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ORIGINAL RESEARCH

Analysts forecasts: the secret sauce stirring up CEOs' abnormal pay

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Abstract

Jensen and Meckling (J Financ Econ 3(4):305–360, 1976) claim that by facilitating firms' activity monitoring, security analysis by financial analysts can reduce agency costs between management and external capital providers, and thereby increase shareholder value. Additionally, boards are required to design executive pay structures to minimise agency problems and related costs. Among the limited studies that explore the relationship between analysts' forecasts and CEOs' compensation, one strand reports a positive relation supporting the agency theory, while the other reports a negative relation contradicting the agency theory. This disagreement may stem from the unobserved determinants of CEOs' compensation structures. Thus, we use CEOs' abnormal compensation (*ACOMP*, the proportion of pay that economic determinants cannot accurately determine) to reinvestigate this relation and find conclusive evidence of its negative association with analysts' forecast metrics. Although consistent with agency theory, this negative relationship is mainly witnessed in firms subject to stronger external monitoring, as indicated by higher corporate governance scores, takeover vulnerability, institutional ownership, and firm-level political risk. Our findings suggest that analysts serve as a proxy for unobserved factors influencing *ACOMP* and play a key role in aligning CEO interests with those of shareholders.

Keywords Executive compensation · Abnormal compensation · Earnings forecasts · Information asymmetry · Agency theory · Corporate governance

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1 Introduction

The literature examining the drivers of CEOs' compensation has gained momentum recently, identifying factors such as experience, gender, incentives, and ability, among others, that affect CEOs' compensation levels (e.g., Core and Guay 2010; Bragaw and Misangyi 2015; Conyon et al. 2019; Malhotra et al. 2021). The growing focus on these factors aims to provide a comprehensive assessment of managerial performance, thereby improving the effectiveness of compensation contracts. This, in turn, helps to reduce agency conflicts and better align executives' interests with those of shareholders.

Considering the role of sell-side security analysts as information intermediaries (Tan 2021) and corporate governance monitors (Hussain et al. 2021), their assessment of firms may be considered when setting compensation contracts for CEOs. With the forecasts and interpretations of a firm's performance and strategic decisions, analysts may influence the evaluation of a manager's leadership efficacy, potentially affecting key board decisions such as CEO dismissal (Park et al. 2021) and their compensation levels. An example of the influence of analysts' expectations on executive decisions is seen in GE's board's decision to oust CEO John Flannery in 2018, following analyst warnings about cash flow issues.[1] Recent literature also examined the relationship between analysts' information environment and CEOs' total compensation (Kanagaretnam et al. 2012; Liu 2017; Mamatzakis and Bagntasarian 2020). However, the limited findings remain inconclusive.

Financial analysts play a crucial role in reducing information asymmetry and agency costs by interpreting and assessing the information disclosed by managers. In line with the *interest alignment effect* under *agency theory*, firms can align the interests of managers with those of shareholders by implementing efficient compensation contracts. To achieve this efficiency, the compensation contract should reflect the manager's effort, even though it is not entirely transparent in practice. Thus, efforts to improve the information environment and align with analysts' forecasts are expected to positively influence CEO compensation. Conversely, negative earnings surprises and large analyst forecast errors signal poor disclosure quality, elevate agency costs, harm stock prices, and reduce executive pay (Hall and Liebman 1998; Zhang and Gong 2018). However, the inconclusive evidence in prior studies examining the relationship between analysts' information environment and CEOs' compensation (Kanagaretnam et al. 2012; Liu 2017; Mamatzakis and Bagntasarian 2020) might have been due to the unobservable factors influencing CEOs' compensation and a lack of emphasis on the *ex-post recognition* achieved by variable pay (Edmans et al. 2023).

One strand argues that higher executive compensation and incentives encourage opportunistic behaviour, which increases information complexity for analysts, subsequently leading to a positive relation between CEOs' compensation and analysts' earnings forecast error (i.e., higher compensation leads to higher earnings forecast error) (e.g., Huang and Boateng 2017; Kanagaretnam et al. 2012; Liu 2017). This implies that CEOs are rewarded when information asymmetry is high (e.g., higher forecast errors). On the other hand, a few studies report a negative relationship between executive compensation and analysts' earnings forecast error (e.g., Hui and Matsunaga 2015; Mamatzakis and Bagntasarian 2020), sug-

[1] See, General Electric replaces CEO with outsider; shares soar. Accessed on September 12, 2024.

gesting that CEOs are penalised when information asymmetry increases. This negative relation is in line with the predictions of *agency theory*, as external monitoring by analysts is expected to encourage CEOs to minimise agency costs (Andrei et al. 2024) and work in the best interest of shareholders.

It is important to note that, for a given CEO in a given year, the actual compensation amount used in the studies above may differ from the expected level of compensation if it does not account for *ex-post recognition*. Compensation contracts provide *consumption incentives*, as CEOs are likely to enhance firm value when the utility, they gain from consumption outweighs their effort (Edmans et al. 2023). However, CEOs may also expect fair rewards for their performance, whether due to their contributions to the firm or relative to their peers, a concept known as *ex-post recognition* (Edmans et al. 2023). This expectation is particularly pronounced in highly competitive industries, where firms are more likely to offer higher compensation to retain top executives (Du et al. 2025), and variable compensation is normally used to address this need for *ex-post recognition*. Thus, we investigate whether the mixed findings in the prior literature are due to the unobserved determinants of executive compensation. To reach this goal, we use abnormal compensation (*ACOMP*, the difference between the predicted/expected total compensation based on known factors such as experience and other economic determinants, and the actual total compensation) and study the impact of analysts' forecasts on CEOs *ACOMP*. By focusing on *ACOMP*, we shed light on the impact of unobservable factors, including analyst assessments, that influence how compensation aligns with CEO effort and shareholder value. Analysts are expected to reduce information asymmetry and monitor firms. If governance committees and investors value these forecasts, we should observe a negative relationship between analyst forecast metrics and CEOs *ACOMP*.

Thus, we examine whether analysts, as key information intermediaries and external monitors, play an unobserved role in determining CEO compensation. Analysts are expected to possess superior insights into firms and, through their earnings forecasts and other disclosures, significantly influence investor decisions and, consequently, stock prices (Frankel et al. 2006; Wiersema and Zhang 2011). If analysts' information reflects these unobserved factors, we contend that it will also impact CEOs *ACOMP*. To investigate this assertion, we focus on the impact of analysts' one-year ahead earnings forecasts related metrics. Our sample is publicly listed firms in the United States (U.S.) from 1992 to 2022. We measure the *ACOMP* of CEOs using the difference between their actual total compensation and expected total compensation estimated following Core et al. (2008). For the information issued by analysts, we use four metrics, specifically, Analysts' Earnings Forecast Error (*FEEPS*), Dispersion of Earnings Forecasts (*DISP*), Earnings Forecast Walk Downs (*WLKDN*), and Negative Earnings Surprise (*NSURP*).

Our results provide persistent and strong evidence that *FEEPS*, *DISP*, *WLKDN*, and *NSURP* are negatively associated with CEOs' *ACOMP*. This evidence indicates that CEOs receive higher variable pay when analysts' earnings forecast error is lower, there are fewer walkdowns, lower dispersion, and fewer negative earnings surprises. We find that a one-standard deviation increase in *FEEPS*, *DISP*, *WLKDN*, and *NSURP* is associated with a decrease of around 1.76%, 1.41%, 0.07%, and 1.90% in *ACOMP*, respectively. To address potential concerns of endogeneity, we first apply entropy balancing to correct for any self-selection bias. Next, we incorporate firm-fixed effects in our regression models to control for the influence of time-invariant omitted variables. Additionally, we employ two-stage least squares (2SLS) regression to further mitigate issues related to omitted variable bias and reverse causality. Finally, we conduct Oster's (2019) coefficient sensitivity test, which addresses concerns around time-varying omitted variables. Collectively, these approaches support the robustness of our results, confirming that our findings remain qualitatively consistent. The negative relation between analysts' unfavourable metrics and CEOs' *ACOMP* is in line with the prediction of *agency theory* and the *information asymmetry hypothesis*. This also indicates that analysts are indeed a proxy for unobserved characteristics that affect CEOs' *ACOMP*.

Next, we examine the role of external monitoring mechanisms in driving this negative association. Understanding the impact of these monitoring mechanisms on CEOs' compensation can help boards and governance committees design more effective incentive structures, ensuring that compensation is truly aligned with managerial performance. We consider four proxies: (i) the *Takeover Index* (Cain et al. 2017), (ii) corporate governance scores (*CGOV Score*), (iii) firm-level political risk (*FLPR*) (Hassan et al. 2019), and (iv) institutional investor ownership (*IO*). Firms with strong governance provide more transparency, leading to better monitoring and more accurate analyst forecasts, helping reduce agency costs (Adut et al. 2011; Yu 2010). Additionally, firms with higher takeover likelihood, political risk, and institutional ownership face greater analyst scrutiny (Cain et al. 2017; Gupta et al. 2024). Empirical results show that the impact of analysts' forecasts on CEOs *ACOMP* is statistically significant only in firms with strong external monitoring, i.e., firms with high *Takeover Index*, *CGOV Score*, *FLPR*, and *IO*. This indicates that CEOs need to uphold stronger disclosure practices to effectively manage analyst expectations and prevent reductions in their compensation.

Overall, our contribution adds clarity to the previous inconclusive findings on the impact of analysts' information on CEOs' compensation by demonstrating a consistent negative relationship between analyst forecast metrics and CEOs' *ACOMP*. This aligns with the *interest alignment effect* in *agency theory*, where firms can align managers' interests with those of shareholders by designing effective compensation contracts. For practitioners and boards, our study offers valuable insights, as prior research provides limited guidance on creating CEO compensation metrics based on analysts' data. Additionally, we find that this negative association between CEOs' *ACOMP* and unfavourable analyst forecasts is driven by firms with stronger external monitoring mechanisms, where analysts play a significant role in shaping CEO pay as key stakeholders. Overall, this evidence is valuable for practitioners in designing compensation structures that drive CEO performance and align executive behaviour with shareholder interests.

2 Theory and hypothesis development

2.1 Role of financial analysts in mitigating agency costs

Information asymmetry between firms and shareholders is a persistent challenge, making it difficult to accurately evaluate both financial performance and CEO efforts. *Agency theory* suggests that firms could mitigate such issues by using efficient compensation contracts that align executives' interests with those of shareholders (Jensen and Meckling 1976). Effective contracts depend on how well shareholders and managers can observe managerial efforts together. If these efforts are observable, either directly or indirectly, this represents an ideal "*first-best contract*" (Scott 2015). Such a contract is an ideal arrangement where both shareholders and managers have complete information about managerial efforts, enabling perfect alignment of incentives.

However, in practice, achieving such contracts is nearly impossible due to the complexities and hidden nature of managerial activities. Shareholders, especially when ownership is dispersed, may lack the ability to monitor executive behaviour closely. Additionally, performance measures such as net income, may not be fully informative about managerial efforts, due to factors like bias from weak internal controls and recognition lags (Scott 2015).[2] Such a situation further leads to information asymmetry. Holmström (1979), in an extension of the agency model, suggests that the efficiency of compensation contracts can be improved by incorporating additional information about the agent's action, which could be observed by both managers and the board, that conveys information about the managerial effort.

As information intermediaries, analysts evaluate and predict firm performance over a given period to provide investors and shareholders with more accurate and efficient information (Chava et al. 2010). Their assessments are jointly observable, and the information goes beyond just current earnings. Analysts reduce information asymmetry by providing accurate earnings forecasts, thereby helping align managerial actions with shareholder expectations (Bednar et al. 2015; Park et al. 2017). Beyond their role in disseminating information, analysts also serve as key external monitors. Analysts exercise monitoring through direct and indirect mechanisms (Benlemlih et al. 2024). Directly, they could request specific information from managers during the conference call. Indirectly, they influence corporate transparency by publicly expressing concerns through media channels. Experienced analysts with professional knowledge and a better understanding of firms' operation strategies are likely to incorporate firms' information and evaluate the forward-looking financial performance more precisely, and hence, monitor firms more effectively (Jung et al. 2012; Yu, 2008). Analysts are suggested to play a particularly impactful role in firms with relatively weak regulatory oversight, serving as a crucial alternative to traditional monitoring mechanisms (Jing et al. 2024). Thus, analysts' evaluations provide an independent assessment that can be crucial in evaluating the CEO's performance when direct monitoring is impractical.

2.2 Impact of analysts' forecast on *ACOMP* of CEOs

According to the *agency theory*, the information analysts provide is jointly observable and conveys information about manager effort, which should be linked to the firm's value. To avoid negative earnings surprises, one of the primary financial performance benchmarks of firms is to see whether executives meet or beat analysts' earnings forecast consensus. In addition, a superior disclosure environment, which reflects the manager's effort, increases analyst forecast accuracy and decreases dispersion (Taylor and Koo 2015; Maaloul et al. 2016). Therefore, analysts' forecasts are expected to be an important factor in executives' efforts and performance evaluation.

Despite clear theoretical motivations, the prior literature reports mixed results on the association between the quality of analysts' forecasts and executive compensation levels. A few studies find that executives with higher stock option compensation may undertake higher risk to improve firms' short-term performance, leading to opportunistic behaviour,

[2] For example, the results of current R&D expenditures may not be reflected in current earnings.

which increases the information complexity and, thus, the forecast error (Kanagaretnam et al. 2012; Liu 2017). Managers may strategically postpone the disclosure of bad news due to compensation and career concerns, increasing information asymmetry and complicating analysts' ability to generate accurate forecast (Yin et al. 2024). In addition, Huang and Boateng (2017) find that high executive cash compensation is associated with high forecast error and dispersion. Contrary to the *agency theory*, this implies that CEOs are incentivized to make firms riskier. While in line with the *agency theory*, Hui and Matsunaga (2015) and Mamatzakis and Bagntasarian (2020) show that forecast error is negatively associated with CEOs' bonuses, total compensation, and cash bonuses.

The mixed results could stem from inadequacies in the design of compensation contracts, such as insufficient *consumption incentives* or a lack of *ex-post recognition*. It is argued that CEOs will only enhance firm value if the personal utility they derive from their pay increment exceeds the effort they must exert (Edmans et al. 2023). In some cases, rather than seeking additional financial incentives set in the contract for personal consumption, certain CEOs may be more motivated by *ex-post recognition* for their achievements (Edmans et al. 2023). Moreover, the value of such recognition is particularly pronounced in highly competitive labour and product markets, where a CEO's personal attributes significantly influence compensation and perceived value (Du et al. 2025). This recognition is often linked to variable pay components, which require discretionary board decisions and are subject to shareholder approval. *Ex-post recognition* not only signals a CEO's efforts but also enhances their reputation among external stakeholders.

ACOMP represents the abnormal compensation component of a CEO's pay. That is, the portion that exceeds what would be expected based on observable factors (Core et al. 2008). It indicates the variable portion of total compensation that is not economically justifiable (Guest et al. 2022). Executives' total compensation is designed by firms and boards to optimise the structure of the pay package and align CEOs' interests with firms' interests (Conyon et al. 2009). However, it's hard to define a generally acceptable compensation level in practice. Therefore, variable pay becomes important to allow for necessary adjustments. For example, firms may use variable pay proportion as a form of *ex-recognition* to motivate CEOs. Based on the *agency theory* and *information asymmetry* hypothesis, due to the difficulty of monitoring CEOs directly, analysts serve as a bridge to gather, process, and convey important information about firm performance, thus reducing the asymmetry between managers and shareholders. With fewer analysts monitoring, the consequences of misbehaviour across various areas, including environmental practices (Jing et al. 2024), may receive less scrutiny, leading firms to loosen internal corporate governance mechanisms, such as compensation contracts. Therefore, the jointly observable forecasts issued by analysts assess firms' financial performance and may be associated with CEOs' *ACOMP*.

Disclosure quality, as part of a CEO's managerial effort, also plays a key role in their compensation (Scott 2015). CEOs often receive positive recognition and build a reputation of transparency through greater disclosure, attracting more attention from investors (Marquez-Illescas and Zhou 2023). High-quality disclosure not only reduces the firm's cost of capital (Hui and Matsunaga 2015) but also attracts external cash flows (Biddle and Hilary 2006). This improvement in the disclosure environment leads to more accurate and reliable analyst forecasts, characterised by lower forecast error and dispersion (Taylor and Koo 2015; Maaloul et al. 2016). Conversely, managerial behaviours that decrease disclosure quality, such as reducing the firm's news timeliness, may lead to biased analyst forecasts

(Yin et al. 2024). Consequently, lower forecast error and dispersion signal better disclosure quality and reflect the CEO's effort to improve transparency.

In some cases, analysts can identify and signal potential issues such as fraud or high levels of information asymmetry through downgraded earnings forecasts, which external stakeholders perceive as red flags (He et al. 2020). Considering the cost of disclosure quality, managers also forgo manipulative activities for their own benefit. Cheng and Lo (2006) show that managers must avoid indulging in insider trading, which increases the value of their option-based incentives to provide better disclosure quality. CEOs with positive traits, such as high conscientiousness and agreeableness, are more likely to reduce information asymmetry and are subsequently rewarded with higher compensation (Du et al. 2025). Hence, firms' financial disclosure quality is an indicator of executives' abilities to enhance firm performance and value (Chang et al. 2010). More accurate forecasts suggest that CEOs invest considerable effort into providing high-quality information to reduce information asymmetry (Byard et al. 2006), leading to increased variable pay (i.e., *ACOMP*) as a reward.

Based on the above discussions, we predict a negative association between analysts' forecast metrics (*FEEPS*, *DISP*, *WLKDN*, and *NSURP*) and CEOs' *ACOMP*. Therefore, we expect CEOs' *ACOMP* to be higher if the forecast error is lower; there is less dispersion, fewer walkdowns, and fewer negative earnings surprises. Thus, our hypothesis is the following:

> H1: Analysts' earnings forecast metrics (FEEPS, DISP, WLKDN, and NSURP) are negatively associated with CEOs' ACOMP.

2.3 External monitoring mechanisms, analysts' metrics, and *ACOMP* of CEOs

Monitoring mechanisms are generally applied to align the interests of top executives with those of shareholders. Corporate governance has been suggested as the most prevalent mechanism for aligning the interests of shareholders and CEOs (Sauerwald et al. 2019; Anderson et al. 2009). In firms with weak corporate governance, CEOs can use their considerable organisational power to pursue personal interests (Brahma and Economou 2024), potentially exploiting information asymmetries and managerial discretion at the expense of shareholder value. Conversely, strong monitoring mechanisms promote transparency, reduce managerial discretion, and improve the quality of analysts' forecasts (Liu et al. 2024). This, in turn, helps decrease information asymmetry between firms and investors (Burgstahler and Eames 2006; Adut et al. 2011; El Diri et al. 2020; Elyasiani et al. 2017). Thus, we expect that the relationship between analysts' forecasts and *ACOMP* will be stronger in firms with robust external monitoring mechanisms. In summary, improved forecast quality due to stronger monitoring mechanisms ensures that CEO compensation more accurately reflects managerial effort and performance, hence influencing *ACOMP*.

We employ four proxies for external monitoring mechanisms. First, the *Takeover index* is an important disciplinary mechanism as it indicates the threat of a hostile takeover, which motivates managers to align their actions with shareholder interests (Cain et al. 2017). This aligns with prior evidence suggesting that the threat of a takeover disciplines managerial behaviour and aligns executive incentives with shareholder interests (Aktas et al. 2016). Firms with a higher *Takeover Index* face higher monitoring than their peers (Cain et al. 2017). Second, the *CGOV Score* is the corporate governance score from Refinitiv's database, which encompasses aspects such as board independence, shareholder rights, and transparency, reflecting the overall strength of a firm's governance practices. A higher value of *CGOV Score* indicates stronger monitoring. Third, we use firm-level political risk (*FLPR*) from Hassan et al. (2019) as it is considered one of the major risk factors faced by managers, and firms exposed to higher *FLPR* are likely to be under greater scrutiny by external stakeholders (Gupta et al. 2024). Finally, we use institutional investor ownership (*IO*), as institutional investors are key external monitors who often advocate for governance improvements and can exert significant influence over managerial decisions (Elyasiani et al. 2017). Together, given that stronger external monitoring mechanisms enhance transparency and limit managerial discretion, we posit that these mechanisms amplify the impact of analysts' forecasts on CEOs' *ACOMP*. As a result, we propose the following hypotheses:

> H2: Stronger external monitoring mechanisms drive the negative association between analysts' earnings forecast metrics and CEOs' ACOMP.

3 Data, covariates and descriptive statistics

Our sample includes all non-financial listed firms in the United States (U.S.) with available data for CEOs' compensation from ExecuComp, analysts' earnings forecast data from Institutional Brokers Estimate System (I/B/E/S), accounting data from Compustat, and stock return data from CRSP. The sample period covers fiscal years 1992 to 2022. We exclude firms in regulated industries (SIC codes between 4400 and 5000), banks, and financial institutions (SIC codes between 6000 and 6500) from our sample. Moreover, we restrict our sample to those firms that report a positive book value. We also exclude observations that have missing SIC codes, missing or negative total assets, and firms that are not incorporated in the U.S.[3]

3.1 Measurement of *ACOMP*

Following prior literature (Core et al. 2008; Robinson et al. 2011; Alissa 2015), we first estimate *Expected Compensation* by regressing the log of CEOs' total compensation on several proxies for economic determinants in a given year and industry, as follows:

$$\begin{aligned} Log\left(Total\ Compensation_{i,t}\right) = \beta_0 + \beta_1 Log\left(Tenure_{i,t}\right) + \beta_2\left(S\&P500_{i,t-1}\right) \\ + \beta_3 Log\left(Sales_{i,t-1}\right) + \beta_4\left(BM_{i,t-1}\right) + \beta_5\left(RET_{i,t}\right) \\ + \beta_6\left(RET_{i,t-1}\right) + \beta_7\left(ROA_{i,t}\right) + \beta_8\left(ROA_{i,t-1}\right) + u_{i,t} \end{aligned} \tag{1}$$

where i indexes firm and t indexes year. We include fixed effects for year and 2-digit SIC codes in the above OLS model.

We separate the CEO's total compensation into two parts: the *Expected Compensation* estimated from Eq. (1),[4] and the *ACOMP* (the residual from Eq. (1)). We estimate the *ACOMP* as:

[3] Identified as FIC with value of "USA" in Compustat database.

[4] We estimate *Expected Compensation* by exponentiating the expected value of Eq. (1).

$$ACOMP_{i,\,t} = Total\,Compensation_{i,\,t} - Expected\,Compensation_{i,\,t} \tag{2}$$

3.2 Analysts' earnings forecasts metrics

We use four metrics related to analysts' earnings forecasts: *FEEPS*, *WLKDN*, *DISP*, and *NSURP*, which are common metrics used in prior literature (Doyle et al. 2006; Hui and Matsunaga 2015; Lang 2016). Unlike prior studies, we focus on the first forecasts issued within the first three-month window of the forecast period end date, as these are the ones which are one-year forecasts in the true sense.[5] Our first metric, the forecast error, is calculated as follows:

$$FEEPS_{i,\,t} = \left| \frac{(Consensus\,Forecast_{\,i,\,t} \; - Actual\,Value_{i,\,t})}{Price_{i,t-1}} \right| \tag{3}$$

where i indexes firm and t indexes year, $Consensus\,Forecast_{\,i,\,t}$ is the mean of the first forecast of each analyst for each firm in the fiscal year, and $Actual\,Value_{i,\,t}$ is the announced earnings per share (*EPS*).[6]

The second metric we use is analysts' *EPS* forecast *Walk Down (WLKDN)*. Analysts are often alleged to be involved in "games of nods and winks".[7] They may issue optimistic earnings forecasts at the start and then "walk down" their estimation to a lower level, which may be due to the unpleasant performance of the firm during the fiscal period or the cooperative game between analysts and managers (Lang 2016). In both cases, the *WLKDN* of analysts' forecasts indicates the relatively weak financial performance in the future and a related pessimistic estimation of CEOs' ability and effort to meet the initial forecast. Therefore, it is expected to be negatively correlated to CEO's *ACOMP*. In other words, the more the extent of analysts' *WLKDN*, the less excessive pay CEOs would receive.

We calculate the *WLKDN* as the following:

$$WLKDN_{i,t} = \frac{(First\,Forecast_{i,\,t} \; - Last\,Forecast_{i,\,t})}{Total\,Assets_{i,t-1}} \times 1000 \tag{4}$$

[5] In I/B/E/S database, the Forecast Period End Date (FPEDATS) correspond to the financial year-end date of the corresponding firms. For example, if FY0 corresponds to December 2017 (the last reported annual), the FY1, FY2 and FY3 mean estimates are for the periods ending December 2018, 2019, and 2020, respectively. In this study, we focus only on FY1, the 1 st one-year ahead forecast issued by the analyst. Further, for the same firms, 1 st forecast announcement dates are different for different analysts for the same FPEDATS, and many analysts issue 1 st forecast just 3 months before the FPEDATS. It's inappropriate to include such forecasts, as it's like looking at the dark clouds and predicting rain. Thus, to keep the forecasts true to the one-year horizon, we include only those analysts who issue the 1 st forecast within the first 90 days, i.e., we consider only those 1 st forecasts where the difference between the FPEDATS and the forecast announcement date (ANNDATA) is ≥ 275 and ≤ 365 days.

[6] Analysts may revise their forecasts several times before the firm's earnings announcement date, and the closer to the firm's announcement date, the more accurate the EPS forecast. We use the variable of *WLKDN* to evaluate such behaviour.

[7] Arthur Levitt characterised the behaviour that analysts may walk down their initial earnings forecasts so that managers can meet or beat these targets as "games of nods and winks" in his 1998 speech at the New York University.

where $First\ Forecast_{i,\,t}$ is the mean of analysts' first EPS forecast for each firm in the fiscal year, $Last\ Forecast_{i,\,t}$ is the mean of analysts' last *EPS* forecast for each firm in the fiscal year.

The third metric we use is analysts' *EPS forecast Dispersion (DISP*), which is defined as the standard deviation of firms' earnings forecasts during a fiscal year and is also deflated by the stock price at the beginning of the fiscal year. The final metric we use is a dummy variable *NSURP*, which equals one if the earnings surprise (*SURP*) is negative, and zero otherwise. We compute *SURP* as the difference between firms' actual *EPS* and the median of analysts' *EPS* forecast, scaled by the stock price at the beginning of the fiscal year.

3.3 Measures of external monitoring mechanisms

We use *Takeover Index*, *CGOV Score*, firm-level political risk (*FLPR*) and Institutional Ownership (*IO*) to proxy a firm's external monitoring environment. Following Cain et al. (2017), the firm-level *Takeover Index* indicates the hostile takeover hazard and susceptibility to takeovers. Corporate governance score, *CGOV Score*, is obtained from the Refinitiv database. *FLPR* data is obtained from Hassan et al. (2019). Our annual measure of *FLPR* for a given firm-year observation is calculated using the average of four quarters of political risk.[8] *IO* data is obtained from Thomson Reuters 13 F.

3.4 Measurement of control variables

Besides the variables of primary interest discussed above, we include several firm-level control variables in our multivariate regression models. Consistent with prior studies, we include firm-level control variables: *Leverage (LVG)*, *SIZE*, *Research and Development Expenditure (RDEXP)*, *Advertising Expense (ADEXP)*, *Total Q (TQ)*, and *Volatility (VOL)* (see Chaney et al. 2011; Zang 2012; Dah and Frye 2017). Appendix Table 8 lists and explains all variables used in our empirical analyses. We also include industry (2-digit SIC codes) and year dummies to control for the industry and time-specific fixed effects.

3.5 Descriptive statistics

We report descriptive statistics of all main variables used in this study in Table 1. All continuous variables are winsorized at their 1 st and 99th percentiles. Column (1) shows the list of variables used in our subsequent regression models. The mean and standard deviation of all variables, as shown in Columns (2) and (3), are as expected with no extreme values and comparable to the previous literature, with some differences in reasonable range due to the variations in the sample (Core et al. 2008; Bugeja et al. 2016; Dah and Frye 2017).

ACOMP has a mean close to zero, with a value of -0.003. The mean of *FEEPS* is 0.035, and the mean of *WLKDN* is 0.150. The positive value of *WLKDN* suggests analysts on average initially issue optimistic forecasts and then adjust their forecasts downwards to reflect the firm's true performance. The mean of *NSURP* is 0.491, implying that analysts issue relatively optimistic forecasts roughly 50% of the time. We also examined the correlations among these variables and found that all key variables exhibit low to moderate correlations with one another, as reported in Appendix Table 9.

[8] We do this because the *FLPR* data obtained from Hassan et al. (2019) is quarterly instead of annual.

Table 1 Summary statistics

Variables	Mean	Standard Deviation	Median	Minimum	Maximum
(1)	(2)	(3)	(4)	(5)	(6)
ACOMP	–0.003	0.620	0.000	–4.960	3.541
FEESP	0.035	0.114	0.007	0.000	0.943
DISP	0.010	0.035	0.002	0.000	0.291
WLKDN	0.150	1.228	0.001	–4.505	7.437
NSURP	0.491	0.500	0.000	0.000	1.000
LEV	0.230	0.198	0.211	0.000	1.019
SIZE	7.194	1.589	7.109	1.233	10.561
RDEXP	0.042	0.074	0.005	0.000	0.409
ADEXP	0.015	0.035	0.000	0.000	0.209
TQ	1.596	2.329	0.902	–0.306	15.737
VOL	0.438	0.218	0.384	0.150	1.256

This table reports summary statistics for all variables used in the multivariate analysis. All variables are winsorized at their 1 st and 99th percentiles. The sample is based on the annual data of non-financial U.S. firms from 1992 to 2022

4 Empirical results and discussions

4.1 Empirical model

To investigate the effects of analysts' forecasts on CEOs' *ACOMP*, we construct our baseline regression model as the following:

$$\begin{aligned} ACOMP_{i,t} = \beta_0 + \ & \beta_1 Analyst\ Forecast\ Metrics_{i,t-1} + \beta_2 LVG_{i,\,t-1} \\ & + \beta_3 SIZE_{i,\,t-1} + \beta_4 RDEXP_{i,\,t-1} + \beta_5 ADEXP_{i,\,t-1} + \beta_6 TQ_{i,\,t-1} \\ & + \beta_7 VOL_{i,\,t} + Year_t + Industry_j + u_{i,t} \end{aligned} \tag{5}$$

where *i* indexes firm, *t* indexes year, and *j* indexes the industry group classified by 2-digit SIC code. $Analyst\ Forecast\ Metrics$ are the earnings forecast-related variables, including *FEEPS*, *WLKDN*, *DISP*, and *NSURP*. All $Analyst\ Forecast$ variables are lagged by one year because their effect on CEOs' *ACOMP* is expected to be reflected one year after the earnings announcement date. $Year_t$ indicates year fixed effects, and $Industry_j$ indicates industry-fixed effects based on 2-digit SIC codes. We estimate the regression models using pooled cross-section OLS with standard errors clustered at the firm level.

4.2 Effect of analysts' forecast on CEOs' *ACOMP* (Test of H1)

We start by examining the relation between analysts' earnings forecast metrics and *ACOMP.* Empirical results in support of H1 are reported in Table 2. Table 2 presents the main regression result with different analysts' metrics using Eq. (5). In Columns (2) to (5), we report the effect of *FEEPS*, *DISP*, *WLKDN*, and *NSURP* on *ACOMP*, respectively.

We expect CEOs' *ACOMP* to be negatively associated with *FEEPS*, *DISP*, *WLKDN*, and *NSURP*, and we find strong support for our hypothesis, H1. Column (2) shows that the estimated coefficient of *FEEPS* is negative and significant at the 1% level, suggesting that CEOs receive less *ACOMP* when *FEEPS* increases. In addition, we measure the economic

Table 2 Multivariate regressions of ACOMP

Variables	*ACOMP*			
(1)	(2)	(3)	(4)	(5)
FEEPS	–0.154***			
	(–2.973)			
DISP		–0.402**		
		(–2.287)		
WLKDN			–0.006**	
			(–1.992)	
NSURP				–0.038***
				(–4.323)
LEV	0.108**	0.121***	0.106**	0.103**
	(2.570)	(2.817)	(2.381)	(2.449)
SIZE	0.028***	0.022**	0.024***	0.028***
	(3.434)	(2.542)	(2.968)	(3.438)
RDEXP	0.869***	0.870***	0.852***	0.853***
	(5.701)	(5.495)	(5.462)	(5.561)
ADEXP	–0.388	–0.482*	–0.391	–0.397
	(–1.493)	(–1.789)	(–1.501)	(–1.528)
TQ	–0.001	0.001	–0.000	–0.001
	(–0.129)	(0.221)	(–0.283)	(–0.271)
VOL	0.034	0.031	0.005	0.018
	(0.923)	(0.819)	(0.145)	(0.486)
Constant	–0.255***	–0.209***	–0.223***	–0.231***
	(–3.906)	(–2.984)	(–3.518)	(–3.495)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	30,369	27,945	30,369	30,369
Ad. R–squared	0.010	0.009	0.009	0.010

This table presents multivariate regression estimates, with *ACOMP* as the dependent variable and the variable of interest, analysts' earnings forecast error (*FEEPS*), analysts' earnings forecast dispersion (*DISP*), analysts' walk down of earnings forecast (*WLKDN*), and a dummy variable indicating the negative forecast surprise (*NSURP*). The sample is based on the annual data of non-financial U.S. firms from 1992 to 2022. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively

significance of a variable by multiplying its standard deviation with its regression coefficient.[9] We find that the effect of *FEEPS* on *ACOMP* is economically significant. The estimated coefficient in Column (2) indicates that a one-standard deviation increase in *FEEPS* reduces CEOs' *ACOMP* by 1.76% (–0.154 × 0.114).

We also find significantly negative coefficients of *DISP*, *WLKDN*, and *NSURP* at the 5% level, 5% level, and 1% level, respectively (see Columns (3) to (5)). The regression estimate suggests that when there is one standard deviation increase in *DISP*, *WLKDN*, and *NSURP* from the mean, the expected decrease in *ACOMP* is 1.41% (–0.402 × 0.035), 0.07%

[9] If a regressor X is normally distributed, replacing x with its standardised counterpart [x-mean(x)]/std(x) in the regression results in a new coefficient estimate that equals the original estimated x multiplied by its standard deviation, without changing its statistical significance. Based on this, it is common to measure economic significance of a variable in terms of a one standard deviation change in that variable, i.e. coefficient(x)×std(x).

(–0.006 × 1.228) and 1.90% (–0.038 × 0.500), respectively. Therefore, as predicted by H1, *ACOMP* is likely to decrease when the accuracy of earnings forecasts and related metrics decline or show unfavourable trends.

4.3 Mitigating endogeneity concern

Endogeneity in regression-based empirical research may arise due to four issues: self-selection, reverse causality, omitted variables, and measurement error (Hill et al. 2021; Roberts and Whited, 2013). Measurement error is not an issue in our context, as the measurement of all independent variables follows widely accepted practices, minimising the likelihood of any bias created in measuring independent variables. Therefore, we perform tests addressing endogeneity concerns arising from sample selection bias, reverse causality, and omitted variables.

4.3.1 Entropy balancing approach

Firms in our sample have different firm-specific attributes, which may lead to an imbalance in covariates and selection bias (McMullin and Schonberger 2020). We re-estimate our baseline model by employing an entropy balancing approach, considering the potential sample selection bias problem. Entropy balancing is a preprocessing method that achieves balance in covariates between treated and untreated groups (Hainmueller 2012). This approach addresses systematic differences in firm-level characteristics between treatment and control groups by reweighting the sample, ensuring that the distributions (mean, variance, and skewness) of control variables are nearly identical across groups (Hainmueller 2012). Compared to other adjustment techniques, e.g., propensity score matching, entropy balancing focuses on covariates balance directly. This advanced approach has been adopted by several recent studies (e.g., McMullin and Schonberger, 2020; Chino 2021).

Table 3 Presents the regression results from the sample matched by the entropy balancing method. We separate our sample into treatment and control groups based on the median of *FEEPS*, *DISP*, *WLKDN*, and *NSURP* in a given year and industry.[10] We match on following control variables, namely, *SIZE*, *RDEXP*, *ADEXP*, *TQ*, and *VOL*. Consistent with our baseline regression results, we find that *FEEPS*, *WLKDN*, *DISP*, and *NSURP* still have a negative effect on *ACOMP*. Thus, our baseline results reported in Table 2 are robust to sample selection bias.

4.3.2 Firm-fixed effects model

To address the concern of omitted variable bias due to time-invariant omitted variables, we re-estimate our baseline model by including firm and year-fixed effects. Table 4 reports the results. Similar to the main results reported in Table 2, the coefficients of the variables of interest, *FEEPS*, *WLKDN*, *DISP*, and *NSURP* are negatively and statistically significant at conventional levels. This confirms that our findings do not suffer from endogeneity arising due to time-invariant omitted variables.

[10] Appendix Table 10 Presents treatment and control samples' mean, variance, and skewness before and after entropy balancing.

Table 3 Multivariate Regressions of ACOMP with Entropy Balancing Weights

Variables	*ACOMP*			
(1)	(2)	(3)	(4)	(5)
FEEPS	–0.147**			
	(–2.220)			
DISP		–0.418**		
		(–2.106)		
WLKDN			–0.007**	
			(–1.985)	
NSURP				–0.033***
				(–3.914)
LEV	0.079**	0.071	0.063	0.072*
	(2.073)	(1.576)	(1.546)	(1.849)
SIZE	0.042***	0.037***	0.033***	0.030***
	(6.670)	(5.547)	(4.751)	(4.692)
RDEXP	0.703***	0.752***	0.758***	0.777***
	(5.222)	(4.760)	(5.194)	(5.184)
ADEXP	–0.418	–0.410	–0.489*	–0.451*
	(–1.551)	(–1.514)	(–1.908)	(–1.782)
TQ	0.009*	0.000	–0.000	0.001
	(1.948)	(0.061)	(–0.407)	(0.294)
VOL	0.036	0.050	0.027	–0.022
	(0.892)	(1.053)	(0.726)	(–0.611)
Constant	–0.359***	–0.320***	–0.282***	–0.228***
	(–6.678)	(–5.456)	(–5.042)	(–4.186)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	29,719	27,319	29,673	28,719
Ad. R–squared	0.015	0.012	0.009	0.009

This table presents multivariate regression with entropy balancing weights. The regression model employs *ACOMP* as the dependent variable and the variable of interest, analysts' earnings forecast error (*FEEPS*), analysts' earnings forecast dispersion (*DISP*), analysts' walk down of earnings forecast (*WLKDN*), and a dummy variable indicating the negative forecast surprise (*NSURP*). The sample is based on the annual data of non-financial U.S. firms from 1992 to 2022. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively

4.3.3 Instrumental variables regression

We propose that the idiosyncrasies of the CEOs' compensation may be endogenous to firm behaviour, thereby influencing analysts' forecasts. In addition, omitted variable bias remains a concern despite the inclusion of multiple firm-specific controls. Therefore, we use the instrumental variable (IV) regression method to address the above endogeneity. We employ the jack-knife method to construct our instrument variables following Acemoglu et al. (2019). Our instrumental variables are calculated as the mean of the respective variable in a given year, industry, and firm size group *(FSG)*, excluding the firm itself. Using firms' market values, we generate the categorical variable *FSG* by classifying our sample into large (top 1/3rd percentile), medium (middle 1/3rd percentile), and small (bottom 1/3rd percentile) firms' subgroups.

Table 4 Multivariate regressions of ACOMP with firm fixed effect

Variables	*ACOMP*			
(1)	(2)	(3)	(4)	(5)
FEEPS	–0.105**			
	(–2.117)			
DISP		–0.565***		
		(–3.026)		
WLKDN			–0.014***	
			(–4.493)	
NSURP				–0.014**
				(–2.109)
LEV	–0.082**	–0.057	–0.110***	–0.084**
	(–2.036)	(–1.381)	(–2.908)	(–2.082)
SIZE	0.030***	0.022*	0.040***	0.031***
	(2.617)	(1.890)	(3.956)	(2.731)
RDEXP	–0.493**	–0.419**	–0.448**	–0.492**
	(–2.512)	(–2.029)	(–2.559)	(–2.502)
ADEXP	0.025	0.056	0.128	0.024
	(0.084)	(0.182)	(0.421)	(0.082)
TQ	0.001	0.001	0.000*	0.001
	(0.189)	(0.215)	(1.786)	(0.120)
VOL	–0.053*	–0.051	–0.062**	–0.058*
	(–1.652)	(–1.497)	(–2.024)	(–1.819)
Constant	–0.143*	–0.089	–0.213***	–0.146*
	(–1.672)	(–0.986)	(–2.760)	(–1.707)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	30,231	27,775	30,231	30,231
Ad. R–squared	0.339	0.335	0.325	0.339

This table presents multivariate regression with firm and year-fixed effects. The regression model employs *ACOMP* as the dependent variable and the variable of interest, analysts' earnings forecast error (*FEEPS*), analysts' earnings forecast dispersion (*DISP*), analysts' walk down of earnings forecast (*WLKDN*), and a dummy variable indicating the negative forecast surprise (*NSURP*). The sample is based on the annual data of non-financial U.S. firms from 1992 to 2022. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively

Table 5 reports the results. First, we find that the magnitudes of Wald F-statistics in all specifications are higher than the standard threshold of 10, indicating that the instrumental variable is not weakly correlated with the endogenous regressors. Additionally, the magnitudes of Kleibergen-Paap Rk LM tests suggest that the structural equation is not underidentified. With a p-value of <0.01, this test suggests a correlation between the instrument and endogenous variables. Columns (6) to (9) in Table 5 show that the results with instrumental variables are consistent with our baseline model in Table 2. We find that the coefficients of *FEEPS*, *DISP*, *WLKDN*, and *NSURP* remain negative and significant. This further supports that our findings are robust to endogeneity concerns. Overall, the tests indicate that our instrumental variable Meets the relevant criterion for the validity of an instrumental variable. And our findings are robust to reverse causality and omitted variable bias concerns.

Table 5 Multivariate regressions of abnormal compensation – Instrumental variables

Variables	*ACOMP*							
	First Stage				2SLS			
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FEEPS	0.119***				–3.007***			
	(3.780)				(–2.740)			
DISP		0.170***				–7.242***		
		(3.751)				(–2.610)		
WLKDN			0.240***				–0.087***	
			(9.642)				(–2.587)	
NSURP				0.117***				–0.192**
				(18.412)				(–2.527)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleiber-gen-Paap rk Wald F statistic	–	–	–	–	14.267	14.098	92.994	339.009
Kleiber-gen-Paap rk LM statistic	–	–	–	–	14.101***	14.201***	108.620***	278.776***
Observa-tions	29,604	27,098	29,604	26,299	29,604	27,098	29,604	26,299
Centered R-squared	–	–	–	–	–0.224	–0.114	–0.013	–0.003

This table presents the results employing the mean of the respective variable in a given year, industry and firm size, excluding the firm itself (jackknife average) as instrument variables. Column (2)–(5) reports the results of first-stage regression results. Column (6)–(9) reports the 2-stage least square (2SLS) regression results. The underidentification test (Kleibergen–Paap rk LM statistic) and the weak identification test (Kleibergen-Paap rk Wald F statistic) are reported. All variables are winsorised at their 1 st and 99th percentiles. The sample is based on the annual data of non-financial U.S. firms from 1992 to 2022. ***, **, * indicate significance at the 1, 5, and 10% level of a two-tailed *t*-test

4.3.4 Oster's coefficient stability test

While we employ models with firm fixed effects to address concerns related to time-invariant omitted variables, time-variant omitted variables may still persist. Additionally, fully accounting for all factors associated with CEOs' *ACOMP* may not be feasible. Thus, we use a coefficient sensitivity test proposed by Oster (2019) to further address the omitted variable bias concern. This test examines the robustness of OLS inferences to omitted variable bias, based on a proportional selection relationship between observable control variables and unobservable factors. For this purpose, Oster (2019) defines two parameters: the ratio of degree of selection on unobservables to observables (δ) and R-squared from a hypothetical regression of the outcome on the treatment and both observable and unobservable controls (R_{max}). If the coefficient of interest remains relatively stable (i.e., if magnitude of δ is substantially greater than one) when the R-squared from the baseline regression is increased

Table 6 Oster test for omitted variable bias

Variables		*ACOMP*			
	(1)	(2)	(3)	(4)	(5)
(1)	*FEESP*	–0.154***			
(2)	*DISP*		–0.402**		
(3)	*WLKDN*			–0.006**	
(4)	*NSURP*				–0.038***
(5)	R-squared	0.013	0.012	0.012	0.013
(6)	δ	1	1	1	1
(7)	$\mathrm{R_{max}} = 1.3 \times \mathrm{R^2_{baseline}}$	0.017	0.015	0.015	0.017
(8)	Bounds on Treatment effect	(–0.159, –0.154)	(–0.422, –0.402)	(–0.006, –0.006)	(–0.037, –0.038)
(9)	Treatment effect excludes 0	Yes	Yes	Yes	Yes
(10)	Oster's δ	7.056	3.907	–10.195	28.575
(11)	$\mid \delta \mid > 1$	Yes	Yes	Yes	Yes

This table reports the results of Oster's (2019) approach to estimate the robustness to omitted variable bias. Row (1) to (4) present the coefficient of *FEESP*, *DISP*, *WLKDN*, and *NSURP*. Row (5) reports R-squared estimated from our baseline multivariate regressions (We use Stata code regress instead of reghdfe in order to use psacalc. The coefficients are slightly different from Table 2, but results are qualitatively similar.). Row (6) and (7) present the assumption of δ and *Rmax*, we define *Rmax* as 1.3 times R-squared. Rows (8) and (9) report the bounds on the coefficient which is estimated using Stata code psacalc. Rows (10) and (11) report the value of δ. The sample is based on the annual data of non-financial U.S. firms from 1992 to 2022. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively

to $\mathrm{R_{max}}$, then we conclude that omitted variable bias is not strong enough to invalidate our findings.

Table 6 reports the results of this analysis. Rows (1) to (4) represent the coefficients of the *FEEPS*, *DISP*, *WLKDN*, and *NSURP*. Row (5) reports the R-squared from the multivariate baseline model results in Table 2.[11] Row (6) and (7) present the assumption of δ and $\mathrm{R_{max}}$. Following Oster (2019) δ is set to 1, and the $\mathrm{R_{max}}$ (i.e., the upper bound on R-squared) equals 1.3 times the R-squared from our baseline regression results. Then, we compute the bounds of treatment effects as $\left[\beta_{\mathrm{baseline}}, \ \beta \times \left(\min\left\{1.3 \times \mathrm{R^2_{baseline}}, \ 1\right\}, 1\right)\right]$ and check whether the interval excludes zero. Rows (8) and (9) present that there is very little movement in the respective coefficients, and the values exclude zero. This indicates that including unobservable control variables will not lead to a significant difference from our baseline results. Rows (10) and (11) present the estimated δ would be required to change the respective forecast-related metrics' coefficient equal to zero when R-squared is increased to $\mathrm{R_{max}}$. We find that the absolute value of δ is substantially greater than 1. As the magnitude of δ ranges between 3.907 to 28.575, it is highly unlikely that unobservable covariates would be 3.907 to 28.575 times more important than the observable covariates. Based on the recommendations of Oster (2019), we conclude that the unobservable covariates have less effect on the respective coefficients compared to observable covariates. These findings further support that our results are robust to omitted variable bias concerns.

Overall, the endogeneity tests reported above support the robustness of our main findings that CEOs' *ACOMP* is affected by analysts' forecasts. Specifically, a higher *FEEPS*, *DISP*, *WLKDN*, and *NSURP* lead to a lower *ACOMP*.

[11] We use Stata code regress instead of Reghdfe to use psacalc. The coefficients are slightly different from Table 1, but results are qualitatively unchanged.

4.4 Channel analyses (Test of H2)

In this section, we classify our sample into different sub-samples based on external monitoring metrics – *Takeover Index*, *CGOV Score*, *FLPR*, and *IO*. Specifically, firms above (below) the median level (in a given year and industry) of different proxies of monitoring mechanisms are classified as strong (weak) monitoring sub-samples.

Table 7 presents the results, showing that the findings from Table 2 are significant only for firms subject to strong external monitoring mechanisms. In firms with a high *Takeover index*, we observe a negative and significant association between analysts' forecast-related metrics and *ACOMP*, but not in firms with a low *Takeover index*. Specifically, the coefficients for *FEEPS*, *DISP*, *WLKDN*, and *NSURP* are negative and significant, with values of −0.216, −0.726, −0.019, and −0.052, respectively, while the coefficients for firms with a low *Takeover index* are insignificant. Similarly, for the *CGOV Score*, the estimated coefficients for *FEEPS*, *DISP*, *WLKDN*, and *NSURP* are negative and significant in the high subsample, with values of −0.124, −0.213, −0.007, and −0.041. The negative effect of analysts' forecast metrics is concentrated in firms with high *FLPR*, where the coefficients for *FEEPS*, *DISP*, *WLKDN*, and *NSURP* are also negative and significant, at −0.168, −0.384, −0.007, and −0.040, respectively. Finally, for *IO*, the results are consistent with previous observations, as the coefficients for *FEEPS*, *DISP*, *WLKDN*, and *NSURP* are negative and significant only in firms with high *IO*, with values of −0.183, −0.595, −0.009, and −0.037, respectively. Collectively, these findings suggest that the relationship between analysts' forecast metrics and *ACOMP* is predominantly driven by firms facing a high level of external monitoring.

Table 7 Channel analysis – External monitoring mechanisms

Variables	Low	High	Low	High
(1)	(2)	(3)	(5)	(6)
	Takeover Index		CGOV Score	
FEEPS	–0.066	–0.216**	–0.119	–0.124**
	(–0.893)	(–2.337)	(–0.682)	(–2.001)
DISP	–0.134	–0.726**	–0.556	–0.213***
	(–0.495)	(–2.131)	(–0.825)	(–3.004)
WLKDN	0.004	–0.019***	–0.000	–0.007*
	(0.795)	(–3.153)	(–0.030)	(–1.730)
NSURP	0.001	–0.052***	0.007	–0.041***
	(0.101)	(–4.035)	(0.517)	(–3.798)
	FLPR		*IO*	
FEEPS	–0.094	–0.168**	–0.169	–0.183***
	(–1.395)	(–2.195)	(–1.656)	(–3.077)
DISP	–0.247	–0.384***	–0.301	–0.595***
	(–1.150)	(–3.123)	(–1.016)	(–5.602)
WLKDN	–0.005	–0.007**	–0.001	–0.009**
	(–0.956)	(–2.097)	(–0.165)	(–2.508)
NSURP	–0.012	–0.040***	–0.003	–0.037***
	(–1.151)	(–2.857)	(–0.336)	(–3.610)

This table reports multivariate regression results of channel analysis. Our sample is classified based on four monitoring proxies: *Takeover Index*, *CGOV Score*, *FLPR*, and *IO*. The untabulated control variables retain their expected sign and significance. The sample is based on the annual data of non-financial U.S. firms from 1992 to 2022. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively

5 Additional tests

5.1 Correction when using regression residuals as dependent variables

Using regression residuals derived from an OLS regression as the dependent variable in the second stage may cause potential Type I and Type II classification errors (Chen et al. 2018).[12] They argue that one of the possible solutions is to include the first-stage regressors as controls in the second-stage regression. Considering our dependent variable *ACOMP* is calculated as the residual components using OLS regression, we follow the procedure of Chen et al. (2018) by including the regressors used to derive *ACOMP* in our test equation.

Before including all controls again in the second-stage regression, we check the correlation among all covariates and find that all variables show low or moderate correlation with each other. Therefore, we add all covariates in Eq. (1) as additional control variables to Eq. (5). We find the coefficients of *FEEPS*, *DISP*, *WLKDN*, and *NSURP* remain negative and significant.[13] Such results further suggest that CEOs are likely to be penalised by reduced *ACOMP* when the accuracy of analysts' forecasts and the expectation of the firm's earnings decreases and the volatility of forecasts and *NSURP* increases. The broadly qualitatively similar results indicate that our results retain their interpretation after considering the correction suggested by Chen et al. (2018).

5.2 Additional control variables

To test the robustness of our findings, in this section, we focus on the additional control variables that may affect CEOs' *ACOMP*. Previous research indicates that managers are likely to receive inappropriate rewards in firms with weak corporate governance mechanisms (Edmans et al. 2017; Diri et al. 2020). Governance mechanisms can help prevent unintended consequences associated with incentive compensation, such as CEOs being rewarded for factors beyond their ability or performance (Bertrand and Mullainathan 2001). Additionally, prior literature shows that CEO characteristics are likely to affect the level of compensation (Byard et al. 2006; Francoeur et al. 2022; Hsu et al. 2021). Therefore, we include corporate governance and CEO characteristic proxies as additional control variables and re-estimate our baseline model.[14]

Prior literature suggests various proxies for the firm's internal and external corporate governance mechanisms. We explore additional indicators of external monitoring, including analyst coverage, the presence of Big 4 auditors, *Takeover Index*, *CGOV Score*, *FLPR*, and *IO*. Higher values of the *Takeover Index*, *CGOV Score*, *FLPR*, and *IO* indicate higher external monitoring. Firms followed by a larger number of analysts or audited by Big 4 auditors (Ernst & Young, Deloitte & Touche, KPMG, and PricewaterhouseCoopers) are exposed to stronger external monitoring. In untabulated results, we find that the negative effect of *FEEPS*, *DISP*, *WLKDN*, and *NSURP* on *ACOMP* persists after controlling for the external monitoring mechanisms.

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[12] Prior literature has discussed the potential empirical issues related to using the residuals generated from an ordinary least squares expectations model as the dependent variable in the second stage (Chen et al. 2018). It is argued that the implementation of such methods may result in biased coefficients and standard errors in the second stage regression, which may lead to unreliable inferences with Type I and Type II errors.

[13] Results of this analysis are available upon request.

[14] Results are available upon the request.

Next, we investigate the indicators of internal board monitoring, including board size (Diri et al. 2020), board independence (Ryan and Wiggins 2004), director tenure (Kim et al. 2014), gender diversity (Garel et al. 2021), and CEO duality (Johnson et al. 2009). Firms with larger boards, a higher proportion of independent directors, longer director tenure, more female board members, and a CEO without a dual role in the board tend to exhibit stronger internal governance. Similarly, in untabulated results, we find that the negative association between analysts' forecast metrics and *ACOMP* remains.

To further deal with the robustness of our results, we also incorporate the variables related to CEO characteristics as additional control variables in our baseline regression. Specifically, we include CEO luck, CEO skill,[15] CEO age, tenure, gender,[16] ability,[17] and overconfidence[18] find that the negative relation between *FEEPS*, *DISP*, *WLKDN*, *NSURP* and *ACOMP* remains significant after controlling for these CEO characteristic proxies.

Moreover, we conduct further analyses by re-estimating our main regression models, incorporating controls for external corporate governance, internal corporate governance, and CEO characteristics together. Again, our main findings remain qualitatively unchanged. Thus, our results indicate that the significant negative effect of analysts' forecast metrics on *ACOMP* is robust to firms' corporate governance mechanisms and CEO characteristics.

5.3 Analysts' recommendations and *ACOMP*

Finally, we investigate the relationship between analysts' recommendations and CEOs' *ACOMP*. There are key differences between recommendations and earnings forecasts. Investors may be better able to evaluate analysts' recommendations than analysts' forecasts, as they are issued using a straightforward scale (*Strong Buy*, *Buy*, *Hold*, *Underperformance*, and *Sell*) with a clear recommendation about the future of the firms to investors (Frankel et al. 2006; Wiersema and Zhang 2011). However, compared to earnings forecasts, the accuracy of analyst public recommendations tends to be questionable. Prior literature finds that CEOs prefer to receive optimistic recommendations issued by analysts since it is associated with their interests (Malmendier and Shanthikumar 2014). Hirshleifer et al. (2024) find that analysts often issue optimistic public recommendations to attract small retail investors while providing more accurate, and sometimes more pessimistic, information privately to institutional investors such as fund managers. This strategy, known as "whisper-sell behaviour", suggests that public recommendations may not reflect analysts' true assessments of a firm's performance.

Additionally, the accuracy of analyst recommendations is hard to evaluate due to the ambiguous benchmark (Hirshleifer et al. 2021). Previous academic literature finds that analysts are more likely to issue a *Buy Recommendation* to firms that have overvalued stocks (Mohanram et al. 2020). The overoptimistic recommendations contribute to mispricing in

[15] We obtain CEO's luck and skill following Daniel et al. (2020) from the link: https://sites.temple.edu/lnaveen/data/.

[16] We obtain CEO age, tenure, and gender from Execucomp.

[17] We obtain CEO's managerial ability scores following Demerjian et al. (2012) from the link: https://peterdemerjian.weebly.com/managerialability.html.

[18] We measure CEO overconfidence as a dummy variable, which equals one if the CEO holds the stock options that are more than 67% in the money (i.e., the stock price exceeds the exercise price by more than 67%), and zero otherwise.

the market if investors tend to follow the recommendations (Engelberg et al. 2020; Guo et al. 2020). This mispricing further complicates the assessment of recommendation accuracy as it introduces additional biases into market evaluations. Therefore, while analyst recommendations may convey information about future firm earnings and reflect assessments of CEO performance, the link between these recommendations and *ACOMP* remains unclear and potentially distorted by these biases.

We use four metrics to test the effect of analysts' recommendations on CEOs' *ACOMP*, including Average Analyst Recommendation *(RAVG)*, Changes in Average Analyst Recommendation *(RCHG)*, Buy Analyst Recommendation *(RBUY)*, and Sell Analyst Recommendation *(RSELL)*. The Buy recommendations (*RBUY*) indicate the optimistic estimation of analysts of a firm's future performance, and vice versa, Sell recommendations (*RSELL*) indicate that the evaluation of a firm's performance is poor. We re-estimate the regression model in Eq. (5) by replacing the original analyst forecast metrics with the recommendation metrics.

In untabulated results, we find that the coefficients for *RAVG*, *RCHG*, and *RBUY* are positive and significant, while the coefficient for *RSELL* is negative and significant. However, when we perform additional endogeneity tests, such as re-estimating the regression models, with firm fixed effects, entropy balanced weights, or using 2SLS regression (with jack-knife method instrumental variables), we do not find consistent results. This inconsistency may stem from the unreliability of analyst recommendations, as recommendations can be biased or misaligned with actual firm performance. Consequently, this could contribute to the challenges of achieving robust findings in the endogeneity tests.

6 Summary and concluding remarks

We provide persistent empirical evidence that analysts' forecast metrics, *FEEPS*, *DISP*, *WLKDN*, and *NSURP*, are negatively associated with CEOs' *ACOMP*. The negative relation is robust to the endogeneity concerns due to selection bias, reverse causality, and omitted variable issues. Our results suggest that CEOs are likely to be rewarded in the form of increased *ACOMP* when the analysts' information environment is favourable, indicating that CEOs contribute to disclosing higher quality information, which affects their variable compensation positively, as predicted by the *agency theory* and *information asymmetry hypothesis*. Our results also suggest that this relation is driven by firms subjected to stronger external monitoring mechanisms. Therefore, taken together, our results show that analysts contribute to compensation levels, particularly in strong monitoring environments. Overall, we expect our results to shed light on the mixed results found in the previous literature regarding the relationship between CEOs' compensation and the information issued by analysts.

While we provide evidence of a negative effect of analysts' forecast metrics on CEOs' *ACOMP*, we acknowledge several limitations of this study. First, rather than identifying all determinants of CEO compensation, our objective is to examine whether analysts' information conveys insights about unobservable factors in CEO compensation. Second, although analysts' expectations are increasingly important in board decision-making, data limitations prevent us from directly testing whether compensation committees explicitly consider analyst forecasts when setting CEO compensation contracts. Investigating how corporate boards incorporate analyst information in executives' compensation decisions could therefore be a valuable avenue for future research.

Appendix 1

Table 8 Variable definition

Variables	Definitions
FEEPS	Analysts' forecast error of *EPS* of the firm in the fiscal year end in consideration
WLKDN	Analysts' first forecast minus last forecast, scaled by total assets and finally multiplied by 1000
DISP	The standard deviation of a firm's earnings forecasts during a fiscal year deflated by the stock price at the beginning of the fiscal year
SURP	The difference between firm's actual EPS and the median of analysts' *EPS* forecast, scaled by the stock price at the beginning of the fiscal year.
NSURP	An indicator which equals one (and zero otherwise) if firm's *SURP* is negative
Total Compensation	The sum of salary, bonus, long-term incentive plan payouts, value of restricted stock grants, proceeds from options exercised during the year, and any other annual pay.
LogTenure	The logarithm of the CEO's tenure (in years).
S&P500	Indicator variable equal to one (and zero otherwise) for firms in the S&P500 index at the end of this fiscal year.
LogSale	Logarithm of the firm's sales.
BM	Book-to-market ratio measured at the end of fiscal year.
RET	Firm's buy-and-hold return.
ROA	Return on assets (income before extraordinary items divided by average total assets).
Expected Compensation	$Log\left(\mathrm{Total\ Compensation}_{i,t}\right) = \beta_0 + \beta_1 Log\left(\mathrm{Tenure}_{i,t}\right) + \beta_2\left(\mathrm{S\&P500}_{i,t-1}\right) + \beta_3 Log\left(\mathrm{Sales}_{i,t-1}\right) + \beta_4\left(\mathrm{BM}_{i,t-1}\right) + \beta_5\left(\mathrm{RET}_{i,t}\right) + \beta_6\left(\mathrm{RET}_{i,t-1}\right) + \beta_7\left(\mathrm{ROA}_{i,t}\right) + \beta_8\left(\mathrm{ROA}_{i,t-1}\right) + u_{i,t}\#$
LVG	The ratio of total debt to total assets at the end of fiscal year.
SIZE	Firm size calculated as the natural log of the firm's assets at of the end of fiscal year.
RDEXP	The ratio of Research and Development expenditure over total assets at the end of fiscal year.
ADEXP	The ratio of Advertising expenditure over total assets at the end of fiscal year.
TQ	Download from Peters and Taylor (2017)'s website.
VOL	The standard deviation of daily stock price over one year at the end of fiscal year
ACOMP	$\mathrm{Abnormal\ Compensation} = \mathrm{Total\ Compensation} - \mathrm{Expected\ Compensation}$
FMV	A categorical variable indicating the position of firm's market value (firm's share price at the end of fiscal year times the number of shares). The sample is classified in large (top 1/3rd observations), medium (middle 1/3rd observations) and small (bottom 1/3rd observations) market value subsamples.
CGOV Score	Corporate governance score from Refinitiv database.
Takeover Index	Following Cain et al. (2017), data downloaded from website: https://pages.uoregon.edu/smckeon/.
FLPR	An indicator equals one (and zero otherwise) if the firm-level political risk following Hassan et al. (2019) of each firm-year is above the median of industry-year.
IO	An indicator equals one (and zero otherwise) if the institutional ownership size (percent of share outstanding) of each firm-year is above the median of industry-year.

Appendix 2

Table 9 Correlation matrix

Variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ACOMP	(1)	1.000										
FEEPS	(2)	–0.021	1.000									
DISP	(3)	–0.015	0.798	1.000								
WLKDN	(4)	–0.030	0.254	0.165	1.000							
NSURP	(5)	–0.062	0.083	0.043	0.379	1.000						
LEV	(6)	0.019	0.114	0.125	0.016	0.071	1.000					
SIZE	(7)	0.042	–0.076	–0.062	–0.124	–0.053	0.331	1.000				
RDEXP	(8)	0.064	0.039	0.063	0.017	–0.045	–0.231	–0.279	1.000			
ADEXP	(9)	–0.017	–0.023	–0.043	–0.009	–0.022	–0.036	–0.049	–0.047	1.000		
TQ	(10)	0.010	–0.096	–0.097	–0.130	–0.190	–0.121	–0.109	0.205	0.052	1.000	
VOL	(11)	0.007	0.295	0.265	0.145	0.129	–0.015	–0.353	0.244	–0.002	0.049	1.000

This appendix table reports correlation metrics for all covariates used in the multivariate analysis. All variables are winsorized at their 1 st and 99th percentiles. The sample is based on the annual data of non-financial U.S. firms from 1992 to 2022

Appendix 3

Table 10 Descriptive statistics of entropy balanced sample

Variables	Treat Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: *FEEPS* as Treatment Variable						
Before Entropy Balancing						
LEV	0.245	0.043	0.935	0.219	0.033	0.898
SIZE	7.134	2.284	0.231	7.680	2.200	0.116
RDEXP	0.044	0.006	2.499	0.038	0.004	2.628
ADEXP	0.014	0.001	3.616	0.016	0.001	3.333
TQ	1.154	3.219	4.917	2.012	6.238	3.321
VOL	0.479	0.053	1.303	0.370	0.030	1.625
After Entropy Balancing						
LEV	0.245	0.043	0.935	0.245	0.043	0.935
SIZE	7.134	2.284	0.231	7.134	2.284	0.231
RDEXP	0.044	0.006	2.499	0.044	0.006	2.499
ADEXP	0.014	0.001	3.616	0.014	0.001	3.616
TQ	1.154	3.219	4.917	1.155	3.222	4.915
VOL	0.479	0.053	1.303	0.479	0.053	1.303
Panel B: *DISP* as Treatment Variable						
Before Entropy Balancing						
LEV	0.249	0.043	0.899	0.220	0.033	0.893
SIZE	7.302	2.298	0.188	7.761	2.082	0.132
RDEXP	0.046	0.006	2.387	0.036	0.004	2.700
ADEXP	0.014	0.001	3.630	0.016	0.001	3.241
TQ	1.138	2.918	5.019	2.063	6.184	3.244
VOL	0.467	0.051	1.349	0.368	0.032	1.715

Table 10 (continued)

Variables	Treat Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
(1)	(2)	(3)	(4)	(5)	(6)	(7)
After Entropy Balancing						
LEV	0.249	0.043	0.899	0.249	0.043	0.899
SIZE	7.302	2.298	0.188	7.302	2.298	0.188
RDEXP	0.046	0.006	2.387	0.046	0.006	2.387
ADEXP	0.014	0.001	3.630	0.014	0.001	3.630
TQ	1.138	2.918	5.019	1.138	2.921	5.017
VOL	0.467	0.051	1.349	0.467	0.051	1.349
Panel C: *WLKDN* as Treatment Variable						
Before Entropy Balancing						
LEV	0.240	0.040	0.893	0.224	0.037	1.009
SIZE	7.264	2.331	0.221	7.529	2.255	0.116
RDEXP	0.040	0.005	2.708	0.043	0.005	2.495
ADEXP	0.014	0.001	3.570	0.015	0.001	3.397
TQ	1.251	3.241	4.600	1.921	6.424	3.352
VOL	0.447	0.050	1.392	0.405	0.038	1.560
After Entropy Balancing						
LEV	0.240	0.040	0.893	0.240	0.040	0.893
SIZE	7.264	2.331	0.221	7.264	2.331	0.221
RDEXP	0.040	0.005	2.708	0.040	0.005	2.707
ADEXP	0.014	0.001	3.570	0.014	0.001	3.570
TQ	1.251	3.241	4.600	1.251	3.242	4.600
VOL	0.447	0.050	1.392	0.447	0.050	1.392
Panel D:*NSURP* as Treatment Variable						
Before Entropy Balancing						
LEV	0.247	0.039	0.827	0.221	0.037	1.027
SIZE	7.362	2.219	0.191	7.552	2.315	0.126
RDEXP	0.038	0.005	2.783	0.044	0.005	2.459
ADEXP	0.014	0.001	3.529	0.015	0.001	3.383
TQ	1.174	2.666	4.782	1.973	6.564	3.310
VOL	0.449	0.049	1.362	0.393	0.034	1.588
After Entropy Balancing						
LEV	0.247	0.039	0.827	0.247	0.039	0.827
SIZE	7.362	2.219	0.191	7.362	2.219	0.191
RDEXP	0.038	0.005	2.783	0.038	0.005	2.782
ADEXP	0.014	0.001	3.529	0.014	0.001	3.529
TQ	1.174	2.666	4.782	1.174	2.672	4.783
VOL	0.449	0.049	1.362	0.449	0.049	1.362

This table reports the summary statistics before and after entropy-balanced matching. All variables have been winsorized at the 1 st and 99th percentiles. The sample is based on the annual data of non-financial U.S. firms from 1992 to 2022

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Declarations

Conflict of interest All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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