Employees' voluntary disclosures about business outlook and labor investment efficiency

Abstract: We examine how employee business outlook affects firm-level labor investment efficiency by using data from Glassdoor. We hypothesize that due to the popularity and informativeness of employee voluntary disclosure through social media as a form of crowd wisdom in labor markets, more positive business outlook disclosed by employees can significantly reduce firms' labor adjustment costs by attracting more job applicants in a timely matter, resulting in higher labor investment efficiency. Consistent with the hypothesis, we document that positive employee business outlook enhances labor investment efficiency by reducing both over-investment and under-investment in labor. Extending our first hypothesis, we also hypothesize and find that when peer firms' employee business outlook is more positive than that of focal firms, focal firms' labor adjustment costs increase because of the relative disadvantage in obtaining talented labor in labor markets, resulting in less efficient labor investment. We mitigate the endogeneity concerns by employing sub-sample analysis and using Anti-SLAPP laws as an exogenous shock.

Keywords: Voluntary disclosure; Employees; Business outlook; Glassdoor;
Labor investment efficiency; Labor adjustment costs

Employees' voluntary disclosures about business outlook and labor investment efficiency

"Recruiting informed candidates can result in big savings for any employer, while also delivering them the quality talent they want."

- Glassdoor's Chief Economist, Dr. Andrew Chamberlain

1. Introduction

Emerging employee disclosures through social media have drawn much attention and interest from academic scholars (e.g., Huang, Li, Meschke, & Guthrie, 2015; Landers, Brusso, & Auer, 2019). A nascent line of research suggests that employee business outlook from Glassdoor, as a non-traditional information source, provides valuable information (e.g., Fan, Ji, Thomas, & Wang, 2019; Chemmanur, Rajaiya, & Sheng, 2020; Huang, Li, and Markov 2020, 2021).[1] For example, Hales, Moon, and Swenson (2018) and Huang, et al. (2020) show that the employee outlook disseminated through Glassdoor is informative and has predictive power for future sales, gross margins, and operating performance. Li, Wang, and Zhu (2019) document that employee outlook is positively related to analysts' earnings forecast revisions. Fan et al. (2021) also use employee outlook from Glassdoor and show that employees provide information withheld by managers, particularly about bad news, through disclosure on social media.

While numerous papers examine capital market consequences of employee business outlook, to our best knowledge, the implication of predictive and informative employee voluntary disclosures on real corporate operational decisions, particularly corporate employment, is unexplored. Little research speaks directly to whether the collective opinions on social media facilitate information dissemination and whether such information has real effects on labor markets.

[1] As Hales et al. (2018) emphasize, rather than using the general public's opinion about the firm from Twitter, Seeking Alpha, and Estimize, we focus on a public platform, Glassdoor which collects insider information about business outlook from employees and share the information with the public. A business outlook variable is also unique in Glassdoor.

We believe that examining the real effects of employees' forward-looking voluntary disclosures (e.g., business outlooks) on their firms' labor investment is important. As a factor of production, labor is one of the most valuable assets for a firm and plays an essential role in contributing to company success. Great business depends on its employee performance (Cao & Rees, 2020), and labor expenses represent around 67% of economy-wide value added (Bernanke, 2004). Moreover, as labor has a relatively higher level of mobility, compared to other types of assets, firms have to bear significant costs related to employee searches, hiring, firing, and training. For example, it typically costs six to nine months' salary to replace an employee.[2] Given the difficulty in replacing employees' skills, experience, and knowledge, inefficient labor investment is costly and detrimental to business. Thus, efficient labor investment is vital to a firm's success, particularly for knowledge-based firms, which have become more and more prevalent.

While the importance of social media in human resource management has significantly increased recently because of advances in technology (Roth, Bobko, Van Iddekinge, & Thatcher, 2016; Landers & Schmidt, 2016), prior literature has largely overlooked the effectiveness of rank-and-file employees' opinions from social media in terms of mitigating corporate labor-related issues such as hiring and employee turnover (Teoh, 2018). In this paper, we attempt to fill this void in the literature by investigating the real impact of employees' forward-looking voluntary disclosures on firm's labor investment efficiency.[3] Specifically, given that business outlook from Glassdoor represents employees' projection of firms' future prospects in the next six months, we

---

[2] That is, if an employee's annual salary is $60,000, then $30,000 to $45,000 will be spent on searching, recruiting, and training. See more details in the following website: https://www.peoplekeep.com/blog/employee-retention-the-real-cost-of-losing-an-employee.
[3] Throughout the paper, we interchangeably use labor investment efficiency and hiring efficiency.

examine whether and how employee business outlook reduces firms' labor adjustment costs, thereby improving labor investment efficiency.

As insiders working within firms, employees always attempt to obtain more useful information about firms' future to reduce unemployment risk and costs arising from firm-specific investments in their human capital (Agrawal & Matsa, 2013). For instance, prior literature (e.g., Hales et al., 2018; Green, Huang, Wen, & Zhou, 2019; Huang et al., 2020) indicates that employees are knowledgeable with respect to their employers' financial prospects, particularly downside risks. When firms suffer from financial constraints, they tend to cut their spending for employee benefits and safety (Edmans, 2011, 2012). If employees believe that financial distress negatively affects their job security or future career advancement opportunities, they are more likely to leave their current employers (Agrawal, Hacamo, & Hu, 2020; Baghai, Silva, Thell, & Vig, 2020; Gortmaker, Jeffers, & Lee, 2020). Having access to direct and inside information, employees are generally at information advantages over outsiders regarding firms' future prospects. Farhadi and Nanda (2020) suggest that employees have private and predictive information that is not available to investors and even firms' executives.

More importantly, as the wisdom of crowds theory suggests (Surowiecki, 2005), the collective employee voluntary disclosures about business outlook tend to contain more accurate and reliable information. Accordingly, we argue that employees' voluntary disclosures on social media (e.g., Glassdoor) about their firms' positive business outlook are informative and will attract high-quality job applicants to a larger extent, thus, reducing firms' costs of searching, hiring, and training new employees. Because of the reduction of these costs, the cost of firing less able employees is also lower for such firms. In addition, since employees with more positive business outlook of their employers are less likely to voluntarily leave their companies, managers of such firms do not need to make additional efforts or spend more resources in retaining their valuable employees. Based on the above arguments, we expect that firms with more employee positive outlooks tend to have lower labor adjustment costs. Therefore, we predict that those firms tend to make more efficient hiring decisions. However, employee outlook on social media can be inaccurate or biased since it is anonymous, and may suffer from self-selection bias to some extent. In this case, employee voluntary disclosure is less informative and thus, may not play an important role in reducing labor market frictions, leading to no significant association between employee outlook and labor investment efficiency.

To test our first hypothesis, we obtain data of employee business outlooks from Glassdoor, a major social media platform where employees can rate their current and former employers anonymously and truthfully. Our final sample consists of 5,799 firm-years from 2012 to 2019. Following Jung, Lee, and Weber (2014), we measure labor investment efficiency by first estimating the normal (or expected) level of labor hiring based on firm fundamentals. Then, we compute the absolute difference between actual hiring and expected hiring, and consider the higher absolute difference as more inefficient hiring or labor investment. Thus, if a firm's actual level of hiring is greater (lower) than the expected level, the firm is more likely to over-invest (under-invest) in labor. Finally, we estimate the relation between employee outlook and hiring efficiency.

Consistent with our first hypothesis, we find that employee business outlook is positively associated with labor investment efficiency, suggesting that employees' positive outlook significantly reduces labor adjustment costs. Furthermore, we explore whether the positive relation between employee outlook and labor investment efficiency is due to the reduction in the extent of over-investment or under-investment in labor. We find that employee positive outlook reduces both over-investment and under-investment in labor. This finding suggests that firms with more positive employee outlooks are less likely to need to over-hire employees for future labor demand, since they can hire new employees in a timelier manner whenever they need to. In addition, because of the strong labor supply for such firms with positive employee outlook in labor markets, *all other things equal*, the likelihood that managers of such firms under-invest in labor than the optimal level due to labor market frictions is lower.

As our second hypothesis, we also explore how peer firms' employee business outlook affects focal firms' labor investment efficiency. We hypothesize that if peer firms' employee outlook is more positive than that of focal firms, focal firms' labor adjustment costs will increase due to competition in labor markets for employees, therefore, reducing labor investment efficiency. To test this prediction, we construct a measure that incorporates the difference between peer firms' and focal firm's employee outlook. Its higher value indicates the extent to which peer firms' business outlook is more positive than that of focal firms. Consistent with our second hypothesis, we find that the measure of business outlook difference is negatively related to focal firms' labor investment efficiency. This suggests that peer firms' more positive employee business outlooks increase the focal firm's labor adjustment costs and, thus, hamper investment efficiency in labor.

To further strengthen our main arguments, we also examine various cross-sectional variation tests. Specifically, we investigate whether the following four factors predictably moderate the positive association between employee outlook and labor investment efficiency – (1) the number of current employees participating in the survey; (2) the number of reviews from long-tenured employees; (3) the number of business outlook reviews; and (4) labor skill.

First, we examine whether the positive relation will be stronger when there are more business outlooks disclosed by current employees. We predict that business outlook from current employees will be more informative to job candidates since it is likely to deliver more relevant information about the firms. To test this prediction, we construct the measure of the number of current employees among the total number of responders on Glassdoor and find that the positive relation is more pronounced when more positive employee outlooks are from current employees. In a similar vein, we further create a variable indicating the number of employees that have worked in a firm for more than five years among the total number of responders on Glassdoor. We expect and find that the positive relation is stronger when longer-tenured employees provide more positive business outlooks, which further corroborates our main results.

Next, we predict that employee outlook will be more reliable and relevant to potential job applicants when the same evaluation of business outlook is supported by a greater number of reviews. More employee reviews reduce idiosyncratic noise from individual opinions, leading to more useful employee business outlooks (Fan et al., 2019). Consistent with our expectation, we show that the positive association is more pronounced when employee outlook is accompanied by a larger number of reviews. Moreover, we document that the positive relation is stronger for firms that require higher labor skills since such firms are more subject to labor adjustment costs (e.g., Ghaly, Anh Dang, & Stathopoulos, 2017).

Finally, we employ labor cost stickiness as a proxy for labor adjustment cost and examine the association between employee outlook and labor cost stickiness. Following the literature (e.g., Weiss, 2010), we measure labor cost stickiness as the difference between the rate of labor increase with respect to sales increase and the corresponding rate of labor decrease with respect to sales decrease. By using this measure as a dependent variable in our main model, we document a negative relation between employee outlook and labor cost stickiness, suggesting that positive business outlook significantly reduces labor adjustment costs. This finding further strengthens our argument underlying the main results.

To address the endogeneity and reverse causality concerns, we implement the following two robustness tests. First, we perform sub-sample analyses based on firm performance metrics such as accounting performance and stock performance. We claim that unobservable firm characteristics (e.g., better management teams and corporate governance mechanisms), which potentially cause the endogeneity in the positive relation between employee outlook and labor investment efficiency, tend to be positively associated with observed firm performance such as accounting and stock performance. Thus, we split our sample into two sub-groups based on the accounting performance measure (profit vs. loss firms), and the sample median of stock performance, respectively. Then we re-estimate our main regressions to sub-samples based on accounting and stock performance metrics. The results show that our findings are not driven by sub-samples of profit firms and high stock return firms, mitigating the endogeneity concerns. These findings also indicate that employee business outlook still matters in reducing labor adjustment costs even when firms currently report accounting losses or experience low stock performance.

Second, we employ the state-level staggered adoption of Anti-SLAPP laws as an exogenous shock to employee outlooks of the firms. SLAPP (strategic lawsuit against public participation) refers to a retaliatory lawsuit filed against an opponent who had spoken against the plaintiff in a public forum. After the adoption of Anti-SLAPP statutes, anonymous reviews on Glassdoor will be less affected by the threat of litigation compared to those in states with no Anti-SLAPP laws. That is, in Anti-SLAPP states, employees are more likely to express their opinions truthfully and disclose negative reviews of their firms and are less likely to intentionally bias their business outlooks upward to curry favor with upper management. Consistent with this expectation, we confirm a negative effect of the adoption of Anti-SLAPP laws on employee outlooks. While its adoption is negatively associated with employee outlooks, there is no reason to believe that the adoption of Anti-SLAPP laws is directly related to firm-level labor investment efficiency, which suggests that the adoption can be a reasonable exogenous shock. Similar to our main results, we find that after the passage of Anti-SLAPP laws, when employee outlook is generally less biased upward, labor investment is more inefficient. By nature of this research design, the analysis based on the exogenous shock also alleviates the reverse-causality concern.

We follow the literature and choose a business outlook variable to proxy for employees' perception about their firm's growth and future prospects instead of other variables such as overall employee satisfaction in Glassdoor. The literature (e.g., Sheng 2022) claims that employee outlook variable has more predictive power about future earnings and fundamentals than other Glassdoor variables such as overall satisfaction ratings since it is forward-looking. While employees' job search is also affected by employee satisfaction, we believe that the effect of business outlook on job search can be more important due to the strong link between employee outlook and future firm performance (Sheng 2022) and the monetary implication of firm performance in terms of employees' wages and salaries. Nonetheless, to further mitigate this concern that our results may be driven by other Glassdoor variables, particularly, including employee overall satisfaction, we re-estimate our main models after including additional control variables such as other ratings of Glassdoor. We find that our results remain robust with these control variables, suggesting that employee outlook is unique in improving labor investment efficiency.[4]

Moreover, we further employ two alternative measures to proxy for employee business outlook. First, we modify our business outlook variable using a different rating scale. Second, we

[4] To mitigate the concern that our results can be driven by firm reputation or firm visibility, we re-estimate our main regressions after controlling for a variable that indicates whether a firm is listed as Most-Admired firms. We find that our results are qualitatively similar with this additional control variable.

conduct textual analysis and extract the proportion of forward-looking information from employees' written reviews about their firm's pros and cons, respectively. We then use the proportion of forward-looking content in the pros (cons) category to capture employee positive (negative) outlook. Our main findings still hold using these alternative measures.

Our study makes several contributions to the literature. First, our paper adds to a burgeoning literature on the economics and real effects of voluntary disclosures by rank-and-file employees. By taking a new perspective from this line of literature, we examine how employee voluntary disclosures about their employers' future prospects on social media affect their firms' hiring efficiency. Specifically, we show that employees' voluntary disclosures about business outlook help reduce labor market frictions and thus improve hiring efficiency. Our findings also shed light on prior studies such as Huang et al. (2020) and Sheng (2019) by documenting labor investment efficiency as one mechanism through which employee business outlook is positively associated with future operating performance as well as stock returns.

Second, our findings also contribute to the growing body of research which examines the frictions in the labor market (e.g., Jung et al., 2014; Weiss, 2010) by showing that employees' voluntary disclosure is an important determinant of corporate hiring efficiency. Third, our paper adds to the nascent line of research regarding social media. This study answers the call for research on examining the informativeness of employee voluntary disclosures through social media websites (i.e., Glassdoor) (Teoh, 2018). Our findings suggest that employees, the insiders of firms, possess private information, serving as a collective information source. Our paper supports the wisdom of crowds theory (i.e., the collective information provided by rank-and-file employees is useful) and empirically shows that the collective opinions from employees on social media help mitigate information asymmetry between firms and job seekers and, therefore, decrease social losses due to information asymmetry in labor markets, highlighting the economic benefits of social media. In light of our findings, we view the technological shift in the information environment as one that can help mitigate labor market frictions.

The remainder of the paper is organized as follows. Section 2 discusses the literature review and develops our hypotheses. Section 3 describes the Glassdoor data and sample selection. Section 4 discusses research design. Section 5 reports our main empirical results. Section 6 contains additional analysis, and section 7 concludes.

2. Literature Review and Hypothesis

As participants of company operations, employees have direct access to firm's inside information and maintain information advantages over outsiders. Thus, employees' disclosures can serve as a source of revealing unique and fundamental information about their companies (Green et al., 2019). Glassdoor provides a rapidly growing platform that allows employees to make their own disclosures, express their opinions, and convey private information. With its help, rank-and-file employees can disseminate information about their firms at a faster rate and to a greater extent, which is highly visible on the internet and significantly impacts firms' information environment. Employee disclosures on Glassdoor uncover salient, insightful, and forward-looking information about the firms that may not be distributed through management and is not directly accessible to potential job applicants. Thus, by using the Glassdoor website, job seekers can use these aggregated employee disclosures about their firms' future prospects as potential information sources to better evaluate firms and make job application decisions.

Employees' disclosures on business outlook from Glassdoor could potentially affect and be beneficial to corporate employment efficiency in several ways. First, employee outlook functions as an information source about the firms. According to the wisdom of crowds theory (Surowiecki, 2005), collective employee outlooks serve as a form of crowd wisdom and contain a great amount of information. The aggregated employees' beliefs about business outlook could be incrementally informative and superior to individual disclosures such as management disclosure. Consistent with this notion, prior studies demonstrate the reliability and predictability of the information contained in employee outlook from Glassdoor (Li, Wong, & Zhou, 2019; Sheng, 2019; Huang et al., 2020), suggesting that employees' expectations could be a rich source for job applicants of information such as development opportunities and employee recognition. For example, Hales et al. (2018) show that employee outlook is useful in predicting growth in key income statement information. Fan et al. (2019) find that such outlook is reliable and decision-relevant, suggesting that forward-looking disclosure from employees contains useful information. Huang et al. (2021) suggest that employee outlook disseminates private information beyond the management disclosure and can capture information that is only available in certain corporate hierarchies.

In addition, Glassdoor is the largest employee review website in the U.S., and a survey indicates that 48% of job applicants have used it (Forbes, 2014). Compared to gathering the information from other potential social media platforms such as Twitter, the aggregated and qualitative outlook disclosures from Glassdoor require relatively low processing costs and collection efforts, which makes data collection and processing easier and more efficient. As an anonymous platform, Glassdoor is committed to protecting users' identities and offering free unlimited access without registration. Thus, current and former employees and job applicants use this crowdsourcing platform to exchange and diffuse their work experience and feedback. We claim that job applicants actively searching for critical information about employers' future prospects are willing to pay attention to Glassdoor and learn about the firms from employees' opinions about firms' business outlook. More importantly, the highly accessible employee outlooks can contribute to the optimization of personnel. For instance, based on Glassdoor's own survey data, informed job applicants who use Glassdoor tend to make better decisions and have higher retention rates than those who do not, and firms can avoid significant retention and recruiting costs by finding and retaining the right match.[5]

Positive employee outlook disclosures through Glassdoor enable managers to make and maintain timely labor investments. They enhance firms' recruiting efficiency in searching, hiring, and training new employees by attracting job applicants to a larger extent and lowering the related costs. Moreover, employee turnover is a major concern for firms (Boswell, Ren, & Hinrichs, 2008). Employee turnovers come with high costs of selection and replacement of former employees (Kacmar, Andrews, Van Rooy, Steilberg, & Cerrone, 2006), resulting in negative outcomes such as declining organizational performance and morale (Mobley, 1982; Shaw, Gupta, & Delery, 2005). Prior literature also suggests that potential developmental opportunities impact the retention of high-potential employees (Fernández-Aráoz, Groysberg, & Nohria, 2011), and that quality employees tend to work for companies with chances for them to grow (Ryan, 2010). With positive employee outlooks, managers are also more likely to retain talented employees and reduce their voluntary turnovers.

Collectively, positive employee outlook disclosures could lower labor adjustment costs and improve the efficiency of labor investment through attracting and retaining talented employees, which reduces both over-investment and under-investment in labor. Firm managers receiving positive outlooks are less likely to face challenges in hiring quality employees whenever they need to, and therefore do not need to over-hire or hoard underperforming or unnecessary employees to

[5] Please see more details about the survey in https://www.glassdoor.com/employers/blog/glassdoor-retention-study/.

prepare for potential labor shortages in the future, lowering the likelihood of over-investment in labor. With respect to the effect of positive employee outlooks on under-investment in labor, information asymmetry between employers and potential/current employees may create adverse selections in their employment-related decisions, resulting in under-investment in labor. Since positive employee outlooks can increase labor supply, the likelihood of under-investment in labor is lower for firms receiving positive employee outlooks.

Based on the above arguments, we expect that positive employee outlooks contribute to more efficient labor investment, leading to our first hypothesis as follows (in an alternative form):

> ***H1:*** *Employees' disclosure of more positive business outlooks on Glassdoor improves their firms' labor investment efficiency.*

In the second hypothesis, we explore the impact of employee business outlook of peer firms on focal firms' labor investment efficiency. If peer firms' outlooks are more positive, focal firms' labor adjustment costs will increase due to labor market competition regarding talents, leading to a reduction in focal firms' labor investment efficiency. Therefore, we expect to find that the difference between peer firms' and focal firms' employee outlooks is negatively associated with focal firms' labor investment efficiency. This leads to our second hypothesis as follows (in an alternative form):

> ***H2:*** *Peer firm employees' disclosure of more positive business outlooks on their firms reduces the focal firm's labor investment efficiency.*

3. Data and Sample

3.1. Glassdoor data

We obtain employee business outlooks from Glassdoor, a social media website that collects in-depth and real-time reviews directly from rank-and-file employees; and therefore, it provides a rich source of inside information about the company and management team of the company from the employees' perspectives (Teoh, 2018; Li et al., 2019). Launched in June 2008, Glassdoor accommodates an online platform in which (both current and former) employees are encouraged to voluntarily and anonymously convey their own opinions about employers, senior management, compensation and benefits, and interview experiences (Green et al., 2019; Sheng, 2019). Since then, hundreds of thousands of employees have posted over 33 million ratings and comments for roughly 700,000 companies around the world (Chemmanur et al., 2020). Given its popularity and rapid growth, Glassdoor is now the second-most popular job listings and reviews site in the U.S. with 50 million unique users (Yahoo Finance, 2018).

Additionally, to safeguard the content and quality of each employee rating from manipulation, Glassdoor validates each user based on his/her permanent email or social network account, and closely monitors user accounts to prevent fake or multiple reviews or ratings (Chen, Tang, Yao, & Zhou, 2020). Glassdoor also constantly employs several fraud-detection models to eliminate fraudulent or inappropriate language, and strictly applies the community guidelines to ensure that information available to users is authentic and voluntary without coercion by management (Hales et al., 2018; Truong, 2018; Green et al., 2019; Li et al., 2019). Furthermore, since online reviews may suffer from selection bias, Glassdoor adopts a "give-to-get" policy to incentivize a less extreme distribution of employer reviews and consequently reduces bias in reviews (Marinescu, Klein, Chamberlain, & Smart, 2018; Li et al., 2019).[6] Therefore, Glassdoor as a social media platform provides a reliable resource for employee voluntary disclosure.

3.2. Sample

[6] Glassdoor's 'give to get' policy, which grants employees access to valuable information about their employers only if they provide reviews about their current or former employers, encourages reviews from individuals who would otherwise tend not to contribute (Huang et al., 2020).

We obtain employee outlooks from Glassdoor for the period between 2012 and 2019.[7] We start with approximately 2.5 million individual employee outlook ratings for 6,039 unique public firms from Glassdoor. To convert individual employee outlook ratings to firm-year level measures, we use the arithmetic average of employee outlooks made in the current year, leading to 32,186 firm-year business outlooks. After removing firms in the utilities and financial services industries and merging with the Compustat universe, the sample is reduced to 22,852 firm-years. Matching with CRSP and IBES databases further reduces the sample size to 10,754 and 9,012, respectively. Finally, we drop firm-years with missing labor union information from Union Membership and Coverage Database (www.unionstats.com), resulting in our final sample of 5,799 firm-years with 1,707 unique firms. All continuous variables are winsorized at their 1 and 99 percent levels to reduce the effects of outliers on our results.

4. Research Design

4.1. Main variables

4.1.1. Employee business outlook

When employees review their employers on Glassdoor, they have options to provide their own opinions about their firm's future six-month business outlook based on the following question: "*In the next six months, do you believe your company's business will perform better, worse or remain the same?*" Specifically, rank-and-file employees can rate a firm's business outlook as "negative," "neutral," or "positive," which we code as -1, 0, and 1, respectively (e.g., Huang et al., 2020; Farhadi & Nanda, 2020). We aggregate all individual employee outlooks at the firm-year level to create our main variable, *Outlook*, which is the average rating of all employee outlooks of the firms each year.

---

[7] Business outlook ratings are only available on Glassdoor starting from 2012.

4.1.2. Labor investment efficiency

Following Jung et al. (2014), to measure labor investment efficiency, we first run the following Equation (1) to estimate the normal (or expected) level of net hiring. Then, we define abnormal net hiring as the absolute difference between actual net hiring and the expected level of hiring. Thus, the higher (lower) absolute difference (i.e., *AB_NetHire*) indicates the higher labor investment inefficiency (efficiency). We also define over-investment in labor (under-investment in labor) when actual net hiring is greater (less) than the expected level of hiring – positive (negative) abnormal net hiring or residual from estimating Equation (1).

$$\begin{aligned} Net\_Hire_{it} = {} & \beta_0 + \beta_1 Sales\_Growth_{it\text{-}1} + \beta_2 Sales\_Growth_{it} + \beta_3 \Delta ROA_{it} + \beta_4 \Delta ROA_{it\text{-}1} + \\ & \beta_5 ROA_{it} + \beta_6 Return_{it} + \beta_7 SizeR_{it\text{-}1} + \beta_8 Quick_{it\text{-}1} + \beta_9 \Delta Quick_{it\text{-}1} + \\ & \beta_{10} \Delta Quick_{it} + \beta_{11} Leverage_{it\text{-}1} + \beta_{12} LOSSBIN1_{it\text{-}1} + \beta_{13} LOSSBIN2_{it\text{-}1} + \\ & \beta_{14} LOSSBIN3_{it\text{-}1} + \beta_{15} LOSSBIN4_{it\text{-}1} + \beta_{16} LOSSBIN5_{it\text{-}1} + \varepsilon_{it} \end{aligned} \quad (1)$$

Where Net_Hire_t is the percentage change in the number of employees from year t-1 to year t; *Sales_Growth* is the percentage change in sales; *ROA* is net income scaled by total assets; *Return* is the annual stock return; *SizeR* is the percentile of the log of market value of equity; *Quick* is the ratio of cash and short-term investments plus receivables to current liabilities; *Leverage* is the ratio of long-term debt to total assets; *LOSSBIN* variables are indicator variables for each 0.005 interval of prior-year *ROA* from 0 to -0.025. For example, *LOSSBIN1* (*LOSSBIN2*) equals one if prior-year *ROA* is between 0 and -0.005 (between -0.005 and -0.01) and zero otherwise. *LOSSBIN3* to *LOSSBIN5* are defined in the same way. We also include industry fixed effects to control for a variation in hiring across industries (i.e., industry-specific hiring practice).[8] All variables are also defined in more details in Appendix I.

[8] Following prior studies (e.g., Jung et al., 2014) and for better comparison with prior studies in terms of results, we do not include year fixed effects in estimating Equation (1). However, our main results are robust to the inclusion of year fixed effects in Equation (1).

Descriptive statistics for variables used in Equation (1) and the results of estimating Equation (1) are presented in Appendix II. The sample for this estimation consists of 46,847 firm-year observations, which is larger than our main analysis, since we do not restrict the availability of Glassdoor data to estimate abnormal hiring. With this choice, we can mitigate measurement error concerns and more accurately estimate labor investment efficiency. Descriptive statistics and estimation results are largely similar to those reported in prior literature (e.g., Jung et al., 2014). Specifically, we find that sales growth in the current and previous years is significantly positively correlated with net hiring, suggesting that growth opportunity is one important determinant of managers' hiring decisions.[9] Managers' hiring also increases with firm size, stock returns (capturing growth opportunities that are not reflected in sales growth), and liquidity while it decreases with leverage. The coefficient on *ROA* is significantly negative and somewhat counterintuitive, but consistent with prior studies (e.g., Jung et al., 2014).[10]

4.2. Research design

To test H1, we estimate the following model (2) (Jung et al., 2014; Ghaly, Dang, & Stathopoulos, 2020):

$$\begin{aligned} AB\_NetHire_{it} = {} & \beta_0 + \beta_1 Outlook_{it} + \beta_2 MTB_{it\text{-}1} + \beta_3 SIZE_{it\text{-}1} + \beta_4 Quick_{it\text{-}1} + \beta_5 Leverage_{it\text{-}1} + \\ & \beta_6 DIVDUM_{it\text{-}1} + \beta_7 CFO5_{it\text{-}1} + \beta_8 SALES5_{it\text{-}1} + \beta_9 Tangible_{it\text{-}1} + \\ & \beta_{10} LOSS_{it\text{-}1} + \beta_{11} NetHire\_sd_{it\text{-}1} + \beta_{12} LaborIntensity_{it\text{-}1} + \\ & \beta_{13} Union_{it\text{-}1} + \beta_{14} AB\_InvestOther_{it} + \beta_{15} INST_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

[9] For a parsimonious analysis and since sales growth measures are the most significant determinants of managers' hiring decisions (Biddle, Hilary, & Verdi, 2009; Jung et al., 2014), we also estimate Equation (1) only with sales growth measures. We find that our results on the relation between positive business outlook and labor investment efficiency are robust to this alternative estimation of labor investment efficiency.

[10] Jung et al. (2014) argue that its sign depends on two competing forces – the positive effect of profitability on labor hiring and the negative mechanical effect of more hiring on firm profitability. The negative coefficient on ROA_t indicates that the negative effect of the increased hiring (thus, more operating expenses) on firm profitability dominates the positive effect.

Where *AB_NetHire* is the absolute value of the difference between actual net hiring and the expected level, indicating labor investment inefficiency. *Outlook* is employee business outlook. We also control for factors that are generally related to overall investment and specifically related to labor investment such as growth (*MTB*), firm size (*Size*), liquidity (*Quick*), leverage (*Leverage*), dividends payout (*DIVDUM*), cash flow volatility (*CFO5*), sales volatility (*SALES5*), tangibility (*Tangible*), loss (*LOSS*), hiring volatility (*NetHire_sd*), labor intensity (*LaborIntensity*), industry-level unionization rate (*Union*), and institutional shareholdings (*INST*).

Furthermore, we include *AB_InvestOther*, which captures the extent to which non-labor investments such as capital expenditure deviate from the expected level. Similar to our measure of labor investment efficiency, *AB_InvestOther* is defined as the absolute value of the residual from the following model (Biddle et al., 2009): $INVEST\_OTHER_{it} = \beta_0 + \beta_1 Sales\_Growth_{it-1} + \varepsilon_{it}$, where *INVEST_OTHER* equals the sum of capital expenditures, acquisitions, and research and development expenditures, less cash receipts from the sale of property, plant, and equipment, and scaled by total assets. *AB_InvestOther* is included to control for the complementarity between labor investment and non-labor investment. Since both labor investment and non-labor investment generally move in the same direction, we intend to minimize the effect of non-labor investment efficiency on labor investment efficiency. Lastly, we include industry and year fixed effects to control for variations in labor investment efficiency across industries and over time, respectively. This and all subsequent regressions are estimated with heteroscedasticity robust standard errors that are clustered by firm.[11]

[11] To control for the effect of firm invariant characteristics on our results, we re-estimate our main regressions with firm fixed effects and find qualitatively similar results (untabulated). In addition, we find that our results are robust to two-way clustering by firm and year.

To test our second hypothesis, H2, we re-estimate Equation (2) after replacing *Outlook* with *OutlookComparison*, which is defined as the average of peer firms' employee business outlooks minus the focal firm's employee outlooks. Thus, the higher value of *OutlookComparison* indicates the greater extent to which peer firms have more positive employee outlooks than the focal firm.

5. Empirical Results

5.1. Descriptive statistics

In Table 1, we present descriptive statistics for the variables in our main model (i.e., Equation (2)). The mean (median) values of *AB_NetHire* are 0.111 (0.067). The mean (median) *Outlook* is 0.181 (0.190). Since the value of *Outlook* ranges from -1 (negative) to 1 (positive) by definition, the above mean value indicates that, on average, employees in our sample expect their firm prospects and economic outlooks to improve in the near future. Compared to the sample used to estimate Equation (1) (mean firm size = 6.054), our final sample firms are relatively large (mean size = 7.312), and tend to have high growth opportunities (mean market-to-book ratio = 3.886).

Table 2 presents the Pearson and Spearman correlation coefficients for all variables that are used to test our hypothesis. We find a negative and significant correlation between *AB_NetHire* and *Outlook*, suggesting that firms receiving more positive business outlooks from employees are more likely to have low abnormal net hiring (i.e., higher labor investment efficiency). This provides preliminary support to our first hypothesis, H1. The positive correlation between *OutlookComparision* and *AB_NetHire* also provides preliminary support to our second hypothesis, H2. In addition, *AB_NetHire* is significantly positively correlated with *CFO5*, *SALES5*, and *NetHire_sd*, indicating that firms with high volatilities regarding cash flow, sales, and hiring tend to have high abnormal net hiring (i.e., low labor investment efficiency). *AB_NetHire* is also significantly negatively correlated with dividend payout (*DIVDUM*), which suggests that labor investments tend to be more efficient for dividend-paying firms. Moreover, *AB_NetHire* is significantly positively correlated with the abnormal level of non-labor investments (*AB_InvestOther*), indicating that labor investment and other investments generally comove and highlighting the importance of controlling for non-labor investment in our main regressions. In summary, descriptive statistics of variables used for our main regressions are generally consistent with prior literature (e.g., Jung et al., 2014).

5.2. Main results

5.2.1. The effect of employee business outlook on labor investment inefficiency

Table 3 contains our main results for the relation between employee business outlook and abnormal net hiring (i.e., labor investment inefficiency). Column (1) shows that the coefficient on *Outlook* is significantly negative, consistent with our H1 that employee outlook is negatively (positively) related to labor investment inefficiency (efficiency). Our results are also economically significant. When *Outlook* moves from the first to the third quartile, labor investment inefficiency is reduced by about 8.5%, relative to its mean.[12] Its effect on the reduction in labor investment inefficiency is lower than, but comparable to, the effect of institutional shareholdings (*INST*) on labor investment inefficiency.[13] In Column (2) of Table 3, we further include two additional control variables in our main model, managerial ability (*MA*) and accounting quality (*AQ*), which are documented to be related to investment efficiency (e.g., Biddle et al., 2009; Jung et al., 2014), although the inclusion of these variables significantly reduces our sample size from 5,799 to 3,847 firm-years. To measure managerial ability, we follow Demerjian, Lev, and McVay (2012), who evaluate managers' efficiency in transforming corporate resources into revenues relative to their

[12] It is computed as {(0.482+0.041)*-0.018}/0.111.

[13] When *INST* moves from its first to the third quartile, it reduces labor investment inefficiency by about 13%, compared to its mean.

industry peers. Accounting quality is defined as the standard deviation of firm-level residuals from estimating the modified Dechow and Dichev model over the past five years and then multiplied by negative one so that the higher value indicates better accounting quality (e.g., Biddle et al., 2009; Jung et al., 2014). Overall, results in Column (2) show that the inclusion of these two additional control variables does not alter the results for *Outlook*, supporting our H1.[14]

5.2.2. The effect of employee business outlook on over-investment and under-investment in labor

To further understand how employee voluntary disclosure about business outlook reduces labor investment inefficiency, we decompose labor investment inefficiency into the extents of over-investment and under-investment and separately examine the impact of employee outlook on the reduction in over-investment and under-investment. We create two sub-samples based on the sign of abnormal net hiring and re-estimate Equation (2) to two subsamples, where positive (negative) abnormal net hiring indicates over-investment (under-investment). Table 4 Panel A presents the results. The coefficients of *Outlook* in Columns (1) and (2) are significantly negative when the dependent variable is over-investment and under-investment, respectively. These results suggest that more positive employee outlooks improve labor investment efficiency through mitigating both over-investment and under-investment in labor. Similarly, we find that the results are still robust in Columns (3) and (4) of Table 4 when we further control for both managerial ability and accounting quality.

Additionally, we further decompose over- and under-investment cases based on whether the expected level of net hiring from Equation (1) is positive or negative — i.e., whether economic fundamentals suggest a firm's labor force should grow or shrink. In other words, the positive

[14] To mitigate the concern that our results can be driven by firm reputation or firm visibility, we also re-estimate our main regressions after controlling for a variable that indicates whether a firm is listed as *American Most-Admired* Firms. We find that our results are qualitatively similar with this additional control variable.

(negative) expected level of net hiring indicates that firms should increase (decrease) labor forces according to economic fundamentals. Thus, we can create the following four sub-samples based on both the expected level of net hiring and the sign of abnormal hiring: (1) *over-hiring* (over-investment case when the expected net hiring is positive): 2,096 observations, (2) *under-firing* (over-investment case when the expected net hiring is negative): 115 observations, (3) *under-hiring* (under-investment case when the expected net hiring is positive): 3,316 observations, and (4) *over-firing* (under-investment case when the expected net hiring is negative): 272 observations. Then we re-estimate Equation (2) to each sub-sample separately and report the results in Table 4, Panel B. Across all columns, the estimated coefficients on *Outlook* are consistently negative and significant except when the extent of under-firing is a dependent variable. A negative but insignificant coefficient on *Outlook* for under-firing cases may be due to the small sample size for the sub-sample. Overall, our results suggest that managers of firms with more positive employee outlooks are more likely to reduce hiring inefficiency in most possible cases since they face relatively lower labor adjustment costs.

5.2.3. The effect of employee business outlook of peer firms on focal firms' labor investment efficiency

Table 5 presents the results of testing our second hypothesis, H2, that is if peer firms' employee outlooks are more positive than those of focal firms, focal firms' labor investment efficiency will be reduced. We find that the coefficients of *OutlookComparision* are all positive and significant across the three columns — when a dependent variable is labor investment inefficiency, the extent of over-investment and the extent of under-investment, respectively, supporting H2. These results suggest that when peer firms have more positive business outlooks than those of focal firms, focal firms' labor adjustment costs are higher, leading to a decrease in focal firms' labor investment efficiency.

6. Additional Analysis

6.1. Cross-sectional variation tests

In this section, we perform several cross-sectional analyses to examine variations in the relation between employee business outlook and labor investment efficiency and thus, further corroborate our main argument.

6.1.1. The number of employee business outlooks disclosed by current employees

First, we consider the role of current employees in disclosing business outlooks about their firms on Glassdoor. Based on the basic organizational theory, unlike former employees, current employees as direct participants in business operations have more precise knowledge of their company's future prospects since they stay abreast of firm operations currently and possess timelier inside information about their firms (e.g., Huang et al., 2020). Current employees, by virtue of their greater engagement with the firm, acquire more real-time information about the firm and thus can provide more informative business outlooks. Therefore, we claim that the value of information embedded in the aggregated employee outlooks is greater when it is based more on the disclosures from current employees. This argument leads to our prediction that the negative relation between employee outlook and labor investment inefficiency is stronger when the number of business outlooks disclosed by current employees is higher.

To test this prediction, we add *Ncurrent* which captures the number of business outlooks disclosed by current employees in Equation (2) and then interact it with *Outlook*. Panel A of Table 6 presents the results. Consistent with our expectation, the coefficient on the interaction term is significantly negative, indicating that the negative relation between employee outlook and labor investment inefficiency is stronger when the aggregated business outlooks consist of more disclosures from current employees. This finding suggests that positive business outlooks from current employees are perceived to be more informative and relevant than those from former employees, and thus can enhance labor investment efficiency to a larger extent.

6.1.2. The number of employee business outlooks disclosed by long-tenured employees

As a similar construct, we further create a variable, *N5yrtenure*, indicating the portion of employees who have worked in a firm for more than five years. We argue that longer-tenured employees are more likely to have more precise knowledge of their company and provide more informative business outlooks. In other words, as tenure increases, employees' ability to obtain more insider information and thus, make better predictions on firm business outlooks should increase. Therefore, we expect that our main results are more pronounced when such outlooks are provided by longer-tenured employees. The results in Panel B of Table 6 support our prediction and indicate that longer-tenured employees provide more informative business outlooks, further corroborating our main results.

6.1.3. The number of employee business outlooks

Next, we examine whether our results are stronger when employee business outlooks are more reliable. Similar to Fan et al. (2019), we use the number of business outlooks as a proxy for the reliability of employees' disclosure. Fan et al. (2019) claim that more employee reviews reduce idiosyncratic noise from individual opinions, leading to more reliable employee outlooks. For instance, with a limited number of reviews, job candidates will hesitate to rely on business outlooks i even when such outlooks are highly positive. As a result, job seekers are less likely to incorporate information from business outlook into their decisions. Hence, we predict that a large number of outlooks are perceived to be more reliable, thus enhancing labor investment to a greater extent.

We test this argument by adding and interacting the number of reviews (*NReview*) with employee business outlook (*Outlook*) in Equation (2). Panel C of Table 6 shows the results of this cross-sectional variation test. As expected, the coefficient on the interaction term is significantly negative, indicating that the negative relation between employee outlooks and labor investment inefficiency is more pronounced when outlooks are provided by a large number of employees.

6.1.4. The effect of employee business outlook for firms requiring more skillful labor

Lastly, we investigate how the relation between positive employee outlook and labor investment efficiency varies with the extent of labor skills required by firms. We expect that employee outlook plays a greater role in improving labor investment efficiency when the required labor skills are higher. When a firm adjusts its labor demand, it incurs the costs of firing, search, selection, hiring, and training, as well as costs due to productivity losses. These labor adjustment costs are economically significant and increase with the extent of required labor skills (e.g., Hamermesh & Pfann, 1996; Ghaly et al., 2017). Firms with high-skilled labor are subject to greater labor market frictions because of fierce competition in these high-skilled sectors, which increases labor adjustment costs and makes it difficult for these firms to adjust labor investments efficiently (e.g., Chang & Jo, 2019). Therefore, employee positive outlook will play a more prominent role in retaining and attracting high-skilled employees in such firms. Based on the above arguments, we expect that the impact of positive outlooks on labor investment efficiency is stronger for firms with high demand for skillful labor.

To measure labor skill, we follow previous studies (Belo, Lin, & Bazdresch, 2014; Ghaly et al., 2017) and use labor skill index, *LSI* which is constructed as the occupation-weighted sum of the job skill indexes from the U.S. Department of Labor's O*NET program.[15] Similar to other cross-sectional variation analyses, we add and interact *LSI* with employee outlook (*Outlook*) in Equation (2). In Panel D of Table 6, we find that the coefficient on the interaction term is significantly negative, consistent with our expectation. The results indicate that the effect of employee positive outlooks on labor investment efficiency is more pronounced for firms in which employees possess a higher level of labor skills due to potential higher labor adjustment costs.[16]

6.2. The effect of employees' business outlooks on cost stickiness

As our H1 hinges on the argument that positive outlook reduces labor adjustment costs, we examine the relation between employee outlook and labor adjustment costs by using labor cost stickiness as a proxy of labor adjustment costs. Labor cost stickiness indicates that firms do not reduce labor costs in a timely manner when sales activity falls. Firms that exhibit high labor cost stickiness tend to retain excess labor in downturns because of the value of talents (Okun & Potential, 1962) and the adjustment costs associated with downsizing labor forces. In contrast, non-sticky firms are more able to re-deploy labor and incur lower costs to adjust the level of labor force (Grubb & Wells, 1993), thus more effectively saving costs in economic downturns and adapting to the competitive business environments (Landsbergis, Cahill, & Schnall, 1999). As previously discussed, firms with positive outlooks can more easily attract talents and thus adjust the level of labor force in a timely manner. Hence, such firms can incur lower costs to adjust labor during downturns and attract talents when activities rise. Based on the above arguments, we expect a negative association between employee positive outlook and labor cost stickiness.

---

[15] For more details on how to construct the LSI index, see Ghaly et al. (2017).

[16] We also capture labor skill by creating a dummy variable, *HighTech*, which equals one if the firm is in high-tech industries (two-digit SICs = 28, 35, 36, 38, 73). Results based on this measure (untabulated) are qualitatively similar.

Based on the prior studies (Anderson, Banker, & Janakiraman, 2003; Weiss, 2010), we use the following model to measure labor cost stickiness. Specifically, we estimate the difference between the rate of labor increase scaled by sales increase and the corresponding rate of labor decrease scaled by sales decrease.

$$LaborCostStickiness_{it} = \log\left(\frac{\Delta \text{Labor}}{\Delta \text{Sales}}\right)_{i,\tau 1} - \log\left(\frac{\Delta \text{Labor}}{\Delta \text{Sales}}\right)_{i,\tau 2} \quad \tau 1, \tau 2 \in \{t{-}1,\ldots,{-}5\} \tag{3}$$

where $\tau 1$ is the most recent of the last five years with an increase in sales and $\tau 2$ is the most recent of the last five years with a decrease in sales. A higher (lower) value of *LaborCostStickiness* represents more (less) sticky labor cost behavior, suggesting that managers are less (more) inclined to respond to sales drops by reducing labor costs than they are to increase labor costs when sales rise. To reduce measurement error in labor cost stickiness variable, we create *LowCostStickinessDummy*, an indicator variable equal to one (less sticky) if *LaborCostStickiness* is lower than the sample median and zero (stickier) otherwise. Then, we re-estimate Equation (2) after employing *LowCostStickinessDummy* as a dependent variable. The results presented in Table 7 echo our main findings. We document a positive relation between positive outlook and *LowCostStickinessDummy*, indicating that employee positive business outlook reduces labor adjustment costs, supporting our main arguments.

6.3. Addressing the endogeneity concern using sub-sample analysis

A potential concern is that our results are simply driven by past firm performance, such as accounting performance or stock returns instead of business outlook. In other words, superior operating performance may be positively related to both employee outlook and labor investment efficiency, driving their positive association. To alleviate this concern, we directly add these variables as control variables in either Equation (1) or Equation (2).

To further mitigate this concern, we examine whether our results are concentrated in sub-samples of firms with better accounting performance or higher stock returns. Specifically, we split our sample into two sub-groups based on accounting performance (i.e., profit vs. loss firms) and stock performance (i.e., high vs. low stock return firms based on the sample median), respectively. Then, we re-estimate our main models to these sub-samples. Results are reported in Table 8. In Panel A, we find that the coefficients of *Outlook* are significantly negative in both sub-samples of profit and loss firms and the difference in coefficients between the two sub-samples is not significant. These results suggest that accounting performance does not lead to the positive relation between employee outlook and labor investment efficiency. Similarly, in Panel B, we show that the coefficients of *Outlook* are significantly negative in both high and low stock performance firms and that the difference in coefficients between the two sub-samples is not statistically significant. This finding indicates that our results are not simply driven by the positive effect of stock performance on both employee outlook and labor investment efficiency. Taken together, our sub-sample analysis mitigates the concern that our main results may be driven by firm performance.[17]

6.4. Addressing the endogeneity concern using Anti-SLAPP laws as an exogenous shock

To further address the endogeneity concern, we use the staggered passage of Anti-SLAPP laws in the U.S. as an exogenous shock (Chemmanur et al., 2020). SLAPP stands for "strategic lawsuit against public participation," a retaliatory lawsuit filed against an opponent who had spoken against the plaintiff in a public forum. SLAPP is used to silence and harass critics by

[17] As a robustness test, we also create a business outlook variable which is orthogonal to past firm performance – *RESIDUAL_Outlook*. Specifically, we first regress our original business outlook variable on ROA, stock returns, and sales growth, all of which are measured right before our business outlook variable is constructed. Then we use the residual, *RESIDUAL_Outlook* instead of *Outlook* in our main model (2). We find that the results based on *RESIDUAL_Outlook* are qualitatively similar to our main results, suggesting that our main inferences are not driven by past firm performance.

forcing opponents to spend money and time to defend these suits. Specifically, in such lawsuits, the plaintiff's goals are accomplished if the defendant succumbs to fear, intimidation, mounting legal costs, or exhaustion and eventually abandons the criticism. In other words, SLAPP causes freedom of speech concerns due to its chilling effect, given that even a meritless lawsuit can take years and thousands of dollars to defend.[18]

More importantly, SLAPP applies to online reviews and brings credible litigation threats to anonymous reviewers on Glassdoor (Chemmanur et al., 2020). For example, courts have ordered Glassdoor to reveal the identity of anonymous reviewers.[19] As a response, Glassdoor funds Anti-SLAPP motions on behalf of anonymous reviewers to offer protection.[20] Since SLAPP suits can bring substantial legal and time costs, and each party in litigation needs to bear its legal fees unless the state adopts Anti-SLAPP statutes, Anti-SLAPP laws protect the First Amendment rights of citizens and affect the propensity of individuals to provide online ratings through the following ways: mandatory coverage of the defendant's legal fees by the plaintiff, dropping of frivolous lawsuits, immediate appeal against denials of Anti-SLAPP motions, and more burden placed on plaintiffs to establish the merit of the case. As of 2019, 28 states had adopted Anti-SLAPP statutes.[21] After the adoption of Anti-SLAPP statutes, anonymous reviews on Glassdoor are expected to be less affected by the threat of litigation compared to those in states with no Anti-SLAPP laws. In Anti-SLAPP states, employees could express their opinions more freely and disclose more honest reviews regarding their firms, instead of intentionally biasing their business

[18] https://anti-slapp.org/what-is-a-slapp
[19] https://www.gdhm.com/news-post/texas-supreme-court-grants-review-in-glassdoor-v-andra-group/
[20] For more information about Glassdoor's policy on Anti-SLAPP funding and user defense, see https://help.glassdoor.com/article/What-else-does-Glassdoor-do-to-protect-and-defend-the-anonymous-free-speech-of-its-users/en_US/Legal_FAQs
[21] Please see Appendix III for the list of states adopting Anti-SLAPP laws and years of adoptions.

outlooks upward to curry favor with upper management. Therefore, the adoption of Anti-SLAPP laws can be used as an exogenous shock to our research setting, since the state-level adoption is unlikely to be correlated with firm level labor investment efficiency.

We first verify our argument that employee business outlooks for firms located in states with Anti-SLAPP laws are less biased upward and thus, we expect a negative effect of the adoption of Anti-SLAPP laws on employee outlooks. To examine the impact of Anti-SLAPP laws on employee outlooks (*Outlook*), we first define *AntiSLAPP* as an indicator variable equal to one if a firm is headquartered in a state adopting Anti-SLAPP laws in that year and zero otherwise. In Table 9 Panel A, the results show that, after the adoption of Anti-SLAPP laws, employee outlooks become lower, supporting the notion that Anti-SLAPP laws lead to more negative business outlooks.

Next, we estimate the following Equation (4) which replaces *Outlook* with *AntiSLAPP* in Equation (2) to examine how Anti-SLAPP laws affect firms' labor investment efficiency.

$$AB\_NetHire_{it} = \beta_0 + \beta_1 AntiSLAPP_{it} + Controls_{it} + \varepsilon_{it} \tag{4}$$

We include state and industry fixed effects in Equation (4) and cluster standard errors by state since *AntiSLAPP* is a state-level variable (Chemmanur et al. 2020). If the staggered adoption of Anti-SLAPP laws corrects upward bias in employee disclosure on Glassdoor, labor investment efficiency will be lower after the adoption as a result of the higher labor adjustment costs caused by more negative outlooks. Thus, the coefficient on *AntiSLAPP* is expected to be significantly positive. In Panel B of Table 9, consistent with our expectation, we find that the coefficient on *AntiSLAPP* is significantly positive. It is noteworthy that this analysis not only alleviates the endogeneity concern, but also provides novel evidence on the unintended consequence of the passage of Anti-SLAPP laws — while Anti-SLAPP laws encourage more honest disclosures by employees, labor investment efficiency is lower after the adoption of Anti-SLAPP laws.

6.5. Alternative measures for employees' business outlooks

To further show the robustness of our results, we adopt two alternative proxies to capture employee business outlook. First, we code outlook variable differently. Specifically, we assign different numerical values to each individual outlook (positive = 5, neutral = 3, negative = 1) (e.g., Li et al., 2019) and then aggregate all of them at the firm-year level to create this alternative measure, *AltOutlook*, which is the average rating of a firm's business outlooks each year.

Additionally, to answer a research call from Teoh (2018) for conducting textual analysis of employee opinions within Glassdoor data, we use a novel approach to construct the second alternative measure of employee business outlook. Conducting textual analysis on employees' written comments regarding pros and cons of a firm, we calculate the proportion of forward-looking information[22] mentioned in pros and cons, respectively. We assume that the proportion of forward-looking content in pros (cons) category should proxy for positive (negative) business outlooks. Then, we aggregate all individual level data to the firm-year level by taking the average of forward-looking percentage in pros and cons, respectively, of a firm's reviews each year. Finally, to calculate the net value of this text-based outlook measure, *TextOutlook*, we use the firm-year level proportion of forward-looking content in pros category minus that in cons category.

Table 10 presents the results of using these two alternative measures. Panel A shows the results using *AltOutlook* and Panel B provides the results using the text-based measure, *TextOutlook*. In both panels, the coefficients on our variables of interest are all negative and

[22] Following the list of words provided by previous literature (Muslu et al., 2015; Bozanic et al., 2018), we calculate the proportion of forward-looking content as the ratio of the number of future years plus horizon references (e.g., future years, two years, short-term, and upcoming year) over total number of words in the comments.

significant, consistent with our first hypothesis (H1) that employee positive outlooks are negatively related to labor investment inefficiency.

7. Conclusion

The emerging employee voluntary disclosure through social media has drawn much attention and interest from researchers. Rapid advancements in media have the potential to greatly alter firms' information environment and performance. To fill the gap and respond to the call on investigating whether the collective opinions on social media websites facilitate information dissemination and have real effects on corporate operational decisions, we examine how employee business outlook affects firm-level labor investment efficiency. We obtain data on employees' voluntary disclosures about business outlooks from Glassdoor and argue that more positive employee outlooks can attract job applicants to a larger extent, thus reducing firms' costs of searching, hiring, firing, and training new employees. Based on this argument, we hypothesize and find that employee business outlook positively affects labor investment efficiency, suggesting that positive outlook significantly improves labor investment efficiency by reducing labor adjustment costs. Furthermore, we document that positive outlook enhances labor investment efficiency by reducing both over-investment and under-investment in labor. Also, we hypothesize and find that when peer firms' employee outlooks are more positive than those of focal firms, focal firms' labor adjustment costs increase because of the relative disadvantage in obtaining talented labor in labor markets, resulting in less efficient labor investment.

In the cross-sectional variation tests, we find that the positive relation between employee business outlooks and labor investment efficiency is stronger when the outlooks are provided by current or long-tenured employees and when there is a larger number of reviews. This positive relation is also more pronounced for firms requiring higher labor skill. Finally, consistent with our main arguments underlying our hypothesis, we document a negative relation between employee outlooks and labor cost stickiness.

To address the endogeneity concern, we use the staggered implementation of Anti-SLAPP laws across the U.S. as an exogenous shock to employee voluntary disclosure on business outlooks. We find that, after the passage of Anti-SLAPP laws, when employee outlooks are no longer biased upward and therefore, the aggregated business outlooks are more negative in firms affected by Anti-SLAPP laws, labor adjustment costs become higher, and thus, impair labor investment efficiency, consistent with our main results. Overall, our findings suggest that positive employees' voluntary disclosures on social media (e.g., Glassdoor) about their firms' business outlook are informative and beneficial for employment management and affect corporate operational decisions.

References

Agrawal, A.K., Hacamo, I., & Hu, Z. (2020). Information dispersion across employees and stock returns. *Review of Financial Studies, forthcoming*.

Agrawal, A.K., & Matsa, D.A. (2013). Labor unemployment risk and corporate financing decisions. *Journal of Financial Economics*, *108*(2), 449–470.

Anderson, M.C., Banker, R.D., & Janakiraman, S.N. (2003). Are selling, general, and administrative costs "sticky"? *Journal of Accounting Research*, *41*(1), 47–63.

Baghai, R., Silva, R., Thell, V., & Vig, V. (2020). *Talent in distressed firms: Investigating the labor costs of financial distress* (SSRN Scholarly Paper No. ID 2854858). Rochester, NY: Social Science Research Network. Retrieved from https://ssrn.com/abstract=2854858.

Bozanic, Z., Roulstone, D. T., & Van Buskirk, A. (2018). Management earnings forecasts and other forward-looking statements. *Journal of Accounting and Economics*, *65*(1), 1-20.

Belo, F., Lin, X., & Bazdresch, S. (2014). Labor hiring, investment, and stock return predictability in the cross section. *Journal of Political Economy*, *122*(1), 129–177.

Bernanke, B., (2004). Monetary policy and economic outlook. In *Federal Reserve Board speech delivered at the meetings of the American Economic Association*.

Biddle, G.C., Hilary, G., & Verdi, R.S. (2009). How does financial reporting quality relate to investment efficiency? *Journal of Accounting and Economics*, *48*(2-3), 112–131.

Boswell, W.R., Ren, L.R., & Hinrichs, A.T. (2008). Voluntary employee turnover: Determinants, processes, and future directions. *Handbook of Organizational Behavior*, 196–216.

Cao, Z., & Rees, B. (2020). Do Employee-Friendly Firms Invest More Efficiently? Evidence from Labor Investment Efficiency. *Journal of Corporate Finance (January 8, 2020)*.

Chang, S., & Jo, H. (2019). Employee-friendly practices, product market competition and firm value. *Journal of Business Finance & Accounting*, *46*(1-2), 200–224.

Chemmanur, T.J., Rajaiya, H., & Sheng, J. (2020). How does Soft Information Affect External Firm Financing? Evidence from Online Employee Ratings. Working paper.

Chen, J., Tang, G., Yao, J., & Zhou, G. (2020). *Employee Sentiment and Stock Returns* (SSRN Scholarly Paper No. ID 3612922). Rochester, NY: Social Science Research Network. Retrieved from https://ssrn.com/abstract=3612922.

Dechow, P. M., & Dichev, I. D. (2002). The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review*, *77*(s-1), 35-59.

Demerjian, P., Lev, B., & McVay, S. (2012). Quantifying managerial ability: A new measure and validity tests. *Management Science*, *58*(7), 1229–1248.

Edmans, A. (2011). Does the stock market fully value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics*, *101*(3), 621–640.

Edmans, A. (2012). The link between job satisfaction and firm value, with implications for corporate social responsibility. *Academy of Management Perspectives*, *26*(4), 1–19.

Fan, Y., Ji, Y., Thomas, W.B., & Wang, C. (2019). *The Relevance and Reliability of Employee Business Outlook Disclosures* (SSRN Scholarly Paper No. ID 3411883). Rochester, NY: Social Science Research Network. Retrieved from https://ssrn.com/abstract=3411883.

Farhadi, R., & Nanda, V. (2020). What do employees know? Quality perception and 'over-satisfaction' in firms going public. *Journal of Corporate Finance*, p.101779.

Fernández-Aráoz, C., Groysberg, B., & Nohria, N. (2011). How to hang on to your high potentials. *Harvard Business Review*, *89*(10), 76–83.

Forbes. (2014). How negative online company reviews can impact your business and recruiting. *Forbes*. Sept. 09 https://www.forbes.com/sites/jaysondemers/2014/09/09/how-negative-onlinecompany-reviews-can-impact-your-business-and-recruiting/#1409f0c91d9b.

Ghaly, M., Dang, V.A., & Stathopoulos, K. (2017). Cash holdings and labor heterogeneity: the role of skilled labor. *The Review of Financial Studies*, *30*(10), 3636–3668.

Ghaly, M., Dang, V.A., & Stathopoulos, K. (2020). Institutional investors' horizons and corporate employment decisions. *Journal of Corporate Finance*, *64*, p.101634.

Gortmaker, J., Jeffers, J., & Lee, M. J. (2020). Labor reactions to credit deterioration: Evidence from LinkedIn activity. Working paper.

Green, T.C., Huang, R., Wen, Q., & Zhou, D. (2019). Crowdsourced employer reviews and stock returns. *Journal of Financial Economics*, *134*(1), 236–251.

Grubb, D., & Wells, W. (1993). Employment regulation and patterns of work in EC countries. *OECD Economic Studies*, 7–7.

Hales, J., Moon Jr, J.R., & Swenson, L.A. (2018). A new era of voluntary disclosure? Empirical evidence on how employee postings on social media relate to future corporate disclosures. *Accounting, Organizations and Society*, *68*, 88–108.

Hamermesh, D.S., & Pfann, G.A. (1996). Adjustment costs in factor demand. *Journal of Economic Literature*, *34*(3), 1264–1292.

Huang, M., Li, P., Meschke, F., & Guthrie, J.P. (2015). Family firms, employee satisfaction, and corporate performance. *Journal of Corporate Finance*, *34*, 108–127.

Huang, K., Li, M., & Markov, S. (2020). What do employees know? Evidence from a social media platform. *The Accounting Review*, *95*(2), 199–226.

Huang, K., M. Li, and S. Markov. (2021). The information asymmetry between top management and rank-and-file employees: Determinants and consequences. Working paper.

Jung, B., Lee, W.J., & Weber, D.P. (2014). Financial reporting quality and labor investment efficiency. *Contemporary Accounting Research*, *31*(4), 1047–1076.

Kacmar, K., Andrews, M.C., Van Rooy, D.L., Chris Steilberg, R., & Cerrone, S. (2006). Sure everyone can be replaced… but at what cost? Turnover as a predictor of unit-level performance. *Academy of Management Journal*, *49*(1), 133–144.

Landers, R.N., Brusso, R.C., & Auer, E.M., 2019. Crowdsourcing job satisfaction data: Examining the construct validity of Glassdoor. com ratings. *Personnel Assessment and Decisions*, *5*(3), 6.

Landers, R.N., & Schmidt, G.B. (2016). Social Media in Employee Selection and Recruitment. *Theory, Practice, and Current Challenges. Cham: Springer International Publishing AG*.

Landsbergis, P.A., Cahill, J., & Schnall, P. (1999). The impact of lean production and related new systems of work organization on worker health. *Journal of Occupational Health Psychology*, *4*(2), 108.

Li, N., Wong, M.H., & Zhou, F. (2019). Analysts' Underreaction to Employee Business Outlooks. Working paper.

Marinescu, I., Klein, N., Chamberlain, A., & Smart, M. (2018). Incentives can reduce bias in online employer reviews. In *Academy of Management Proceedings* (Vol. 2018, No. 1, p. 11189). Briarcliff Manor, NY 10510: Academy of Management.

McNichols, M.F. (2002). Discussion of the quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review*, *77*(s-1), 61–69.

Mobley, W.H. (1982). *Employee turnover, causes, consequences, and control*. Addison-Wesley.

Muslu, V., Radhakrishnan, S., Subramanyam, K. R., & Lim, D. (2015). Forward-looking MD&A disclosures and the information environment. *Management Science*, *61*(5), 931-948.

Okun, A., & Potential, G.N.P. (1962). Its Measurement and Significance. In *Proceedings of the Business and Economic Statistics Section, American Statistical Association*.

Roth, P.L., Bobko, P., Van Iddekinge, C.H., & Thatcher, J.B. (2016). Social media in employee-selection-related decisions: A research agenda for uncharted territory. *Journal of Management*, *42*(1), 269–298.

Ryan, R. (2010). Hanging onto high potentials. *Accounting Today, 24(10),* 38.

Shaw, J.D., Gupta, N., & Delery, J.E. (2005). Alternative conceptualizations of the relationship between voluntary turnover and organizational performance. *Academy of Management Journal*, *48*(1), 50–68.

Sheng, J. (2019). *Asset pricing in the information age: Employee expectations and stock returns* (SSRN Scholarly Paper No. ID 3321275). Rochester, NY: Social Science Research Network. Retrieved from https://ssrn.com/abstract=3321275.

Surowiecki, J., (2005). *The wisdom of crowds*. Anchor.

Teoh, S.H. (2018). The promise and challenges of new datasets for accounting research. *Accounting, Organizations and Society*, *68*, 109–117.

Truong, P. (2018). The Impact of Audit Employee Job Satisfaction on Audit Quality (SSRN Scholarly Paper No. ID 3257437). Rochester, NY: Social Science Research Network. Retrieved from https://ssrn.com/abstract=3257437.

Weiss, D. (2010). Cost behavior and analysts' earnings forecasts. *The Accounting Review*, *85*(4), 1441–1471.

Yahoo Finance. (2018). *How Glassdoor became the No. 2 jobs site in the US, viewed 30 May 2021.* https://finance.yahoo.com/news/glassdoor-became-no-2-jobs-site-us-222246364.html.

Appendix I

Variable Definitions

Variable	Description
Equation (1) variables	
Net_Hire	Percentage change in the number of employees from t-1 to t
Sales_Growth	Percentage change in sales
ROA	Return on assets
Δ*ROA*	Change in ROA
Return	Total stock return
Size	Log of market value
SizeR	Percentile rank of Size
Quick	Quick ratio
ΔQuick	Percentage change in the quick ratio
Leverage	The sum of debt in current liabilities and total long-term debt, divided by total assets
LOSSBINX	Five separate loss bins to indicate each 0.005 interval of ROA from 0 to -0.025. *LOSSBIN1* is equal to 1 if ROA ranges from -0.005 to 0. *LOSSBIN2* is equal to 1 if ROA is between -0.005 and -0.010. *LOSSBIN3*, *LOSSBIN4*, and *LOSSBIN5* are defined similarly.

Variable	Description
Equation (2) variables	
AB_NetHire	The absolute difference between actual net hiring and the expected level of hiring. The higher (lower) absolute difference (i.e., *AB_NetHire*) indicates the higher labor investment inefficiency (efficiency).
Outlook	The average of business outlooks issued by company employees on Glassdoor.com during the year.
MTB	Market-to-book ratio
DIVDUM	Indicator variable coded as 1 if the firm paid dividends
CFO5	Standard deviation of cash flows from operations from year t-5 to t-1
SALES5	Standard deviation of sales from year t-5 to t-1
Tangible	Property, plant, and equipment, divided by total assets
LOSS	Indicator variable coded as 1 if the firm had negative ROA
NetHire_sd	Standard deviation of change in the number of employees from year t-5 to t-1
LaborIntensity	The number of employees divided by total assets
Union	Industry-level rate of labor unionization
AB_InvestOther	Abnormal nonlabor investment, defined as the absolute residual from the following model: $INVEST\_OTHER_{it} = \beta_0 + \beta_1 Sales\_Growth_{it-1} + \varepsilon_{it}$, where *INVEST_OTHER* is the sum of capital expenditures, acquisition expenditures, and research and development expenditures, less cash receipts from the sale of property, plant, and equipment, all scaled by total assets.
INST	Institutional shareholdings

Additional variables	
MA	CEO ability measure from Demerjian et al. (2012).
AQ	Accounting quality measure based on the Dechow and Dichev (2002) model as modified by McNichols (2002). It is the standard deviation of the firm-level residuals during the years t-5 to t-1 and multiplied by -1. The modified Dechow and Dichev model is a regression of working capital accruals on lagged, current, and future cash flows as well as the change in revenues and the amount of property, plant, and equipment. It is estimated cross-sectionally by industry-year.
OutlookComparison	The difference between peer firms' outlook and focal firms' outlook (*OutlookComparison* = peer firm outlook – focal firm outlook).
Ncurrent	The number of current employees posted on Glassdoor.com.
N5yrtenure	The number of employees who have worked in a firm for more than five years.
NReview	The number of individual business outlook reviews.
LSI	The industry-level index of labor skill, constructed as the occupation-weighted sum of the job skill indexes from the U.S. Department of Labor's O*NET program.
LowCostStickiness Dummy	Indicator variable equal to 1 if a firm's labor adjustment cost is lower than the sample median (less sticky) and 0 otherwise (stickier). Labor cost stickiness is calculated using the following model: $LaborCostStickiness_{it} = \log(\Delta Labor/\Delta Sales)_{i\tau 1} - \log(\Delta Labor/\Delta Sales)_{i\tau 2}$ $\tau 1, \tau 2 \in \{t-1, \ldots, t-5\}$, where $\tau 1$ is the most recent of the last five years with an increase in sales and $\tau 2$ is the most recent of the last five years with a decrease in sales. A lower value of *LaborCostStickiness* suggests more sticky labor cost behavior.
AntiSLAPP	Indicator variable which is equal to 1 if a firm is headquartered in a state having Anti-SLAPP laws in that year and 0 otherwise.
AltOutlook	We assign numerical values to employee business outlook review (positive = 5, neutral = 3, negative = 1) (e.g., Li et al, 2019) and then aggregate all individual employee ratings of business outlook at the firm-year level by calculating the average rating of a firm's business outlook reviews each year.
TextOutlook	We conduct textual analysis on employees' comments of a firm and calculate the proportion of forward-looking information mentioned (Muslu et al., 2015; Bozanic et al., 2018) in pros and cons categories, respectively. Then, we aggregate all individual level data to the firm-year level by taking the average of forward-looking percentage in pros and cons, respectively, of a firm's reviews each year. Finally, we use the firm-year level proportion of forward-looking content in pros category minus the proportion of forward-looking content in cons category.

Appendix II

Estimating the expected level of net hiring (Equation (1))

Panel A: Descriptive statistics for variables in Equation (1)

Variables	N	Mean	STD	P25	P50	P75
Net_Hire_{it}	46,847	0.056	0.320	-0.053	0.015	0.107
$Sales\_Growth_{it-1}$	46,847	0.214	0.951	-0.050	0.061	0.207
$Sales\_Growth_{it}$	46,847	0.145	0.810	-0.066	0.046	0.173
ΔROA_{it}	46,847	-0.204	4.145	-0.778	-0.170	0.290
ΔROA_{it-1}	46,847	-0.201	4.068	-0.782	-0.171	0.287
ROA_{it}	46,847	-0.186	1.476	-0.086	0.024	0.075
$Return_{it}$	46,847	0.115	0.393	-0.128	0.097	0.311
$Size_{it-1}$	46,847	6.054	2.471	4.295	6.139	7.789
$Quick_{it-1}$	46,847	2.098	3.047	0.740	1.241	2.243
$\Delta Quick_{it-1}$	46,847	0.273	1.880	-0.212	-0.009	0.228
$\Delta Quick_{it}$	46,847	0.209	1.701	-0.223	-0.019	0.203
$Leverage_{it-1}$	46,847	0.332	0.877	0.019	0.195	0.381

Panel B: Regression results

	Net_Hire	***Net_Hire***
$Sales\_Growth_{it-1}$	0.027***	0.026***
	(23.762)	(17.326)
$Sales\_Growth_{it}$	0.124***	0.099***
	(89.371)	(55.769)
ΔROA_{it}		0.000
		(1.302)
ΔROA_{it-1}		0.001
		(1.575)
ROA_{it}		-0.004***
		(-3.398)
$Return_{it}$		0.018***
		(4.992)
$Size\_R_{it-1}$		0.001***
		(21.959)
$Quick_{it-1}$		0.008***
		(16.240)
$\Delta Quick_{it-1}$		0.008***
		(9.786)
$\Delta Quick_{it}$		-0.001
		(-0.619)
$Leverage_{it-1}$		-0.008***
		(-4.365)
$LOSSBIN1_{it-1}$		-0.016
		(-1.294)
$LOSSBIN2_{it-1}$		-0.009
		(-0.679)
$LOSSBIN3_{it-1}$		-0.018
		(-1.382)
$LOSSBIN4_{it-1}$		0.009
		(0.706)
$LOSSBIN5_{it-1}$		-0.013
		(-0.899)
Industry fixed effects	Yes	Yes
N	46847	46847

adj. R-sq	0.105	0.098

This table contains the results of estimating the expected level of hiring to measure the extent of abnormal hiring for each firm-year. See Appendix I for variable definitions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix III

Year of Enactment of Anti-SLAPP

States	Year
Arizona	2006
Arkansas	2005
California	1992
Connecticut	2017
Delaware	1992
Florida	2000
Georgia	1996
Hawaii	2002
Illinois	2007
Indiana	1998
Kansas	2016
Louisiana	1999
Maine	1995
Maryland	2004
Massachusetts	1994
Missouri	2004
Nebraska	1994
Nevada	1993
New Mexico	2001
New York	1992
Oklahoma	2014
Oregon	2001
Pennsylvania	2000
Rhode Island	1995
Texas	2011
Tennessee	1997
Utah	2001
Vermont	2005

Table 1
Summary statistics

Variable	N	Mean	STD	P25	P50	P75
$AB\_NetHire_{it}$	5799	0.111	0.150	0.033	0.067	0.130
$Outlook_{it-1}$	5799	0.181	0.432	-0.041	0.190	0.482
$OutlookComparison_{t-1}$	5799	0.052	0.426	-0.220	0.039	0.300
MTB_{it-1}	5799	3.886	10.078	1.555	2.681	4.727
$Size_{it-1}$	5799	7.312	1.985	6.048	7.374	8.704
$Quick_{it-1}$	5799	1.940	1.998	0.904	1.396	2.255
$Leverage_{it-1}$	5799	0.239	0.270	0.010	0.189	0.355
$DIVDUM_{it-1}$	5799	0.405	0.491	0.000	0.000	1.000
$CFO5_{it-1}$	5799	0.060	0.085	0.023	0.039	0.068
$SALES5_{it-1}$	5799	0.156	0.170	0.056	0.103	0.192
$Tangible_{it-1}$	5799	0.189	0.177	0.064	0.130	0.251
$LOSS_{it-1}$	5799	0.282	0.450	0.000	0.000	1.000
$NetHire\_sd_{it-1}$	5799	0.178	0.443	0.056	0.099	0.183
$LaborIntensity_{it-1}$	5799	0.007	0.013	0.002	0.003	0.006
$Union_{it-1}$	5799	0.043	0.094	0.007	0.017	0.042
$AB\_InvestOther_{it}$	5799	0.114	0.133	0.042	0.080	0.145
$INST_{it-1}$	5799	0.566	0.383	0.092	0.710	0.900

This table presents descriptive statistics for the sample period from 2012 to 2019. See Appendix I for variable definitions.

Table 2
Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) AB_NetHire $_{it}$		**-0.058**	**0.072**	**-0.019**	**-0.111**	**0.109**	**-0.031**	**-0.141**	**0.161**	**0.104**	**-0.117**	**0.176**	**0.205**	**-0.059**	**-0.058**	**0.183**	**-0.088**
(2) Outlook $_{it-1}$	**-0.050**		**-0.947**	**0.329**	**0.302**	**0.117**	**-0.037**	**0.029**	**-0.048**	**-0.092**	-0.008	**-0.160**	**-0.081**	**-0.110**	**-0.073**	0.015	**0.114**
(3) OutlookComparison $_{it-1}$	**0.065**	**-0.959**		**-0.292**	**-0.310**	**-0.077**	**0.040**	**-0.070**	**0.052**	**0.076**	**-0.056**	**0.176**	**0.096**	**0.093**	**0.038**	**0.049**	**-0.119**
(4) MTB $_{it-1}$	0.025	**0.106**	**-0.090**		**0.381**	**0.086**	0.011	**0.026**	-0.024	**-0.091**	**-0.053**	**-0.129**	**-0.109**	**-0.041**	-0.025	**0.049**	**0.159**
(5) Size $_{it-1}$	**-0.119**	**0.298**	**-0.306**	**0.113**		**-0.114**	**0.246**	**0.390**	**-0.441**	**-0.363**	**0.167**	**-0.399**	**-0.269**	**-0.308**	**-0.178**	**-0.078**	**0.239**
(6) Quick $_{it-1}$	**0.167**	**0.082**	**-0.051**	0.025	**-0.086**		**-0.353**	**-0.197**	**0.213**	**0.032**	**-0.256**	**0.064**	**0.102**	**-0.168**	**-0.193**	**0.109**	**0.075**
(7) Leverage $_{it-1}$	0.006	-0.017	0.022	-0.009	**0.132**	**-0.199**		**0.113**	**-0.202**	**-0.109**	**0.209**	**-0.035**	0.015	**-0.113**	-0.011	**0.050**	**0.029**
(8) DIVDUM $_{it-1}$	**-0.128**	**0.037**	**-0.076**	-0.023	**0.386**	**-0.178**	**0.035**		**-0.339**	**-0.214**	**0.217**	**-0.345**	**-0.284**	-0.009	**0.069**	**-0.052**	**0.019**
(9) CFO5 $_{it-1}$	**0.164**	-0.015	**0.033**	**0.043**	**-0.304**	**0.246**	**-0.043**	**-0.239**		**0.524**	**-0.112**	**0.338**	**0.311**	**0.064**	-0.010	**0.065**	**-0.171**
(10) SALES5 $_{it-1}$	**0.129**	**-0.038**	**0.040**	-0.012	**-0.286**	**0.040**	-0.018	**-0.191**	**0.358**		**-0.045**	**0.204**	**0.290**	**0.210**	**0.147**	0.018	**-0.102**
(11) Tangible $_{it-1}$	**-0.072**	-0.005	**-0.049**	**-0.046**	**0.121**	**-0.189**	**0.204**	**0.171**	**-0.095**	**-0.065**		**-0.123**	**-0.139**	**0.192**	**0.283**	**-0.204**	0.023
(12) LOSS $_{it-1}$	**0.144**	**-0.169**	**0.189**	0.016	**-0.403**	**0.113**	0.012	**-0.345**	**0.281**	**0.153**	**-0.087**		**0.280**	**-0.048**	**-0.042**	**0.092**	**-0.149**
(13) NetHire_sd $_{it-1}$	**0.087**	**-0.059**	**0.064**	0.007	**-0.144**	**0.048**	**0.061**	**-0.124**	**0.164**	**0.170**	-0.013	**0.153**		**-0.088**	**-0.058**	**0.096**	**-0.102**
(14) LaborIntensity $_{it-1}$	**-0.036**	**-0.058**	**0.061**	-0.012	**-0.186**	**-0.063**	**-0.053**	-0.005	0.018	**0.099**	0.008	**-0.052**	-0.016		**0.655**	**-0.089**	**-0.064**
(15) Union $_{it-1}$	-0.022	**-0.042**	**0.036**	0.009	**-0.184**	**-0.049**	**-0.040**	-0.007	**0.060**	**0.120**	**0.037**	-0.003	0.017	**0.781**		**-0.095**	**-0.083**
(16) AB_InvestOther $_{it}$	**0.361**	0.021	0.018	**0.041**	**-0.079**	**0.067**	0.023	**-0.060**	**0.115**	**0.082**	**-0.110**	**0.081**	**0.049**	0.021	0.014		**-0.047**
(17) Institute $_{it-1}$	**-0.068**	**0.129**	**-0.134**	**0.068**	**0.258**	**0.032**	-0.003	**0.037**	**-0.151**	**-0.096**	-0.014	**-0.157**	**-0.084**	**-0.088**	**-0.115**	**-0.028**	

This table presents the correlation matrix for key variables (Spearman above/Pearson below). Correlations with significance levels <0.05 are in bold.

Table 3
The effect of employee business outlook on labor investment inefficiency (abnormal net hiring)

	(1)	(2)
	Dependent variable = Labor investment inefficiency	***Dependent variable = Labor investment inefficiency***
Outlook $_{t-1}$	**-0.018*** **	**-0.017*** **
	(-2.988)	**(-2.596)**
MTB $_{t-1}$	0.001*	0.001
	(1.718)	(1.359)
Size $_{t-1}$	0.001	0.001
	(0.664)	(0.668)
Quick $_{t-1}$	0.011***	0.007***
	(5.486)	(4.685)
Leverage $_{t-1}$	0.016*	0.015
	(1.853)	(1.307)
DIVDUM $_{t-1}$	-0.014***	-0.015***
	(-3.324)	(-2.739)
CFO5 $_{t-1}$	0.103**	0.031
	(2.294)	(0.413)
Sales5 $_{t-1}$	0.040**	0.027
	(2.151)	(1.320)
Tangible $_{t-1}$	-0.016	-0.008
	(-0.993)	(-0.495)
Loss $_{t-1}$	0.018***	0.014***
	(3.339)	(2.647)
NetHire_sd $_{t-1}$	0.008	0.001
	(1.366)	(0.134)
LaborIntensity $_{t-1}$	-0.525**	-0.585**
	(-2.291)	(-1.994)
Union $_{t-1}$	-0.024	-0.000
	(-0.688)	(-0.005)
AB_InvestOther $_{t}$	0.407***	0.372***
	(10.308)	(7.982)
INST $_{t-1}$	-0.016***	-0.018***
	(-2.865)	(-2.639)
MA $_{t-1}$		-0.012
		(-0.594)
AQ $_{t-1}$		-0.064
		(-1.336)
Intercept	0.038***	0.050***
	(2.914)	(3.199)
Year and industry fixed effects	Yes	Yes
Firm clustering	Yes	Yes
N	5799	3847
adj. R-sq	0.188	0.154

This table presents the OLS regression results of estimating the relation between employee business outlook and labor investment inefficiency. We measure labor investment inefficiency by using the abnormal net hiring variable, *AB_NetHire*, developed in Jung et al. (2014). We measure employee business look using *Outlook* which is the average employee rating of business outlook at the firm-year level. See Appendix I for variable definitions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4
The effect of employee business outlook on over-investment and under-investment in labor

Panel A: The effect of employee business outlook on labor over-investment (under-investment)

	(1)	(2)	(3)	(4)
	Over-investment	***Under-investment***	***Over-investment***	***Under-investment***
Outlook $_{t-1}$	**-0.028****	**-0.028*****	**-0.024***	**-0.028*****
	(-2.547)	**(-4.668)**	**(-1.803)**	**(-4.492)**
MTB $_{t-1}$	0.001	0.001	0.000	-0.001
	(0.700)	(0.952)	(0.995)	(-0.204)
Size $_{t-1}$	0.000	0.001	-0.001	0.002
	(0.048)	(0.976)	(-0.394)	(1.069)
Quick $_{t-1}$	0.014***	0.009***	0.009***	0.005***
	(3.253)	(4.686)	(2.912)	(3.454)
Leverage $_{t-1}$	0.047**	0.016*	0.036	0.018
	(2.407)	(1.829)	(1.455)	(1.442)
DIVDUM $_{t-1}$	-0.013	0.003	-0.012	0.000
	(-1.319)	(0.752)	(-1.014)	(0.079)
CFO5 $_{t-1}$	0.069	0.160***	-0.002	0.046
	(0.993)	(3.193)	(-0.013)	(0.811)
Sales5 $_{t-1}$	0.051	0.008	0.016	0.009
	(1.556)	(0.570)	(0.429)	(0.479)
Tangible $_{t-1}$	-0.012	-0.020	-0.010	-0.014
	(-0.435)	(-1.188)	(-0.309)	(-0.876)
Loss $_{t-1}$	0.002	0.028***	-0.001	0.026***
	(0.162)	(5.966)	(-0.083)	(4.965)
NetHire_sd $_{t-1}$	0.005	0.017**	-0.006	0.013
	(0.545)	(2.187)	(-0.810)	(1.375)
LaborIntensity $_{t-1}$	-1.287**	0.064	-1.507*	0.023
	(-2.222)	(0.403)	(-1.893)	(0.134)
Union $_{t-1}$	-0.026	-0.038	0.013	-0.019
	(-0.376)	(-1.204)	(0.119)	(-0.508)
AB_InvestOther $_{t}$	0.481***	-0.012	0.439***	0.016
	(11.460)	(-0.428)	(8.347)	(0.530)
Institute $_{t-1}$	-0.012	-0.021***	-0.011	-0.026***
	(-1.053)	(-4.326)	(-0.784)	(-3.969)
MA $_{t-1}$			-0.043	-0.002
			(-0.997)	(-0.081)
AQ $_{t-1}$			-0.132	-0.022
			(-1.375)	(-0.548)
Intercept	0.052**	0.061***	0.076***	0.068***
	(2.331)	(4.544)	(2.870)	(4.598)
Year and industry fixed effects	Yes	Yes	Yes	Yes
Firm clustering	Yes	Yes	Yes	Yes
N	2211	3588	1482	2365
adj. R-sq	0.229	0.142	0.190	0.094

Panel B: The effect of employee business outlook on labor over- and under-hiring (and firing)

	(1)	(2)	(3)	(4)
	Over-hiring	***Under-firing***	***Under-hiring***	***Over-firing***
Outlook $_{t-1}$	**-0.030****	**-0.003**	**-0.021*****	**-0.045****
	(-2.529)	**(-0.122)**	**(-3.361)**	**(-2.561)**
Intercept and controls	Yes	Yes	Yes	Yes
Year and industry fixed effects	Yes	Yes	Yes	Yes
Firm clustering	Yes	Yes	Yes	Yes
N	2096	115	3316	272
adj. R-sq	0.239	0.078	0.148	0.110

This table presents the OLS regression results of estimating the relation between employee business outlook and over-investment (Columns 1 and 3) and under-investment (Columns 2 and 4) in Panel A. Panel B presents the OLS regression results of estimating the relation between employee business outlook and over-hiring (Column 1), under-firing (Column 2), under-hiring (Column 3), and over-firing (Column 4). See Appendix I for variable definitions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5
The effect of employee business outlook from peer firms

	(1)	(2)	(3)
	Labor investment inefficiency	***Over-investment***	***Under-investment***
OutlookComparison $_{t-1}$	**0.018***	**0.029**	**0.028***
	(3.026)	**(2.574)**	**(4.716)**
Intercept and Controls	Yes	Yes	Yes
Year and industry fixed effects	Yes	Yes	Yes
Firm clustering	Yes	Yes	Yes
N	5799	2211	3588
adj. R-sq	0.188	0.229	0.143

This table presents the OLS regression results of estimating the relation between employee business outlook from peer firms and labor investment inefficiency. *OutlookComparison* is defined as the difference of employee business outlook between peer firms and focal firms. See Appendix I for variable definitions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6
Cross-sectional variation tests

Panel A: The number of employee business outlooks disclosed by current employees

	Labor investment inefficiency
Outlook $_{t-1}$	-0.015**
	(-2.383)
Ncurrent $_{t-1}$	0.005**
	(2.202)
Outlook $_{t-1}$****Ncurrent*** $_{t-1}$	-0.014***
	(-2.586)
Intercept and Controls	Yes
Year and industry fixed effects	Yes
Firm clustering	Yes
N	5799
adj. R-sq	0.188

Panel B: The number of employee business outlooks disclosed by long-tenured employees

	Labor investment inefficiency
Outlook $_{t-1}$	-0.015**
	(-2.437)
N5yrtenure $_{t-1}$	0.009
	(1.616)
Outlook $_{t-1}$****N5yrtenure*** $_{t-1}$	-0.039***
	(-2.868)
Intercept and Controls	Yes
Year and industry fixed effects	Yes
Firm clustering	Yes
N	5799
adj. R-sq	0.188

Panel C: The number of employees' voluntary reviews about business outlook

	Labor investment inefficiency
Outlook $_{t-1}$	-0.015**
	(-2.388)
NReview $_{t-1}$	0.034**
	(1.969)
Outlook $_{t-1}$****NReview*** $_{t-1}$	-0.099***
	(-2.625)
Intercept and Controls	Yes
Year and industry fixed effects	Yes
Firm clustering	Yes
N	5799
adj. R-sq	0.188

Panel D: The effect of employee business outlook for firms requiring more skillful labor

	Labor investment inefficiency
Outlook $_{t-1}$	0.044
	(1.463)
LSI $_{t-1}$	0.011
	(1.298)
Outlook $_{t-1}$****LSI*** $_{t-1}$	-0.022**
	(-2.020)
Intercept and Controls	Yes
Year and industry fixed effects	Yes
Firm clustering	Yes
N	5273
adj. R-sq	0.194

This table presents the OLS regression results of estimating the relation between employee business outlook and labor investment inefficiency conditional on the number of employee business outlooks disclosed by current employees (Panel A), the number of employee business outlooks disclosed by long-tenured employees (Panel B), the number of employees' voluntary reviews about business outlook (Panel C), and the labor skill required by firms (Panel D). See Appendix I for variable definitions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7
The effect of employee business outlook on cost stickiness

	(1)
	LowCostStickinessDummy
Outlook $_{t-1}$	**0.088*****
	(5.534)
MTB $_{t-1}$	0.001*
	(1.899)
Size $_{t-1}$	0.015***
	(3.081)
Quick $_{t-1}$	0.005
	(1.631)
Leverage $_{t-1}$	-0.034
	(-1.275)
DIVDUM $_{t-1}$	-0.060***
	(-3.423)
CFO5 $_{t-1}$	0.027
	(0.357)
Sales5 $_{t-1}$	0.057
	(1.541)
Tangible $_{t-1}$	0.063
	(1.132)
Loss $_{t-1}$	-0.035**
	(-2.227)
NetHire_sd $_{t-1}$	0.003
	(0.213)
LaborIntensity $_{t-1}$	-1.295
	(-1.066)
Union $_{t-1}$	0.223
	(1.586)
AB_InvestOther $_{t}$	0.014
	(0.353)
INST $_{t-1}$	0.046**
	(2.121)
Intercept	0.638***
	(15.678)
Year and industry fixed effects	Yes
Firm clustering	Yes
N	5799
adj. R-sq	0.049

This table presents the OLS regression result of estimating the relation between employee business outlook and cost stickiness. *LowCostStickinessDummy* is equal to 1 if our labor cost stickiness measure is less than our sample median and 0 otherwise. Labor cost stickiness indicates that managers are less inclined to respond to sales drops by reducing labor costs than they are to increase labor costs when sales rise. See Appendix I for variable definitions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8
Addressing the endogeneity concern I: Sub-sample analysis

Panel A: The effect of employee business outlook on labor investment inefficiency (abnormal net hiring) between loss and profit firms

	Loss firms	**Profit firms**	**Difference**
	Labor investment inefficiency	***Labor investment inefficiency***	**P-value**
Outlook $_{t-1}$	**-0.018*** **(-1.653)**	**-0.019***** **(-3.013)**	**[0.902]**
Intercept and Controls	Yes	Yes	
Year and industry fixed effects	Yes	Yes	
Firm clustering	Yes	Yes	
N	1636	4163	
adj. R-sq	0.163	0.185	

Panel B: The effect of employee business outlook on labor investment inefficiency (abnormal net hiring) between high and low stock returns

	Low stock returns firms	**High stock returns firms**	**Difference**
	Labor investment inefficiency	***Labor investment inefficiency***	**P-value**
Outlook $_{t-1}$	**-0.017**** **(-2.164)**	**-0.019**** **(-2.259)**	**[0.372]**
Intercept and Controls	Yes	Yes	
Year and industry fixed effects	Yes	Yes	
Firm clustering	Yes	Yes	
N	2871	2928	
adj. R-sq	0.171	0.205	

This table presents the OLS regression results of estimating the relation between employee business outlook and labor investment inefficiency separately on subsamples of loss firms and profit firms (Panel A), and low stock returns firms and high stock returns firms (Panel B). See Appendix I for variable definitions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 9
Addressing the endogeneity concern II: Results based on an exogenous shock from Anti-SLAPP

Panel A: The effect of Anti-SLAPP laws on employee business outlook

	(1)
	Outlook
AntiSLAPP	**-0.050****
	(-2.266)
Return $_{t-1}$	0.173***
	(17.315)
MTB $_{t-1}$	0.002***
	(5.774)
Size $_{t-1}$	0.058***
	(8.671)
Leverage $_{t-1}$	-0.026
	(-0.958)
DIVDUM $_{t-1}$	-0.001
	(-0.074)
ROA $_{t-1}$	-0.007
	(-0.299)
Sales_Growth $_{t-1}$	0.033**
	(2.327)
Tangible $_{t-1}$	0.086***
	(3.390)
MA $_{t-1}$	0.103***
	(3.137)
Intercept	-0.275***
	(-6.185)
State, year and industry fixed effects	Yes
State clustering	Yes
N	11655
adj. R-sq	0.128

Panel B: Difference-in-differences analysis: The effect of staggered adoption of Anti-SLAPP laws on labor investment efficiency

	(1)
	Labor investment inefficiency
AntiSLAPP	**0.020*****
	(3.736)
Intercept and Controls	Yes
State, year and industry fixed effects	Yes
State clustering	Yes
N	6492
adj. R-sq	0.165

This table presents the result of examining the impact of Anti-SLAPP laws on employee business outlook ratings in Panel A. Panel B presents the result of the difference-differences analysis of the effect of staggered adoption of Anti-SLAPP laws on labor investment efficiency. *AntiSLAPP* is an indicator variable, which takes the value 1 if a firm is headquartered in a state having Anti-SLAPP laws in that year and takes the value 0 otherwise. See Appendix I for variable definitions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 10
Additional employee business outlook proxies

Panel A: Alternative employee business outlook measure

	Labor investment inefficiency
AltOutlook $_{t-1}$	**-0.009***** **(-2.988)**
Intercept and Controls	Yes
Year and industry fixed effects	Yes
Firm clustering	Yes
N	5799
adj. R-sq	0.188

Panel B: Text-based employee business outlook measure

	Labor investment inefficiency
TextOutlook $_{t-1}$	**-0.454**** **(-1.998)**
Intercept and Controls	Yes
Year and industry fixed effects	Yes
Firm clustering	Yes
N	5749
adj. R-sq	0.183

This table presents the OLS regression results of estimating the relation between employee business outlook and labor investment inefficiency using alternative employee business outlook measures. See Appendix I for variable definitions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.