possible that the review content is quite different? Table A2 reports the mean values of employee outlook and star ratings for each month. Although there is some small variation among months, the differences are small and not significantly different from zero.

Overall, despite concerns for potential issues, the quality of the Glassdoor data seems to be high. The polarization bias is less severe than other online reivew websites, and the distributions of the number of review and mean values of review variables across different months are stable.

B. Machine learning

B1. Using machine learning to extend the sample to 2008

Although using a short-sample period for online data in finance is common, the sample period should be extended for a robustness test. The outlook variable starts from 2012, while other variables (recommend this company, overall ratings, 5 subcategory ratings) start from 2008. Because outlook is correlated with other variables (Table A4), one can infer employees' opinions of outlook based on their responses to other questions.

The goal is to predict employee outlook in each review from June 2008 to February 2012. This problem is a classification exercise where each review is labeled as either positive or negative outlook in the end.[29] I use machine learning, which is a method of data analysis that automates analytical model building to perform the prediction. The machine learning methods I use include k-nearest mean (KNN), logistic classification with L1 and L2, linear SVC, decision tree, random forest, and gradient boosted regression trees. I also use a deep learning method, which is an advanced machine learning method with hidden layers. The advantage of deep learning is that it allows more complex and non-linear functions between output and input variables. A detailed discussion of these methods can be found in Friedman, Hastie, and Tibshirani (2001) and LeCun, Bengio, and Hinton (2015).

[29]For simplicity, I merge neutral and negative outlook into one class and just call it negative outlook.

The machine learning procedure is as follows. I first use all reviews from March 2012 to December 2016 as training and test samples. The split between training and test samples is random. Typically, 75% of observations are assigned as training samples (0.5 million reviews), and the remaining 25% are assigned as test samples. I also use various cross-validation with different splits of samples for robustness tests. For each method, the relationship between outlook and other variables is formed using training samples. The out-of-sample test uses these relationships to predict outlook in test samples. Test samples also have the true values for employee outlook. The out-of-sample accuracy is calculated by comparing the predicted outlook and the true outlook. Each machine learning method has parameters that can affect its performance. For example, for KNN, the number of neighbors is important; for random forest, the number of trees and the depth of each tree are important. To avoid overfitting, I use cross-validation to ensure the performance is robust; only the robust performance is reported.

Table A5 presents the results of out-of-sample performance for different methods. Regular machine learning methods such as KNN, logistic classification with L1 and L2, linear SVC, decision tree, random forest, and gradient boosted regression trees have decent performance with accuracy scores of 0.76-0.77. Using deep learning significantly improves the out-of-sample performance, and can reach an accuracy score of 0.91. Deep learning performs better for two reasons. First, the training sample is relatively large with 0.5 million observations, and deep learning often performs better with large data. Second, the deep learning method with a neural network is more likely to capture complex nonlinear functions, such as the underlying relationships between outlook and other variables.

B2. Machine learning with LDA

In Section 5.3, I use LDA to detect the topics in review texts. This type of machine learning is called "Natural language processing" (NLP). As LDA here is an unsupervised learning, evaluating its performance is challenging.. One popular method is "word intrusion," suggested by Chang et al. (2009). For each trained topic, it takes the first ten words and substitutes one with another, randomly chosen word (intruder!) and sees whether a human can reliably tell which word is the intruder. If so, the trained topic is topically coherent; if not, the topic has no discernible theme. In the end, I find ten topics in LDA: business growth, personnel development, leadership, salary, flexibility, benefits, career opportunities, work hours, culture, and work environment. The top five words for each topic based on reviews from all firms are reported in Table A6.

C. Insider trading

In this section, I test whether employee outlook is related to insider trading. Although the overlap between employees who are required to report insider trading (top executives or directors) and employees who post reviews on Glassdoor is not big, they may share the same information source as the reviewers. For example, both non-executive employees and top executives know that their company is doing well this quarter. Before the earnings announcement, non-executive employees might post reviews with positive outlook, while top executives might buy more shares of their company. SEC requires high-level employees to report transactions involving their own company stocks under certain conditions.[30] I use the reported insider trading transactions from SEC EDGAR to test whether the information reported on Glassdoor is associated with insider trading. Specifically, I aggregate the sells (buys) of insider trading for each firm to the monthly level and calculate the abnormal sells (buys), which is the difference between sells (buys) and their mean in the prior three months. To test the conjecture, I regress the one-month-ahead insider abnormal sells (buys) on abnormal positive outlook and control variables.

Table A7 presents the results for the insider trading test. In Columns (1)-(3), where the dependent variable is insider sells, the coefficient on abnormal positive outlook is negative and significant for univariate regression and multivariate regressions with various controls and fixed effects. This finding suggests that insiders reduce their sells if employee outlook is very positive. As I show in Section 3, positive outlook predicts higher future returns, and it is rational for insiders to reduce their sales if their know stock prices will increase in the following month. Thus, it seems that top insiders are sharing similar opinions of the firm's future prospects with employees who write reviews on Glassdoor. Interestingly, this is not the case for insider buys. In Columns (4)-(6), I find that the coefficient on abnormal positive outlook is not significant for inside buys. This has something to do with the fact that it is relatively easier to sell a stock than to buy one as an employee. For many companies, employees can only buy shares of their own company in the middle or at the end of each month, but they can sell their shares at any time.

Overall, the evidence regarding insider trading suggests that the online information of employee outlook is strongly linked to information possessed by top employees, which is revealed in their insider trading activities.

[30] Every director, officer, or owner of more than 10% of a class of equity securities registered under Section 12 of the Securities Exchange Act of 1934 must file a statement of ownership regarding such security with the United States Securities and Exchange Commission. This file is called Form 4; see SEC website (https://www.sec.gov/files/form4data%2C0.pdf) for more details.

Figure A1: Review Form

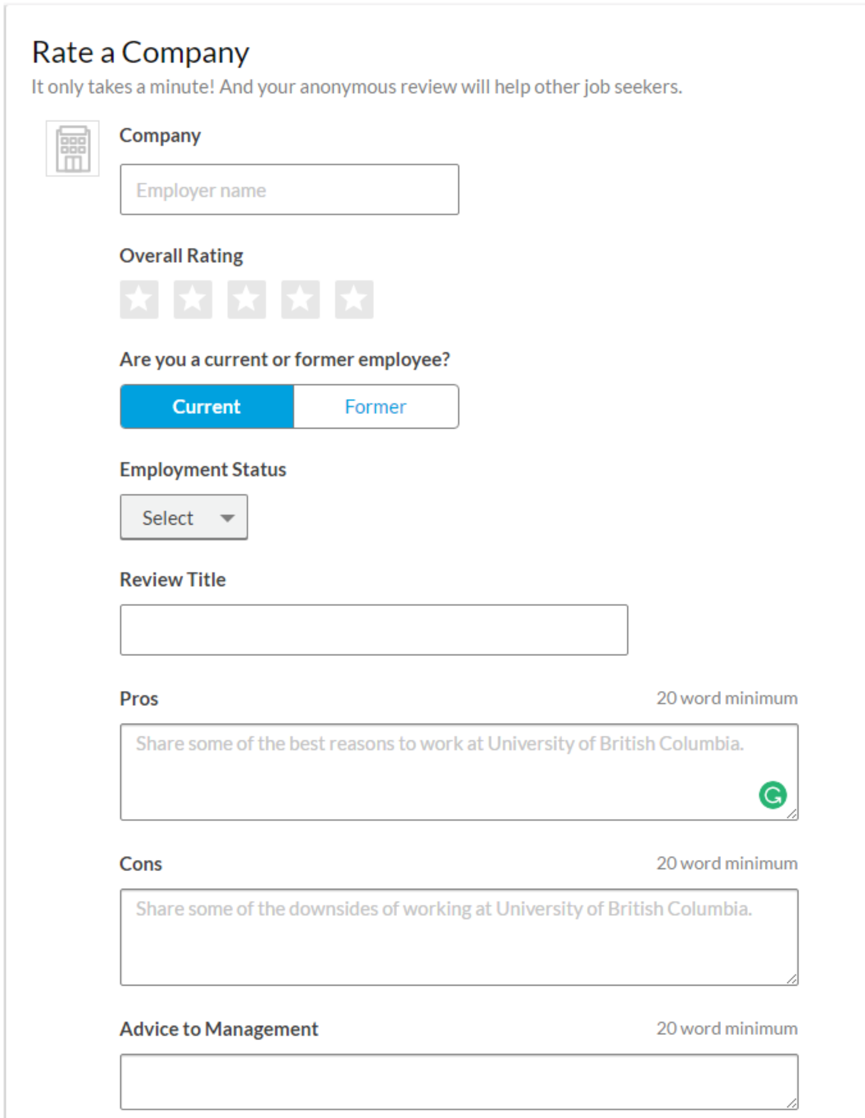
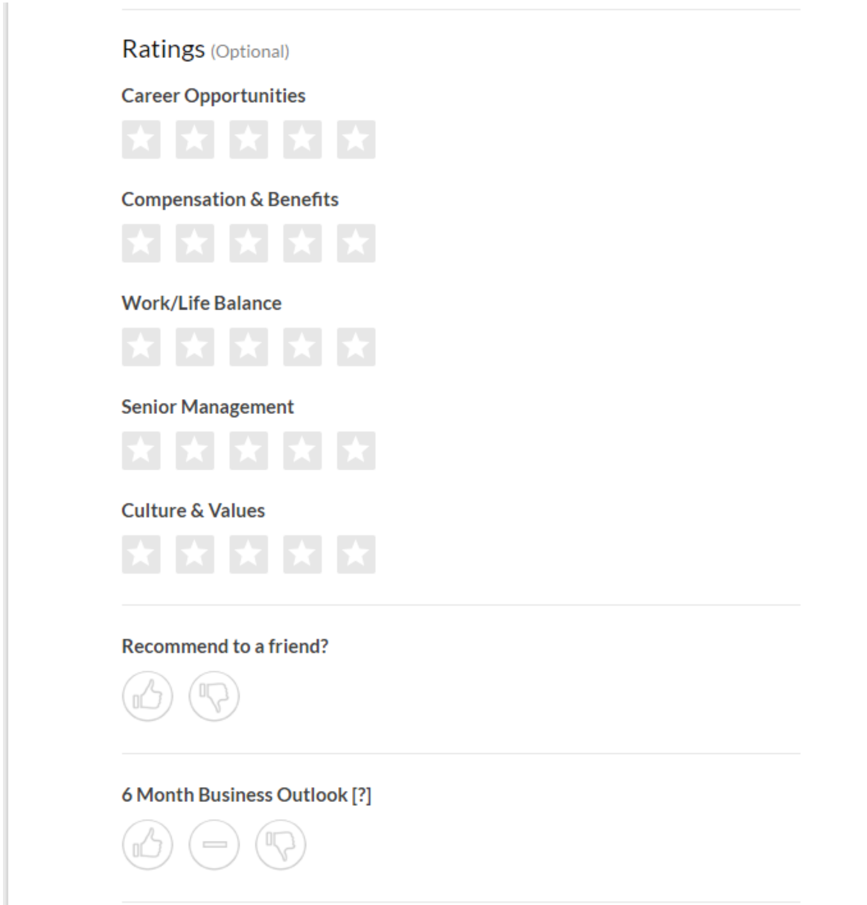


Figure A1 (continued)


Ratings (Optional)

Career Opportunities

Compensation & Benefits

Work/Life Balance

Senior Management

Culture & Values

Recommend to a friend?

6 Month Business Outlook [?]

Figure A2: Salaries information

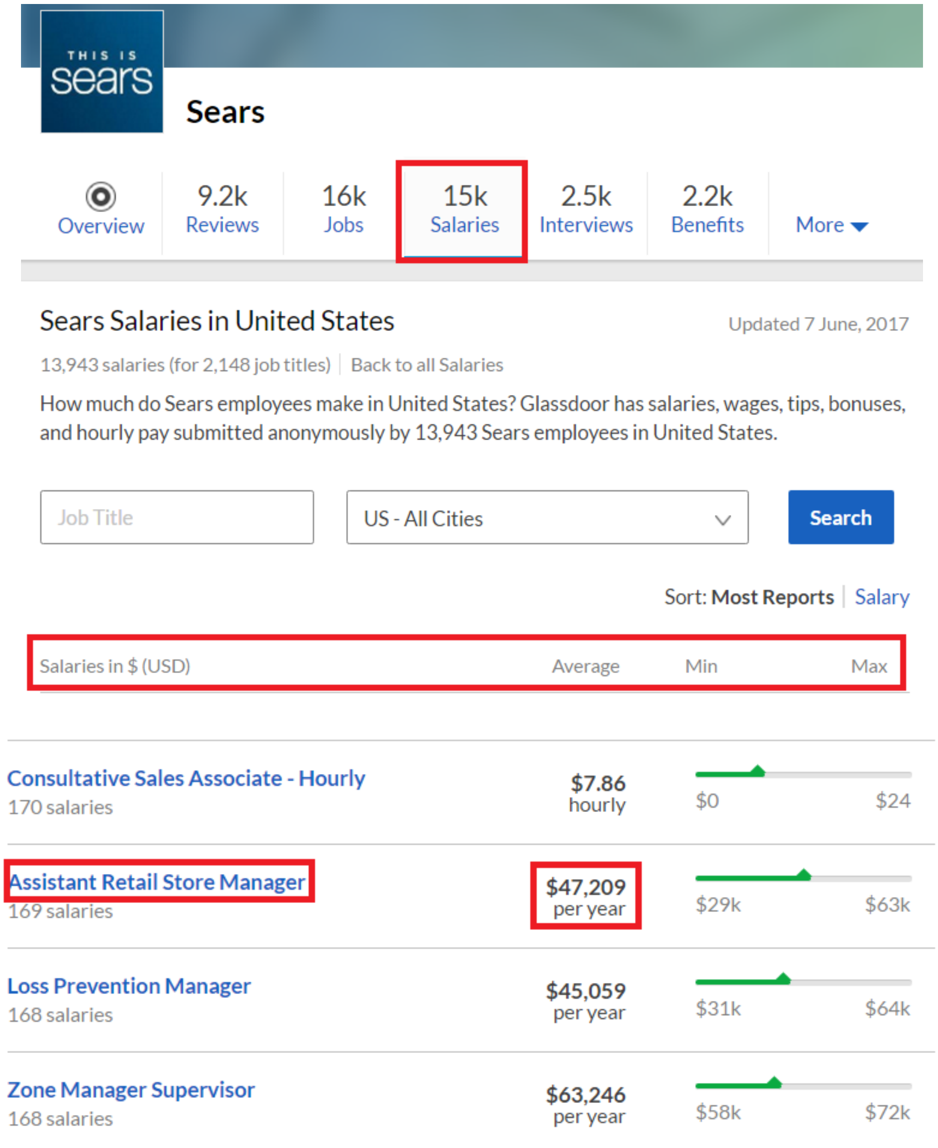
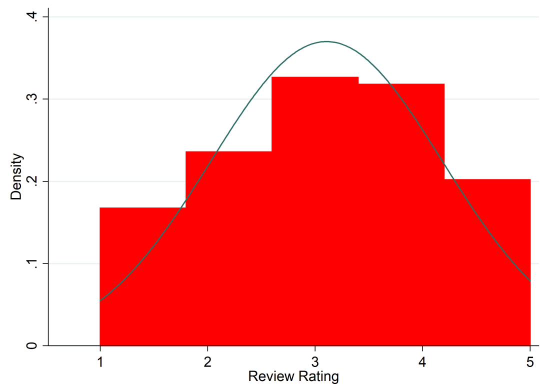


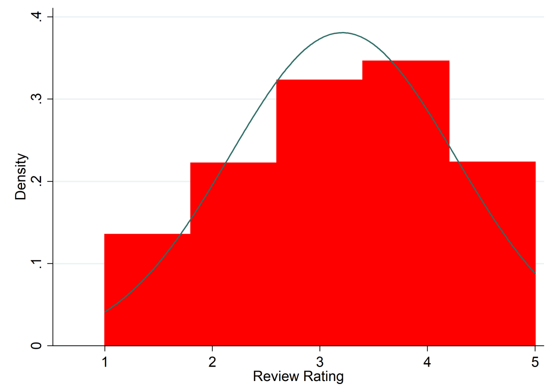
Figure A3: Histogram of reviews by star ratings

This figure presents the histogram of star ratings in employee reviews. The star rating is the mean of six numerical ratings in each review. The curve shows the normal distribution. Panel A shows the histogram based on reviews by all employees; Panels B, C, and D show the histograms of reviews by high-, middle-, and low-level employees, respectively. The definition of high-, middle-, and low-level employees is discussed in Section 5.

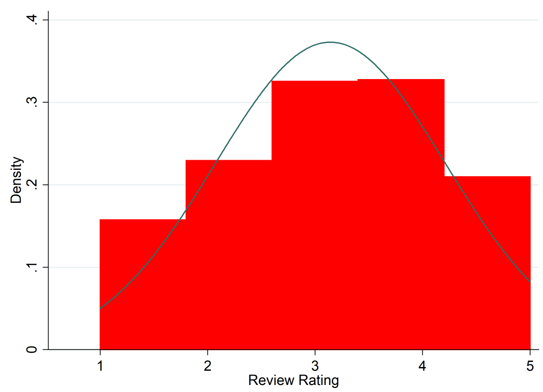
Panel A: Reviews by all employees



Panel B: Reviews by high-level employees



Panel C: Reviews by middle-level employees



Panel D: Reviews by low-level employees

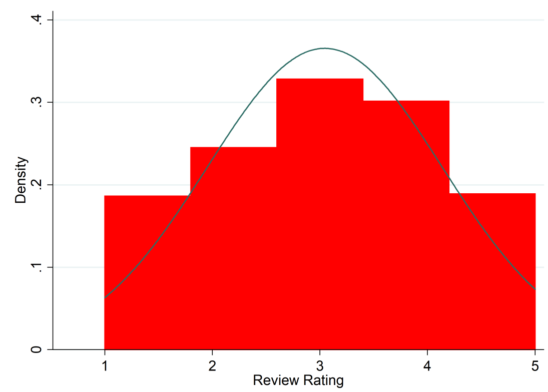


Figure A4: The distribution of reviews over different months

This figure plots the distribution of the number of reviews in each month. For each month, I calculate the total number of reviews posted for S&P 1500 firms. The fraction of reviews is the number of reviews in each month divided by the total number of reviews.

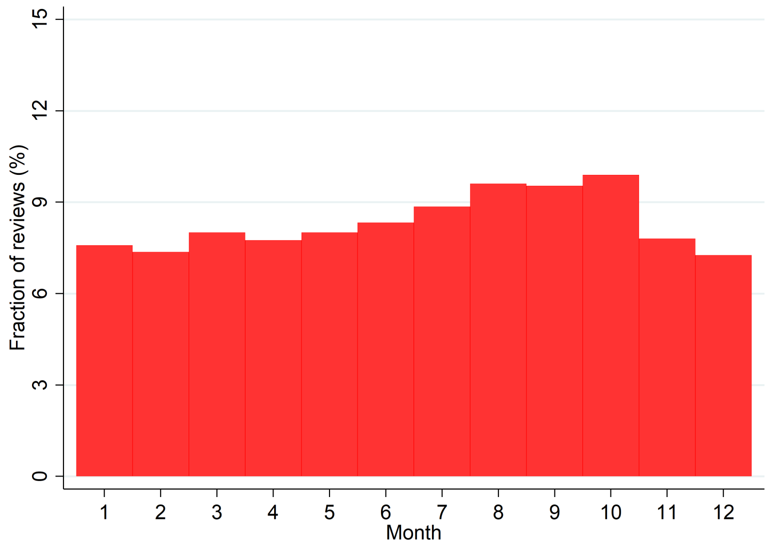


Table A1: Descriptive statistics on the user profiles of the employee review website

This table reports descriptive statistics of the employee review website user profiles obtained from the web analysis portal quantcast.com as of June 2017 (monthly). The website provides audience data and compiles visitor profiles by installing tracking pixels on the pages of websites. User profiles include data on gender, age, household income, education level, and ethnicity.

Characteristic	Category	Percentage of web traffic
Gender	Female	53%
	Male	47%
Age	<18	12%
	18-24	18%
	25-34	23%
	35-44	20%
	45-54	17%
	55-64	8%
	65+	2%
Household income	$0-50k	46%
	$50-100k	30%
	$100k-150k	13%
	$150k+	11%
Education level	No College	28%
	College	51%
	Grad school	21%
Ethnicity	Caucasian	64%
	African American	14%
	Asian	9%
	Hispanic	11%
	Other	2%

Table A2: Mean values of positive outlook and star ratings in each month

This table presents the mean values of outlook and star ratings in each month. *Positive outlook* is the number of reviews with positive outlook divided by the total number reviews in each month for each firm. *Recommend* is the number of reviews that state "recommend to a friend" divided by the total number of reviews in each month for each firm. *Overall* is the average overall star rating (on a scale of 1 to 5) in each month for each firm. The monthly means of culture and values rating (Culture), work-life balance rating (WorkLife), senior management rating (Management), compensation and benefits (Compensation), and career opportunities (Career) are calculated in the same way. The reported values are the mean of all of these variables in each month across all firms.

Month	Positive outlook	Recommend	Overall	Culture	WorkLife	Management	Compensation	Career
January	0.44	0.61	3.30	3.28	3.22	2.87	3.28	3.13
February	0.41	0.59	3.25	3.23	3.20	2.83	3.25	3.07
March	0.42	0.58	3.24	3.23	3.18	2.81	3.23	3.07
April	0.42	0.59	3.25	3.23	3.18	2.80	3.24	3.07
May	0.42	0.59	3.24	3.22	3.18	2.80	3.24	3.07
June	0.43	0.60	3.27	3.26	3.19	2.81	3.23	3.10
July	0.42	0.59	3.25	3.23	3.18	2.81	3.25	3.09
August	0.42	0.59	3.25	3.23	3.18	2.81	3.25	3.09
September	0.42	0.59	3.27	3.26	3.20	2.84	3.27	3.11
October	0.43	0.60	3.29	3.27	3.21	2.86	3.29	3.12
November	0.43	0.60	3.28	3.26	3.19	2.84	3.27	3.10
December	0.44	0.60	3.28	3.27	3.20	2.86	3.27	3.12

Table A3: Employee outlook and other components in reviews

This table reports results of regression Equation (1), where the dependent variable is a dummy variable (one for positive outlook) and independent variables include employee characteristics, star ratings, and variables constructed from texts. Current employee is equal to one if the reviewer is a current worker, and zero otherwise; Headquarter state is equal to one if that reviewer works in the headquarter state, and zero otherwise; and Recommend is equal to one if a reviewer states "recommend to a friend", and zero otherwise. *Overall* is the overall star rating (on a scale of 1 to 5). Similarly, work-life balance rating (WorkLife), senior management rating (Management), compensation and benefits (Compensation), and career opportunities (Career) have subcategory ratings with a scale of 1 to 5. The independent variables in Panel B are number of words calculated from different sections of a review text. Numbers in parentheses are t-statistics that are adjusted for heteroscedasticity and clustered by firms. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Employee characteristics and star ratings

VARIABLES	(1)	(2)	(3)	(4)
Current employee	0.13***			
	(34.60)			
Headquarter state		0.00		
		(0.49)		
Recommend			0.51***	
			(138.89)	
Overall				0.10***
				(79.71)
Career				0.05***
				(66.11)
Compensation				0.01***
				(10.73)
Management				0.08***
				(56.92)
WorkLife				0.00***
				(3.27)
Observations	656,204	455,111	656,204	656,204
Adjusted R2	0.082	0.063	0.294	0.351

Panel B. Review texts

VARIABLES	(1)	(2)
# of words in review title	-0.62***	
	(-20.18)	
# of words in review pros	0.32***	
	(51.85)	
# of words in reivew cons	-0.16***	
	(-48.66)	
# of words in reivew advice	-0.17***	
	(-31.83)	
# of words in the whole reivew		-0.09***
		(-48.34)
Observations	656,204	656,204
Adjusted R2	0.117	0.086

Table A4: Correlations and PCA analysis

Panel A reports correlations between outlook and other variables from employee reviews. Outlook is the positive outlook defined as the number of reviews with positive outlook divided by the total number of reviews in each month for each firm. *Recommend* is the fraction of reviews that state "recommend to a friend" divided by the total number of reviews in each month for each firm. *Overall* is the average overall star rating (on a scale of 1 to 5) in each month for each firm. The monthly mean of culture and values rating (Culture), work-life balance rating (WorkLife), senior management rating (Management), compensation and benefits (Compensation), and career opportunities (Career). Panel B reports the principal component analysis (PCA) results for the top three components. Eigenvalues for each component are also reported.

Panel A. Correlations

	Outlook	Recommend	Overall	Culture	WorkLife	Management	Compensation	Career
Outlook	1.00							
Recommend	0.61	1.00						
Overall	0.62	0.75	1.00					
Culture	0.57	0.68	0.78	1.00				
WorkLife	0.41	0.52	0.62	0.59	1.00			
Management	0.59	0.67	0.77	0.75	0.59	1.00		
Compensation	0.42	0.49	0.61	0.51	0.44	0.51	1.00	
Career	0.55	0.62	0.74	0.65	0.48	0.67	0.57	1.00

Panel B. PCA

	Component 1	Component 2	Component 3
Outlook	**0.64**	-0.28	-0.15
Recommend	0.43	0.07	-0.03
Overall	0.32	0.19	0.16
Culture	0.30	0.30	0.00
WorkLife	-0.08	**0.85**	-0.04
Management	0.33	0.25	0.01
Compensation	-0.05	-0.03	**0.91**
Career	0.30	-0.04	0.35
Eigenvalues	5.24	0.62	0.60
% Variance Explained	0.66	0.08	0.08

Table A5: Machine learning methods and their performance

This table presents the out-of-sample accuracy of different machine learning methods. For each method, the relationships between outlook and other variables are formed using training samples. The out-of-sample test uses these relationships to predict outlook in test samples. Test samples also have the true value for the outlook. The accuracy is calculated by comparing the predicted outlook and the true outlook.

Method	Accuracy
KNN	0.76
Logistic (L1)	0.77
Logistic (L2)	0.77
Linear SVC	0.76
Decision tree	0.77
Random forest	0.76
Gradient boosted trees	0.77
Deep learning	0.91

Table A6: Top five words in each topic from LDA

Topics	Top five words
business growth	business, growth, development, industry, opportunity
personnel development	coworkers, training, learn, friendly, team
leadership	leadership, supervisors, listen, upper-level, communication
salary	salary, paid, advancement, compensation, money
flexibility	flexible, balance, work, home, family
benefits	vacation, health, insurance, 401k, holidays
career opportunities	career, growth, opportunity, promotions, move
work hours	shift, busy, hour, workers, workload
culture	performance, goals, clear, focus, expectations
work environment	treat, respect, care, hr, hire

Table A7: Employee outlook and insider trading

This table reports the results of regressions of one-month-ahead insider trading on employee outlook. *Abnormal positive outlook* is the number of reviews with positive outlook divided by the total number of reviews in each month for each firm minus its mean over the past three months. *Stock returns* is the stock returns in that month. *Stock returns 12 months* is the cumulative stock returns over the past 12 months. *Size* is the logarithm of market capitalization of the firm, calculated as the number of shares outstanding multiplied by the stock price. *Book-to-market* is a firm's book value divided by its market value. *Beta* is a firm's exposure to market risk, calculated from a rolling regression of monthly excess stock returns of the firm on market returns. *Positive media coverage* is the number of positive news articles that mentioned the firm in the Dow Jones News Archives, provided by RavenPack. *Institutional ownership* is the fraction of shares owned by institutional investors. *Analyst coverage* is the number of analysts that cover a firm. *Profitability* is gross profitability, calculated as the ratio of income before extraordinary items to book value of assets. *Dollar volume* is trading volume multiplied by stock price. Numbers in parentheses are t-statistics that are adjusted for heteroscedasticity and clustered by industry and time. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	one-month-ahead insider sells			one-month-ahead insider buys		
Abnormal positive outlook	-0.025***	-0.024***	-0.029***	-0.007	-0.009	-0.014
	(-2.69)	(-2.62)	(-3.06)	(-0.69)	(-0.84)	(-1.26)
Stock returns		-0.400***	-0.443***		0.369***	0.360***
		(-11.29)	(-10.74)		(7.89)	(7.01)
Stock returns 12 months		0.039***	0.018**		-0.048***	-0.032***
		(6.76)	(1.98)		(-7.32)	(-3.14)
Size		0.005***	0.072***		-0.002*	-0.050***
		(4.07)	(8.29)		(-1.72)	(-4.68)
Book-to-market		0.000	0.019**		0.001	-0.033**
		(0.12)	(2.00)		(0.21)	(-2.13)
Beta		0.003	0.006		0.007**	0.012
		(1.32)	(0.78)		(2.57)	(1.42)
Media coverage		-0.001***	-0.001*		-0.000	-0.000
		(-3.27)	(-1.79)		(-1.64)	(-0.21)
Analyst coverage		-0.000**	-0.001		0.001**	0.002**
		(-2.51)	(-0.82)		(2.55)	(2.03)
Institutional ownership		-0.014	-0.078**		-0.017	-0.040
		(-1.39)	(-2.15)		(-1.57)	(-0.91)
Profitability		-0.019**	-0.058*		-0.002	0.059
		(-2.33)	(-1.65)		(-0.16)	(0.90)
Log(Dollar volume)		-0.000	-0.000		0.000	-0.000
		(-0.25)	(-0.69)		(0.20)	(-0.84)
Time, Firm FEs	N	N	Y	N	N	Y
Observations	26,226	26,226	26,226	26,226	26,226	26,226
Adjusted R2	0.000	0.004	0.139	0.000	0.003	0.112