Journal of Corporate Finance 69 (2021) 101995

Contents lists available at ScienceDirect

Journal of Corporate Finance

journal homepage: www.elsevier.com/locate/jcorpfin

Do analysts'' forecast properties deter suboptimal labor investment decisions? Evidence from Regulation Fair Disclosure

Mohammed Aminu Sualihu [a], Alfred Yawson [b,*], Iliyas Yusoff [c]

[a] College of Business, Zayed University, Abu Dhabi, United Arab Emirates
[b] University of Adelaide Business School, University of Adelaide, 10 Pulteney Street, Adelaide, SA 5005, Australia
[c] Deakin Business School, Deakin University, 221 Burwood Highway, Burwood, VIC 3125, Australia

ARTICLE INFO

Keywords:
Analysts properties
Reg FD
Labor cost stickiness
Labor investment

ABSTRACT

We examine whether analysts' forecast properties deter inefficient labor investment decisions. Using accuracy and dispersion as analysts' forecast properties, we find that more accurate and less dispersed forecasts are associated with less inefficient corporate labor investments. Utilizing Regulation Fair Disclosure (Reg FD) as an exogenous variation to analysts' forecast activities, we find a causal relationship between analysts' forecast properties and labor investment inefficiency. We also find that more accurate and less dispersed forecasts decrease labor cost stickiness. Our results are consistent with the view that analysts' forecast properties enhance the information environment, which, in turn, improves corporate labor investment decisions.

1. Introduction

Labor costs constitute a significant proportion of the costs of producing goods and services. According to Paycor (2020), labor costs account for about 70% of the total business costs in the U.S.[1] Sandle (2017) documents that, in every year, Fortune 500 firms spend between US$1 billion and US$2 billion on labor. Most of these expenditures result from hiring, training, separating and transferring employees. For example, a report by the U.S. Census Bureau's Annual Survey of Manufacturers shows that payroll and employee benefits in the manufacturing sector totaled US$828 billion in 2015 compared with US$175 billion in total capital expenditures.[2] Although firms spend an enormous amount of money on labor costs, this expenditure is often prone to inefficiencies,[3] which adversely affects operating performance (Ghaly et al., 2020). In this paper, we examine whether analysts' forecast properties (i.e., forecast accuracy and dispersion) can promote efficient labor investment.

Analysts have a keen interest in intangible assets' information and often include it in their earnings forecast (Barth et al., 2001; Gu

* Corresponding author.
E-mail addresses: mohammed.sualihu@zu.ac.ae (M.A. Sualihu), alfred.yawson@adelaide.edu.au (A. Yawson), i.yusoff@deakin.edu.au (I. Yusoff).

[1] Retrieved from https://www.paycor.com/resource-center/articles/the-biggest-cost-of-doing-business-a-closer-look-at-labor-costs/ on 05/08/2020.

[2] These figures are sourced from the website of the U.S. Census Bureau on 27/11/2020 using the following link: https://www.census.gov/data/tables/2015/econ/asm/2015-asm.html.

[3] Following prior studies such as Ghaly et al. (2020) and Jung et al. (2014) we define inefficient labor investment as an investment that deviates from an optimal level. A deviation of investment from the optimal level is classified as either over-investment and/or under-investment. Over- and under-investment in labor are, collectively, inefficient labor investment (Ghaly et al., 2020).

https://doi.org/10.1016/j.jcorpfin.2021.101995
Received 4 September 2020; Received in revised form 28 May 2021; Accepted 2 June 2021
Available online 9 June 2021

and Wang, 2005) because such information is crucial for firm valuations (Edmans, 2011). Barth et al. (2001) show that analysts' coverage is greater for firms with huge investments in intangibles such as research and development and advertising expenditures. Given that human capital investment such as expenditure in on-the-job-training is a form of an intangible investment and contributes significantly to a firm's earnings and competitive success (Barney, 1991; Pfeffer, 1996), analysts often include labor information in their earnings forecast. Kim et al. (2017) find that analysts incorporate labor cost information into their forecasts after controlling for other earnings components such as sales revenue and non-labor expenses. In describing how employment decisions at Ford Motor Company could affect the firm's earnings, Adam Jonas, an analyst at Morgan Stanley, notes: "Ford Motor Co. cannot reach its stated profit goals for 'Smart Redesign' by laying off just 7000 salaried workers total worldwide by August"…"The company must cut 'a further' 23,000 salaried jobs in the near term to fulfill its goals".[4] The evidence put forward suggests that analysts care about labor information and are more likely to incorporate it into their forecasts. It is, therefore, important to understand how analysts' forecast properties can discourage managers from engaging in inefficient labor investment.

We argue that analysts' forecast properties can affect labor investment efficiency via three channels. First, analysts routinely track firms, continuously scrutinize management behavior and raise questions when they interact with managers. This monitoring role can prevent managers from corporate wrongdoing. Yu (2008) posits that in researching firms and making earnings forecasts, analysts often come into contact with managers, which allows them to monitor and influence a firm's decision-making. Therefore, when analysts' earnings forecasts are more accurate, their impact on managerial actions will be stronger. In contrast, when analyst monitoring is absent, managers can shirk and engage in non-value maximizing actions (Chung and Jo, 1996). Given that analysts interact with managers regularly and include labor information in earnings forecasts, it is possible for analysts to raise concerns about the investment priorities of the firm. Under the monitoring agent role, we expect analysts' forecast properties to increase labor investment efficiency.

Second, by playing the role of information intermediary, analysts can produce reports that augment the information in financial reports. This can help investors gain more insight into the firm's investment decisions and future prospects, which can prevent managers from engaging in suboptimal investment behaviors. For example, Healy and Palepu (2001) argue that analysts' reports can help investors monitor a firm's investment decisions, thus reducing suboptimal investment decisions. Furthermore, Ghaly et al. (2020) posit that investors generally have a keen interest in a firm's labor investment decisions because inefficient labor investment can affect stock prices and investors' returns. Consequently, investors can use analysts' earnings forecasts to monitor employment decisions in a firm. Under the information intermediary role, we expect analysts' forecast properties to increase labor investment efficiency.

Third, contrary to the above two channels, analysts can also create undue pressure on managers by setting external performance benchmarks (i.e., earnings forecasts) that managers typically accept as targets (Allen et al., 2016). Irani and Oesch (2016) find that managers use real earnings management to enhance short-term performance in response to analyst pressure while He and Tian (2013) conclude that analysts exert undue pressure on managers to meet short-term goals at the expense of long-term projects. Further, Graham et al. (2005) report that most managers are willing to sacrifice projects that will be profitable in the long-run to meet short-run earnings targets. Of particular interest to our setting is the evidence that managers do postpone or eliminate hiring to avoid missing earnings targets (Graham et al., 2005). This action can create inefficiencies in labor investments. Accordingly, under the market pressure view, analysts' forecast properties will decrease labor investment efficiency.

While similar arguments can be advanced for non-labor investments (see for e.g. Chen et al., 2017), the findings in prior research on analysts' forecast properties and non-labor investments cannot be meaningfully extrapolated to labor for the following reasons. First, unlike capital expenditure and R&D investments which are controlled by managers, labor investment cannot be controlled because employees cannot be owned and can act strategically; they can choose where to work and whether to stay on a job or quit (Donangelo, 2014; Matsa, 2018). Second, the adjustment costs associated with labor, compared with for example capital expenditure and R&D investments, are frequent because labor can easily be adjusted via transfers, retentions and replacements (Hamermesh, 1995); and these adjustments can have a continuous impact on operating performance (Merz and Yashiv, 2007). Finally, even though capital expenditure is a line item on a firm's balance sheet, the value of human capital is not disclosed because it is difficult to attach a monetary value to it.

To test the competing channels on the effect of analysts' forecast properties on labor investment efficiency, we follow Jung et al. (2014) to estimate the level of net hiring (i.e., the percentage change in the number of employees) justified by economic fundamentals including profitability, liquidity, leverage, sales growth and losses. Our main proxy for labor investment efficiency is the absolute value of abnormal net hiring, which is estimated as the deviation of actual net hiring from its expected level. The lower the abnormal net hiring, the higher the labor investment efficiency. To measure analysts forecast properties, we follow Yu (2010) and Chen et al. (2017) and use the standard deviation of earnings forecasts multiplied by minus one, denoted by *Dispersion*, and the absolute difference between the forecast consensus and actual earnings multiplied by minus one, denoted by *Accuracy*.

Using a sample of U.S. firms from 1983 to 2017, we find results consistent with the predictions that analysts' forecast properties dissuade managers from engaging in inefficient labor investment. Our results show that analysts' forecast properties mitigate inefficient labor investment. This result is consistent with the view that analyst forecasts improve the information environment of firms so outsiders can more effectively monitor a firm's investment choices. The results hold across different measures of inefficient labor investment and are robust to alternative subsamples (over- and under-investment) and controlling for wrongful discharge laws (WDL).

While the baseline results are consistent with the monitoring and information intermediation roles, an important concern is that

[4] Retrieved from https://www.freep.com/story/money/cars/ford/2019/05/21/ford-job-cuts-analysts/3754205002/ on 03/11/2020.

analysts' forecast properties (i.e., accuracy and dispersion) are likely to be endogenous. Unobservable firm heterogeneity correlated with both forecast properties and labor investment inefficiency could confound the results (i.e., omitted variable concern). Also, whilst analysts' forecast properties are significant determinants of labor investment inefficiency, inefficient labor investment can also impact analysts' forecast properties, creating reverse causality concerns. To establish causality, we employ three different identification strategies.

In our first identification strategy, we use Reg FD as an exogenous shock to analysts' forecast properties. Reg FD, passed on October 23, 2000, was intended to stop the practice of "selective disclosure," in which firms give material information exclusively to a certain selected group of market participants before public disclosure (Gomes et al., 2007). This resulted in some firms replacing private earnings guidance with non-disclosure. Wang (2007) finds that firms that replaced private earnings guidance with non-disclosure suffered a deterioration in their information environment compared to firms that replaced the private earnings guidance with public disclosure. Coffee (2000) however argues that Reg FD either leads to a diminished role for analysts, since information is publicly available, or a large-scale reduction in analysts' jobs because they cannot simply perform a useful analysis without the aid of selective disclosure. We argue that the non-disclosure of private earnings information is likely to reduce analyst forecast accuracy and increase forecast dispersion. We use the difference-in-differences (DiD) approach to analyze whether Reg FD weakened analyst forecasts for firms that relied on private guidance in the pre-Reg FD period and became a post-Reg FD new non-disclosers relative to a counterfactual set of firms that had an open disclosure policy. Our results from the DiD approach suggest a causal link between analysts' forecast accuracy and dispersion and inefficient labor investment.

In our second identification strategy, we follow Petacchi (2015) and employ the two-stage least squares (2SLS) regression approach in which the Reg FD is used as a shock-based instrument. This is because if the Reg FD impacted analyst activities as a result of non-disclosure of private earnings information, then it should have a negative impact on forecast accuracy and worsen forecast dispersion to create a change in labor investment inefficiency. We find results consistent with this prediction. We also use the impact threshold of a compounding variable (ITCV) approach to estimate how large an omitted correlated variable should be in order to overturn our results. Our ITCV analysis suggests that the negative effects of forecast *accuracy* and *dispersion* on inefficient labor investment are unlikely to be driven by a correlated omitted variable. Taken together, our evidence is consistent with the monitoring and information intermediation predictions that analysts' forecast properties reduce inefficient labor investments.

We further examine the association between analysts' forecast properties and labor cost stickiness as it contributes to our understanding of labor investment efficiency. Prior studies have shown that when managers have an incentive to build their corporate empires, they disproportionately increase wages and salaries when sales peak in order to attract more employees and also to prevent existing employees from leaving (Prabowo et al., 2018). However, when sales decline, they fail to reduce wages and salaries by a proportionate amount because if they do so, disgruntled employees may leave causing a reduction in employee numbers (Prabowo et al., 2018). These actions can lead to greater labor investment inefficiencies. We find that more forecast accuracy and less forecast dispersion mitigate labor investment inefficiencies stemming from disproportional use of labor (i.e., labor cost stickiness).

Our study contributes to the literature in several ways. First, we contribute to prior research that investigates the impact of analysts' activities on corporate investment decisions. For example, Chen et al. (2017) examine the impact of analysts' forecast quality on capital expenditure, research and development (R&D) and acquisition expenditure and find that analysts' forecast accuracy and dispersion improve investment efficiency. To et al., (2018) explore the effect of analysts' coverage on the quality of corporate investment decisions and find that analysts' coverage increases total factor productivity. Our study differs from these studies because we examine the impact of analysts' forecast properties on labor investment inefficiency.

Second, our study extends the research on labor cost stickiness. Prabowo et al. (2018) examine the impact of state ownership on labor cost stickiness and find that managerial self-interest restrains managers from laying off staff or reducing staff wages when sales decrease. We examine the impact of analysts' forecast properties on labor cost stickiness and find that more accurate and less dispersed forecasts reduce labor cost stickiness. This finding suggests that analysts' forecast properties mitigate suboptimal labor cost decisions in the firm. Third, our study is related to Lee and Mo (2020) who make a significant attempt to link analysts' coverage to labor investment efficiency. The authors find that higher analysts' coverage is associated with lower inefficient investment in labor. Our study differs from Lee and Mo (2020) in several important dimensions. Evidence in prior studies suggests that analysts' coverage and analysts' forecast properties (i.e., accuracy and dispersion) are two different concepts that capture different aspects of analysts' activities (e.g., Chen et al., 2017). In support of this view, Lehavy et al. (2011) show that investors are more likely to find analyst coverage useful for firms with less readable communication; however, earnings forecasts (accuracy and dispersion) for these firms are less accurate. Instead of using analysts' coverage (measured as the number of analysts covering a firm), we use analysts' forecast properties (i.e., accuracy and dispersion) to examine the causal effect of analysts' activities on labor investment efficiency. Consistent with prior studies such as Chen et al. (2017), we control for analysts' coverage in our estimated models and find consistent results for the negative effect of analysts' forecast properties on labor investment inefficiency. In addition, we use a quasi-experimental approach that relies on an exogenous shock and a shock-based instrumental variable approach to examine the causal impact of analysts' forecast properties on labor investment inefficiency.

Finally, our study adds to studies that have examined the impact of Reg FD on analysts' forecast accuracy and dispersion (e.g., Bailey et al., 2003; Agrawal et al., 2006). By documenting that analyst forecasts properties do not improve labor investment efficiency after Reg FD, we show that Reg FD has worsened the information environment. This is consistent with the belief that, with the enactment of Reg FD, a number of firms experienced deterioration in their information environment as a result of choosing not to publicly disclose information (Wang, 2007).

The remainder of the paper is structured as follows. In the next section, we discuss the theoretical underpinnings and hypotheses. Section 3 presents the research design. In Section 4, we present the empirical results and Section 5 concludes the study.

2. Related literature and hypothesis development

2.1. Analyst forecasts and firm outcomes

Financial analysts are information intermediaries who collect, organize, and distribute information about firms (Kirk et al., 2014). This information is usually included in their earnings forecasts. By doing this, financial analysts help enhance the information environment and increase the monitoring role of investors. Givoly and Lakonishok (1979) find that analyst forecasts have information content and are value-relevant; and Fried and Givoly (1982) show that analysts' forecasts affect security prices, suggesting that investors recognize the information disclosed to the market by analysts. Consistent with this view, subsequent studies have explored the link between analyst forecasts and stock returns. For example, Diether et al. (2002) and Johnson (2004) provide evidence that analysts' forecast properties affect stock returns.

Other works including Dyck et al. (2010), Mansi et al. (2011) and Chen et al. (2017) have shown that analyst forecast quality can discourage firms from making decisions that deviate from the optimum. Chen et al. (2017) find that high-quality forecasts (more accurate and less dispersed forecasts) improve capital investment efficiency via the information intermediary and monitoring roles played by analysts. Mansi et al. (2011) show that analysts' forecast properties (i.e., accuracy, dispersion and revision volatility) reduce bond yield spread. The authors also find that the negative relationship between analysts' forecast properties and cost of debt is stronger when the firm has high idiosyncratic risk. Dyck et al. (2010) conclude that financial analysts are directly involved in the detection of corporate fraud by interpreting firms' information and generating insightful analysis that can help detect such fraud. Chen et al. (2015) find that firms that are less exposed to analysts' activities are more likely to engage in value-destroying acquisitions and earnings management. Accordingly, we argue that analysts' activities can help dissuade managers from engaging in suboptimal investment decisions.

There is however a large body of research that points to the dark side of financial analysts activities, arguing that pressure from analysts can lead managers to engage in suboptimal corporate decisions. For example, Graham et al. (2005) show that most CFOs forego a project with a positive net present value (NPV) if the project is likely to cause them to fall short of the current quarter consensus forecast. Eighty percent of CFOs surveyed suggest that they are likely to reduce discretionary spending, including R&D and advertising expenses, to meet earnings benchmarks. Similarly, He and Tian (2013) demonstrate that analysts, through their activities, exert excessive pressure on managers to meet short-term goals at the expense of long-term value-enhancing investments. Taken together, the pressure imposed on managers by analysts can lead managers to engage in sub-optimal investment decisions.

2.2. Linking analyst forecasts to efficient labor investment

The monitoring hypothesis assumes that, when delegating decision-making authority to one party as proposed in agency theory, the agent is motivated to agree to be monitored by the principal if the benefits from monitoring exceed the related costs. The agent (i.e., the manager) has access to inside information compared with the principal (i.e., the shareholder) and can opportunistically act on it. Therefore, the shareholder is likely to rely on information from various sources including analysts' earnings forecasts to monitor the manager's behavior (Jensen and Meckling, 1976). Financial analysts typically provide information about firms to investors. By collecting, organizing and releasing information about firms, financial analysts help reduce the possibility of managers withholding material information from shareholders and potential investors (Yu, 2008; To et al., 2018); they can also reveal negative information about a firm to outsiders which can be used to correct corporate wrongdoing.

Shleifer and Vishny (1986) suggest that large shareholders have a strong incentive to actively monitor and influence managers to protect their investment and may rely on the information provided by financial analysts through their research reports to do so (Kirk et al., 2014). Given that analysts regularly collect and process information and subsequently disseminate it, they act as information intermediaries between the firm and outside investors. In fact, investors, both individual and institutional, depend on information (e.g., earnings forecasts) provided by analysts in their portfolio selection (Chung and Jo, 1996). Prior research demonstrates that information produced by analysts through earnings forecasts helps investors to monitor managers' behavior (DeFond and Hung, 2007). It is therefore conceivable that, when the forecasts are accurate, investors can use them to monitor managerial behavior.

In addition to providing information to outsiders to monitor managers, analysts can themselves play such a monitoring role.[5] Yu (2008) argues that, in the process of researching firms and making earnings forecasts, analysts interact with management via direct communications and company visits. This enables them to directly monitor firms and influence managers' decision-making. Jensen and Meckling (1976) argue that the most important group of market participants who can monitor managerial performance are analysts. This is because analysts' activities can help reduce the agency costs associated with the separation of ownership and control. Knyazeva (2007) examines the potential role of analysts as an additional monitoring mechanism and finds that the quality of analysts' activities helps reduce M&A activity and excessive firm investments.

In summary, though the monitoring role is assumed to be performed by analysts through direct interactions with the firm, the information intermediation role comes from investors who act on the information produced by analysts for investment decisions. The activities of current and potential investors who use analysts' reports for investment decisions can discourage managers from engaging

[5] Generally speaking, analysts are not monitors per se; their main function is to collect, analyze, and disseminate information rather than to audit and reward or punish managerial performance (Chung and Jo, 1996). It is conceivable, however, that the very act of collecting and publicizing information tends to discipline managerial behavior, thus providing an indirect monitoring function that can help reduce corporate wrongdoing.

in suboptimal investment decisions. Consequently, we hypothesize that both the monitoring and information intermediation roles of financial analysts can reduce inefficient labor investment.

Inefficient labor investment is a suboptimal managerial behavior that can occur in a firm (Jung et al., 2014). Williamson (1963) argues that opportunistic managers may expand the size of the labor force beyond optimal levels, to gain more security, power, status and prestige, and greater professional attainment. The desire to show strong short-term performance can also lead managers to reduce the size of the labor force (Graham et al., 2005; Oyer and Schaefer, 2010). These suboptimal labor investments can affect earnings and ultimately destroy firm value. Given that analysts can improve the monitoring and information environment of a firm and prevent suboptimal managerial behavior, their actions can reduce inefficient labor investment decisions.

Conversely, the market pressure view suggests that managers, in desiring to meet analysts' forecasts of future earnings, may sacrifice a firm's long-term value to meet short-term reporting goals (Graham et al., 2005; He and Tian, 2013). This may happen if managerial compensation is tied to current firm performance. Matsunaga and Park (2001) find that CEOs' annual cash bonus drops when firms' quarterly earnings fall short of the consensus analyst forecasts. He and Tian (2013) conclude that analysts exert too much pressure on managers to meet short-term goals, which may inhibit firms' investment in long-term projects. Similarly, Irani and Oesch (2016) conclude that analysts can pressure managers to meet forecast expectations via activity manipulation, especially through reducing discretionary expenses. Given that labor investment takes time to yield results, when managers are pressured to meet analysts' earnings forecasts, they may, for example, delay hiring or reduce hiring to meet such forecasts. Graham et al. (2005) provide evidence that managers may postpone or eliminate hiring in order to meet earnings targets. Under the market pressure view, we expect analysts' forecast properties to reduce labor investment inefficiency.

In summary, given the competing predictions, the net effect of analysts' forecast properties on labor investment efficiency is an empirical question. Our empirical analyses are designed to answer this question.

3. Research design

3.1. Data and sample

We obtain U.S. data from 1983 to 2017 from several sources: financial data from *Compustat*; firm and market stock returns from *CRSP*; analyst data from the Summary History file of the Institutional Brokers Earning System (IBES); institutional ownership data from the Thomson Financial Institutional Holdings (13f) database; and industry labor unionization data from Hirsch and Macpherson's (2003) database of Union Membership and Coverage. Starting in 1983, the sample begins with 92,175 firm-year observations. The sample commences in 1983 because it is the first year covered by the Union Membership and Coverage database. The number is then reduced to 31,624 firm-year observations when merged with the required test and control variables. To mitigate the effect of outliers, all continuous variables are winsorized at the 1st and the 99th percentiles.[6]

3.2. Variable construction

3.2.1. Measure of labor investment inefficiency

The study uses Eq. (1) to estimate abnormal net hiring (the difference between the expected and actual net hiring), which is labeled inefficient labor investment.

$$Y = f\ (X) + \varepsilon_{it} \tag{1}$$

where Y is the percentage change in the number of employees from financial year *t-1* to financial year *t* for *firm i* and X represents all the set of factors that determine net hiring including sales growth, return on asset, stock return, firm size, quick ratio, leverage, asset utilization ratio, and loss. The inclusion of these controls is motivated by Jung et al. (2014), Khedmati et al. (2020) and Sualihu et al. (2021). Abnormal net hiring is the absolute difference between the actual and expected net hiring (Jung et al., 2014).[7] The lower the figure, the higher is the labor investment efficiency. The results from estimating Eq. (1) are reported in Appendix B. The model is estimated with industry and year fixed effects. Subsequent to estimating Eq. (2), we apply the estimated coefficients to each firm-year in the sample to determine the expected net hiring level. The measure of inefficient labor investment is calculated as the absolute difference between the actual and expected net hiring.

3.2.2. Analyst forecast accuracy and dispersion

Following prior literature such as Adhikari (2016), Datta et al. (2011), Platikanova and Mattei (2016) and Wang et al. (2020), analyst data are obtained from the IBES unadjusted summary file. The use of the unadjusted files allows us to have a greater precision without rounding errors since the adjusted files controlling for stock splits over time are rounded to two decimal places (Payne and Thomas, 2003). We also use forecasts closest to the end of the earnings announcement date for the firm-year following Datta et al.

[6] We note that our inferences remain the same when the main model (Eq. (2)) is run without winsorization.

[7] The number of employees includes all employees of consolidated domestic and foreign subsidiaries, all part-time and seasonal employees, full-time equivalent employees, and officers, and excludes consultants, contract workers, directors, and employees of unconsolidated subsidiaries as reported to shareholders (e.g., Jung et al., 2014; Ghaly et al., 2020).

(2011). To be consistent in the measurement of earnings forecasts and actual earnings, we also obtain actual earnings per share (EPS) from the IBES database (instead of Compustat) since IBES forecasts usually exclude extraordinary items and a few special items (Datta et al., 2011). To ensure the EPS data items (i.e. EPS forecasts and EPS actuals) are based on the same number of shares outstanding, we multiply the unadjusted IBES actual EPS by the ratio of cumulative adjustment factor (from CRSP) as of the forecast date to that of the actual EPS report date.

Forecast accuracy (*ACC)* is defined as the absolute earnings forecast error (i.e., the difference between the firm's mean EPS forecast and the firm's actual EPS) scaled by the stock price at the beginning of the period and then multiplied by negative one. Forecast dispersion (*DISP)* is defined as the standard deviation of analysts' earnings forecasts scaled by the stock price at the beginning of the period and multiplied by negative one. Deflating the forecast measures by the stock price facilitates comparison across firms, while multiplying by negative one allows for more accurate and less dispersed forecasts to be represented by higher values (Lang and Lundholm, 1996).

3.3. Model specification

To test the hypothesis that analysts' forecast properties are negatively associated with inefficient labor investment, we use Eq. (2). The dependent variable (*Inefflabor*) is generated from Eq. (1).

$$IneffLabor_{i,t} = \beta_0 + \beta_1 Analyst_{i,t-1} + \sum \beta_\gamma Controls_{i,t-1} + Year\ FE + Industry\ FE + \varepsilon_{i,t} \quad (2)$$

The dependent variable, $IneffLabor_{i,t}$, is calculated for firm *i* at the end of financial year *t*. The test variable in Eq. (2) ($Analyst_{i,t-1}$) is the mean analyst forecast accuracy (*ACC*) and dispersion (*DISP*) for firm *i* at the end of financial year *t-1*. The controls are motivated by Jung et al. (2014) and are defined in Appendix A. Specifically, we follow Ben-Nasr and Alshwer (2016) and control for the following variables: firm size, dividend payouts, cash flow volatility, sales volatility, tangibility, loss, net hiring volatility, labor intensity, accruals quality, labor unionization rate and non-labor investments (capital expenditure, R&D expenditure, and acquisitions). We also control for analyst coverage following To et al., (2018) and Chen et al. (2017) and Lee and Mo (2020). Eq. (2) is estimated with industry and year fixed effects; all standard errors are corrected for firm-level clustering.

4. Empirical results

4.1. Descriptive statistics

Table 1 reports the descriptive statistics for the variables in the main analysis. The mean (median) value of *IneffLabor* is 0.0951 (0.0669). The mean values of *ACC* and *DISP* are −0.0113 and − 0.0063, respectively. The descriptive statistics for the other variables are generally consistent with prior research (e.g., Jung et al., 2014; Ben-Nasr and Alshwer, 2016). Table 2 presents the correlation statistics of the variables in Eq. (2). The correlations between *IneffLabor* and *ACC* and *DISP* are negative (−0.0686 and − 0.0839, respectively) and significant ($p < 0.01$), providing preliminary evidence that more accurate and less dispersed forecasts are associated with lower inefficient labor investment. The correlation coefficients between the independent variables are relatively low, with the highest (absolute) coefficient being 0.6462, between *Cov* and *FirmSize*. The largest VIF (untabulated) is 3.25 (*Tangibles*), which suggests that there are no unstable regression coefficients because of highly correlated independent variables.

We conduct additional tests to assess the continuous impact of analysts' forecast properties on inefficient labor investment when we move from the lowest quartile to the highest quartile of the analysts' forecast properties. The results (Fig. 1) suggest that the median value of *IneffLabor* is significantly ($p < 0.01$) lower for observations in the highest quartile of *ACC* and *DISP* relative to observations in the lowest quartile of *ACC* and *DISP*. In addition, the median values of *IneffLabor* decrease monotonically from the lowest quartile of *ACC* and *DISP* to the highest quartile of *ACC* and *DISP* (Fig. 1). This provides initial evidence that firms with more accurate and less dispersed forecasts are associated with lower inefficient labor investment.

4.2. Main results

Table 3 reports the results of the effect of analysts' forecast properties on inefficient labor investment. The coefficients for *ACC* (Column 1) and *DISP* (Column 2) are negative and statistically significant ($p < 0.01$), suggesting that analysts' forecast properties reduce inefficient labor investment. To gauge economic significance, the results demonstrate that a one standard deviation increase in *ACC* and *DISP* decreases inefficient labor investment by 3.5% and 4.5%, respectively.[8] The results for the control variables indicate that *IneffLabor* is positively (negatively) related to *MTB*, *Quick*, *StdCFO*, *StdSales*, *Loss, StdNetHire* and *AbInvestOther* (*Cov*, *FirmSize*, *DivDum*, *Tangibles*, *Insto,* and *AQ*) at the 5% level or better. These results are consistent with our expectations and prior research (e.g., Jung et al., 2014). The explanatory power of both the forecast accuracy and dispersion regressions is about 15.4%, with Gujarati (2003, p. 263) *F*-statistics (44.65 and 67.02, respectively) indicating that analysts' forecast properties significantly ($p < 0.01$) increases the explanatory

[8] The average value of *IneffLabor* is 0.0951. The coefficient for *ACC* (*DISP*) is −0.0876 (−0.2544) and its standard deviation is 0.0379 (0.0169). Thus, a one standard deviation increase in *ACC* (*DISP*) is associated with 3.5% (4.5%) decrease in inefficient labor investment [i.e., (−0.0876 *0.0379)/0.0951; (−0.2544*0.0169/0.0951)].

Table 1
Summary statistics.

Variable	N	Mean	Median	25 Pctl.	75 Pctl.	Std. Dev.
$IneffLabor_{i,t}$	31,624	0.0951	0.0669	0.0309	0.1263	0.0929
$ACC_{i,t\text{-}1}$	31,624	−0.0113	−0.0025	−0.0072	−0.0008	0.0379
$DISP_{i,t\text{-}1}$	31,624	−0.0063	−0.0018	−0.0049	−0.0007	0.0169
$Cov_{i,t\text{-}1}$	31,624	1.8789	1.7918	1.0986	2.4849	0.7738
$FirmSize_{i,t\text{-}1}$	31,624	6.7411	6.6233	5.5079	7.8371	1.7339
$MTB_{i,t\text{-}1}$	31,624	3.1128	2.2261	1.4244	3.6867	3.5750
$Quick_{i,t\text{-}1}$	31,624	2.0417	1.3183	0.8033	2.3056	2.5748
$Lev_{i,t\text{-}1}$	31,624	0.2094	0.1813	0.0198	0.3307	0.2039
$DivDum_{i,t\text{-}1}$	31,624	0.4321	0.0000	0.0000	1.0000	0.4954
$StdCFO_{i,t\text{-}1}$	31,624	0.0648	0.0420	0.0245	0.0718	0.0985
$StdSales_{i,t\text{-}1}$	31,624	0.1632	0.1136	0.0636	0.2015	0.1920
$Tangibles_{i,t\text{-}1}$	31,624	0.2977	0.2168	0.0983	0.4465	0.2460
$Loss_{i,t\text{-}1}$	31,624	0.2235	0.0000	0.0000	0.0000	0.4166
$Insti_{i,t\text{-}1}$	31,624	0.4033	0.3951	0.0000	0.7263	0.3631
$AQ_{i,t\text{-}1}$	31,624	−0.0472	−0.0364	−0.0580	−0.0222	0.0424
$StdNetHire_{i,t\text{-}1}$	31,624	0.2052	0.1259	0.0671	0.2353	0.2599
$LaborIntensity_{i,t\text{-}1}$	31,624	0.0082	0.0038	0.0018	0.0081	0.0351
$LabUnion_{i,t\text{-}1}$	31,624	0.1368	0.1183	0.0780	0.1620	0.0934
$/AbInvestOther/_{it}$	31,624	0.1147	0.0837	0.0444	0.1228	0.1754

The table presents the descriptive statistics of the variables used in the Eq. (2). The sample consists of 31,624 firm-year observations from 1988 to 2017. For every variable, the mean, median, lower quartile, upper quartile and standard deviation are presented. All variables are winsorized at the 1st and the 99th percentiles. Our main dependent variable, *IneffLabor*, is obtained from Eq. (1) and it is the absolute difference between actual and expected net hiring. Our main test variables are analysts' forecast accuracy and dispersion: *ACC* is the absolute earnings forecast error scaled by the opening stock price and then multiplied by minus one; and *DISP* is the standard deviation of analysts' earnings forecasts scaled by the opening stock price and multiplied by minus one. See Appendix A for variable definitions.

power of the regressions.[9]

4.3. Endogeneity concerns

4.3.1. Difference-in-differences approach

To establish causality, we use the regulation fair disclosure (Reg FD) issued in August 2000, as an exogenous shock to the relationship between analysts' forecast properties and inefficient labor investment. Reg FD is a rule promulgated by the Securities and Exchange Commission (SEC) in an effort to prevent selective disclosure by public companies to market participants. Reg FD states that when a publicly traded company or issuer of stock discloses any material nonpublic information regarding that issuer or its securities to a limited group of individuals, the issuer must make public disclosure of that information. Such disclosures must be made simultaneously if it is an intentional release of information. Non-intentional sharing of such information must be promptly followed by public disclosure. Thus, the enactment of Reg FD affected the disclosure environment because firms that do not want to make information public may choose not to disclose their private information to analysts. The non-disclosure of private earnings guidance is likely to reduce information flow to analysts and, thus, affect the quality of their forecasts.[10]

Consistent with Petacchi (2015) and Wang (2007), we use publicly available data that allows us to identify firms that either rely on public or private disclosures to convey information in the pre-Reg FD period. Firms with an open disclosure policy and do not rely on private guidance, are expected not to be negatively affected by Reg FD. These firms become our control group. On the other hand, firms that relied on private guidance in the pre-Reg FD period and became post-Reg FD new non-disclosers are our treatment firms. Such firms are pre-Reg FD private disclosers that do not increase their earnings-related public disclosures after Reg FD. Compared to pre-Reg FD public disclosers (i.e., control group), we expect that the non-disclosure of private earnings guidance in the post-Reg FD period of our treatment firms is likely to negatively affect the quality of analysts' forecasts.

Given that private disclosure to analysts is largely unobservable, the use of Wang's (2007) methodology to construct the treatment and control samples is advantageous, because it uses only public information and, thus, can apply to all firms with available data. For

[9] The Gujarati (2003, pp. 260-264) F-statistic is given by: $\frac{\left(R^2_{New}-R^2_{Old}\right)/n}{\left(1-R^2_{New}\right)/df}$, where $R^2_{New}(R^2_{Old})$ is the R^2 value of the regression model with the inclusion (exclusion) of *ACC* or *DISP*, *n* equals the number of new regressors being considered (one, that is, *ACC* or *DISP*), and *df* is the number of observations minus the number of parameters in the regression model that includes *ACC* or *DISP*.

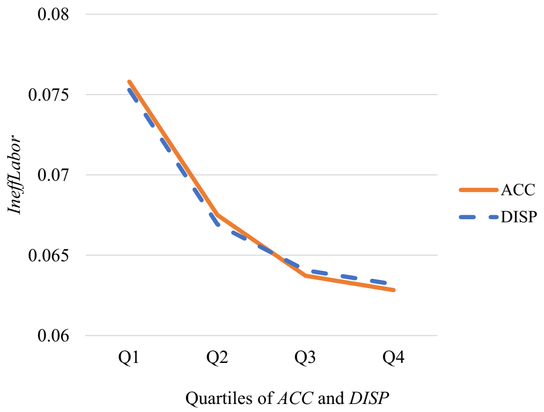
[10] We acknowledge that there are mixed findings on the consequences of prohibiting selective disclosure resulting from Reg FD. For example, studies that find a decline in forecast accuracy after Reg FD include Agrawal et al. (2006) and Kross and Suk (2012). On the other hand, there are other studies that report no change (Heflin et al., 2003) and even improved accuracy of short-term forecasts after Reg FD (Srinidhi et al., 2009). However, similar to Bushee et al. (2004), we rely on identifying and conditioning on the aspects of firms' disclosure policies most impacted by Reg FD to tease out the effect of Reg FD as well as to separate its effects from other changes in the economy. Our selection of treatment and control groups, rather than using the general population of US firms, allows us to select a set of firms which are most likely to be affected by Reg FD and a comparative sample that is largely unaffected by Reg FD.

Table 2
Pearson correlation coefficients.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	$IneffLabor_{i,t}$												
(2)	$ACC_{i,t\text{-}1}$	**−0.0686**											
(3)	$DISP_{i,t\text{-}1}$	**−0.0839**	**0.6042**										
(4)	$Cov_{i,t\text{-}1}$	**−0.1172**	**0.1184**	**0.0957**									
(5)	$FirmSize_{i,t\text{-}1}$	**−0.1643**	**0.1441**	**0.1303**	**0.6462**								
(6)	$MTB_{i,t\text{-}1}$	**0.0426**	**0.0488**	**0.0460**	**0.1385**	**0.2289**							
(7)	$Quick_{i,t\text{-}1}$	**0.2060**	**0.0259**	**0.0192**	**−0.0945**	**−0.1340**	**0.0670**						
(8)	$Lev_{i,t\text{-}1}$	**−0.0239**	**−0.0802**	**−0.0889**	**0.0532**	**0.0810**	**−0.1019**	**−0.2633**					
(9)	$DivDum_{i,t\text{-}1}$	**−0.1822**	**0.0391**	**0.0233**	**0.1511**	**0.3489**	**−0.0396**	**−0.2304**	**0.1276**				
(10)	$StdCFO_{i,t\text{-}1}$	**0.2301**	**−0.0429**	**−0.0537**	**−0.1521**	**−0.2184**	**0.1303**	**0.2378**	**−0.1075**	**−0.2409**			
(11)	$StdSales_{i,t\text{-}1}$	**0.1259**	**−0.0281**	**−0.0160**	**−0.1282**	**−0.2072**	**0.0357**	**0.0326**	**−0.0712**	**−0.1735**	**0.2719**		
(12)	$Tangibles_{i,t\text{-}1}$	**−0.0743**	**−0.0405**	**−0.0838**	**0.1092**	**0.0782**	**−0.1552**	**−0.2912**	**0.3368**	**0.2916**	**−0.2194**	**−0.1979**	
(13)	$Loss_{i,t\text{-}1}$	**0.1744**	**−0.1326**	**−0.1305**	**−0.1546**	**−0.2654**	**−0.0124**	**0.1566**	**0.0544**	**−0.2961**	**0.2583**	**0.0857**	**−0.1028**
(14)	$Insti_{i,t\text{-}1}$	**−0.0586**	**0.0983**	**0.1292**	**0.1508**	**0.1559**	**0.0769**	**0.0684**	**−0.0407**	**−0.0836**	**−0.0470**	**−0.0362**	**−0.1599**
(15)	$AQ_{i,t\text{-}1}$	**−0.1874**	**0.0702**	**0.0634**	**0.2090**	**0.2614**	**−0.0883**	**−0.1113**	**0.1163**	**0.2550**	**−0.4668**	**−0.3017**	**0.2788**
(16)	$StdNetHire_{i,t\text{-}1}$	**0.1944**	**−0.0489**	**−0.0379**	**−0.0958**	**−0.1570**	−0.0075	**0.0692**	**0.0421**	**−0.2297**	**0.1822**	**0.2023**	**−0.0983**
(17)	$LaborIntensity_{i,t\text{-}1}$	−0.0080	0.0001	0.0030	**−0.0300**	**−0.0647**	**−0.0143**	**−0.0330**	**−0.0490**	**0.0228**	**−0.0213**	**0.0769**	−0.0085
(18)	$LabUnion_{i,t\text{-}1}$	**−0.0361**	**−0.0581**	**−0.0911**	**0.0484**	**0.0175**	**−0.0882**	**−0.0771**	**0.1431**	**0.2404**	**−0.0840**	**−0.1169**	**0.3279**
(19)	$/AbInvestOther/_{i,t}$	**0.1790**	**−0.0125**	**−0.0311**	**−0.0451**	**−0.0575**	**0.0663**	**0.0404**	**0.0734**	**−0.1085**	**0.2040**	**0.1081**	**−0.0709**

		(13)	(14)	(15)	(16)	(17)	(18)
(14)	$Insti_{i,t\text{-}1}$	**−0.0424**					
(15)	$AQ_{i,t\text{-}1}$	**−0.2182**	**0.0505**				
(16)	$StdNetHire_{i,t\text{-}1}$	**0.1863**	**−0.0494**	**−0.1978**			
(17)	$LaborIntensity_{i,t\text{-}1}$	**−0.0434**	**−0.0274**	0.0049	**−0.0180**		
(18)	$LabUnion_{i,t\text{-}1}$	**−0.0645**	**−0.0695**	**0.1247**	**−0.0713**	**−0.0758**	
(19)	$/AbInvestOther/_{i,t}$	**0.1255**	−0.0020	**−0.1450**	**0.1620**	**−0.0165**	**−0.0363**

The table presents the Pearson correlation coefficients between the variables in Eq. (2). Our main dependent variable, *IneffLabor,* is obtained from Eq. (1) and it is the absolute difference between actual and expected net hiring. Our main test variables are analysts' forecast accuracy and dispersion: *ACC* is the absolute earnings forecast error scaled by the opening stock price and then multiplied by minus one; and *DISP* is the standard deviation of analysts' earnings forecasts scaled by the opening stock price and multiplied by minus one. Bold correlations are significant at the 5% level or better. See Appendix A for variable definitions.



	Q1	Q4	Difference
ACC	0.0758	0.0628	0.0130***
DISP	0.0752	0.0631	0.0121***

Fig. 1. The figure shows the effect of analyst forecast accuracy (*ACC*) and dispersion (*DISP*) on labor investment inefficiency across the lowest (Q1) to the highest quartile (Q4) of forecast accuracy and dispersion. The y-axis variable, *IneffLabor*, is obtained from Eq. (1) and is the absolute difference between actual and expected net hiring. Our main test variables (x-axis) are quartiles of *ACC* and *DISP*. ***, ** and * represents statistical significance at the 1%, 5% and 10% level respectively.

example, while the use of open vs. closed conference calls may be an alternative identification of the treatment and control group, conference calls are only one form of disclosure and it is difficult to rule out the possibility that firms use other means other than conference calls to release information. Hence, we rely on Wang (2007) to identify pre-Reg FD private and public disclosers for the DiD analysis.[11]

To implement the DiD analysis, we first test the parallel trend assumption. He and Tian (2013, pg. 866) argue that "[t]he success of a DiD approach hinges on the satisfaction of the key identifying assumption behind this strategy, the parallel trend assumption, which states that, in the absence of treatment, the observed DiD estimator is zero". This assumption requires similar trends in labor investment inefficiency during the pre-Reg FD period for both the treatment and control groups. Hence, it is important to analyze the parallel trend to ensure the validity of the DiD results. We do this in two ways. First, we plot in Fig. 2 the difference in inefficient labor investment between the treatment and control firms over a 9-year window around the exogenous shock to analysts' forecasts.[12] Fig. 2 illustrates that the difference between the average *IneffLabor* of the treatment and control observations is relatively stable in the pre-period (1996 to 1999) but increases significantly in the post-period (2001 to 2004). This suggests that the change in inefficient labor investment for the treatment firms is likely caused by the exogenous shock. As a second test, we follow Lennox (2016) and estimate the following model using observations from only the pre-period window (1996 to 1999):

$$IneffLabor_{i,t} = \beta_0 + \beta_1 Treat_i + \beta_2 Trend_t + \beta_3 Treat_i{*}Trend_t + \varepsilon_{i,t} \tag{3}$$

The treatment variable (*Treat)* equals 1 if a firm is a pre-Reg FD private discloser that is a non-discloser in the post-Reg FD period and zero if the firm is a pre-Reg FD public discloser. The *Trend* variable is a count of the years to the end of the pre-event window. We report the results in Column 1, Table 4. Consistent with the parallel trends assumption, we find no significant differences in the trend rate between the treatment and the control sample during the pre-event window.

The DiD regression is estimated using the following regression model:

$$IneffLabor_{i,t} = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Treat_i{*}Post_t + \beta_n Controls + \varepsilon_{i,t} \tag{4}$$

Treat is equal to 1 if a firm is a pre-Reg FD private discloser that is a non-discloser in the post-Reg FD period and zero if the firm is a pre-Reg FD public discloser. *Post* is an indicator variable coded as 1 after the event year 2000 and zero otherwise. The regression is estimated within a 9-year window (1996 to 2004) excluding the event year. The interaction term is included to capture the effect of Reg FD on firms that are pre-Reg FD private disclosers and non-disclosers in the post-Reg FD period. We also include control variables from Eq. (2) and industry and year fixed effects. In Column 2, Table 4, the interaction term (*Treat*Post*) is positive and statistically significant at the 1% level, suggesting that treatment firms in the post-period are associated with more inefficient labor investment.

[11] Refer to Appendix 1 for the outline of Wang's (2007) methodology to identify pre-Reg FD private and public disclosers.

[12] Consistent with Petacchi (2015) and Wang (2007), our DiD window is set at nine years (1996 to 2004). This is so because Petacchi (2015) notes that the former SEC Chairman Christopher Cox (in office from 2005 to 2009) adopted policies that delayed the SEC's investigations and discouraged corporate penalties. Hence, it is unclear to what extent Regulation FD was enforced while Cox was the Chairman and thus we limit our DiD analysis to end in 2004. Further, to ensure that the pre- and post-periods have an equal number of years, the pre-period starts in 1996.

Table 3
The relationship between analysts' forecast properties and inefficient labor investment.

Variable	(1) ACC	(2) DISP
$Analyst_{i,t-1}$	−0.0876***	−0.2544***
	(−4.65)	(−5.54)
$Cov_{i,t-1}$	−0.0025**	−0.0024**
	(−2.49)	(−2.43)
$FirmSize_{i,t-1}$	−0.0019***	−0.0019***
	(−3.53)	(−3.58)
$MTB_{i,t-1}$	0.0006***	0.0006***
	(3.46)	(3.47)
$Quick_{i,t-1}$	0.0052***	0.0052***
	(15.97)	(15.97)
$Lev_{i,t-1}$	0.0007	0.0004
	(0.19)	(0.11)
$DivDum_{i,t-1}$	−0.0098***	−0.0097***
	(−7.24)	(−7.16)
$StdCFO_{i,t-1}$	0.0763***	0.0755***
	(7.26)	(7.24)
$StdSales_{i,t-1}$	0.0152***	0.0152***
	(4.47)	(4.50)
$Tangibles_{i,t-1}$	−0.0115***	−0.0120***
	(−2.60)	(−2.72)
$Loss_{i,t-1}$	0.0109***	0.0107***
	(6.98)	(6.85)
$Insti_{i,t-1}$	−0.0055***	−0.0052***
	(−3.81)	(−3.62)
$AQ_{i,t-1}$	−0.1105***	−0.1100***
	(−5.47)	(−5.46)
$StdNetHire_{i,t-1}$	0.0298***	0.0300***
	(10.19)	(10.25)
$LaborIntensity_{i,t-1}$	0.0045	0.0047
	(0.44)	(0.45)
$LabUnion_{i,t-1}$	−0.0025	−0.0027
	(−0.26)	(−0.28)
$/AbInvestOther/_{i,t}$	0.0549***	0.0545***
	(12.19)	(12.10)
Constant	0.0871***	0.0845***
	(4.86)	(4.74)
Industry and year fixed-effects	Yes	Yes
N	31,624	31,624
Adjusted R^2	0.1535	0.1542

The table presents the results on the impact of forecast accuracy and dispersion on inefficient labor investment. The dependent variable, *IneffLabor,* is obtained from Eq. (1) and it is the absolute difference between actual and expected net hiring. Our main test variables are analysts' forecast accuracy and dispersion: *ACC* is the absolute earnings forecast error scaled by the opening stock price and then multiplied by minus one; and *DISP* is the standard deviation of analysts' earnings forecasts scaled by the opening stock price and multiplied by minus one. *t*-statistics (in parentheses) are based on standard errors clustered by firm. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. See Appendix A for variable definitions.

As a robustness check on the DiD approach, we checked the covariate balance between the treatment and control groups and noted that there were differences between the control variables across the treatment and control groups. To ensure covariate balance, we use coarsened exact matching (CEM) (Iacus et al., 2012). We execute our CEM analysis by temporarily coarsening our continuous variables into terciles with the exception of the dichotomous variables, which are set to exact matching since they have a natural break (i.e., 1 or 0). We match each treatment firm to a control firm ensuring that both the matched firms have the same values of all coarsened covariates. This is done separately for the pre- and post-periods, respectively. This results in a precise match between the means of the covariates between the treatment and control groups. The results from re-estimating the DiD estimates based on this matched sample of 490 observations, reported in Column 3, Table 4, continue to show that treatment firms in the post-period experienced more inefficient labor investment.

In another sensitivity test to our DiD design, we recognize that compared to the pre-Reg FD period, the post-Reg FD period could in fact be very different in terms of a multitude of factors, including managerial skills and incentives, and corporate financial reporting and governance. We limit this concern by focusing on a narrow band of years (a 9-year event window, Column 2, Table 4) in which other extraneous factors are less likely to change but long enough to detect meaningful changes in labor inefficiency. To mitigate other potential confounding events in the pre- vs. post-Reg FD period, we have narrowed the DiD window in robustness tests, and our results remain consistent with both a 7-year window (untabulated) and a 5-year window (Column 4, Table 4). Taken together, our results suggest a causal link between analyst forecast accuracy and dispersion and inefficient labor investment, highlighted by Reg FD where

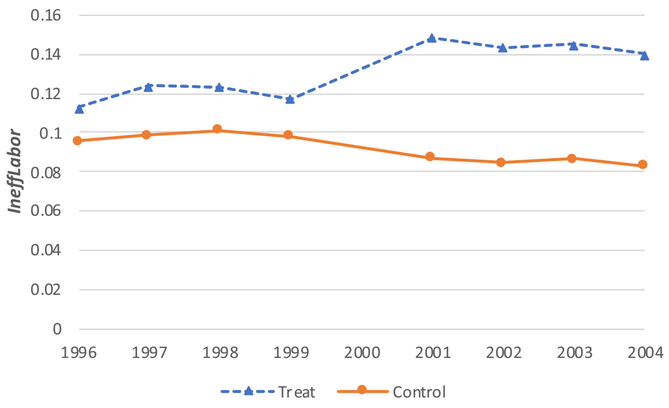


Fig. 2. Parallel trend analysis. The figure presents the DiD parallel trend assumption for labor investment inefficiency. The figure shows the mean labor investment inefficiency for the treatment and control samples surrounding the pre and post Regulation Fair Disclosure period in 2000 (a nine-year window, excluding the event year). Treat is equal to 1 if a firm is a pre-Reg FD private discloser that are non-disclosers in the post-Reg FD period and zero (control) if the firm is a pre-Reg FD public discloser.

Table 4
Difference-in-differences estimates.

Variable	(1) Parallel trend	(2) 9-year window DiD	(3) Matched DiD	(4) 5-year window DiD
Treat	0.0207	0.0043	0.0053	0.0001
	−1.02	−0.55	−0.39	−0.01
Trend	0.0009			
	−0.35			
*Treat*Trend*	0			
Post		−0.0094	−0.0371	−0.0155
		(−1.17)	(−1.52)	(−1.39)
*Post*Treat*		0.0341***	0.0428**	0.033**
		−3.13	−2.35	−2.18
Control variables	No	Yes	Yes	Yes
Industry fixed-effects	No	Yes	Yes	Yes
Year fixed-effects	No	Yes	Yes	Yes
N	1204	2205	490	1199
Adjusted R^2	0.0032	0.1154	0.0615	0.1004

The table presents the results for the difference-in-differences (DiD) analysis using Regulation Fair Disclosure introduced in the year 2000 as an exogenous shock to analysts' activities. The dependent variable, *IneffLabor,* is obtained from Eq. (1) and it is the absolute difference between actual and expected net hiring. *Treat* is equal to 1 if a firm is a pre-Reg FD private discloser that are non-disclosers in the post-Reg FD period and zero if the firm is a pre-Reg FD public discloser. *Trend* is a count of the years to the end of the pre-event window. *Post* is an indicator variable coded as 1 after the event year in 2000 and 0 otherwise. Column 1 reports the results of the parallel trend analysis in the pre-period. Column 2 reports the main DiD results. Column 3 reports the results of the matched DiD. Column 4 reports the results of the DiD over a shorter 5-year window instead of a 9-year window in Column 2. *t*-statistics (in parentheses) are based on standard errors clustered by firm. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. See Appendix A for variable definitions.

the information environment of pre-Reg FD private disclosers weakened as they became post-Reg FD non-disclosers because of the restrictions imposed on selective information disclosure.

4.3.2. Instrumental variable

Similar to Petacchi (2015), we also use the Reg FD as a shock in a shock-based instrumental variable approach. This identification strategy is predicated on the idea that pre-Reg FD private disclosers that are non-disclosers in the post-Reg FD period should have poorer analysts' forecast properties after Reg FD than it would have before, ceteris paribus. Thus, Reg FD is a valid shock-based instrument because it directly affects the forecast accuracy and dispersion for the treatment firms, which in turn, should impact labor investment inefficiency. Following Yawson and Zhang (2021), our instrument for the shock-based 2SLS analysis is the interaction between the *Post* and *Treat* indicator variables. Table 5 reports the results for the 2SLS regression for the period surrounding Reg FD (1996 to 2004), excluding the year 2000. For brevity, only the coefficients on the IV and analyst measures are reported.

The results for the first-stage regressions are reported in Columns 1 and 3, Table 5. As expected, the instrument is negative and significantly associated ($p < 0.01$) with *ACC* and *DISP*, suggesting that in the post-Reg FD period, the quality of analysts' forecasts deteriorated for the non-disclosure of firms that were pre-Reg FD private disclosures. The Kleibergen and Paap (2006) under-identification test rejects ($p < 0.01$) the null hypothesis that the first-stage equation is under-identified, suggesting that the instrument is relevant. Further, the F-statistic for the weak identification test of the first-stage model for *ACC* and *DISP* is 34.98 and 49.81, respectively. These are larger than the suggested critical F-values (Stock and Yogo, 2005) of 16.38, implying that the instrument is not weak. In the second stage, we replace *ACC* and *DISP* with their fitted values from the first stage and repeat the main analysis. The results presented in Columns 2 and 4, Table 5, indicate that the instrumented *ACC* and *DISP* are negatively associated ($p < 0.05$) with inefficient labor investment. This corroborates the main finding between analysts' forecast properties and inefficient labor investment.

4.3.3. *The impact threshold of a confounding variable*

Even though we include several control variables in the empirical model to improve causal inferences, the control variables are far from being exhaustive. Therefore, it is plausible that causality attributed to analyst forecasts is weakened if an alternative factor is correlated with inefficient labor investment as well as analysts' forecast properties. We, therefore, follow Frank (2000) and Larcker and Rusticus (2010) and investigate how strongly correlated an omitted variable needs to be with the test variable (*ACC* and *DISP*) and outcome (*IneffLabor*) variables to make our results statistically insignificant. The impact threshold of a confounding variable (ITCV) procedure provides a score of 0.0173 and 0.0217 for *ACC* and *DISP*, respectively. This implies that the correlation between a confounding variable with both forecast properties and labor investment inefficiency has to be greater than 13.2% (i.e., $\sqrt{0.0173}$ and $\sqrt{0.0217}$) to overturn our results. The ITCV analysis also provides the threshold for the percentage bias to invalidate the results. To invalidate the inference for analysts' forecast properties, 64.92% and 69.86% of the estimate of *ACC* and *DISP*, respectively, would have to be due to bias. In other words, 20,530 and 22,093 cases, respectively, would have to be replaced with cases for which there is an effect of zero.[13] The discussions above suggest that the negative effects of *ACC* and *DISP* on inefficient labor investment are less likely to be driven by a correlated omitted variable. While this approach does not eliminate all concerns related to omitted variables, it does help mitigate some of those concerns.

4.3.4. *Other robustness tests*

It is possible that our baseline results may be influenced by potential outliers. Though we winsorize our variables to minimize the effect of outliers, there may be outliers remaining in the data. To allay this fear, following Ben-Nasr and Alshwer (2016), we use a median regression approach for our estimation to ensure that our estimates are robust, or less sensitive to outliers. The results from this robustness test are consistent with our main analyses that analysts' forecast properties are negatively associated with inefficient labor investment at the 1% level (untabulated).

We account for the effect of other time-invariant firm attributes on inefficient labor investment by repeating our main analysis after replacing the industry fixed effects with firm fixed effects. Further, as our sample period is relatively long (1983 to 2017), we also cluster across both firm and year as the residuals may be correlated across both space and time (Petersen, 2009). Given that our dependent variable (*IneffLabor*) is a residual from Eq. (1) and to ensure that our inferences are not sensitive to the potential derived coefficient bias, we follow Chen et al. (2018) and repeat our main analysis by including the regressors from Eq. (1) into Eq. (2). Our findings in Panel A, Table 6 continue to reveal robust findings for the effect of analysts' forecast properties on inefficient labor investment after controlling for firm fixed effects (Columns 1 and 2), two-way clustering (Columns 3 and 4) and potential derived coefficient bias (Columns 5 and 6).

Following Ben-Nasr and Alshwer (2016), we expand Eq. (1) with the additional control variables: capital expenditure, industry unionization rate, R&D expenditure, acquisition expenditure, and Chicago Fed National Activity Index (CFNAI).[14] The residuals from this regression are labeled as inefficient labor investment and then regressed on analysts' forecast properties, including all controls as in Eq. (2). The results reported in Columns 1 and 2, Panel B, Table 6, remain qualitatively similar to the baseline results.

Next, we use labor cost (measured as the natural logarithm of wages and other benefits paid to employees and officers) as an alternative proxy for net-hiring in Eq. (1) following prior research (e.g., Li, 2011).[15] We obtain the abnormal labor cost (i.e., the difference between actual and expected labor cost) and label it inefficient labor investment. We then assess the effect of analysts' forecast properties on inefficient labor investment with this new measure. We find that the *Analyst* coefficients are negative and statistically significant (Columns 3 and 4, Panel B, Table 6).

Finally, we control for wrongful discharge laws (WDLs) because the hiring decisions of firms located in states that recognize the WDLs might be different.[16] It is likely that a reduction in inefficient labor investment is as a result of the WDLs that are in place and not analysts' forecast properties. To rule out this alternative explanation, we use the WDLs indicator variable as a control in Eq. (2) and find the coefficients of *Analyst* to be negative and statistically significant at the 1% level (Columns 5 and 6, Panel B, Table 6). Thus, the

[13] To generate the ITCV statistics, we use the konfound command in Stata (Xu et al., 2019).

[14] The CFNAI developed by Stock and Watson (1999) is available at https://www.chicagofed.org/research/data /cfnai/current-data.

[15] The downside of using labor cost is that only 20% of the firm years in COMPUSTAT report a non-missing labor expense (Li, 2011). Ballester et al. (2002) argue that the U.S. GAAP does not require separate disclosure of labor related expenses, so they voluntarily disclose. This explains why most firms do not have labor costs in their financial statements. Hence, we adopt Hartman-Glaser et al.'s (2019) imputation procedure to construct the extended labor cost (extended XLR) for firms that fail to report staff expenses (see section 6.3 for further details).

[16] The WDL are three classes of common-law (i.e., the implied contract, public policy and good-faith exceptions) that limit employers' ability to fire employees (Autor et al., 2006; Serfling, 2016). Although some states recognize all three, others recognize two, one or none (Serfling, 2016).

Table 5
Instrumental variable approach.

Variable	(1) ACC – 1st Stage	(2) ACC – 2nd Stage	(3) DISP – 1st Stage	(4) DISP – 2nd Stage
*Post*Treat*	−0.0094***		−0.0071***	
	(−2.70)		(−2.86)	
Analyst_Instrumented		−2.8556**		−3.8751**
		(−2.34)		(−2.28)
Under-identification Kleibergen-Paap statistic	8.465 ($p < 0.01$)		9.257 ($p < 0.01$)	
Weak identification Cragg-Donald F statistic	34.982		49.812	
Stock-Yogo threshold (10% maximal IV size)	16.38		16.38	
Control variables	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
N	2205	2205	2205	2205
Adjusted R^2	0.1692	0.1704	0.1114	0.1703

The table presents the results using an instrumental variable approach. The dependent variables in the 1st stage are *ACC* and *DISP*; the dependent variable for the 2nd stage is *IneffLabor*, obtained from Eq. (1) and it is the absolute difference between actual and expected net hiring. *ACC* is the absolute earnings forecast error scaled by the opening stock price and then multiplied by minus one. *DISP* is the standard deviation of analysts' earnings forecasts scaled by the opening stock price and multiplied by minus one. *Analyst_Instrumented* is the fitted values of *ACC* and *DISP* from the first-stage model. The identification strategy is predicated on the idea that pre-Reg FD private disclosers that are non-disclosers in the post-Reg FD period (*Treat* = 1) should have poorer analyst forecast quality after Reg FD than it would have before compared to firms that are pre-Reg FD public disclosers (*Treat* = 0), ceteris paribus. We capture the 9-year Reg FD window using *Post*, an indicator variable coded as 1 after the event year in 2000 and 0 otherwise. Our instrument for the 2SLS analysis is the interaction between the *Post* and *Treat* indicator variables. *t*-statistics (in parentheses) are based on standard errors clustered by firm. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. See Appendix A for variable definitions.

Table 6
Further sensitivity analyses.

Panel A: Firm fixed effects, two-way clustering and potential bias from residual as dependent variable						
	Firm fixed effects		Firm and year clustering		Derived regressor bias	
Variable	(1) ACC	(2) DISP	(3) ACC	(4) DISP	(5) ACC	(6) DISP
Analyst$_{i,t-1}$	−0.0591***	−0.2371***	−0.0876***	−0.2544***	−0.0845***	−0.2382***
	(−2.61)	(−3.80)	(−4.86)	(−5.85)	(−4.68)	(−5.44)
N	31,624	31,624	31,624	31,624	31,624	31,624
Adjusted R^2	0.2351	0.2358	0.1535	0.1542	0.1619	0.1624
Panel B: Additional controls for Eq. (1), using abnormal labor cost and controlling for wrongful discharge laws						
	Additional controls for Eq. (1)		Labor Cost		WDL	
Variable	(1) ACC	(2) DISP	(3) ACC	(4) DISP	(5) ACC	(6) DISP
Analyst$_{i,t-1}$	−0.1343***	−0.3358***	−0.2714***	−0.6043***	−0.0871***	−0.2536***
	(−4.86)	(−5.44)	(−2.62)	(−2.58)	(−4.63)	(−5.51)
N	30,592	30,592	25,594	25,594	31,624	31,624
Adjusted R^2	0.1102	0.1106	0.0850	0.0892	0.1535	0.1542

The table presents the results of various sensitivity analyses on the association between analyst forecasts and inefficient labor investment. The dependent variable for Columns 1 to 6, Panel A, and Columns 5 and 6, Panel B is *IneffLabor* measured as the absolute difference between actual and expected net hiring using Eq. (1). The dependent variable in Columns 1 and 2, Panel B, is *IneffLabor* when Eq. (1) is augmented with additional control variables such as GDP industry unionization rate, capital expenditure, R&D expenditure and acquisition expenditure. The dependent variable for Columns 2 and 4, Panel B is *IneffLabor* is the absolute value of the difference between actual and expected labor cost from Eq. (1) when the natural logarithm of wages and salaries are used as the dependent variable. Our main test variables are analysts' forecast accuracy and dispersion: *ACC* is the absolute earnings forecast error scaled by the opening stock price and then multiplied by minus one; and *DISP* is the standard deviation of analysts' earnings forecasts scaled by the opening stock price and multiplied by minus one. *t*-statistics (in parentheses) are based on standard errors clustered by firm. Controls from Eq. (2) and industry and year fixed effects are included in all regressions except for Columns 1 and 2, Panel A, where industry fixed effects are not included. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. See Appendix A for variable definitions.

association between analysts' forecast properties and inefficient labor investment is not significantly diminished by the presence of WDLs.

4.4. *Additional analyses*

4.4.1. *Over and under-investment*

We complement our main analysis by separating inefficient labor investment into over-investment (i.e., over-hiring and under-firing) and under-investment (i.e., under-hiring and over-firing), and examine their relationships with analysts' forecast properties. The level of economic activity (growth and/or a downturn) may influence a firm's hiring decisions. During periods of economic growth, more employees are likely to be hired because there is a higher prospect for increased demand for goods and services whereas, during a downturn, firms are less likely to hire because there may be less demand for goods and services. It is crucial for firms to focus on efficiency and cost management during economic downturns because they are characterized by falling demand and reduced consumer purchasing power. This has implications for firm hiring decisions. Therefore, to proxy the likelihood of over-investment during periods of economic growth and the likelihood of under-investment during periods of economic downturn, we create four subsamples based on whether the firm is over-hiring (under-firing) or under-hiring (or over-firing) during periods of economic growth and downturns, respectively (Jung et al., 2014).[17] We re-estimate our main model based on the subsamples and present the results in Table 7. The coefficients for analysts' forecast properties are negative and significant at the 10% level or better.[18] Thus, in general, our results hold during periods of economic growth (and economic downturns) where firms are more likely to under-fire (and over-fire) for normal operations.

4.4.2. Labor cost stickiness

We argue that analysts' forecast properties can affect labor cost stickiness because analysts include labor cost information when predicting a firm's earnings (Kim et al., 2017). The cost stickiness hypothesis suggests that changing committed resource levels is costly because it entails incurring resource adjustment costs, such as wages paid to hired employees and severance payments to fired staff (Anderson et al., 2003; Banker et al., 2014). Prior studies have examined factors that can affect labor cost stickiness. Prabowo et al. (2018) examine the effect of state ownership on the labor cost stickiness of firms in 22 European countries and conclude that managerial self-interest restrains managers from laying off employees or reducing employee wages when sales decrease, but are likely to increase employee numbers disproportionately when sales increase. Therefore, given that labor cost information is included in analysts' earnings forecasts (Kim et al., 2017), we argue that analysts' forecast properties will reduce labor cost stickiness because shareholders can use the information to monitor managers' expenditure on labor. Following Hall (2016) and Prabowo et al. (2018), we use the following model:

$$\begin{aligned}\Delta lnLaborCost_{i,t} &= \beta_0 + \beta_1 \Delta lnSales_{i,t} + \beta_2 Dec_{i,t} + \beta_3 Analyst_{i,t} + \beta_4 Dec_{i,t} {*} \Delta lnSales_{i,t} + \beta_5 Dec_{i,t} {*} Analyst_{i,t} \\ &+ \beta_6 \Delta lnSales_{i,t} {*} Analyst_{i,t} + \beta_7 Dec_{i,t} {*} \Delta lnSales_{i,t} {*} Analyst_{i,t} + \beta_8 AI_{i,t} + \beta_9 SucDec_{i,t} + \beta_{10} Loss_{i,t} + \beta_{11} Insti_{i,t} + \beta_{12} LabUnion_{i,t} \\ &+ \Sigma \text{ Industry FE} + \Sigma \text{ Year FE} + \varepsilon_{i,t} \end{aligned} \tag{5}$$

where:

ΔlnLaborCost is the log change of labor costs; *ΔlnSales* is the log change in total sales; *Dec* is an indicator variable that equals 1 if sales decrease in the current year and 0 otherwise; *AI* is asset intensity measured as the total assets divided by total sales; *SucDec* is an indicator variable for a successive decrease in sales across *t*, *t*-1 and *t*-2; all other variables are as previously defined. As *Compustat* reports labor costs (Compustat item XLR) for only about 13% of firm-year observations, we follow Hartman-Glaser et al. (2019) and use their imputation procedure to construct the extended labor cost (extended XLR) for firms that fail to report staff expenses. To implement this measure, we group firms into the Fama and French, 1997 industry categories and then sort them into 20 size groups within each industry based on their total assets. We estimate the average labor cost per employee using the available XLR observations within each industry-size cell for each year (XLR/EMP), and use this estimate to impute labor costs for firms that have missing XLR data as the number of employees multiplied by the average labor cost per employee of the same industry-size group in that year (Hartman-Glaser et al., 2019).

To support the argument that analyst forecasts can reduce labor cost stickiness, we require $\beta 7 > 0$. Consistent with our prediction, the coefficient of $Dec_{i,t}$ *$\Delta InSales_{i,t}$*Analysts* is positive and statistically significant at the 1% level (Table 8), implying that more accurate and less dispersed forecasts are associated with lower labor cost stickiness. This confirms the theoretical argument that shareholders and investors are likely to use analysts' information to monitor managers' expenditure on labor. Overall, this analysis reconfirms that analyst forecasts do not only affect labor investment efficiency (i.e., optimal hiring and firing), it also affects labor cost stickiness.

4.4.3. Labor versus non-labor investment

Labor investment usually complements other investments (Jung et al., 2014), so we argue that non-labor investments can influence the relationship between analysts' forecast properties and labor investment inefficiency. Accordingly, we examine the effects of non-labor investments on the link between analysts' forecast properties and labor investment inefficiency. Specifically, we examine the influence of capital, acquisition, R&D, and advertising expenditure on the relationship between analysts' forecast properties and labor

[17] Over-hiring (i.e., overinvestment when expected net hiring is positive); under-firing (i.e., overinvestment when expected net hiring is negative; under-hiring (i.e., underinvestment when expected net hiring is positive); over-firing (i.e., under-investment when expected net hiring is negative).

[18] In untabulated results, we also find that analysts' forecast quality mitigates over-investment and under-investment in labor.

Table 7
The effect of analysts' forecast properties on over- and under-hiring (and firing).

	Over-investment				Under-investment			
Variable	(1) Over-hiring	(2) Over-hiring	(3) Under-firing	(4) Under-firing	(5) Under-hiring	(6) Under-hiring	(7) Over-firing	(8) Over-Firing
$ACC_{i,t-1}$	−0.1093***		−0.0901*		−0.0611**		−0.1185***	
	(−4.04)		(−1.95)		(−2.29)		(−3.77)	
$DISP_{i,t-1}$		−0.2330***		−0.2645**		−0.2721***		−0.2775***
		(−3.93)		(−2.25)		(−4.02)		(−2.86)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10,614	10,614	1832	1832	15,707	15,707	3471	3471
Adjusted R^2	0.1049	0.1048	0.1856	0.1867	0.1623	0.1639	0.2124	0.2121

The table presents the results of estimating Eq. (2) on various subsets of the sample capturing over- and under-investment. Over-hiring is actual net hiring that exceeds the expected number (based on Eq. (1)) when expected net hiring is positive. Under-firing is actual net hiring that exceeds expected number when expected net hiring is negative. Under-hiring is actual net hiring that is less than the expected number, when the expected number is positive. Over-firing is actual net hiring that is less than the expected number, when the expected number is negative. Our main test variables are analysts' forecast accuracy and dispersion: *ACC* is the absolute earnings forecast error scaled by the opening stock price and then multiplied by minus one; and *DISP* is the standard deviation of analysts' earnings forecasts scaled by the opening stock price and multiplied by minus one. *t*-statistics (in parentheses) are based on standard errors clustered by firm. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. See Appendix A for variable definitions.

Table 8
The relationship between analysts' forecast properties and labor cost stickiness.

Variable	(1) ACC	(2) DISP
$\Delta lnSales_{i,t}$	0.5681***	0.5700***
	(23.49)	(23.59)
$Dec_{i,t}$	−0.0213	−0.0196
	(−1.36)	(−1.27)
$Analyst_{i,t}$	0.0049*	0.0119**
	(1.82)	(2.55)
$Dec_{i,t}*\Delta lnSales_{i,t}$	−0.2434***	−0.2234***
	(−2.95)	(−2.76)
$Dec_{i,t}*Analyst_{i,t}$	−0.0017	−0.0101***
	(−1.06)	(−2.58)
$\Delta lnSales_{i,t}*Analyst_{i,t}$	0.0001	0.0001
	(0.05)	(0.02)
$Dec_{i,t}*\Delta lnSales_{i,t}*Analyst_{i,t}$	0.2043***	0.3767***
	(2.73)	(2.92)
$AI_{i,t}$	0.0181***	0.0180***
	(6.57)	(6.55)
$SucDec_{i,t}$	−0.0412***	−0.0434***
	(−3.66)	(−3.85)
$Loss_{i,t-1}$	−0.0138**	−0.0140**
	(−1.96)	(−2.01)
$Insti_{i,t}$	0.0056	0.0058
	(0.99)	(1.02)
$LabUnion_{i,t}$	−0.0033	−0.0044
	(−0.10)	(−0.13)
Constant	0.1980***	0.1985***
	(3.16)	(3.22)
Industry and year fixed-effects	Yes	Yes
N	23,833	23,833
Adjusted R^2	0.0774	0.0781

The table presents the results for the effect of analyst forecast accuracy and dispersion on labor cost stickiness. The dependent variable, *ΔlnLaborCost*, is the log change of labor costs, where labor costs represents wages and other benefits paid to employees and officers, imputed from Compustat following Hartman-Glaser et al. (2019). *ACC* is the absolute earnings forecast error scaled by the opening stock price and then multiplied by minus one. *DISP* is the standard deviation of analysts' earnings forecasts scaled by the opening stock price and multiplied by minus one. *ΔlnSales* is the log change in total sales. *Dec* is an indicator variable coded one if total revenue decreased from the previous year, and zero otherwise. *t*-statistics (in parentheses) are based on standard errors clustered by firms. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively. See Appendix A for variable definitions.

Table 9
The effect of other investments on the association between analysts' forecast properties and inefficient labor investment.

	Positive		Negative		Zero	
Variable	(1) ACC	(2) DISP	(3) ACC	(4) DISP	(5) ACC	(6) DISP
Panel A: Acquisition expenditure						
Analyst$_{i,t-1}$	−0.0665**	−0.2621***	−0.1248***	−0.4117***	−0.0884***	−0.2208***
	(−2.18)	(−3.71)	(−3.50)	(−4.61)	(−3.80)	(−4.09)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
N	7003	7003	6037	6037	18,584	18,584
Adjusted R^2	0.1114	0.1126	0.1149	0.1162	0.1689	0.1692
Panel B: Capital expenditure						
Analyst$_{i,t-1}$	−0.0636***	−0.2042***	−0.1377***	−0.3312***	−0.1462**	−0.3998**
	(−2.92)	(−3.98)	(−4.38)	(−4.40)	(−2.02)	(−2.05)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
N	19,527	19,527	10,926	10,926	1171	1171
Adjusted R^2	0.1494	0.1500	0.1490	0.1496	0.1955	0.1992
Panel C: Advertising expenditure						
Analyst$_{i,t-1}$	−0.0867**	−0.2528***	−0.0862**	−0.1745**	−0.0970***	−0.2714***
	(−2.39)	(−2.81)	(−2.27)	(−2.50)	(−4.06)	(−4.65)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
N	6991	6991	3599	3599	21,034	21,034
Adjusted R^2	0.1071	0.1077	0.1069	0.1128	0.1606	0.1613
Panel D: R&D expenditure						
Analyst$_{i,t-1}$	−0.1277***	−0.3403***	−0.0831**	−0.2140**	−0.0779***	−0.2317***
	(−3.52)	(−4.15)	(−1.99)	(−2.01)	(−4.28)	(−5.58)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
N	11,081	11,081	4621	4621	15,922	15,922
Adjusted R^2	0.1811	0.1820	0.1487	0.1489	0.1197	0.1204

The table presents the results for the impact of non-labor investment on the association between analysts' forecast properties and inefficient labor investment across the indicated subsamples. The dependent variable, *IneffLabor,* is obtained from Eq. (1) and it is the absolute difference between actual and expected net hiring. Our main test variables are analysts' forecast accuracy and dispersion: *ACC* is the absolute earnings forecast error scaled by the opening stock price and then multiplied by minus one; and *DISP* is the standard deviation of analysts' earnings forecasts scaled by the opening stock price and multiplied by minus one. The results for the subsamples based on acquisitions are in Panel A. The results for the subsamples based on capital expenditure are in Panel B. The results for the subsamples based on advertising expenditure are in Panel C. The results for the subsamples based on R&D expenditure are in Panel D. Columns 1 and 2 report the results for the subsample of firms for which an increase (a decrease) in labor investment is accompanied with an increase (a decrease) in non-labor investment (i.e., a positive relationship between labor and non-labor investments). Columns 3 and 4 report the results for the subsample of firms for which an increase (a decrease) in labor investment is accompanied with a decrease (an increase) in non-labor investment (i.e., a negative relationship between labor and non-labor investments). Columns 5 and 6 report the results for the subsample of firms with a missing value for non-labor investment (i.e., firms without AQC, CAPX, XAD and XRD) (i.e., zero relationship). *t*-statistics (in parentheses) are based on standard errors clustered by firm. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. See Appendix A for variable definitions.

investment inefficiency. For each of these investments, we split the sample into three groups based on the relationship between net-hiring (the percentage change in the number of employees) and that specific investment (the percentage change in that specific investment). For example, we label the relationship (1) positive, if the net-hiring and the specific investment move in the same direction; (2) negative, if the net-hiring and the specific investment move in the opposite direction; and (3) zero, if there is no relationship or where the values are missing.

If our main results in Table 3 are influenced by non-labor investments, we should expect the results to be concentrated in the subsamples with a positive association between labor investment and non-labor investments (i.e., where the relationship is positive). Table 9 presents the results. Consistent with our main results, the coefficients on analysts' forecast accuracy and dispersion (i.e., *ACC* and *DISP*) in all cases remain statistically significant at conventional levels. Thus, the results in Table 3 are not determined by non-labor investments. This finding confirms that the role of analyst forecasts in improving labor investment efficiency is important even when a firm increases its investment in non-labor investments such as capital expenditure, R&D, advertising, and acquisition expenditure.

4.5. Channel analyses

In this section, we explore the channel through which analyst forecasts affect labor investments. Given that our results support the monitoring and information channels, we further examine which of these channels has a dominant effect. This is because, under the monitoring agent role, firms are monitored by analysts through direct communications with managers and company visits. Under the information intermediation role, investors monitor firms through the reports they receive from analysts (i.e., analyst forecasts).

Table 10

Channels through which analysts' forecast properties improve labor investment efficiency.

Panel A: Monitoring channel				
	Institutional ownership		Board independence	
Variable	(1) ACC	(2) DISP	(3) ACC	(4) DISP
$Analyst_{i,t-1}$	−0.0659***	−0.2033***	−0.0372**	−0.1014***
	(−2.76)	(−3.42)	(−2.25)	(−2.65)
$WeakMonitor_{i,t-1}$	0.0043**	0.0041***	0.0037**	0.0038**
	(2.56)	(2.40)	(2.20)	(2.23)
$Analyst_{i,t-1}*WeakMonitor_{i,t-1}$	−0.0920**	−0.2088**	−0.0950***	−0.1364**
	(−2.02)	(−2.09)	(−3.07)	(−2.00)
Controls	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
N	25,708	25,708	21,673	21,673
Adjusted R^2	0.1402	0.1408	0.1254	0.1251
Panel B: Information channel				
	Bid-ask-spread		Accruals quality	
Variable	(1) ACC	(2) DISP	(3) ACC	(4) DISP
$Analyst_{i,t-1}$	−0.0542***	−0.0910***	−0.0681***	−0.2183***
	(−3.70)	(−2.75)	(−4.21)	(−5.96)
$WeakInfo_{i,t-1}$	0.0094***	0.0095***	0.0108***	0.0108***
	(7.90)	(7.98)	(7.97)	(7.94)
$Analyst_{i,t-1}*WeakInfo_{i,t-1}$	−0.0702***	−0.1419***	−0.0584**	−0.1068*
	(−3.31)	(−2.91)	(−2.16)	(−1.74)
Controls	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
N	28,063	28,063	31,624	31,624
Adjusted R^2	0.1499	0.1504	0.1536	0.1543

The table presents the results on the channels through which analysts' forecast properties affect labor investment efficiency. The dependent variable is *IneffLabor*, and the main test variables ($Analyst_{i,t-1}$) are analysts' forecast accuracy (*ACC*) and dispersion (*DISP*). *WeakMonitor* captures firms with weaker monitoring mechanisms. We use two indicator variables as proxies for weak monitoring. First, dedicated institutional ownership, where the variable is coded 1 if the firm has a percentage of dedicated institutional ownership less than the lower quartile, and 0 otherwise. Second, board independence, where the variable is coded 1 if the firm has an independent director ratio of less than the lower quartile, and 0 otherwise. *WeakInfo* captures firms with weaker information environments. We use two indicator variables as proxies for weak information environments. First, bid-ask spread, where the variable is coded 1 if the firm has a bid-ask spread larger than the upper quartile, and 0 otherwise. Second, accruals quality, where the variable is coded 1 if the firm has poor accruals quality (less than the lower quartile), and 0 otherwise. *t*-statistics (in parentheses) are based on standard errors clustered by firm. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. See Appendix A for variable definitions.

4.5.1. Monitoring channel

Prior research has shown that analysts serve as external monitors of managers. For example, Dyck et al. (2010), in the context of the U.S., find that analysts play a bigger role in detecting corporate fraud than SEC and auditors. Knyazeva (2007) examines the relationship between corporate governance, analysts following, and firm behavior, concluding that information produced by analysts provides a substitute corporate governance mechanism. Yu (2008) finds that firms followed by more analysts manage their earnings less. These findings suggest that analysts act as monitors and prevent managers from engaging in corporate wrongdoing. Consequently, we expect the impact of analysts' forecast properties on labor investment efficiency to be stronger for firms with weaker monitoring. To test this prediction, we use dedicated institutional ownership (Bushee, 1998) and board independence (Adams et al., 2018) as proxies for monitoring quality. For ease of interpretation, we code the indicator variable (*WeakMonitor*) as 1 if the firm has a low percentage of dedicated institutional ownership (less than the lower quartile), and zero otherwise. Alternatively, we code the indicator variable (*WeakMonitor*) as 1 if the firm has a low independent director ratio (less than the lower quartile), and zero otherwise. We also mean center our analyst forecast variables to aid the interpretation of the main effects. Our results reported in Panel A of Table 10 show a negative and significant coefficient on *Analyst*WeakMonitor* at the 5% level or better, suggesting that the impact of analyst forecasts on inefficient labor investment is more pronounced for firms with fewer independent directors and low dedicated institutional ownership. These findings reinforce our prediction that analysts' monitoring is a channel through which analysts' forecast properties impact labor investment efficiency.

4.5.2. Information intermediation channel

As the information intermediary role of analysts suggests, analysts collect, analyze and publicize information; this improves the information environment and helps investors gain insights into the firm's prospects, constraining managers from engaging in non-value maximizing activities. For example, Maffett (2012) examines financial reporting opacity and informed trading by international institutional investors and finds that firms with more opaque information environments experience more privately informed trading by institutional investors. We argue that the role of analysts as information intermediaries improves the information environment and reduces firm opacity to investors. Consequently, we expect the negative effect of analysts' forecast properties on labor investment inefficiency to be more pronounced for firms with greater opacity. To test this conjecture, we use the bid-ask spread (Allen et al., 2016) and accruals quality (Francis et al., 2005) as a measure of firm opacity and information risk. The bid-ask spread is the difference between the ask price and the bid price divided by the average of ask and bid prices. These values are calculated on a monthly basis and then averaged for the year. We measure accruals quality (*AQ*) consistent with Francis et al. (2005) by computing the standard deviation of residuals across the prior 5 years from a cross-sectional industry-year regression of working capital accruals on one-year-lagged, current, and one-year-ahead cash flows from operations, the change in revenue, and property, plant, and equipment. As larger standard deviations of residuals indicate poorer accruals quality, we multiply by negative one so that larger values of *AQ* indicate higher accruals quality. We code an indicator variable (*WeakInfo*) as 1 if the firm has a bid-ask spread greater than the upper quartile, and zero otherwise. Alternatively, we code *WeakInfo* as 1 if the firm has poor accruals quality (less than the lower quartile), and zero otherwise. The results are presented in Panel B of Table 10. We find that the coefficient of *Analyst*WeakInfo* is negative and significant at the 10% level or better, suggesting that the impact of analysts' forecast properties on inefficient labor investment is more pronounced for firms with weak information environments. The result supports the information intermediation role of analysts as a channel through which analysts' forecast properties improve labor investment efficiency.

5. Conclusion

Labor costs constitute a significant portion of the cost of producing goods and services. Even though firms spend a tremendous amount of money on labor, this expenditure is prone to inefficiencies with a devastating impact on operating performance. This paper examines whether analysts' earnings forecast properties (i.e., forecast accuracy and dispersion) affect a firm's labor investment efficiency. Using a sample of U.S. firms from 1983 to 2017, we find results consistent with the prediction that analysts' forecast properties reduce inefficient investment in labor. We provide further evidence suggesting that analysts' forecast properties reduce inefficient labor investment through analysts' monitoring and information intermediary role. When we split the sample into over- and under-investment subsamples, the results continue to hold. These results suggest that analyst forecasts mitigate both over- and under-investment in labor. Further, we find that analyst forecasts mitigate labor cost stickiness.

In summary, the findings in this study support the view that the quality of analyst information gathering and monitoring, as reflected in their earnings forecasts, can mitigate inefficient labor investment. We, therefore, shed light on the potential channel through which the financial analysts can influence firm value.

Appendix A. Variable descriptions

Variable	Description (Compustat data items in parentheses)
Model 1 variables:	
$NetHire_{i,t}$	Percentage change in the number of employees (EMP) from year *t-1* to *t*;
$SalesGrowth_{i,t-1}$	Percentage change in sales (REVT) in year *t-1*;
$SalesGrowth_{i,t}$	Percentage change in sales (REVT) in year *t*;
$\Delta ROA_{i,t}$	Change in return on assets in year *t*;
$\Delta ROA_{i,t-1}$	Change in return on assets in year *t-1;*
$ROA_{i,t}$	Return on assets (NI/lag (AT)) in year *t*;
$Return_{i,t}$	Total stock return during year *t*;
$SizeRank_{i,t-1}$	Percentile rank of the natural logarithm of market value (common shares outstanding multiplied by the share price (CSHO*PRCC_F)) in year *t-1*;
$Quick_{i,t-1}$	Quick ratio ((CHE + RECT)/LCT) in year *t-1*;
$\Delta Quick_{i,t-1}$	Percentage change in the quick ratio in year *t-1*;
$\Delta Quick_{i,t}$	Percentage change in the quick ratio in year *t*;
$Lev_{i,t-1}$	Leverage, measured as the sum of debt in current liabilities and total long-term debt (DLC + DLTT) at the end of year *t-1*, divided by total assets (AT) in year *t-1*;
$AUR_{i,t-1}$	Ratio of annual sales to total assets; and
$LossBinX_{i,t-1}$	Five separate loss bins to indicate each 0.005 interval of ROA from 0 to −0.025 in year *t-1*. Specifically, *LossBin1* equals 1 if ROA is between −0.005 and 0. *LossBin2* equals 2 if ROA is between −0.005 and − 0.010. *LossBin3* equals 3 if ROA is between −0.010 and − 0.015. *LossBin4* equals 4 if ROA is between −0.015 and − 0.020. *LossBin5* equals 5 if ROA is between −0.020 and − 0.025.
Model 2 variables:	
$IneffLabor_{i,t}$	Inefficient labor investment, measured as the absolute values of the residuals from Model 1 in year *t.*
$DISP_{i,t-1}$	The standard deviation of analysts' earnings forecasts scaled by stock price at the beginning of the period and then multiplied by negative one, in year *t-1*;
$ACC_{i,t-1}$	The absolute earnings forecast error (i.e., the difference between the firm's mean EPS forecast and the firm's actual EPS) scaled by stock price at the beginning of the period and then multiplied by negative one, in year *t-1*;
$Cov_{i,t-1}$	The natural logarithm of the number of analysts who provide earnings forecasts in the month immediately preceding that of the earnings announcement, in year *t-1*;
$FirmSize_{i,t-1}$	The percentile rank of the natural logarithm of market value (common shares outstanding at the beginning of the year multiplied by the current share price (CSHO*PRCC_F)) in year *t-1*;
$MTB_{i,t-1}$	The market-to-book ratio (CSHO*PRCC_F/SEQ) in year *t-1*;
$Quick_{i,t-1}$	Quick ratio ((CHE + RECT)/ LCT) in year *t-1*;
$Lev_{i,t-1}$	Leverage, measured as the sum of debt in current liabilities and total long-term debt (DLC + DLTT) at the end of year *t-1*, divided by total assets (AT) in year *t-1*;
$DivDum_{i,t-1}$	Indicator variable coded as 1 if the firm paid dividends (DVPSP_F) in year *t-1*;
$StdCFO_{i,t-1}$	Standard deviation of cash flow from operations (OANCF) from year *t-5* to *t-1*;
$StdSales_{i,t-1}$	Standard deviation of sales from year *t-5* to *t-1*;
$Tangibles_{i,t-1}$	Property, plant, and equipment (PPENT) in year *t-1*, divided by total assets in year *t-1*;
$Loss_{i,t-1}$	Indicator variable coded as 1 if ROA is negative for year *t-1*;
$Insti_{i,t-1}$	Institutional shareholdings in year *t-1*;
$AQ_{i,t-1}$	Accruals quality measure based on the Dechow and Dichev (2002) model as modified by Francis et al. (2005). The model is a regression of working capital accruals on one-year-lagged, current, and one-year-ahead cash flows from operations, the change in revenue, and property, plant, and equipment. We estimate the model cross-sectionally by industry-year and collect the residuals. We then compute the standard deviation of residuals over *t-5* to *t-1*, and multiply by negative one;
$StdNetHire_{i,t-1}$	Standard deviation of the change in the number of employees from year *t-5* to *t-1*;
$LaborIntensity_{i,t-1}$	Labor intensity, measured as the number of employees divided by total assets at the end of financial year *t-1*;
$LabUnion_{i,t-1}$	Industry-level rate of labor unionization for year *t-1*. This is obtained from www.unionstats.com. It is an estimate of industry level union membership and coverage; and
$/AbInvestOther/_{i,t}$	Abnormal other (non-labor) investments in year *t*, defined as the absolute magnitude of the residual from the following model: $Invest\_Other_{it} = \beta_0 + \beta_1 Sales\_Growth_{it-1} + \varepsilon_{i,t}$, where *Invest_Other* is the sum of capital expenditure (CAPEX), research and development expenditures (XRD), less cash receipts from the sale of property, plant, and equipment (SPPE), all scaled by lagged total assets.
Other variables:	
$WeakMonitor_{i,t-1}$	An indicator variable that captures firms with weaker monitoring mechanisms. We use two indicator variables as proxies for weak monitoring. First, dedicated institutional ownership, where the variable is coded 1 if the firm has a percentage of dedicated institutional ownership less than the lower quartile, and 0 otherwise. Second, board independence, where the variable is coded 1 if the firm has an independent director ratio of less than the lower quartile, and 0 otherwise;
$WeakInfo_{i,t-1}$	An indicator variable that captures firms with weaker information environments. We use two indicator variables as proxies for weak information environments. First, bid-ask spread, where the variable is coded 1 if the firm has a bid-ask spread larger than the upper quartile, and 0 otherwise. Second, accruals quality, where the variable is coded 1 if the firm has poor accruals quality (less than the lower quartile), and 0 otherwise;
$LabCost_{i,t}$	Staff expense (XLR) in year *t*, which represents wages and other benefits paid to employees and officers, estimated following Hartman-Glaser et al. (2019);

(*continued on next page*)

(*continued*)

Variable	Description (Compustat data items in parentheses)
$\Delta lnLaborCost_{i,t}$	Natural logarithm change in *LabCost* in year *t*;
$Sales_{i,t}$	Natural logarithm of total revenue in year *t*;
$\Delta lnSales_{i,t}$	Natural logarithm change in total sales in year *t*;
$Dec_{i,t}$	Indicator variable coded one if total revenue decreased from the previous year, and zero otherwise;
$SucDecr_{i,t}$	Indicator variable coded one if a firm had a decrease in revenue during the current and the previous year, and zero otherwise;
$WDL_{i,t\text{-}1}$	The strength of Wrongful Discharge Laws (WDLs) in the state where the firm is headquartered constructed by summing three distinct indicator variables for each of the three WDLs exceptions, where each dummy is coded one if the firm is in a state that has adopted the exception in question, and zero otherwise;
$High\_Skill_{i,t\text{-}1}$	Indicator variable coded one for firms that belong to industries relying more on skilled labor, and zero otherwise. We use the industry average number of employees working in occupations with a *JobZones* index equal to 4 or 5 as a proxy for the degree of reliance on skilled labor. We collect *JobZones* data from Occupational Information Network (O*Net). We collect the data on the number of employees by occupation from the Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics;

Appendix B. Descriptive statistics and regression output for Model 1

Variable	N	Mean	Median	25 Pctl.	75 Pctl.	Std. Dev.
$NetHire_{i,t}$	92,175	0.0695	0.0257	−0.0412	0.1251	0.2655
$SalesGrowth_{i,t}$	92,175	0.1294	0.0765	−0.0184	0.2008	0.3578
$SalesGrowth_{i,t-1}$	92,175	0.1557	0.0828	−0.0149	0.2173	0.4327
$\Delta ROA_{i,t}$	92,175	0.0002	−0.0001	−0.0360	0.0306	0.1480
$\Delta ROA_{i,t-1}$	92,175	0.0034	−0.0001	−0.0367	0.0311	0.1718
$ROA_{i,t}$	92,175	0.0125	0.0432	−0.0087	0.0896	0.1752
$Return_{i,t}$	92,175	0.1396	0.0352	−0.2271	0.3278	0.6158
$SizeRank_{i,t-1}$	92,175	56.1167	60.0000	31.0000	82.0000	28.9858
$Quick_{i,t-1}$	92,175	1.8864	1.2369	0.7792	2.1587	1.9388
$\Delta Quick_{i,t-1}$	92,175	0.0793	−0.0089	−0.1933	0.1989	0.5276
$\Delta Quick_{i,t}$	92,175	0.0687	−0.0082	−0.1901	0.1953	0.4804
$Lev_{i,t-1}$	92,175	0.2227	0.1958	0.0379	0.3453	0.2002
$AUR_{i,t-1}$	92,175	1.1265	0.9637	0.5637	1.4508	1.0428
$LossBin1_{i,t-1}$	92,175	0.0109	0.0000	0.0000	0.0000	0.1041
$LossBin2_{i,t-1}$	92,175	0.0111	0.0000	0.0000	0.0000	0.1050
$LossBin3_{i,t-1}$	92,175	0.0106	0.0000	0.0000	0.0000	0.1025
$LossBin4_{i,t-1}$	92,175	0.0106	0.0000	0.0000	0.0000	0.1023
$LossBin5_{i,t-1}$	92,175	0.0088	0.0000	0.0000	0.0000	0.0932

Variable	(1) $NetHire_{i,t}$
$SalesGrowth_{i,t}$	0.3370***
	(150.93)
$SalesGrowth_{i,t-1}$	0.0419***
	(22.82)
$\Delta ROA_{i,t}$	−0.2319***
	(−38.35)
$\Delta ROA_{i,t-1}$	−0.0378***
	(−7.88)
$ROA_{i,t}$	0.1333***
	(26.18)
$Return_{i,t}$	0.0358***
	(27.63)
$SizeRank_{i,t-1}$	0.0003***
	(9.35)
$Quick_{i,t-1}$	0.0073***
	(15.33)
$\Delta Quick_{i,t-1}$	0.0272***
	(18.03)
$\Delta Quick_{i,t}$	−0.0358***
	(−21.61)
$Lev_{i,t-1}$	−0.0344***
	(−7.81)
$AUR_{i,t-1}$	0.0067***
	(7.83)
$LossBin1_{i,t-1}$	−0.0287***
	(−3.95)
$LossBin2_{i,t-1}$	−0.0164**
	(−2.27)
$LossBin3_{i,t-1}$	−0.0238***
	(−3.23)
$LossBin4_{i,t-1}$	−0.0085
	(−1.15)
$LossBin5_{i,t-1}$	−0.0271***
	(−3.35)
Constant	−0.0299**
	(−1.98)
Industry and year fixed-effects	Yes
N	92,175
Adjusted R^2	0.2564

The table presents the descriptive statistics of the variables used in Eq. (1). The sample consists of 92,175 firm-year observations from 1983 to 2017. For every variable, the mean, median, lower quartile, upper quartile and standard deviation are presented. All variables are winsorized at the 1st and the 99th percentiles. $NetHire_{i,t}$ is the percentage change in the number of employees from year *t-1* to *t*. $SalesGrowth_{i,t/t-1}$ is the percentage change in sales in year *t* or *t-1*. $ROA_{i,t}$ is the return on assets in year *t*. $\Delta ROA_{i,t/t-1}$ is the change in return on assets in year *t* or *t-1*. $Return_{i,t}$ is the total stock return during year *t*. $SizeRank_{i,t-1}$ is the percentile rank of the natural logarithm of market in year *t-1*. $Quick_{i,t-1}$ is the quick ratio in year *t-1*. $\Delta Quick_{i,t/t-1}$ is the

percentage change in the quick ratio in year *t* or *t-1*. $Lev_{i,t-1}$ is leverage measured as the sum of debt in current liabilities and total long-term debt in year *t-1*, divided by total assets in year *t-1*. $AUR_{i,t-1}$ is the ratio of annual sales to total assets. $LossBinX_{i,t-1}$ are five separate loss bins to indicate each 0.005 interval of ROA from 0 to −0.025 in period *t-1* for firm *i*. Specifically, *LossBin1* equals 1 if ROA is between −0.005 and 0. *LossBin2* equals 2 if ROA is between −0.005 and − 0.010. *LossBin3* equals 3 if ROA is between −0.010 and − 0.015, *LossBin4* equals 4 if ROA is between −0.015 and − 0.020. *LossBin5* equals 5 if ROA is between −0.020 and − 0.025.
This table presents the results for estimating Eq. (1). $NetHire_{i,t}$ is the dependent variable which is measured as the percentage change in the number of employees (EMP) from year *t-1* to year *t* for firm *i*. $SalesGrowth_{i,t/t-1}$ is the percentage change in sales in year *t* or *t-1*. $ROA_{i,t}$ is the return on assets in year *t*. $\Delta ROA_{i,t/t-1}$ is the change in return on assets in year *t* or *t-1*. $Return_{i,t}$ is the total stock return during year *t*. $SizeRank_{i,t-1}$ is the percentile rank of the natural logarithm of market in year *t-1*. $Quick_{i,t-1}$ is the quick ratio in year *t-1*. $\Delta Quick_{i,t/t-1}$ is the percentage change in the quick ratio in year *t* or *t-1*. $Lev_{i,t-1}$ is leverage measured as the sum of debt in current liabilities and total long-term debt in year *t-1*, divided by total assets in year *t-1*. $AUR_{i,t-1}$ is the ratio of annual sales to total assets. $LossBinX_{i,t-1}$ are five separate loss bins to indicate each 0.005 interval of ROA from 0 to −0.025 in period *t-1* for firm *i*. Specifically, *LossBin1* equals 1 if ROA is between −0.005 and 0. *LossBin2* equals 2 if ROA is between −0.005 and − 0.010. *LossBin3* equals 3 if ROA is between −0.010 and − 0.015, *LossBin4* equals 4 if ROA is between −0.015 and − 0.020. *LossBin5* equals 5 if ROA is between −0.020 and − 0.025. *t*-statistics are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Appendix C. Identification of private and private disclosers

Wang (2007) uses Matsumoto's (2002) models first to estimate each firm's total earnings guidance:

$$\frac{\Delta EPS_{ijtq}}{P_{ijt-1,q}} = \alpha_{ijt} + \beta_{1ijt}\left(\frac{\Delta EPS_{ijtq-1}}{P_{ijt-1,q-1}}\right) + \beta_{2ijt}CRET_{ijtq} + \varepsilon_{ijt} \tag{A1}$$

$$E\left[\Delta EPS_{ijtq}\right] = \left[\widehat{\alpha}_{ijt-1} + \widehat{\beta}_{1ijt-1}\left(\frac{\Delta EPS_{ijtq-1}}{P_{ijt-1,q-1}}\right) + \widehat{\beta}_{2ijt-1}CRET_{ijtq}\right] \times P_{ijt-1,q} \tag{A2}$$

$$E\left[F_{ijtq}\right] = EPS_{ijt-1,q} + E\left[\Delta EPS_{ijtq}\right] \tag{A3}$$

$$UF_{ijtq} = F_{ijtq} - E\left[F_{ijtq}\right] \tag{A4}$$

Eq. (A1) estimates the expected seasonal change in analyst forecasts for firm *i* in industry *j* during quarter *q* of year *t*. The dependent variable is the seasonal change in EPS ($\Delta EPS_{ijtq} = EPS_{ijtq} - EPS_{ijt-1,q}$) scaled by stock price in quarter *q* of year *t-1* ($P_{ijt-1,q}$). The control variables are the seasonal change in the prior quarter's earnings per share ($\Delta EPS_{ijtq-1} = EPS_{ijtq-1} - EPS_{ijt-1,q-1}$) and firm-specific daily excess returns ($CRET_{ijtq}$) cumulated from three days after the year *t-1* quarter *q* earnings announcement to 20 days before the year *t* quarter *q* earnings announcement. Eq. (A1) is estimated for each firm-year using all firm quarters in year *t* for firm *i*'s industry (four-digit SIC), excluding firm *i*'s data.

Eq. (A2) calculates the expected change in firm *i*'s analyst forecasts ($E[\Delta EPS_{ijtq}]$) in the current quarter using the estimates from Eq. (A1). Eq. (A3) defines the expected analyst forecast ($E[F_{ijtq}]$) absent of any earnings guidance as the sum of the EPS in the same quarter of the previous year and the expected change in analyst forecasts ($E[\Delta EPS_{ijtq}]$) from Eq. (A2). Eq. (A4) estimates the total earnings guidance from both public and private disclosures (UF_{ijtq}) by subtracting the expected analyst forecast ($E[F_{ijtq}]$) from the actual analyst forecast (F_{ijtq}). Larger magnitudes of the absolute value of UF_{ijtq} indicate more earnings guidance.

To separate private guidance from total guidance, Wang (2007) estimates the following equation:

$$\left|UF_{iq}\right| = \gamma_{0i} + \gamma_1 Std\Delta EPS_{iq} + \gamma_2 Loss_{iq} + \gamma_3 \#PublicDisclosure_{iq} + \mu_{iq} \tag{A5}$$

Eq. (A5) estimates total earnings guidance ($|UF_{iq}|$) as a function of (1) earnings volatility, measured as the standard deviation of seasonal changes in earnings per share during the previous three years ($Std\Delta EPS_{iq}$); (2) incidence of losses, an indicator variable that equals 1 if a firm reports a loss in the current quarter and 0 otherwise ($LOSS_{iq}$); and (3) the number of earnings-related public disclosures issued for each quarter ($\#PublicDisclosure_{iq}$). We use the IBES Guidance database to capture publicly disclosed management earnings guidance. Firms with less predictable earnings are more likely to provide guidance, and thus we expect a positive coefficient on *StdΔEPS* and *LOSS*. As management guidance forms part of total guidance, *#PublicDisclosure* should be positively associated with $|UF_{iq}|$.

Wang (2007) defines quarterly private earnings guidance as the absolute value of the sum of the firm-specific intercept and the error term. The average of the quarterly private guidance for each firm-year provides us with an estimate of the annual private guidance. Firms are private disclosers if their annual private guidance ranks in the top 40% every year of the firms' available years in the pre-Regulation FD period. Firms are classified as public disclosers in the pre-Regulation FD period if their mean earnings-related public disclosures are 30% more than the average of all private disclosers. For private disclosers in the pre-Reg FD period, Wang (2007) further categorizes them into post-Reg FD non-disclosers if a pre-Reg FD private discloser's quarterly average number of public disclosures did not increase.

The table below provides the results for our estimation of Eq. (A5) for all firms with available data and the descriptive statistics on the various firm disclosure types. The coefficients estimated in Panel A are similar in direction and magnitude to Wang (2007). From Panel B, there are 897 firms classified as private disclosers, 808 as public disclosers, and 310 as new non-disclosers in the post-Reg FD period that were previously private disclosers in the pre-Reg FD period. In the pre-Reg FD period, public disclosers issue on average 0.30 earnings-related public disclosures per quarter and private disclosers issue 0.08 per quarter. In the post-Reg FD period, previously private disclosers that are now non-disclosers issue 0.02 earnings-related public disclosures per quarter.

Estimation of private and public disclosers

Panel A: Estimation of pre-Reg FD quarterly private earnings guidance	
Variable	$\lvert UF_{iq} \rvert$
StdΔEPS	0.0614***
	(11.07)
Loss	0.0237***
	(8.22)
#PublicDisclosure	0.0190***
	(6.35)
Firm fixed-effects	Yes
Year fixed-effects	Yes
N	37,569
Adjusted R^2	0.4123

Panel B: Descriptive statistics on the average number of public disclosures per quarter				
Type of discloser	N	Mean	Median	Std. Dev.
Pre-reg FD private discloser	897	0.0805	0.0000	0.1874
Pre-reg FD public discloser	808	0.2957	0.2307	0.2057
Post-reg FD new non-discloser	310	0.0229	0.0000	0.0675

This table presents the classification results of pre-Reg FD private disclosers, pre-Reg FD public disclosers, and post-Reg FD new non-disclosers that were previously private disclosers in the pre-Reg FD period. The methodology follows Wang (2007). Panel A reports the estimation results of quarterly private earnings guidance in the pre-Reg FD period. Panel B reports descriptive statistics on earnings related public disclosers by discloser type. $\lvert UF \rvert$ is unexpected analyst forecast; *StdΔEPS* is seasonal changes in EPS during the prior three years; *Loss* is an indicator variable coded 1 if the firm reports a loss in the quarter, and 0 otherwise; *#PublicDisclosure* is the number of earnings related public disclosure in the quarter. *t*-statistics (in parentheses) are based on robust standard errors. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

References

Adams, J.C., Nishikawa, T., Rao, R.P., 2018. Mutual fund performance, management teams, and boards. J. Bank. Financ. 92, 358–368.
Adhikari, B.K., 2016. Causal effect of analyst following on corporate social responsibility. J. Corp. Finan. 41, 201–216.
Agrawal, A., Chanda, S., Chen, M., 2006. Who is afraid of Reg FD? The behavior and performance of sell-side analysts following the SEC's fair disclosure rules. J. Bus. 79, 2811–2834.
Allen, A., Francis, B.B., Wu, Q., Zhao, Y., 2016. Analyst coverage and corporate tax aggressiveness. J. Bank. Financ. 73, 84–98.
Anderson, M.C., Banker, R.D., Janakiraman, S.N., 2003. Are selling, general, and administrative costs sticky? J. Account. Res. 41, 47–63.
Autor, D.H., Donohue III, J.J., Schwab, S.J., 2006. The costs of wrongful discharge laws. Rev. Econ. Stat. 88, 211–231.
Bailey, W.H., Li, H., Mao, C., Zhong, R., 2003. Regulation fair disclosure and earnings information: market, analyst, and corporate responses. J. Financ. 58, 2487–2514.
Ballester, M., Livnat, J., Sinha, N., 2002. Tracks: labor costs and investments in human capital. J. Acc. Audit. Financ. 17, 351–373.
Banker, R.D., Byzalov, D., Ciftci, M., Mashruwala, R., 2014. The moderating effect of prior sales changes on asymmetric cost behaviour. J. Manag. Account. Res. 26, 221–242.
Barney, J.B., 1991. Firm resources and sustained competitive advantage. J. Manag. 17, 99–120.
Barth, M.E., Kasznik, R., McNichols, M.F., 2001. Analyst coverage and intangible assets. J. Account. Res. 39, 1–34.
Ben-Nasr, H., Alshwer, A.A., 2016. Does stock price informativeness affect labor investment efficiency? J. Corp. Finan. 38, 249–271.
Bushee, B., 1998. The influence of institutional investors on myopic R&D investment. Account. Rev. 73, 305–333.
Bushee, B.J., Matsumoto, D.A., Miller, G.S., 2004. Managerial and investor responses to disclosure regulation: the case of Reg FD and conference calls. Account. Rev. 79, 617–643.
Chen, T., Harford, J., Lin, C., 2015. Do analysts matter for governance? Evidence from natural experiments. J. Financ. Econ. 115, 383–410.
Chen, T., Xie, L., Zhang, Y., 2017. How does analysts' forecast quality relate to corporate investment efficiency? J. Corp. Finan. 43, 217–240.
Chen, W., Hribar, P., Melessa, S., 2018. Incorrect inferences when using residuals as dependent variables. J. Account. Res. 56, 751–796.
Chung, K.H., Jo, H., 1996. The impact of security analysts' monitoring and marketing functions on the market value of firms. J. Financ. Quant. Anal. 31, 493–512.
Coffee, J., 2000. Tackling new regulation FD. Nat.l Law J. B6. September 18.
Datta, S., Iskandar-Datta, M., Sharma, V., 2011. Product market pricing power, industry concentration and analysts' earnings forecasts. J. Bank. Financ. 35, 1352–1366.
Dechow, P., Dichev, I., 2002. The quality of accruals and earnings: the role of accrual estimation errors. Account. Rev. 77, 35–59.
DeFond, M.L., Hung, M., 2007. Investor protection and analysts' cash flow forecasts around the world. Rev. Acc. Stud. 12, 377–419.
Diether, K., Malloy, C., Scherbina, A., 2002. Differences of opinion and the cross-section of stock returns. J. Financ. 57, 2113–2141.
Donangelo, A., 2014. Labor mobility: implications for asset pricing. J. Financ. 69, 1321–1346.
Dyck, A., Morse, A., Zingales, L., 2010. Who blows the whistle on corporate fraud? J. Financ. 65, 2213–2253.
Edmans, A., 2011. Does the stock market fully value intangibles? Employee satisfaction and equity prices. J. Financ. Econ. 101, 621–640.
Fama, E., French, K., 1997. Industry costs of equity. J. Financ. Econ. 43, 153–193.
Francis, J., Lafond, R., Olsson, P., Schipper, K., 2005. The market pricing of accruals quality. J. Account. Econ. 39, 295–327.
Frank, K., 2000. Impact of a confounding variable on a regression coefficient. Sociol. Methods Res. 29, 147–194.
Fried, D., Givoly, D., 1982. Financial analysts' forecasts of earnings: a better surrogate for market expectation. J. Account. Econ. 4, 85–107.

Ghaly, M., Dang, V.A., Stathopoulos, K., 2020. Institutional investors' horizons and corporate employment decisions. J. Corp. Finan. https://doi.org/10.1016/j.jcorpfin.2020.101634 on 09/05/2020 forthcoming. Retrieved from.
Givoly, D., Lakonishok, J., 1979. The information content of financial analysts' forecasts of earnings. J. Account. Econ. 1, 165–185.
Gomes, A., Gorton, G., Madureira, L., 2007. SEC regulation fair disclosure, information, and the cost of capital. J. Corp. Finan. 13, 300–334.
Graham, J., Harvey, C., Rajgopal, S., 2005. The economic implications of corporate financial reporting. J. Account. Econ. 40, 3–73.
Gu, F., Wang, W., 2005. Intangible assets, information complexity, and analysts' earnings forecasts. J. Bus. Financ. Acc. 32, 1673–1701.
Gujarati, D.N., 2003. Basic Econometrics. McGraw Hill, Boston.
Hall, C.M., 2016. Does ownership structure affect labor decisions? Account. Rev. 91, 1671–1696.
Hamermesh, D.S., 1995. Labor demand and the source of adjustment costs. Econ. J. 105, 620–634.
Hartman-Glaser, B., Lustig, H.A., Xiaolan, M.Z., 2019. Capital share dynamics when firms insure workers. J. Financ. 74, 1707–1751.
He, J.J., Tian, X., 2013. The dark side of analyst coverage: the case of innovation. J. Financ. Econ. 109, 856–878.
Healy, P.M., Palepu, K.G., 2001. Information asymmetry, corporate disclosure, and the capital markets: a review of the empirical disclosure literature. J. Account. Econ. 31, 405–440.
Heflin, F., Subramanyam, K.R., Zhang, Y., 2003. Regulation FD and the financial information environment: early evidence. Account. Rev. 78, 1–37.
Hirsch, B., Macpherson, D., 2003. Union membership and coverage database from the current population survey: note. Ind. Labor Relat. Rev. 56, 349–354.
Iacus, S., King, G., Porro, G., 2012. Causal inference without balance checking: coarsened exact matching. Polit. Anal. 20, 1–24.
Irani, R.M., Oesch, D., 2016. Analysts coverage and real earnings management: quasi-experimental evidence. J. Financ. Quant. Anal. 51, 589–627.
Jensen, M.C., Meckling, W.H., 1976. Theory of the firm: managerial behavior, agency costs and ownership structure. J. Financ. Econ. 3, 305–360.
Johnson, T., 2004. Forecast dispersion and the cross-section of expected returns. J. Financ. 59, 1957–1978.
Jung, B., Lee, W.-J., Weber, D.P., 2014. Financial reporting quality and labor investment efficiency. Contemp. Account. Res. 31, 1047–1076.
Khedmati, M., Sualihu, M.A., Yawson, A., 2020. CEO-director ties and labor investment efficiency. J. Corp. Finan. 65, 1–24.
Kim, S., Park, K., Rosett, J., Shin, Y.-C., 2017. The benefit of labor cost disclosure: evidence from analyst earnings forecast accuracy. Manag. Financ. 43, 510–527.
Kirk, M.P., Reppenhagen, D.A., Tucker, J.W., 2014. Meeting individual analyst expectations. Account. Rev. 89, 2203–2231.
Kleibergen, F., Paap, R., 2006. Generalized reduced rank tests using the singular value decomposition. J. Econ. 133, 97–126.
Knyazeva, D., 2007. Corporate Governance, Analyst Following, and Firm Behavior. Working paper at University of Rochester.
Kross, W.J., Suk, I., 2012. Does regulation FD work? Evidence from analysts' reliance on public disclosure. J. Account. Econ. 53, 225–248.
Lang, M.H., Lundholm, R.J., 1996. Corporate disclosure policy and analyst behavior. Account. Rev. 71, 467–492.
Larcker, D.F., Rusticus, T.O., 2010. On the use of instrumental variables in accounting research. J. Account. Econ. 49, 186–205.
Lee, K.Y., Mo, K., 2020. Do analysts improve labor investment efficiency. J. Contemp. Account. Econ. 16 (100213).
Lehavy, R., Li, R., Merkley, K., 2011. The effect of annual report readability on analyst following and the properties of their earnings forecasts. Account. Rev. 86, 1087–1115.
Lennox, C.S., 2016. Did the PCAOB's restrictions on auditors tax services improve audit quality? Account. Rev. 91, 1493–1512.
Li, F., 2011. Earnings quality based on corporate investment decisions. J. Account. Res. 49, 721–752.
Maffett, M., 2012. Financial reporting opacity and informed trading by international institutional investors. J. Account. Econ. 54, 201–220.
Mansi, S.A., Maxwell, W.F., Miller, D.P., 2011. Analyst forecast characteristics and the cost of debt. Rev. Acc. Stud. 16, 116–142.
Matsa, D.A., 2018. Capital structure and a firm's workforce. Ann. Rev. Finan. Econ. 10, 387–412.
Matsumoto, D., 2002. Management's incentives to avoid negative earnings surprises. Account. Rev. 77, 483–514.
Matsunaga, S.R., Park, C.W., 2001. The effect of missing a quarterly earnings benchmark on the CEO's annual bonus. Account. Rev. 76, 313–332.
Merz, M., Yashiv, E., 2007. Labor and the market value of the firm. Am. Econ. Rev. 97, 1419–1431.
Oyer, P., Schaefer, S., 2010. Personnel economics: Hiring and incentives. In: National Bureau of Economics Working Paper Series, No.15977.
Paycor, 2020. The biggest cost of doing business: A closer look at labor costs. Retrieved from https://www.paycor.com/resource-center/articles/the-biggest-cost-of-doing-business-a-closer-look-at-labor-costs/ on 05/08/2020.
Payne, J.L., Thomas, W.B., 2003. The implications of using stock-split adjusted I/B/E/S data in empirical research. Account. Rev. 78, 1049–1067.
Petacchi, R., 2015. Information asymmetry and capital structure: evidence from regulation FD. J. Account. Econ. 59, 143–162.
Petersen, M., 2009. Estimating standard errors in finance panel data sets: comparing approaches. Rev. Financ. Stud. 22, 435–480.
Pfeffer, J., 1996. Competitive Advantage through People: Unleashing the Power of the Work Force. Havard Business School Press, Cambridge, MA.
Platikanova, P., Mattei, M.M., 2016. Firm geographic dispersion and financial analysts' forecasts. J. Bank. Financ. 64, 71–89.
Prabowo, R., Hooghiemstra, R., Veen-Dirks, P.V., 2018. State ownership, socio-political factors, and labor cost stickiness. Eur. Account. Rev. 27, 771–796.
Sandle, T., 2017. Deloitte Consulting show how to Lower Labor Costs: Interview. Retrieved from http://www.digitaljournal.com/business/interview-laborwise-aiding-fortune-500-with-labor-costs/article/504653#ixzz6UUm1xqa9 on 08/08/2020.
Serfling, M., 2016. Firing costs and capital structure decisions. J. Financ. 71, 2239–2286.
Shleifer, A., Vishny, R., 1986. Large shareholders and corporate control. J. Polit. Econ. 94, 461–488.
Srinidhi, B., Leung, S., Jaggi, B., 2009. Differential effects of regulation FD on short-and long-term analyst forecasts. J. Account. Public Policy 28, 401–418.
Stock, J., Watson, M., 1999. Forecasting inflation. J. Monet. Econ. 44, 293–335.
Stock, J.H., Yogo, M., 2005. Testing for weak instruments in linear IV regression. In: Andrews, D.W.K. (Ed.), Identification and Inference for Econometric Models. Cambridge University Press, New York, pp. 80–108.
Sualihu, M.A., Rankin, M., Haman, J., 2021. The role of equity compensation in reducing inefficient investment in labor. J. Corp. Finan. 66, 1–25.
To, T.Y., Navone, M., Wu, E., 2018. Analyst coverage and the quality of corporate investment decisions. J. Corp. Finan. 51, 164–181.
Wang, I.Y., 2007. Private earnings guidance and its implications for disclosure regulation. Account. Rev. 82, 1299–1332.
Wang, Z., Sun, L., Wei, J., 2020. Does competition induce analyst effort? Evidence from a natural experiment of broker mergers. J. Bank. Finan. 119 (105914).
Williamson, O., 1963. Managerial discretion and business behavior. Am. Econ. Rev. 53, 1032–1057.
Xu, R., Frank, K.A., Maroulis, S.J., Rosenberg, J.M., 2019. Konfound: command to quantify robustness of causal inferences. Stata J. 19, 523–550.
Yawson, A., Zhang, H., 2021. Central hub M&A advisors. Rev. Financ. *forthcoming*.
Yu, F., 2008. Analyst coverage and earnings management. J. Financ. Econ. 88, 245–271.
Yu, M., 2010. Analyst forecast properties, analyst following and governance disclosures: a global perspective. J. Int. Account. Audit. Tax. 19, 1–15.