Essays on Executive Compensation

by

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ABSTRACT

Agency theory suggests that monetary incentives are effective mechanisms to align managers' and shareholders' interests. Specifically, this thesis supports that monetary incentives play a crucial role in promoting value-maximizing managerial decisions. To attain this objective, this thesis is organized into three essays that consider the monitoring mechanisms involved in executive compensation and agency theory, with the aim of providing a comprehensive understanding of the subject matter.

The first essay examines the effect of earnings management (*EM*) on CEOs' abnormal compensation (*ACOMP*). The literature examining the relation between CEOs' total compensation and *EM* remains inconclusive, which may be due to the unobserved determinants of executive compensation. In line with the predictions of agency theory, I provide conclusive evidence of this relation by documenting a negative relation between *ACOMP* (the proportion of pay that cannot be accurately determined by known factors) and *EM*. Suggesting that CEOs involved in *EM* are penalized in form of reduced excess compensation. The results also confirm that CEOs involved in higher levels of real earnings management (*REM*) are penalized more severely than CEOs involved in higher levels of accrual earnings management *(AEM)*. It also documents that, the relation between *ACOMP* and *AEM* is exacerbated in firms facing financial stress.

The second essay examines the relation between analysts' forecasts or recommendations metrics and CEOs' *ACOMP*. Among the limited studies, that explore the relation between analysts' favourable forecasts or recommendations and CEOs' compensation, report mixed results. Instead of total compensation, I use CEOs' *ACOMP* to reinvestigate this relation and find conclusive evidence of its negative association with several unfavourable analysts' forecasts and recommendation metrics. It appears that this relation is primarily driven by firms that are subjected to stronger external monitoring mechanisms.

The third essay reports that the average cash flow risk (*CFR*) of firms in the United States firms shows a significantly increasing trend over the past four decades. The *CFR* also increases dramatically for firms approaching financial distress or bankruptcy, suggesting its important role in predicting a firm's failure. Empirically, I find that *CFR* has a strong positive effect on a firm's financial distress likelihood. In line with the upper echelons theory and the agency theory, I also find that the association between *CFR* and financial distress is negatively moderated in firms with high *EM* and *ACOMP*.

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INTRODUCTION

1.1. Background and motivation

This thesis focuses on executive compensation and the role of agency theory. Agency theory suggests that monetary incentives are effective mechanisms to align managers' and shareholders' interests. Research into the factors that influence CEOs' compensation packages constitutes a major topic in the financial literature. Financial reporting is a matter of concern for executives because the information disclosed in financial statements reflects their managerial performance, which has a direct impact on their compensation levels and structure (Harris *et al.* 2019). Prior literature also examines the factors such as managers' experience, personalities, and compensation consultants, among others, that may have an impact on managers' compensation levels (e.g., Core and Guay 2010; Conyon *et al.* 2019). To further investigate executive compensation, this thesis is organized into three essays. The following section summarises the introduction of the three chapters, which are Chapter 2, Chapter 3 and Chapter 4.

Chapter 2 examines the effect of *EM* on CEOs' *ACOMP*. In light of prior studies, some literature finds that there is a positive relation between executive total compensation and real or accrual *EM* (Bergstresser and Philippon 2006; Adut *et al.* 2013; Demerjian *et al.* 2020). Some studies report negative or weak relation between *EM* activities and manager's compensation packages (O'Connor *et al.* 2006; Armstrong *et al.* 2010). Managers may receive rewards for opportunistic behaviour in firms with weak corporate governance. However, it contradicts the agency theory that monetary incentives are suggested as effective monitoring mechanisms.

The inconclusive results on the association between total compensation and *EM* may have been influenced by unobserved factors that determine executive compensation. Executives' total compensation is expected to reflect their performance, effort, ability, and other economic determinants (Core and Guay 2010). However, determining a universally accepted compensation level for all executives is a challenging task. To address the mixed findings on this topic, chapter 2 aims to investigate the impact of *EM* as an unobserved determinant on executives' *ACOMP*, as opposed to total compensation. Chapter 2 aims to provide a clearer understanding of the role of *EM* in executive compensation using *ACOMP*. As suggested by agency theory, when the interests of the agents and principal are in agreement, a negative relationship between *ACOMP* and *EM* is expected. Thus, I hypothesize that CEOs who engage in *EM* to a greater extent will experience reduced or negative *ACOMP*. In addition, previous studies have reported that after the Sarbanes-Oxley (SOX) in 2002, firms reduced the use of discretionary accruals and increased the use of *REM* (Cohen *et al.* 2008). I investigate the moderating role of SOX regulation in the relation between *EM* and *ACOMP*.

Given the differences between *REM* and *AEM*, executives are often confronted with a trade-off between these two forms of *EM*, which is influenced by their respective costs and benefits (Cohen *et al.* 2008; Cohen and Zarowin 2010). Some executives may choose to engage in more *REM* rather than *AEM* to avoid detection and potential punishment for more obvious forms of manipulation. Furthermore, in pursuit of their earnings objectives, executives may employ various *EM* strategies. However, I expect that CEOs are still be punished by the reduced *ACOMP* even if then use different forms of *EM* strategies due to the interest alignment effect.

In addition, in firms experiencing financial distress, managers are more prone to engage in *EM* to obscure unexpected financial performance, primarily due to career concerns (Habib *et al.* 2013) and to reduce the likelihood of breaching debt covenants (Franz *et al.* 2014). Such practices may further impact the *ACOMP* of executives. Therefore, I investigate whether financial stress is a moderator of the relation between *EM* and *ACOMP*.

Chapter 3 examines the relation between analysts' forecasts and recommendations on *ACOMP*. Recent studies have investigated the connection between the information environment of sell-side security analysts, who function as information intermediaries, and corporate governance monitors (Hussain *et al.* 2021), and the total compensation of CEOs (Liu 2017; Mamatzakis and Bagntasarian 2020). In addition to serving as vital financial advisors to investors, analysts are obliged to monitor firms to produce forecasts and recommendations. Thus, meeting or beating analysts' expectations may have a favourable impact on CEOs' compensation packages, given that negative earnings surprises can have an adverse effect on stock prices, which, in turn, can negatively affect their compensations (Hall and Liebman 1998; Zhang and Gong 2018).

However, prior literature examining the relation between analysts' information environment and compensation incentives shows mixed results. One perspective posits that higher executive compensation and incentives can encourage opportunistic behaviour, which increases information complexity for analysts and subsequently results in a positive correlation between CEOs' compensation and analysts' earnings forecast error (Huang and Boateng 2017; Kanagaretnam *et al.* 2012). In contrast, some studies have found a negative association between executive compensation and analysts' earnings forecast error (Hui and Matsunaga 2015; Mamatzakis and Bagntasarian 2020), indicating that CEOs are penalized when information asymmetry increases.

In some cases, a CEO's total compensation may increase from the previous year despite a higher forecast error issued by analysts, resulting in a positive correlation between the forecast error and the total compensation. Nevertheless, the actual increase in compensation may not meet the expected level. Therefore, aligning with agency theory, executives are penalized by decreased total compensation that falls short of the expected level. Chapter 3 examines whether there is a persistent negative association of analysts' forecasts and recommendations with *ACOMP*, considering the information provided by analysts may be unobserved determinants of compensation packages.

Furthermore, I focus on the factors that may drive the negative association between analysts' information and *ACOMP*. Previous studies argue that firms which provide more comprehensive and transparent disclosures regarding their corporate governance practices tend to have more precise and consistent earnings forecasts made by analysts (Yu 2010). In addition, these firms are more likely to meet or beat analysts' earnings forecasts due to reduced agency costs (Adut *et al.* 2011). As the outside directors' understanding of the manager's behaviour improves over time (Kim *et al.* 2014), it is possible that the excess compensation decreases. Therefore, I consider that stronger external monitoring mechanisms may moderate the relation between the information issued by the analysts and *ACOMP*.

Chapter 4 investigates the role of average cash flow risk (*CFR*) in predicting firm's failures. The stability of a firm's cash flows is a critical factor in determining its financial health. Firms with volatile cash flows are more likely to face difficulties in surviving. I find that the average *CFR* has had a notable upward trend over the past forty years. The significant and persistent increase in *CFR* provides valuable time-dependent information that could be used to predict firm failures more accurately. Indeed, credit rating agencies emphasize the importance of *CFR* when issuing ratings. In addition, the *CFR* experiences a sharp rise as firms approach financial distress or bankruptcy, indicating a noticeable and dependable signal for predicting a firm's failure. I expect that firms with higher *CFR* are more likely to experience financial distress.

Next, considering that firms may use different measures to respond to the increased risk, I investigate the reactions to mitigate the impact of high *CFR* on their probability of failure from two different perspectives. First, the upper echelons theory suggests that managers may engage in opportunism activities as a means of reducing agency costs due to career-related concerns. It suggests that managers dealing with significant job demands in the face of poor company performance are more likely to rely on heuristics.

Second, consistent with the principles of agency theory, effective boards can use appropriate compensation incentives to align the interests of managers with those of the shareholders, enabling managers to serve as responsible stewards (Velte 2020) and alleviate high risk. Therefore, firms with efficient boards may modify their managers' compensation packages in response to high *CFR* as a means of aligning the interests of shareholders and managers through financial incentives. I expect that *EM* and *ACOMP* may moderate the relation between *CFR* and financial distress.

This thesis aims to provide a comprehensive understanding of executive compensation and the role of agency theory in U.S. firms. With regard to corporate governance, this study provides evidence to assist investors and board members in making more informed decisions regarding a firm's performance and suitable compensation arrangements.

1.2. Structure and scope of this thesis

The present thesis comprises five chapters that are organized as follows. First, an introductory chapter provides the background and purpose of the research undertaken. Subsequently, this thesis shows three separate chapters that present independent empirical studies investigating three executive compensation issues. Finally, the concluding chapter of the thesis summarizes the findings of the empirical studies and offers suggestions for potential areas of future research.

Chapter 2 examines the effect of *EM* on CEOs' *ACOMP* using financial data of publicly listed firms in the U.S. from the year 1993 to 2020. I find that there is a negative association between *ACOMP* (the proportion of pay that cannot be accurately determined by known factors) and *EM*, indicating that CEOs engaged in *EM* are likely to receive a reduction in excess compensation due to the interest alignment effect. I further find that CEOs engaged in higher levels of *REM*, which is considered to cause greater damage to the firm's value in the long term, face more severe penalties than those involved in higher levels of *AEM*. Furthermore, I find that the effect of *REM* on *ACMP* is more pronounced after SOX. In addition, I provide evidence that CEOs, regardless of their manipulation strategies, are likely to experience a reduction in *ACOMP* due to the interest alignment effect. Finally, this study highlights that the negative relationship between *ACOMP* and *AEM* is stronger in firms experiencing financial stress.

Chapter 3 investigates the relation between analysts' forecasts or recommendations metrics and CEOs' *ACOMP*. Specifically, I use one-year ahead earnings forecasts, which serve as a short-term representation of a firm's future prospects, and analysts' recommendations, which are oriented towards the long-term. For the information issued by analysts, I use four metrics, specifically, Analysts' Earnings Forecast Error (*FEEPS*), Earnings Forecast Walk Downs (*WLKDN*), Dispersion of Earnings Forecasts (*DISP*), and Negative Earnings Surprise (*NSURP*). For analyst recommendations, I use Average Analyst Recommendation (*RAVG*), Changes in Average Analyst Recommendation (*RCHG*), Buy Analyst Recommendation (*RBUY*) and Sell Analyst Recommendation (*RSELL*). I fins that there is a significantly negative effect of *FEEPS*, *WLKDN*, *DISP*, and *NSURP* on *ACOMP*. And I find that there is a positive relation between favourable recommendations and *ACOMP*. Together, the results indicate that CEOs receive higher excess pay when analysts' earnings forecast error is lower, there are fewer walkdowns, lower dispersion, fewer negative earnings surprises, and favourable recommendations. Furthermore, I find that the significance of analysts' forecasts on CEOs'

ACOMP is primarily driven by firms with strong external monitoring mechanisms. Specifically, firms with high *CGOV Score*, *Takeover Index*, and firm-level political risk (*FLPR*). In addition, those factors are only related to short-term analysts' forecast metrics.

Chapter 4 shows that *CFR* of firms in the U.S. presents a significantly increasing trend over the past four decades. And it increases steeply as firms approach financial distress or bankruptcy, which provides a reliable signal in predicting a firm's failure. I find that *CFR* is consistent and economically significant in predicting financial distress. To improve the discriminatory power, I introduce a transformed version of *CFR* measure, *CFRH*, which equals one, if a firm's *CFR* is above the median in a given year and industry and zero otherwise. Using *CFRH,* I find that the statistical and economic significance remains and the explanatory power also improved. In addition, I examine the firm's reaction to the high risk from two perspectives. On the one hand, with respect to upper echelons theory, executives confronted with heavy job demands resulting from firm's performance challenges are susceptible to relying on heuristics (Hambrick 2007), leading to an increased tendency towards income-seeking behaviour. On the other side, agency suggests that firms with efficient boards may use appropriate compensation packages to align managers' interests with firms' in response to high risk. The empirical results confirm that *EM* is a moderator of the relation between *CFRH* and financial distress. Indicating that managers choose to use *EM* activities to reduce the impact of high *CFR* on firm's failure, In addition, the results confirm that *ACOMP* is a moderator of the relation between *CFRH* and financial distress in line with agency theory. Indicating managers with higher *ACOMP* react and control the risk more efficiently, leading to decreased probability of financial distress. Finally, I investigate the effect of *CFRH* on alternative measures of firm's failure: financial constraints, presumed debt covenant violation and legal bankruptcy filings, and find broadly similar results.

Chapter 5 is the concluding section of the thesis. Chapter 5 includes primary research findings, the implications of the studies, and limitations. In addition, potential areas for future research are mentioned.

Chapter 2:

ARE CEOS PUNISHED FOR MANAGING EARNINGS?

2.1. Introduction

Executives are concerned with financial reporting as financial disclosures reflect upon their managerial ability, which in turn affects their compensation levels and structure (Zhang *et al.* 2008; Gul *et al.* 2017; Harris *et al.* 2019). Several studies examined the link between total compensation of executives and earnings management (accrual and real) and report a positive association (Cheng and Warfield 2005; Bergstresser and Philippon 2006; Efendi *et al.* 2007; Peng and Roell 2008; Johnson *et al.* 2009; Adut *et al.* 2013; Demerjian *et al.* 2020). This is surprising, as a positive relation implies that executives are being rewarded for their beguile behaviour, which contradicts the effectiveness of monetary incentives (Aktas *et al.* 2019) as monitoring mechanisms as suggested by the agency theory. Executives in firms with weak corporate governance are also found to be rewarded for earnings manipulation activities (Edmans *et al.* 2017), however, under appropriate monitoring mechanisms, agency theory suggests that such manipulation activities should be penalized due to the interest alignment effect. Although few studies report negative or no association between earnings management (*EM*) and the CEO's total compensation (Burns and Kedia 2006; O'Connor *et al.* 2006; Armstrong *et al.* 2010; Yan-Xin 2018). Broadly, these findings on the relation between the total compensation of executives and *EM* collectively remain inconclusive.

Intuitively, executives' total compensation should reflect their ability, effort, risk premium, and other determinants (Core and Guay 2010; Armstrong *et al.* 2012), but it's hard to define a generally acceptable compensation level for all executives. Moreover, some executives may not like to disclose the real level of their compensation to investors and regulators (Robinson *et al.* 2011). Prior studies and regulations[1] support the idea that the compensation structure has not been determined properly and discuss the possible determinants (Chalmers *et al.* 2006; Core and Guay 2010; Armstrong *et al.* 2012). Core and Guay (2010) point out that those proposals and findings reflect the failure of the framework for determining an appropriate compensation level.

Thus, prior studies exploring the relation between the total compensation of executives and *EM* might have been confounded by unobserved determinants of executive compensation. Also, when CEOs receive excessive pay, they are likely to omit it or obfuscate the total compensation disclosures (Robinson *et al.* 2011). Therefore, to shed light on these mixed findings, in this study, I use abnormal compensation (*ACOMP*) rather than total compensation to explore whether *EM* is one of the unobserved determinants that affect executives' *ACOMP*. Different from total compensation, *ACOMP* refers to the proportion of pay that cannot be explained by an executive's experience, risk premium, or other determinants (Armstrong *et al.* 2012; Core and Guay 2010). I also explore whether financial stress moderates the relation between *EM* and *ACOMP*.

We begin by investigating the impact of accrual earnings management (*AEM*) and real earnings management (*REM*) on CEOs' *ACOMP*. According to the monitoring mechanisms in the context of the agency theory, if the interests of the principal and agents are aligned, then there must be a negative relation between *ACOMP* and *EM*. Therefore, I expect that the higher the CEOs engage in *EM*, the higher will be the reduced or negative *ACOMP* for these executives.

[1] For example, U.S. Treasury Department has proposed standards for regulating compensation on the Troubled Asset Relief Program to avoid high cash pay to top executives in 2009; European Union has proposed a firm's remuneration policy in 2015.

We investigate this relation using financial data of publicly listed firms in the United States (U.S.) from the year 1993 to 2020. Following Core *et al.* (2008), I measure the *ACOMP* of CEOs using the difference between their actual total compensation and expected total compensation. For *REM*, I use the measures proposed by Roychowdhury (2006), which are the abnormal production costs, discretionary expense, and operating cash flows, and add them according to Zang (2012). As for *AEM*, I use the model proposed by Collins *et al.* (2017), which is an improvement over the models proposed by Jones (1991), Dechow *et al.* (1995), and Kothari *et al.* (2005). I use standard OLS regressions with fixed effects for industry and year, as well as use entropy balanced regression procedure to further validate our results.

We find a negative relation between *EM* metrics and CEOs' *ACOMP*. I also find that *REM* has higher economic effects on *ACOMP* than *AEM*. A unit increase in *REM* is associated with a decrease of around 16.5% in the CEO's *ACOMP*, and the corresponding for *AEM* is around 31.9%. This negative relation indicates that CEOs involved in *EM* are likely to receive reduced excess compensation or lower-than-expected pay. Importantly, the negative association provides evidence supporting the efficiency of incentives as a monitoring mechanism in aligning the interest of agents with that of the principal. Moreover, I find that *REM* has a more pronounced negative effect; CEOs are likely to face not only reduced *ACOMP,* but also negative *ACOMP* when they do *REM*.

Following Sarbanes-Oxley (SOX) in 2002, prior literature has documented that firms decreased the use of *AEM* and increased *REM* (Cohen *et al.* 2008). I find the effect of *REM* on *ACOMP* is more pronounced after SOX, but I find no significant difference in *AEM* before and after SOX. Therefore, this corroborates the findings of Cohen *et al.* (2008) and illustrates that board members have devoted more attention to *REM*. Also, to address potential endogeneity concerns, I implement 2SLS regression analysis and find that our results retain their interpretation and significance.

Next, as I find a negative association between *EM* and *ACOMP*, I investigate how this association differs for different levels of *AEM* and *REM*. Considering the differences between *REM* and *AEM*, executives often face a trade-off between these two forms of *EM*, based on their associated costs and benefits (Ewert and Wagenhofer 2005; Cohen *et al.* 2008; Cohen and Zarowin 2010). Some executives substitute *AEM* with *REM* to avoid easily detectable manipulations and punishment (Zang 2012). In addition, executives may apply different types of *EM* strategies to achieve the earnings objective. I still find a statistically negative effect of *EM* with high *REM* and high *AEM* or high *REM* and low *AEM*, suggesting that even though CEOs use different or complex manipulation strategies, they are still likely to receive reduced *ACOMP* due to the interest alignment effect. In light of the mixed results of prior literature on the relation between *EM* and executives' compensation (e.g., Cheng and Warfield 2005; Bergstresser and Philippon 2006; Johnson *et al.* 2009; Armstrong *et al.* 2010; Demerjian *et al.* 2020), our use of *ACOMP* to disentangle these findings thus confirms that there is indeed a negative effect, and it is more pronounced for *REM* than *AEM*.

Finally, with regard to the influence of financial stress on the degree of *EM,* I investigate whether financial stress moderates the association between *EM* and CEOs' *ACOMP*. Prior literature documents that managers in firms with financial stress are more likely to manage their earnings to conceal the unexpected financial performance due to career concerns (Habib *et al.* 2013; Rosner 2003), and also to avoid the probability of violating a debt covenant (Franz *et al*. 2014), which may further affect the *ACOMP*. I find that financial stress exacerbates the negative effect of *AEM* on *ACOMP*, suggesting that managers in financially stressed firms who engage in *AEM*, are penalized by a higher reduction in *ACOMP*.

Our contribution lies in shedding light on the mixed results of prior literature on the effect of earnings management on executive compensation, by using *ACOMP* to disentangle these findings (e.g., Cheng and Warfield 2005; Bergstresser and Philippon 2006; Johnson *et al.* 2009; Demerjian *et al.* 2020). Taken together, the evidence reported in this study shows that the current monitoring mechanisms in place in U.S. companies are effective in curbing CEOs' *ACOMP* when they engage either in *AEM*, or *REM*. For firms facing financial stress, I suggest that the creditors and analysts may pay more attention to the *AEM* to understand the real financial performance of firms and reduce the information asymmetry.

2.2 Literature review and hypothesis development

2.2.1 Impact of *EM* on *ACOMP* of CEOs

"Managerial power" theories argue that executives have a great deal of control over shareholders and that CEOs may use their power to achieve higher compensation levels. The pay packages are not always in shareholders' best interest, which leads to potential interest conflicts between CEOs and shareholders (Ataullah *et al.* 2014). To avoid conflicts, agency theory suggests firms use outcome-based incentives to align their interests with that of executives. Firms may choose stocks, options, or bonuses to direct CEOs toward making value-enhancing decisions (Coles *et al.* 2006; Kini and Williams 2012; Mohanram *et al.* 2020). Such outcome-based incentives directly link managerial compensation to firms' performance, which encourages CEOs to make financial decisions in the best interest of shareholders. In light of the agency theory, monitoring mechanisms are another way to mitigate conflicting interests, which aims to align the firm's and CEOs' interests and encourage managers to make value-maximizing business decisions.

However, these governance mechanisms are difficult to implement due to relatively higher costs and some executives' unobserved behaviour (Zhang *et al.* 2008). As a result, firms may use long-term outcome-based incentives to avoid conflicts. Stocks and options are the most common mechanisms in such contracts (Mohanram *et al.* 2020; Mamatzakis and Bagntasarian 2020), which link executives' interests and firms' performance closely with sustainable levels of compensation (Zhang *et al.* 2008). However, such incentives may bring compensation risks to CEOs because the direct link increases the inherent uncertainty of their future wealth, thus, increasing their likelihood of managing earnings. But according to the agency theory, CEOs' interests are aligned with that of firms, so in the long-run, value-erosion business decisions like *EM* should adversely affect their personal wealth as well.

Despite clear theoretical motivations, the majority of prior literature reports a positive association between executive compensation and *EM*. Cheng and Warfield (2005) find that executives with high equity incentives are more likely to engage in *EM* activities to meet analysts' forecasts. A similar result is reported by Bergstresser and Philippon (2006) that the level of discretionary *AEM* is positively associated with managers' overall compensation. Other studies that investigate the link between *EM* and executive compensation also show a positive association (Efendi *et al.* 2007; Peng and Roell 2008; Kuang 2008; Johnson *et al.* 2009).

Few studies, however, consider that equity-based compensation does not provide incentives for executives to manage earnings (Burns and Kedia 2006; O'Connor *et al.* 2006). In contrast, they hypothesize that equity compensation may lessen executives' desire for *EM* by aligning their interests with shareholders. Some studies support this argument, Larcker *et al.* (2007), for instance, find that there is actually no significant relation between executives' compensation and *EM*. In addition, Armstrong *et al.* (2010) document a modest negative association between CEOs' equity incentives and accounting regulations. Although the conclusion of prior literature is considered a consensus for this investigation, there are considerable differences across inferences shown within these studies. Broadly, the relation between *EM* and executive compensation remains mixed and inconclusive. The lack of consistency may be due to some unobservable determinants of total compensation and inappropriate compensation structures.

Recent regulations and proposals also highlight the importance of aligning executives' compensation structure that requires their skin in the game. The Treasury Department in the U.S. issued a rule on the Troubled Asset Relief Program in 2009, which requires most of the compensation to be paid in the form of stock to restrict cash payments to top executives. Also, Dodd-Frank Act led to the implementation of the say-on-pay vote for executives in 2011, which gives shareholders a binding vote power on executive pay. In July 2015, European Union also proposed that firms' remuneration policy should explain the performance criteria (including financial and non-financial) used to determine the executive's compensation level. Core and Guay (2010) argue that the concern mentioned by prior literature and the appearance of proposals is because of the failure to articulate an appropriate compensation framework. They propose that executive compensation should reflect a risk premium for their incentives in the contract. CEOs may participate in *EM* activities because they are likely to inflate firms' short-term performance to meet analysts' forecasts and obtain extra incentives (Edmans *et al.* 2017). However, stricter corporate governance and monitoring mechanisms increase the potential risk and difficulties of doing *EM* (Fernandes *et al.* 2013). Therefore, there is a trade-off between the potential risks that CEOs face and the expected additional incentives.

Following prior literature (Feito-Ruiz and Renneboog 2017; Hooghiemstra *et al.* 2017), *ACOMP* is defined as the difference between observed compensation and the expected compensation calculated from several economic components (Core *et al.* 2008). Specifically, Core and Guay (2010) state that the level of compensation should be determined by executives' ability, effort, and risk premium. Compensation for ability should reflect the basic amount of pay to attract executives to the job. Also, compensation should increase with their level of effort. Moreover, as discussed above, there is a risk premium that stems from performance-based incentive risk, and firms should consider the risk premium as well to compensate CEOs. The amount of pay that cannot be explained by these determinants is regarded as *ACOMP*. Therefore, executives may engage in earnings manipulation activities to boost firms' short-term financial performance to gain immediate excess compensation.

Turning to *EM*, there are typically two forms of manipulation, *AEM* and *REM* (Cohen and Zarowin 2010; Dechow *et al.* 2010; Kothari et al. 2016). On the one hand, *AEM* refers to discretionary choices within the scope of the Generally Accepted Accounting Principles (GAAP) to achieve the earnings objective (Garel *et al.* 2021). On the other hand, managers do *REM* by altering operational transactions, such as cutting discretionary expenses, manipulating sales by offering larger discounts, or overproducing to boost inventory and cut the costs of goods sold (Roychowdhury 2006). *REM* is more damaging compared to *AEM* (Graham *et al.* 2005; Kim and Sohn 2013) since it affects firms' cash flows directly and has a detrimental impact on their long-term value (Gunny 2010; Braam *et al.* 2015).

Based on the above discussions, I expect that both types of *EM* should have a negative effect on the *ACOMP* of CEOs. Thus, our hypothesis is as follows:

H1a: *There is a negative association between ACOMP of CEOs and EM.*

Although both types of *EM* have a similar purpose behind manipulating earnings, there are differences between them. *AEM* is relatively easier to detect than *REM* (Braam *et al.* 2015), since CEOs are more likely to be constrained to specific periods (accounting report dates) to do *AEM*. This reduced flexibility and easy detectability often encourage managers to switch to *REM* (Diri *et al.* 2020). Using the generally accepted accounting principles and litigations based on GAAP, auditors can more easily detect firms' *AEM* behaviour (Diri *et al.* 2020). As a less damaging type, *AEM* retains firms' operating and investment policies but only adjusts the earnings reporting measure (Cohen and Zarowin 2010; Kothari *et al.* 2016). Compared to *AEM*, *REM* is more damaging to firms' long-term value (Graham *et al.* 2005; Gunny 2010; Kim and Sohn 2013; Braam *et al.* 2015) and is relatively harder to be monitored since it changes firms' operating and investment policies to achieve firms' short-term earnings target (Edmans *et al.* 2017a). Based on the interest alignment effect, and that *REM* causes more severe damage to firms' value in the long run, I expect the association between *REM* and *ACOMP* will be more pronounced (economically stronger) than with *AEM*. As a consequence, CEOs should be penalized not only by the reduced excessive pay but also by negative *ACOMP*. Therefore, our hypothesis is as follows:

H1b: *REM leads to a higher likelihood of negative ACOMP of CEOs than AEM.*

CEOs in different firms may employ different levels of *REM* and *AEM* to achieve their earnings targets. Considering the difference between *AEM* and *REM,* previous literature argues that executives often trade-off between *AEM* and *REM* based on their associated costs and benefits (Ewert and Wagenhofer 2005; Cohen *et al.* 2008; Cohen and Zarowin 2010). Although *AEM* is less damaging, considering *REM* is relatively harder to be monitored, some executives may switch to using *REM* to avoid easily detectable manipulation and punishment (Cohen *et al.* 2008). Managers engage in fewer *AEM* and more *REM,* especially when firms have strong corporate governance mechanisms and are in highly concentrated markets (Diri *et al.* 2020). Therefore, even though executives realize *REM* has a more severe negative impact on the firms' long-term value (Cohen and Zarowin 2010; Kothari *et al.* 2016), they may still use more *REM* to achieve desired levels of earnings (Zang 2012). Also, *AEM* is less damaging and timeconsuming since it only changes the short-term financial performance measures rather than the firm's business plan and operation (Edmans *et al.* 2017). Therefore, some executives may rely more on *AEM*. Executives may choose to engage in different levels of *REM* and *AEM* to achieve their earnings objectives, considering the different characteristics of *EM* activities. Although using a combination of different levels of *REM* and *AEM* may not be detected instantly, executives should still receive reduced *ACOMP* when their manipulations are detected sometime later, especially for those using more *REM*. Therefore, I expect the *ACOMP* of CEOs, who use complex strategies for manipulating earnings, to be negatively affected as well. Our hypothesis is the following:

H1c: *CEOs using complex EM strategies receive reduced ACOMP.*

2.2.2 Financial stress, *EM* and *ACOMP* of CEOs

Firms facing financial stress or constraints are more likely to perform differently compared to healthy ones. Financially stressed firms are subject to greater scrutiny by creditors and analysts, who may monitor the *EM* activities more effectively (Brown and Hugon 2009). However, prior literature also documents that managers in financially stressed firms are more likely to manage their earnings since they may face career and reputation concerns (Habib *et al.* 2013). To conceal their distress, firms may employ income-increasing *EM* (Rosner 2003). Chen *et al.* (2010) also show that managers are likely to use income-increasing *AEM* while facing delisting threats. In addition, due to the high scrutiny around financial stress, executives may engage in more *EM* prior to covenant violation (Franz *et al*. 2014). Furthermore, *AEM* could go both ways (positive or negative), Charitou *et al.* (2007) show that executives may shift earnings downwards in firms with financial stress.

Overall, CEOs in financially stressed firms may engage in more *AEM* due to the greater scrutiny by creditors and career concerns. Compared to *REM*, in *AEM*, the firm's operating and investment policies remain unchanged, it only changes the short-term financial performance measure (Edmans *et al.* 2017). Thus, in financial stress managers are more likely to engage in *AEM* to avoid immediate unsatisfactory financial reporting. Additionally, these firms might not have enough time or room to engage in *REM* while in financial stress, suggesting an insignificant moderation effect of *REM* on *ACOMP*. To this point, I explore how financial stress moderates the role of *EM* in CEOs' *ACOMP* by testing the following hypothesis:

H2: *Financial stress moderates the relation between EM and ACOMP.*

2.3 Data, variables and descriptive statistics

Our sample includes all listed U.S. firms with available data on CEOs' compensation from the ExecuComp database. I obtain accounting data from Compustat, and stock returns data from CRSP. The sample period covers fiscal years from 1993 to 2020. The Appendix lists and explains all variables used in our empirical analysis.

2.3.1 Measurement of *ACOMP*

As discussed in Section 2.2.1, prior literature shows that CEOs' compensation can be explained by their ability, effort, and risk premium. The amount of pay that cannot be explained by these determinants is regarded as *ACOMP*. I estimate *ACOMP* by subtracting the expected compensation from the actual total compensation of each CEO. I follow prior research in developing a benchmark model to estimate expected and unexplained *ACOMP* (Core *et al.* 2008; Robinson *et al.* 2011; Alissa 2015). These are calculated by regressing total compensation on variables for the firm's performance and CEO's ability (Guest *et al.* 2022). I measure *Total Compensation* as the sum of salary, bonus, the value of restricted stock grants, the value of options granted during the year, and other annual pay (Core *et al.* 2008). Following Core *et al.* (2008), I estimate the expected compensation of the CEO by regressing CEO's total compensation on proxies for several economic determinants in a given year and industry, as follows:

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

where *i* indexes firm and *t* indexes year. *Total Compensation* is described above, and the remaining variables are defined in Appendix 1.1. The above OLS model includes fixed effects for years and 2-digit SIC codes of industries to which respective firms belong. I separate the total compensation of CEOs into two parts: the *Expected Compensation* estimated from Eq. (1), and the *ACOMP* (the residual obtained from the same equation). I compute the *ACOMP* as:

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

2.3.2 Measurement of *EM*

Following previous literature (Huang *et al.* 2017; Ferri *et al.* 2018), I use Collins *et al.* (2017) model to measure *AEM*, which mitigates the effect of firms' growth and nonlinearities in accruals as well as reduces Type I and II errors compared to the traditional methods of Dechow *et al.* (1995) and Kothari *et al.* (2005). Specifically, I estimate the following equation:

$$\frac{ACC_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{ACC_{i,t-1}}{Assets_{i,t-1}} + \beta_2 \frac{(\Delta Sales - \Delta AR)_{i,t}}{Assets_{i,t-1}} + \sum_k \beta_{3,k} \frac{ROA_{Dum_{k,i,t}}}{Assets_{i,t-1}} + \sum_k \beta_{4,k} \frac{SG_{Dum_{k,i,t-1}}}{Assets_{i,t-1}} + \sum_k \beta_{5,k} \frac{MB_{Dum_{k,i,t-1}}}{Assets_{i,t-1}} + u_{i,t} \tag{3}$$

where *ACC* is total accruals, calculated as the sum of the change in accounts receivable, inventories, accounts payable, taxes, and other items from the cash flow statement. *Assets* is the book value of total assets, $\Delta Sales$ denotes the changes in sales, ΔAR denotes the changes in account receivables, dummy variables $ROA_{Dum_{k,i,t}}$, $SG_{Dum_{k,i,t-1}}$, $MB_{Dum_{k,i,t-1}}$ equals one if the variable belongs to the k_{th} quintile in the aggregate data, and 0 otherwise. Similarly, i indexes firm and t indexes year. Using Eq. (3), discretionary accruals are calculated as the residual from the regression estimated for each 2-digit SIC-industry-year group. Each industry-year group has at least 20 observations, otherwise discarded. Since CEOs may use either income-increasing or income-decreasing discretionary accruals to engage in *EM*, I use the absolute value of calculated discretionary accruals to proxy *AEM*.

For *REM*, I follow previous literature (Cohen and Zarowin 2010; Kothari *et al.* 2016; Garel *et al.* 2021) that use the model proposed by Roychowdhury (2006). Specifically, I use *Abnormal production costs*, *Abnormal discretionary expenses*, and *Abnormal operating cash flows* to measure *REM*. I estimate *Abnormal production costs* as follows:

$$\frac{PROD_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{i,t-1}} + \beta_2 \frac{\Delta Sales_{i,t}}{Assets_{i,t-1}} + \beta_3 \frac{\Delta Sales_{i,t-1}}{Assets_{i,t-1}} + u_{i,t} \qquad (4)$$

Where *PROD* is the sum of the cost of goods sold and the change in inventory over a year. Eq. (4) is regressed for each 2-digit SIC code industry-year group with at least 20 observations in each group. I estimate *Abnormal production costs* using the regression residuals, higher values suggest higher *REM*. Then I estimate *Abnormal discretionary expenses* using the following equation:

$$\frac{DISX_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{i,t-1}} + \beta_2 \frac{Sales_{i,t}}{Assets_{i,t-1}} + u_{i,t} \qquad (5)$$

where *DISX* is the sum of R&D, advertising, and selling, general and administrative (SG&A) expenses. I replace missing values of R&D and advertising expenses with zero, as long as there is a valid value of SG&A (Roychowdhury 2006). Similarly, *Abnormal discretionary expenses* are defined as the residuals from the regressions for each industry-year group. Lower values of abnormal discretionary expenses suggest more *REM* since CEOs may cut the expenses on R&D, advertising, and SG&A to increase profits. Finally, I estimate *Abnormal operating cash flow* using the following equation:

$$\frac{CFO_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{i,t-1}} + \beta_2 \frac{Sales_{i,t}}{Assets_{i,t-1}} + \beta_3 \frac{\Delta Sales_{i,t}}{Assets_{i,t-1}} + u_{i,t} \qquad (6)$$

where CFO is the firm's operating cash flow. *Abnormal operating cash flow* is defined as the residual from Eq. (6) obtained from the regressions for each industry-year group. A lower value of *Abnormal operating cash flow* indicates higher *EM* since executives may provide temporary price discounts or relatively lenient credit terms to boost sales. Following Roychowdhury (2006), I use the sum of *Abnormal production costs, Abnormal discretionary expenses* times minus one, and *Abnormal operating cash flow* times minus one, to measure *REM*:

$$\begin{gathered} Real\ Earnings\ Management = Abnormal\ production\ costs + \\ Abnormal\ discretionary\ expenses \times (-1) + \\ Abnormal\ operating\ cash\ flow \times (-1) \end{gathered} \qquad (7)$$

2.3.3 Measure of financial stress

To test H3, I use two proxies for financial stress (*FS*), the *KZ* index and the *WW* index. Following previous literature (Farre-Mensa and Ljungqvist 2016; Kothari *et al.* 2016; Lamont *et al.* 2001), a firm's degree of financial constraints is estimated by five accounting variables: cash flow, market-to-book, leverage, dividends, and cash holdings. A higher index value indicates a firm is more financially constrained. Therefore, I classify firms into two groups based on the KZ index in a given year and industry. A dummy variable *FSKZ* equals one if a firm is in the top quartile indicating the financial stress condition, and zero otherwise. *WW* index is another measure of financial stress which is estimated using several variables as well: cash flow to assets, dividend, long-term debt to assets, total assets, sales growth, and industry sales growth (Whited and Wu 2006). Similarly, I use a dummy variable *FSWW* which equals one if a firm is in the top quartile based upon the *WW* index, indicating that the firm is financially stressed, and zero otherwise.

2.3.4 Control variables

Besides the variables of primary interest discussed above, our multivariate regression models include several firm-level control variables. Consistent with prior studies (Chaney *et al.* 2011; Zang 2012; Dah and Frye 2017), I select firm-level control variables including *Leverage (LVG)*, *SIZE*, *R&D expenditure (RDEXP)*, *advertising expense (ADEXP)*, *Total_Q (TQ)*, and *Volatility*. *LVG* is defined as the ratio of total debt to total assets, *SIZE* is firm size defined as the natural logarithm of a firm's total assets, *RDEXP* and *ADEXP* are scaled by total assets, *TQ* is calculated following Peters and Taylor (2017), and *VOL* is calculated as the standard deviation of the daily stock price over one year period. I also include industry (2-digit SIC codes) and year dummies to control for the industrial sector and time-specific fixed effects.

2.3.5 Descriptive statistics

To eliminate the effect of outliers, I winsorize all continuous control variables, *ACOMP*, *REM* and *AEM* at their 1^{st} and 99^{th} percentile values. I present the descriptive statistics of all main variables, *ACOMP*, *REM*, and *AEM*, in Table 2.1. I report the mean, median, standard deviation, minimum value, and maximum value of all variables. Column 1 shows the list of variables used in our subsequent regression models. The descriptive measures of all variables are as expected with no extreme values or unexpected variations, as they have been winsorized. Descriptive statistics of the remaining control variables are also comparable to the previous literature (Core *et al.* 2008; Bugeja *et al.* 2016; Dah and Frye 2017), with some differences in reasonable range due to the variations in samples.

Table 2.1: Summary statistics

This table reports summary statistics for all variables used in the multivariate analysis. All variables are winsorized at their 1st and 99th percentiles. The sample is based on the annual data of U.S. firms from 1993 to 2020.

Variables	Mean	Standard Deviation	Median	Min	Max
(1)	(2)	(3)	(4)	(5)	(6)
ACOMP	0.000	0.722	0.038	-4.920	3.493
REM	0.029	0.730	-0.048	-3.811	3.501
AEM	0.047	0.050	0.032	0.000	0.277
LVG	0.239	0.204	0.216	0.000	0.931
SIZE	7.196	1.616	7.128	3.435	11.308
RDEXP	0.036	0.063	0.003	0.000	0.344
ADEXP	0.013	0.031	0.000	0.000	0.184
TQ	1.585	2.561	0.881	-3.883	20.760
VOL	11.313	2.075	11.710	5.161	15.493

Further, the correlation among those variables and all main variables of interest shows low or moderate correlation with each other, as reported in Table 2.2. An initial inspection of the correlation between *ACOMP* and *EM* shows a negative correlation, specifically, the correlation between *ACOMP* and *REM* is about -0.183, and a relatively smaller negative correlation of about -0.009 between *ACOMP* and *AEM*. Hence, there is some initial evidence to support our hypothesis that there is a negative relation between *ACOMP* and *EM*. Other control variables also exhibit a reasonable correlation with *ACOMP*, thus indicating their effectiveness as control variables. The correlation among all independent variables is either low or very low, thus I do not expect our results to be affected by multicollinearity.

Table 2.2: Correlation matrix

This table reports the correlation matrix for all variables used in the multivariate analysis. All variables are winsorized at their 1st and 99th percentiles. The sample is based on the annual data of U.S. firms from 1993 to 2020.

Variables									
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ACOMP	1.000								
REM	-0.183	-0.183							
AEM	-0.009	-0.009	-0.009						
LVG	0.044	0.044	0.044	0.044					
SIZE	0.087	0.087	0.087	0.087	0.087				
RDEXP	0.072	0.072	0.072	0.072	0.072	0.072			
ADEXP	-0.021	-0.021	-0.021	-0.021	-0.021	-0.021	-0.021		
TQ	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	
VOL	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	1.000

2.4 Empirical results and discussions

2.4.1 Empirical model

The main objective of our empirical analysis is to investigate the effect of *EM* activities on CEOs' *ACOMP*. To examine this relation, I construct our baseline regression model as the following:

$$ACOMP_{i,t} = \beta_0 + \beta_1\, Earnings\ Management_{i,t-1} + \beta_2\, LVG_{i,t-1} + \beta_3\, SIZE_{i,t-1} + \beta_4\, RDEXP_{i,t-1} + \beta_5\, ADEXP_{i,t-1} + \beta_6\, TQ_{i,t-1} + \beta_7\, VOL_{i,t} + Year_t + Industry_j + u_{i,t} \tag{8}$$

where *i* indexes firm, *t* indexes year, and *j* indexes the industry group classified by 2-digit SIC code. $Earnings\ Management$ is either *AEM*, following Collins *et al.* (2017), or *REM*, as per Roychowdhury (2006). $Year_t$ indicates year fixed effects, and $Industry_j$ indicates industry fixed effects based on 2-digit SIC codes. See Appendix 2.1 for definitions of all variables. Regression models are estimated using pooled cross-section ordinary least squares regressions with standard errors clustered at the firm level. Further, all independent variables are lagged by one financial year in Eq. (8) because the current year's firm performance shapes the next year's compensation of executives. I

2.4.2 Effect of *EM* on *ACOMP* (Test of H1a)

2.4.2.1 The relation between EM and ACOMP

We start by examining the relation between *EM* and *ACOMP*. Empirical results in support of H1a are reported in Table 2.3. Table 2.3 presents the main regression result using Eq. (8). In Columns (2) and (3), I report the effect of *REM* and *AEM* on *ACOMP*, respectively.

Table 2.3, Column (2) shows that the estimated coefficient of *REM* is negative and significant at the 1% level, suggesting that CEOs receive less *ACOMP* when they engage in *REM*. Also, the effect of *REM* on *ACOMP* is economically significant. I measure the economic significance of a variable by multiplying its standard deviation with its regression coefficient.[2] The estimated coefficient in Column (2) implies that a unit increase in *REM* reduces CEOs' *ACOMP* by 16.5% (a one-standard-deviation increase in *REM* reduces CEOs' *ACOMP* by 12.05 percentage points (-0.165×0.730)).

Likewise, the coefficient of *AEM* is negative and significant at the 5% level (see Column (3)). One unit increase of *AEM* decreases *ACOMP* by 31.9%. When there is one standard deviation increase in *AEM*, the expected decrease in *ACOMP* is 1.92% (-0.319×0.050).

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[2] If a regressor X is normally distributed, replacing x with its standardized 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) (Douglas *et al.* 2016).

Thus, the empirical results support the hypothesis that *EM* leads to reduced *ACOMP* as predicted by the agency theory.

In addition, compared to the economic significance of *REM*, the value of *AEM* is significantly lower. Such results suggest that *REM* may have more severe consequences for a firm's long-term value than *AEM* since it involves negative business operations, leading to an unexpected decline in further profitability and valuation (Cohen and Zarowin 2010; Kothari *et al.* 2016). The results are consistent with prior literature that *REM* changes the firms' operating and investment plans (Edmans *et al.* 2017) and inhibits firms' long-term value (Achleitner *et al.* 2014). Therefore, severer *REM* activities are penalized by a greater amount of declines in *ACOMP*. Consistent with our expectations, the coefficients of control variables show expected signs. *LVG*, *SIZE*, and *RDEXP* are positively related to *ACOMP*, in contrast, a firm's *ADEXP* decrease with the level of *ACOMP*.

Furthermore, to ensure that our results are not confounded by possible sample selection bias, I conduct entropy balanced regression analysis to adjust for inequalities in the sample distributions of firms doing high level (above the median) of *EM* with firms doing low level (below the median) of *EM*. I separate our sample based on the median *EM* level in a given year and industry. The entropy balancing procedure accurately matches the three moments (mean, variance and skewness) between firms in control and treatment groups. Entropy balancing reduces model dependence for the estimation of treatment effects, here specifically, the level of *EM*. Compared to other adjustment techniques, for example, propensity score matching or pair matching, entropy balancing directly focuses on covariates balance. In practice, propensity score matching suffers from the drawback that the true propensity score is usually unknown and difficult to estimate accurately to produce the expected covariate balance (Smith and Todd 2001). Some of the balance metrics leave several covariates imbalanced or even decrease the balance in a few instances. Entropy balancing improves the metrics and matches exactly the specific moments (Hainmueller 2012). Recent studies also implement entropy balancing in empirical investigations to reduce the coefficient bias (e.g., McMullin and Schonberger 2020). Based on the superior performance of entropy balancing, I choose this reweighting method to avoid any sample selection bias.

Specifically, I classify *EM* as over-manipulation if the extent of *EM* exceeds the median level in any given industry and year. With the over-manipulation as treatment, I reweight the control group with respect to the first, second, and third moments of covariates distributions (Hainmueller 2012). That is, each observation in the control group receives a weight such that the mean, variance, and skewness of the distribution for each matched variable in the control group is similar to its counterpart in the treatment group. Appendix 1.2 presents the three moments of treatment and control samples before and after entropy balancing. Specifically, I match firms on *LVG, SIZE, RDEXP*, *ADEXP*, *TQ*, and *VOL*. After the reweighting, treatment and control groups show almost identical distributions for the matching variables.

Column (4) and (5) of Table 2.3 presents the regression results with the weights from the entropy balancing procedure. I find broadly qualitatively similar results, as both *REM* and *AEM* still have a negatively significant impact on *ACOMP*, indicating that our results retain their interpretation after entropy balancing.

Table 2.3: Multivariate regressions of abnormal compensation

This table reports multivariate regression results employing abnormal compensation (*ACOMP*) as the dependent variable and the variables of interest, real earnings management (*REM*) and accrual-based earnings management (*AEM*). Columns (2) and (3) show the results of our baseline model using OLS regression. Columns (4) and (5) display the entropy balanced regression results. Control variables include Leverage (*LVG*), Firm size (*SIZE*), R&D expenditure (*RDEXP*), Advertising expenditure (*ADEXP*), Total Q (*TQ*), and Volatility (*VOL*). All variables are winsorized at their 1st and 99th percentiles. The sample is based on annual data of U.S. firms from 1993 to 2020. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Variables	*ACOMP*			
	OLS		Entropy Balanced OLS	
(1)	(2)	(3)	(4)	(5)
REM	**-0.165*** **		**-0.166*** **	
	(-13.395)		(-9.742)	
AEM		**-0.319** **		**-0.022** **
		(-2.458)		(-2.292)
LVG	0.155***	0.189***	0.153***	0.157***
	(3.015)	(3.460)	(2.730)	(2.878)
SIZE	0.048***	0.048***	0.061***	0.058***
	(5.997)	(5.120)	(8.461)	(6.801)
RDEXP	0.758***	1.509***	-0.639	-0.640*
	(3.913)	(7.696)	(-1.577)	(-1.670)
ADEXP	-1.031***	-0.586	1.099***	1.511***
	(-2.926)	(-1.504)	(5.671)	(7.930)
TQ	0.001	0.011**	0.005	0.011**
	(0.134)	(2.004)	(0.988)	(2.113)
VOL	0.008*	0.010**	0.009**	0.011**
	(1.840)	(2.258)	(2.028)	(2.364)
Industry-FE	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes
Constant	-0.212	-0.291**	-0.375**	-0.339**
	(-1.569)	(-1.964)	(-2.008)	(-2.271)
Observations	29,341	28,702	28,273	27,780
Pseudo R-squared	0.053	0.025	0.047	0.032

In addition, to address any potential endogeneity issue, I re-estimate our baseline model with 2-years lagged *REM* and *AEM* as instrument variables. Prior literature implies that dynamic models with the inclusion of a lagged variable partially resolve the endogeneity problem (Chang and Zhang 2015; Hu 2021; Kim *et al.* 2016). Table 2.4 reports the results of the two-stage least square (2SLS) regression. I find that the coefficients of *REM*, and *AEM* remain negative and significant. This further supports that our findings are robust to endogeneity concerns.

Table 2.4: Multivariate regressions of abnormal compensation with instrument variable

This table reports 2SLS regression results employing abnormal compensation (*ACOMP*) as the dependent variable and the variables of interest, real earnings management (*REM)* and accrual-based earnings management (*AEM*). Regressions employ 2-years lagged earnings management as instrument variables. Control variables include Leverage (*LVG*), Firm size (*SIZE*), R&D expenditure (*RDEXP*), Advertising expenditure (*ADEXP*), Total Q (*TQ*), and Volatility (*VOL*). The underidentification test (Kleibergen-Paap rk LM statistic) and the weak identification test (Kleibergen-Paap rk Wald F statistic) are reported. All variables are winsorized at the 1st and 99th percentiles. The sample is based on annual data of U.S. firms from 1993 to 2020. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Variables	*ACOMP*			
(1)	(2)	(3)	(4)	(5)
L2REM	0.838***			
	(110.20)			
L2AEM		0.196***		
		(18.793)		
REM			**-0.246*****	
			(-7.335)	
AEM				**-1.140***
				(-1.649)
Controls			Yes	Yes
Industry-FE			Yes	Yes
Year-FE			Yes	Yes
Constant			-0.225	-0.431***
			(-1.449)	(-2.631)
Kleibergen-Paap rk Wald F statistic	12.043**	352.979***		
Kleibergen-Paap rk LM statistic			288.699***	201.357***
Observations	27,242	26,349	27,242	26,349
Pseudo R-squared	0.022	0.034	0.047	0.021

2.4.2.2 The effect of EM on ACOMP - SOX regulation

To investigate H1a further, I focus on moderating effect of SOX of 2002 on the association between *EM* and *ACOMP*. Prior literature (Cohen *et al.* 2008) has documented a significant change in *EM* activities due to SOX. *REM*, which is not only relatively harder to be detected (Graham *et al.* 2005), but also more costly to the firm, has increased significantly after the passage of SOX, and *AEM* became less prevalent and potent than *REM*.

To test whether the effect of *EM* on *ACOMP* is moderated by the passage of SOX, I use the data corresponding to 2 years before and after the SOX to re-estimate our baseline regression models.[3] I include a dummy variable *PSOX* that equals one for the years 2003 and 2004, indicating the post-SOX period. Table 2.5 reports the result. I find that the coefficient on the interaction term *REM×PSOX* is negative (-0.076) and significant at the 0.05 level, indicating that after SOX, the effect of *REM* on *ACOMP* is stronger. Therefore, managers' *ACOMP* decreased more due to the interest alignment effect. However, as expected, I find that the coefficient of the interaction term *AEM×PSOX* is not significant, indicating that SOX did not have any material impact on the relationship between *AEM* and *ACOMP*. Therefore, the effect of *REM* on *ACOMP* is more pronounced after SOX compared to *AEM*, indicating that CEOs were more penalized for doing *REM* as they shifted from *AEM* to *REM* (Cohen et al. 2008).

[3] I also use 3 years and 4 years before and after the passage of SOX to test our results, our results are qualitatively unchanged.

Table 2.5: Multivariate regressions of abnormal compensation with SOX effect

This table reports multivariate regression results employing abnormal compensation (*ACOMP*) as the dependent variable and the variables of interest, real earnings management (*REM*) and accrual-based earnings management (*AEM*). The regression employs a dummy variable PSOX indicating 2 years after SOX with earnings management activities as interaction terms. Control variables include Leverage (*LVG*), Firm size (*SIZE*), R&D expenditure (*RDEXP*), Advertising expenditure (*ADEXP*), Total Q (*TQ*), and Volatility (*VOL*). All variables are winsorized at the 1st and 99th percentiles. The sample is based on annual data of U.S. firms from 1993 to 2020. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Variables	*ACOMP*	
(1)	(2)	(3)
REM	-0.135***	
	(-4.332)	
AEM		-0.431
		(-0.931)
PSOX	-0.180**	-0.204***
	(-2.571)	(-2.725)
REM× PSOX	**-0.076****	
	(-2.199)	
AEM× PSOX		**0.322**
		(0.555)
Controls	Yes	Yes
Industry-FE	Yes	Yes
Year-FE	Yes	Yes
Constant	-0.249	-0.321
	(-0.709)	(-0.940)
Observations	4,336	4,308
Pseudo R-squared	0.061	0.042

2.4.2.3 The effect of EM on ACOMP – multinomial logit regression

To further test the effect of *REM* and *AEM* on *ACOMP*, I focus on the group of CEOs who are most active in *EM*. Specifically, I classify firms in our sample into four groups based on their relative position in the quartile distribution of *REM* or *AEM* in a given year and industry. CEOs in the top quartile *(Q1_REM* or *Q1_AEM)* firms are most likely to engage in *REM* or *AEM*, indicating they may have better control over firms compared to their peers. Similarly, I classify firms into four groups based upon their relative position in the quartile distribution of *ACOMP* in a given year and industry (*Q1_ACOMP*, *Q2_ACOMP*, *Q3_ACOMP,* and *Q4_ ACOMP*, respectively). CEOs of firms in the top quartile (*Q1_ACOMP*) are the ones with the highest *ACOMP*, and the rest are denoted in declining order (*Q2_ACOMP > Q3_ACOMP > Q4_ ACOMP,* respectively). *Q4_ ACOMP* is set as the benchmark category.

Table 2.6 shows the results using the multinomial logit regression technique. It shows both *REM* and *AEM* remain negative and significant among different quartiles of *ACOMP*, as expected. Notably, I find that the magnitude of *Q1_REM* shows a decreasing trend, it has statistically significant coefficients of -0.947, -0.528, and -0.222, respectively (see Columns (2) to (4)). The negative and decreasing magnitude of coefficients suggests that the CEOs who engage in more *REM* are more likely to witness a greater reduction in their *ACOMP*. The message is clear that, although CEOs receive high *ACOMP* using greater control over firms and high managerial entrenchment, they are penalized by a greater amount of reduced *ACOMP*. Compared to *REM*, *AEM* also has coefficients of -0.075, -0.137, and -0.080, significant at 0.10, 0.01, and 0.10 levels respectively (see Columns (5) to (7)). However, it does not show any clear trend. The plausible explanation is that *AEM'*s effect is relatively moderate compared to *REM*, therefore, CEOs are only likely to receive a similar amount of reduced *ACOMP* if they engage in higher levels of *AEM*. Although CEOs stimulate short-term earnings through *REM* activities, their personal wealth, which is aligned with firms' interests (Diri *et al.* 2020), is negatively affected by *REM* in the long run, leading to a greater amount of reduced *ACOMP*.

Table 2.6: Multinomial logit regression

This table reports multivariate regression results employing the categorical variable *Q_ACOMP* as the dependent variable (from quarter one (Q1) to quarter three (Q3)) and the variables of interest, the dummy variable *Q1_REM* and *Q1_AEM*, which indicates the top quartile of *REM* and *AEM*, respectively. The regression results show the trend of *ACOMP* of the CEOs who engage in the highest level of earnings management in a given year and industry using multinomial logistic regression. Control variables include Leverage (*LVG*), Firm size (*SIZE*), R&D expenditure (*RDEXP*), Advertising expenditure (*ADEXP*), Total Q (*TQ*), and Volatility (*VOL*). All variables are winsorized at the 1^{st} and 99^{th} percentiles. The sample is based on annual data of U.S. firms from 1993 to 2020. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Variables	*ACOMP*					
	Q1	Q2	Q3	Q1	Q2	Q3
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Q1_REM	**-0.947*****	**-0.528*****	**-0.222*****			
	(-12.140)	(-8.115)	(-3.974)			
Q1_AEM				**-0.075***	**-0.137*****	**-0.080***
				(-1.649)	(-3.152)	(-1.867)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.471***	-1.202***	-3.481***	-1.978***	-1.821***	-3.997***
	(-2.824)	(-2.643)	(-4.551)	(-3.306)	(-3.539)	(-4.952)
Observations	29,341	29,341	29,341	28,702	28,702	28,702
Pseudo R-squared	0.026	0.026	0.026	0.019	0.019	0.019

2.4.3 The effect of *EM* on *ACOMP* – the likelihood of negative *ACOMP* (Test of H1b)

Moreover, CEOs engaging in *REM* may be penalized by a lower than average compensation rather than just reduced *ACOMP*. Thus, I turn our attention to firms in our sample with negative *ACOMP* (Variable *NACOMP* is equal to one if the *ACOMP* is negative, zero otherwise). Table 2.7 shows the regression results obtained using logistic regression. The positive and significant coefficient of 0.455 (see Column (2)) suggests that CEOs are more likely to be penalized by *NACOMP* when they do *REM* due to the interest alignment effect.

We find that *AEM* shows an insignificant effect on the likelihood of *NACOMP*, as shown in Column (3). Unlike *REM*, *AEM* just changes the reporting measure and does not change a firm's operating strategy. Thus, CEOs only receive a reduced amount of *ACOMP,* not *NACOMP*, which suggests that firms should also improve the monitoring mechanisms for detecting *REM*. Although CEOs who engaged in *REM* are penalized by *NACOMP,* the interest alignment effect suggests that firms' long-term value has also been compromised. Therefore, to avoid potential loss of firms' value, firms should improve their effectiveness in monitoring *REM*.

Table 2.7: Multivariate regressions of negative abnormal compensation

This table reports multivariate regression results employing a dummy variable *NACOMP* indicating the negative abnormal compensation as the dependent variable, and the variables of interest, real earnings management (*REM*) and accrual-based earnings management (*AEM*). Control variables include Leverage (*LVG*), Firm size (*SIZE*), R&D expenditure (*RDEXP*), Advertising expenditure (*ADEXP*), Total Q (*TQ*), and Volatility (*VOL*). All variables are winsorized at the 1st and 99th percentiles. The sample is based on annual data of U.S. firms from 1993 to 2020. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Variables		*NACOMP*	
	(1)	(2)	(3)
REM		**0.455***** (13.411)	
AEM			**0.029** (0.100)
Controls		Yes	Yes
Industry-FE		Yes	Yes
Year-FE		Yes	Yes
Observations		30,094	29,276
Pseudo R-squared		0.039	0.025

2.4.4 The effect of *EM* on *ACOMP* – complex *EM* strategy (Test of H1c)

As discussed in section 2.2.1, executives are likely to use a combination of *AEM* and *REM* to manage their earnings. To capture the different preferences, I generate two variables to estimate executives' use of both *EM* (Braam *et al.* 2015; Cohen *et al.* 2008; Cohen and Zarowin 2010). The first dummy variable, *REM_H*, indicates a relatively higher use of *REM*, which equals one if the calculated *REM* of each firm-year is above the median of industry-year, and zero otherwise. A firm having *REM_H* equalling one suggests that it uses a relatively higher level of *REM* than its industry peers, while zero suggests the opposite. The second dummy variable, *AEM_H*, indicates the use of *AEM*, which equals one if *AEM* for firm i in year t is above the median of industry-year, and zero otherwise. Similarly, a value of one indicates that the CEO tends to use a relatively higher level of *AEM* than its industry peers. Then, I classify our sample into four groups based on different levels of *EM* to reflect various complex *EM* strategies. Specifically, firms with both relatively high use of *REM* and *AEM* are assigned to the first group, $REM_H\_AEM_H$ (*REM_H* equals one and *AEM_H* equals one). Firms using relatively high *REM* and low *AEM* are assigned to the second group, $REM_H\_AEM_L$ (*REM_H* equals one and *AEM_H* equals zero). Firms using relatively low *REM* and simultaneously high *AEM* are assigned to the third group, $REM_L\_AEM_H$ (*REM_H* equals zero and *AEM_H* equals one). Finally, firms using both relatively low *REM* and *AEM* are assigned to the fourth group, $REM_L\_AEM_L$ (*REM_H* equals zero and *AEM_H* equals zero), which is also the benchmark category. These variables capture varying complex *EM* strategies adopted by firms.

Finally, to test H1c, which expects that a complex *EM* strategy involving different levels of *AEM* and *REM* still has a negative effect on CEOs' *ACOMP*, I include the above categorical variable involving varying combinations of *REM* and *AEM* into the regression model. Table 2.8 reports the results where $REM_L\_AEM_L$ is absorbed by the constant, therefore serving as the reference category. I find that the two most detrimental combinations, $REM_H\_AEM_H$ and $REM_H\_AEM_L$ show statistically significant negative coefficients of -0.195 and -0.172 at the 0.01 level, respectively. Such results suggest that even though firms use different combinations of *REM* and *AEM* strategies, CEOs are still likely to receive reduced *ACOMP*. In addition, the magnitude of $REM_H\_AEM_H$ is higher than that of $REM_H\_AEM_L$, indicating that CEOs are penalized more than their peers due to the use of the highest level of *EM***.** I also find that $REM_L\_AEM_H$ shows an insignificant effect, indicating that there may not be a significant difference in the amount of reduced *ACOMP* for CEOs using low *REM* and high or low *AEM*. Such results are consistent with our expectation that firms' monetary incentives in contracts align managers' and shareholders' interests effectively even though CEOs employ complex *EM* strategies. In addition, it confirms that CEOs are more likely to be penalized for using *REM* due to its more damaging consequence to a firm's value. Therefore, firms may still use the incentives properly to encourage CEOs to follow shareholders' interests (Gayle *et al.* 2016). The remaining control variables retain their expected sign and explanatory power.

Table 2.8: Multivariate regressions of abnormal compensation – complex earnings management strategies

This table reports multivariate regression employing abnormal compensation (*ACOMP*) as the dependent variable and different types of combinations of *EM* strategies, including high *REM* and high *AEM* ($REM_H\_AEM_H$), high *REM* and low *AEM* ($REM_H\_AEM_L$), low *REM* and high *AEM* ($REM_L\_AEM_H$), and low *REM* and low *AEM* ($REM_L\_AEM_L$), as independent variables. I set $REM_L\_AEM_L$ as the base group. Control variables include Leverage (*LVG*), Firm size (*SIZE*), R&D expenditure (*RDEXP*), Advertising expenditure (*ADEXP*), Total Q (*TQ*), and Volatility (*VOL*). All variables are winsorized at the 1st and 99th percentiles. The sample is based on annual data of U.S. firms from 1993 to 2020. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Variables	*ACOMP*
(1)	(2)
$\boldsymbol{REM_H\_AEM_H}$	**-0.195*** **
	(-9.809)
$\boldsymbol{REM_H\_AEM_L}$	**-0.172*** **
	(-8.927)
$\boldsymbol{REM_L\_AEM_H}$	**-0.0140**
	(-1.056)
Controls	Yes
Industry-FE	Yes
Year-FE	Yes
Constant	-0.150
	(-1.065)
Observations	29,325
Pseudo R-squared	0.037

Overall, our main results are consistent with the hypothesis that CEOs' *ACOMP* is affected adversely by *EM*. If CEOs make value-maximizing managerial decisions, their compensation levels are expected to increase as well due to the interest alignment effect. This is in line with agency theory, showing that a firm's monetary incentives align managers' interests with firms' interests. Also, *REM* is more likely to result in negative *ACOMP* due to its potential to cause severer damage to a firm's value. And even though CEOs use complex *EM* strategies, they are still penalized by reduced *ACOMP*. Our results remain robust to endogeneity and correction for sample selection bias.

2.4.5 Moderating role of firms' financial stress (Test of H2)

In this section, I analyse the moderating effect of financial stress on the association between *EM* and *ACOMP*. Table 2.9 reports the results. Using two measures of financial stress *FSKZ* and *FSWW, I* find that the coefficients of interaction terms *AEM*× *FSKZ* and *AEM*× *FSWW* are negative (-1.347, -0.755) and significant at 0.01 and 0.05 levels, respectively. The results indicate that executives in firms with financial stress who engage in *AEM* receive less *ACOMP*. The effect of *AEM* on *ACOMP* is more pronounced in financially distressed firms. As discussed above, one plausible explanation is that, executives in financially distressed firms are more likely to face additional scrutiny from creditors and outsiders, in order to avoid the loss of their reputation and increased pressure, CEOs may choose to manage the firm's earnings, especially *AEM,* to satisfy the creditors and analysts. Column (2) and (4) reports the results considering the interaction between financial stress and *REM*. The insignificant coefficients suggest that there is no significant difference in the degree of *REM* for financially stressed firms. The plausible explanation is that CEOs are more likely to overstate earnings, or strategically time a firm's information releases to manipulate the firm's performance through *AEM* than *REM* as

AEM is timelier (Edmans *et al.* 2017). Besides, there might not be much room or time left to do *REM*.

Table 2.9: Multivariate regressions of abnormal compensation with financial stress

This table reports multivariate regression results employing abnormal compensation (*ACOMP*) as the dependent variable and the variables of interest, real earnings management (*REM*) and accrual-based earnings management (*AEM*). The regression employs financial stress measures, including *FSKZ* and *FSWW* with earnings management activities as interaction terms. Control variables include Leverage (*LVG*), Firm size (*SIZE*), R&D expenditure (*RDEXP*), Advertising expenditure (*ADEXP*), Total Q (*TQ*), and Volatility (*VOL*). All variables are winsorized at the 1st and 99th percentiles. The sample is based on annual data of U.S. firms from 1993 to 2020. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Variables	*ACOMP*			
(1)	(2)	(3)	(4)	(5)
REM	-0.171***		-0.169***	
	(-12.750)		(-12.919)	
AEM		-0.156		-0.249*
		(-1.196)		(-1.854)
FSKZ	-0.058**	-0.003		
	(-2.293)	(-0.100)		
FSWW			0.054	0.073
			(1.140)	(1.376)
REM× FSKZ	**0.033**			
	(0.948)			
AEM× FSKZ		**-1.347*** **		
		(-3.069)		
REM× FSWW			**0.012**	
			(0.210)	
AEM× FSWW				**-0.755*** *
				(-1.988)
Controls	Yes	Yes	Yes	Yes
Industry-FE	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes
Constant	-0.189	-0.299**	-0.175	-0.289*
	(-1.356)	(-2.013)	(-1.248)	(-1.945)
Observations	29,341	28,702	29,341	28,702
Pseudo R-squared	0.048	0.025	0.049	0.026

2.5 Additional tests

We conduct several additional tests. First, to reduce the potential Type I and Type II errors, I follow the correction procedure in Chen *et al.* (2018), and include the regressors used to derive *ACOMP* in our baseline model. I check the correlation among those variables first, and find that the correlation between *LNSALE* and *SIZE* is about 0.9. Therefore, I exclude *LNSALE* as a control variable while re-estimating our models. I find qualitatively unchanged results, as both *REM* and *AEM* remain negatively significant in explaining *ACOMP*.

Second, I focus on whether corporate governance mechanisms play a role in moderating the relation between *EM* and *ACOMP*. Prior literature shows empirically that the degree of a CEO's opportunistic behaviour is likely to be moderated by a strong governance structure (Gompers *et al.* 2003; Wahid 2018; Diri *et al.* 2020), therefore, I re-estimate our main regressions with different variables indicating firm's corporate governance. Specifically, I have tried the takeover index (Cain *et al.* 2017), board co-option (Coles *et al.* 2014), corporate governance score from Refinitiv and MSCI (KLD) databases, and different board characteristics. I find broadly insignificant effect of corporate governance in moderating the relation between *EM* and *ACOMP.* Although I do find that board size and board non-duality have a positive effect on moderating the association between *AEM* or *REM* and *ACOMP,* respectively, I do not find consistent and significant results from other commonly used proxies for corporate governance. Further studies are needed to understand this relation more specifically.

Finally, I investigate whether firm-level political risk moderates the relation between *EM* and *ACOMP.* Political risk is considered one of the major risk factors faced by managers. Prior literature suggests that high political risk is likely to affect firms' investments (Jens, 2017) and equity issuance (Çolak *et al.* 2017) negatively, and increases the stock price volatility

(Pástor and Veronesi 2012), which increases the earnings volatility. On the one hand, executives may engage in *EM* to avoid the increased risk (Ebrahimi *et al.* 2021). On the other hand, firms facing high political risk are more likely to be under the greater scrutiny of outsiders (Ebrahimi *et al.* 2021), which increases the costs of manipulation activities, leading to less *EM*.

Considering the effect of political risk on *EM*, I re-estimate our baseline model with the interaction of *EM* with the firm-level political risk. Firm-level political risk is calculated following Hassan *et al.* (2019) and Ebrahimi *et al.* (2021). I include a dummy variable, *FLPR*, which indicates a relatively higher firm-level political risk, equalling one if the firm-level political risk is above the median of industry-year, and zero otherwise. I find that the coefficient of *REM*×*FLPR* is insignificant, and the coefficient of *AEM*×*FLPR* is positively significant. Therefore, unlike our previous results, these suggest that *FLPR* firms may not be able to properly monitor the CEOs engaging in *AEM* and, as a result, these CEOs receive higher *ACOMP*.

2.6. Conclusions

In this study, I investigate whether CEOs are penalized for engaging in earnings management activities. I find a negative relation between *EM* and *ACOMP*, and find the negative effect is more pronounced between *REM* and *ACOMP* due to its higher potential to cause damage to a firm's long-term value. Our results suggest that CEOs involved in *EM* are penalized in form of reduced excess compensation. Furthermore, I find that the effect of *AEM* on *ACOMP* is exacerbated in firms facing financial stress. Such results suggest that although CEOs engaging in *EM* are penalized by reduced *ACOMP*, financially stressed firms should still improve the monitoring mechanisms to further mitigate and detect the *AEM* activities to avoid firm value destruction. This is the first study to provide comprehensive evidence of the association between *EM* and CEOs' *ACOMP*.

Our findings provide potential implications for different stakeholders. In general, our evidence supports the compensation-based monitoring mechanisms in U.S. firms, as CEOs engaging in *REM* or *AEM* receive lower *ACOMP*. This is further confirmed that CEOs in financially stressed firms who engage in *AEM* also receive lower abnormal compensation. However, CEOs in high political risk firms who engage in *AEM* receive higher abnormal compensation. Illustrating, therefore, that the monitoring mechanisms of these firms may not be detecting this behaviour. Thus, I alert analysts and stakeholders of such firms. Overall, I expect our results to shed some light on shaping future regulations on executives' pay structure by contributing to the mixed results found in the literature regarding the relation between CEOs' compensation and *EM*, as well as contributing to this literature on which factors moderate this relation.

Appendix for Chapter 2

Appendix 2.1: Variable definition

Variable	Description
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 ($million)
$Log\ Tenure$	The logarithm of the CEO's tenure (in years)
$S\&P500$	Indicator variable equals to one for firms in the S&P500 index at the end of this fiscal year, and zero otherwise
$Log\ Sale$	The logarithm of the firm's sales($million)
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, $million)
Expected Compensation	$Log(Total\ Compensation_{i,t}) = \beta_0 + \beta_1 Log(Tenure_{i,t}) + \beta_2(S\&P500_{i,t-1}) + \beta_3 Log(Sales_{i,t-1}) + \beta_4(BM_{i,t-1}) + \beta_5(RET_{i,t}) + \beta_6(RET_{i,t-1}) + \beta_7(ROA_{i,t}) + \beta_8(ROA_{i,t-1}) + u_{i,t}$
LVG	The ratio of total debt ($million) to total assets ($million) at the end of fiscal year
SIZE	The natural log of the firm's assets ($million) as of the end of fiscal year
RDEXP	The ratio of R&D Expenditure ($million) over total assets ($million) at the end of fiscal year
ADEXP	The ratio of advertising Expenditure ($million) over total assets ($million) at the end of fiscal year
TQ	Download from Peters and Taylor (2017)'s website
VOL	The standard deviation of daily stock price over 1 year at the end of fiscal year
ACOMP	$Abnormal\ Compensation = Log(Total\ Compensation) - Log(Expected\ Compensation)$
Abnormal production costs	The residual from $\frac{PROD_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{i,t-1}} + \beta_2 \frac{\Delta Sales_{i,t}}{Assets_{i,t-1}} + \beta_3 \frac{\Delta Sales_{i,t-1}}{Assets_{i,t-1}} + u_{i,t}$

Abnormal discretionary expense	The residual from $$\frac{DISX_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{i,t-1}} + \beta_2 \frac{Sales_{i,t}}{Assets_{i,t-1}} + u_{i,t}$$
Abnormal operating cash flow	The residual from $$\frac{CFO_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{i,t-1}} + \beta_2 \frac{Sales_{i,t}}{Assets_{i,t-1}} + \beta_3 \frac{\Delta Sales_{i,t}}{Assets_{i,t-1}} + u_{i,t}$$
REM	$$Real\ Earnings\ Management = Abnormal\ production\ costs + Abnormal\ discretionary\ expenses * (-1) + Abnormal\ operating\ cash\ flow * (-1)$$
AEM	The residual from the regression: $$\frac{ACC_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{ACC_{i,t-1}}{Assets_{i,t-1}} + \beta_2 \frac{(\Delta SALES - \Delta AR)_{i,t}}{Assets_{i,t-1}} + \sum_k \beta_{3,k} \frac{ROA\_Dum_{k,i,t}}{Assets_{i,t-1}} + \sum_k \beta_{4,k} \frac{SG\_Dum_{k,i,t-1}}{Assets_{i,t-1}} + \sum_k \beta_{5,k} \frac{MB\_Dum_{k,i,t-1}}{Assets_{i,t-1}} + u_{i,t}$$
Q_ACOMP	Categorical variables indicate the firms' relative position in the quartile distribution of *ACOMP*. CEOs in firms in the top quartile (*Q1_ACOMP*) receive the highest *ACOMP*, and the following receive the decreasing amount of *ACOMP* (*Q2_ACOMP, Q3_ACOMP, Q4_ACOMP)*
Q1_REM	Indicator variable equals one if CEO engaging in the top quartile of *REM*, and zero otherwise
Q1_AEM	Indicator variable equals one if the CEO engaging in the top quartile of *AEM*, and zero otherwise
PSOX	Indicator variable equals one for the years 2003 and 2004 indicating the post-SOX period, and zero for the years 2000 and 2001
NACOMP	Indicator variable equals one if the *ACOMP* is negative, zero otherwise
REM_H	Indicator variable equals one if the calculated *REM* of each firm-year is above the median of industry-year, and zero otherwise
AEM_H	Indicator variable equals one if the calculated *AEM* of each firm-year is above the median of industry-year, and zero otherwise
REM_AEM	Categorical variable indicating the firms' relative *EM* strategy, specifically, it includes $REM_H\_AEM_H$, $REM_H\_AEM_L$, $REM_L\_AEM_H$, $REM_L\_AEM_L$
$REM_H\_AEM_H$	The first group of firms that equals one if *REM_H* equals one and *AEM_H* equals one

$REM_H\_AEM_L$	The second group of firms that equals two if *REM_H* equals one and *AEM_H* equals zero
$REM_L\_AEM_H$	The third group of firms equals three if *REM_H* equals zero and *AEM_H* equals one
$REM_L\_AEM_L$	The benchmark group of firms that equals four if *REM_H* equals zero and *AEM_H* equals zero
FSKZ	Indicator variable equals one if a firm is in the top quartile of financial constraint following Kaplan and Zingales (1997), and zero otherwise
FSWW	Indicator variable equals one if a firm is in the top quartile of financial constraint following Whited and Wu (2006), and zero otherwise
FLPR	Indicator variable equals one if the firm-level political risk following Hassan *et al.* (2019) of each firm-year is above the median of industry-year, and zero otherwise

Appendix 2.2: Summary statistics before and after entropy balanced matching

This table reports the summary statistics before and after entropy balanced matching. Control variables include Leverage (*LVG*), Firm size (*SIZE*), R&D expenditure (*RDEXP*), Advertising expenditure (*ADEXP*), Total Q (*TQ*), and Volatility (*VOL*). All variables are winsorised at the 1st and 99th percentiles. The sample is based on annual data of U.S. firms from 1993 to 2020.

Panel A: Entropy balanced matching sample (above median *REM* as treatment)

	Treat (N = 14,783)			Control (N = 14,925)		
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Matching Control Variables before Entropy Balancing						
LVG	0.230	0.034	0.956	0.210	0.038	0.935
SIZE	7.242	2.235	0.276	7.216	2.789	0.273
RDEXP	0.010	0.001	3.756	0.016	0.001	3.050
ADEXP	0.022	0.002	3.945	0.054	0.006	1.809
TQ	1.182	3.826	5.924	1.944	8.006	4.067
VOL	11.390	4.171	-0.850	11.490	3.698	-0.811
Matching Control Variables after Entropy Balancing						
LVG	0.230	0.034	0.956	0.230	0.034	0.956
SIZE	7.242	2.235	0.276	7.242	2.235	0.276
RDEXP	0.022	0.002	3.945	0.022	0.002	3.945
ADEXP	0.010	0.001	3.756	0.010	0.001	3.756
TQ	1.182	3.826	5.924	1.182	3.827	5.923
VOL	11.390	4.171	-0.850	11.390	4.171	-0.850

Panel B: Entropy balanced matching sample (above median *AEM* as treatment)

	Treat (N = 14,176)			Control (N = 14,420)		
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Matching Control Variables before Entropy Balancing						
LVG	0.230	0.034	0.956	0.230	0.034	0.956
SIZE	7.242	2.235	0.276	7.242	2.235	0.276
RDEXP	0.010	0.001	3.756	0.010	0.001	3.756
ADEXP	0.022	0.002	3.945	0.022	0.002	3.945
TQ	1.182	3.826	5.924	1.182	3.827	5.923
VOL	11.390	4.171	-0.850	11.390	4.171	-0.850
Matching Control Variables after Entropy Balancing						
LVG	0.218	0.040	1.049	0.218	0.040	1.048
SIZE	7.100	2.499	0.280	7.101	2.500	0.280
RDEXP	0.014	0.001	3.257	0.014	0.001	3.258
ADEXP	0.043	0.005	2.302	0.043	0.005	2.303
TQ	1.610	6.155	4.410	1.610	6.150	4.411
VOL	11.480	3.806	-0.849	11.480	3.806	-0.849

Chapter 3:

CAN ANALYSTS DISCIPLINE CEOS?

3.1 Introduction

The literature examining the drivers of CEOs' compensation has gained momentum recently, reporting factors such as experience, gender, incentives, compensation consultants, 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). Considering the role of sell-side security analysts as information intermediaries (Tan, 2021) and corporate governance monitors (Hussain *et al.* 2021), recent literature also examined the relation between their information environment, and CEOs' total compensation (Kanagaretnam *et al.* 2012; Liu 2017; Mamatzakis and Bagntasarian 2020). Additionally, analysts are key financial advisors to investors, and thus are required to monitor firms to generate forecasts and recommendations (e.g., Loh and Stulz 2018; Wiesenfeld *et al.* 2008; Yu 2008). To provide accurate forecasts and better guide investors, analysts even consider private communications with CEOs (see Skinner and Sloan 2002; Soltes 2014; Brown *et al.* 2015; Gu *et al.* 2019). Through these communications, CEOs gain by minimizing negative surprises (e.g., failure to achieve consensus forecasts), while analysts gain by accessing superior information (Gu *et al.* 2019).

As a consequence, meeting or beating analysts' expectations should positively affect CEOs' compensation package, as negative earnings surprises adversely affect stock prices which in turn affect related compensations adversely (Hall and Liebman 1998; Zhang and Gong 2018). Therefore, if a firm outperforms (underperforms), CEOs' compensation should increase (decrease), as well as the value of their stock options (Burns and Kedia 2006). However, prior studies examining the relation between analysts' information environment and CEOs' compensation might have been confounded by unobservable determinants of CEOs' compensation (the proportion of pay that cannot be observed or explained by CEOs' ability, experience or other economic determinants), as the results reported by them remain inconclusive (Kanagaretnam *et al.* 2012; Liu 2017; Mamatzakis and Bagntasarian 2020).

On the one hand, one strand argues that higher executive compensation and incentives encourage opportunistic behaviour, which increases information complexity to 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 that executive compensation is negatively related to analysts' earnings forecast error (e.g., Hui and Matsunaga 2015; Mamatzakis and Bagntasarian 2020), suggesting that CEOs are penalized 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 minimize agency costs and work in the best interest of shareholders. Any negative deviation should affect their compensation adversely if agency theory holds.

It is important to note that, for a given CEO in a given year, the actual compensation amount used in the above studies might be different from the expected level of compensation for a similar position in the industry. A CEO may get higher compensation in comparison to the previous year despite analysts issuing a higher forecast error, thus leading to a positive relation between forecast error and total compensation. However, despite an increase in total compensation, this increase may be lower than expected. Suggesting, therefore, that CEOs are indeed penalized in the form of reduced total compensation compared to the expected compensation, which is in line with the predictions of agency theory. Thus, I investigate whether the mixed findings in the prior literature are due to the unobserved determinants of executive compensation. To reach this goal, I use abnormal compensation (*ACOMP*, the difference between the predicted/expected total compensation based on known factors such as experience and other economic determinants, and actual total compensation) to study the impact of analysts' forecasts and recommendations on CEOs *ACOMP*. If analysts are effective in monitoring firms, and governance committees and investors value their forecasts and recommendations, then there should be a persistent negative relation between all analysts' forecast metrics capturing adverse information and *ACOMP*. In other words, analysts should have the power to discipline CEOs by affecting their *ACOMP*.

Thus, I explore whether the information issued by analysts, as key external monitoring parties, is a proxy for unobserved determinants of CEOs' compensation. Analysts are expected to have better information about firms, and by issuing earnings forecasts and recommendations, they exert a significant effect on investors' decisions and hence on firms' stock prices (Frankel *et al.* 2006; Wiersema and Zhang 2011). Thus, I expect that if the information analysts disclose serves as a proxy for the unobserved characteristics, their information will also affect the *ACOMP* received by CEOs.

To investigate this relation, I focus on the impact of analysts' one-year ahead earnings forecasts, a short-term proxy of firms' future, and analysts' recommendations, a long-term oriented proxy focusing on future discounted cash flows. Our sample is publicly listed firms in the United States (U.S.) from 1993 to 2020. I 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, I use four metrics, specifically, Analysts' Earnings Forecast Error *(FEEPS),* Earnings Forecast Walk Downs

(WLKDN), Dispersion of Earnings Forecasts *(DISP),* and Negative Earnings Surprise *(NSURP)*. As for analyst recommendations, I also use four metrics, including Average Analyst Recommendation *(RAVG),* Changes in Average Analyst Recommendation *(RCHG),* Buy Analyst Recommendation *(RBUY)* and Sell Analyst Recommendation *(RSELL)*.

Our results provide persistent and strong evidence that *FEEPS*, *WLKDN*, *DISP*, and *NSURP* are negatively associated with CEOs' *ACOMP*. Together, this evidence indicates that CEOs receive higher pay when analysts' earnings forecast error is lower, there are fewer walkdowns, lower dispersion, and fewer negative earnings surprises. I find that a one-standard-deviation increase in *FEEPS, WLKDN, DISP,* and *NSURP* is associated with a decrease of around 1.93%, 1.67%, 1.58%, and 2.50% in *ACOMP*, respectively. Moreover, I find a positive relation between favourable recommendations (*RAVG*, *RCHG* and *RBUY*), and *ACOMP,* as well as a negative relation between unfavourable recommendations (*RSELL*) and *ACOMP*. That is, higher average recommendations, positive changes in recommendations and buy recommendations are related to higher *ACOMP*. To address potential endogeneity concerns, I implement two-stage least squares (2SLS) regression and find that our results are qualitatively unchanged. Together, our results show a negative relation between analysts' unfavourable metrics and CEOs' *ACOMP*, thus confirming the prediction of agency theory. This also indicates that analysts are indeed a proxy for unobserved characteristics that affect CEOs' *ACOMP*.

Next, I focus on which factors drive this negative relation I observe. One such factor is the role of external monitoring mechanisms. I consider three proxies for external monitoring mechanisms: i) corporate governance score (*CGOV Score*) from the Refinitiv database, ii) the *Takeover Index* developed by Cain *et al.* (2017), and iii) the firm level political risk (*FLPR*) measure from Hassan *et al.* (2019). Firms with strong corporate governance provide a more transparent information environment to analysts and likely have a more efficient internal monitoring mechanism to monitor CEOs' *ACOMP* (Adut *et al.* 2011; Yu 2010). Prior literature documents that firms with better corporate governance disclosures are associated with more accurate and less dispersed analysts' earnings forecasts (Yu 2010); they are more likely to achieve analysts' earnings forecasts since they reduce the agency costs (Adut *et al.* 2011); and that when the outside directors' knowledge about the manager increases over time, the CEOs' *ACOMP* is likely to decrease (Kim *et al.* 2014). Further, firms with a high takeover likelihood and high-level political risks are more likely to be monitored than their peers, so I expect these firms to receive higher scrutiny by analysts (Cain *et al*. 2017; Ebrahimi *et al*. 2021).

Our empirical tests suggest that the significance of analysts' forecasts on CEOs' *ACOMP* is prevalent only in firms exposed to strong external monitoring mechanisms, i.e., firms with high *CGOV Score*, *Takeover Index*, and *FLPR*, and is only related to short-term analysts' forecast metrics. These results might help disentangle the mixed findings from prior literature. Our results suggest that high monitoring of CEOs at these firms drives the relation between analysts' information and *ACOMP*. These CEOs need to manage analysts' short-term expectations, to avoid a reduction in their compensation.

Our contribution lies in shedding light on the inconclusive results of the prior limited literature on the effect of the information issued by analysts on CEOs' compensation, by using *ACOMP*, and external monitoring mechanisms to disentangle these findings (e.g., Kanagaretnam *et al.* 2012; Huang and Boateng 2017; Liu 2017; Mamatzakis and Bagntasarian 2020). For practitioners and the board of directors, our study is a reference as prior literature does not provide clear guidance to design metrics of CEOs' compensation based on analysts' information. Unlike previous studies, which focus simply on the statistical association between analysts' forecast metrics and executive compensations, I are also the first to explore the predictive power of analysts' forecast metrics in determining the future *ACOMP* of CEOs. Further, I also contribute to the literature by showing that the negative relation between the *ACOMP* of CEOs and several unfavourable analysts' forecast and recommendation metrics is primarily driven by firms facing strong monitoring environments. Therefore, under strong scrutiny, analysts can discipline CEOs by serving as key market participants that affect their compensation. Together, I hope this evidence is relevant for practitioners in designing CEOs' pay structures.

3.2 Theory and hypothesis development

3.2.1 Impact of analysts' forecast and recommendations on *ACOMP* of CEOs

There always exists information asymmetry between firms and shareholders, which increases the difficulty of evaluating firms' financial performance and CEOs' efforts. Agency theory suggests firms use outcome-based incentives to align their interests with that of executives to avoid conflicts and information asymmetry (Jensen & Meckling 1976). To encourage CEOs to make financial decisions based upon the interest of shareholders and reduce agency costs, such outcome-based incentives directly link managerial compensation to firms' performance.

Shareholders may not be able to monitor executives' behaviour if they are too diffused. Thus, as an information intermediatory, analysts assess and predict the performance of firms in a given period to provide efficient information to investors and shareholders (Chava *et al.* 2010). The effective monitoring hypothesis suggests that 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).

There are several distinctive characteristics of analysts that make them effective external monitors leading to reduced agency costs. First, analysts provide not only current information in the interest of shareholders but also forward-looking information, which may be against the manager's prospective behaviour, and act as prominent information intermediaries and external monitors (Hussain *et al.* 2021). Second, analysts are more likely to be financially sophisticated and review firms' performance on a regular basis and scrutinize earnings management activities to assess firms' performance (Yu 2008; Irani and Oesch 2013; Chen *et al.* 2015).

According to the agency theory, efficient assessment of a firm's performance should be linked to its output (increase in the firm's value). Thus, to avoid negative earnings surprises, one of the primary financial performance benchmarks of firms is to see whether executives achieve analysts' earnings forecast consensus. Intuitively, firms that fail to beat or meet the forecasts are likely to experience significant volatility in the stock price as investors rely on analysts' information to assess firms' performance. Therefore, as a proxy for performance targets, analysts' forecasts are an important factor in executives' incentives.

Despite clear theoretical motivations, the prior literature report mixed results on the association between the quality of analysts' forecasts and executive compensation levels. On the one hand, 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, which increases the information complexity, and, thus, the forecast error (Kanagaretnam *et al.* 2012; Liu 2017). 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. On the other hand, Hui and Matsunaga (2015) show that forecast error is negatively associated with CEOs' bonuses, and Mamatzakis and Bagntasarian (2020) also find that forecast error is negatively related to total compensation and cash bonus. Suggesting, thus, that CEOs are penalized for making firms riskier in line with the agency theory. The lack of consistency may be due to some unobservable determinants of total compensation and inappropriate compensation structures.

ACOMP is defined as the difference between observed total compensation and the expected compensation calculated from several economic components (Core *et al.* 2008). It indicates the portion of total compensation that is not economically justifiable (Guest *et al.* 2022). Executives' total compensation is designed by firms and boards to optimize 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; hence, firms may use compensation consultants and independent compensation committees to assess and propose an appropriate compensation contract (Conyon *et al.* 2019).

Based on the agency theory, analysts perform essential roles in scrutinizing the value-destroying behaviour of executives and providing more accurate information to investors. Therefore, the forecasts issued by analysts assess firms' financial performance and may be associated with CEO's *ACOMP*. Prior literature also supports this assertion. For instance, Chen *et al.* (2015) find that CEOs receive higher excessive pay when there is an exogenous decrease in analyst coverage.

Another possible explanation for the association between analysts' forecasts and CEOs' *ACOMP* is that compensation is linked to disclosure quality. Disclosure quality should be associated with CEOs' compensation since investors are considered important value-increasing stakeholders (Holmstrom 1979). Therefore, lower forecast error and dispersion could be a sign to investors of better disclosure quality. Better disclosure quality and a transparent information environment could also reduce firms' cost of capital (Hui and Matsunaga 2015), and attract cash flows from outsiders (Biddle and Hilary 2006). Besides, firms' financial disclosure quality signals executives' ability to improve firms' performance and value (Chang *et al.* 2010). More accurate forecasts indicate managers pay more effort into providing high-quality information to reduce information asymmetry, leading to a reduced amount of CEOs' *ACOMP* (Byard *et al.* 2006). In addition, CEOs may pay an effort to analyze, maintain and communicate to obtain a high-quality disclosure environment. Considering the cost of disclosure quality, they also forgo the manipulation 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. Therefore, it is reasonable that CEOs receive excess compensation due to the interest alignment effect when disclosure quality has been improved.

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

H1a: *Analysts' unfavourable earnings forecast metrics (high FEEPS, high WLKDN, high DISP, and NSURP) are negatively associated with CEOs' ACOMP.*

Next, I focus on the relation 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). Barber *et al.* (2010) show that analysts' recommendations and the changes of recommendations can predict firms' future performance and market reaction, indicating their valuable role to investors. Therefore, the recommendations convey information about firms' future earnings and reflect an evaluation of CEOs' abilities. Therefore, recommendations are prominent mechanisms to assess CEO performance, leading to the plausible association with abnormal pay.

Prior academic literature finds that analyst stock recommendations are likely to affect the evaluation of CEOs' efficiency. For instance, the board of directors may rely on analysts' stock recommendations to assess CEOs' ability (Wiesenfeld *et al.* 2008). Prior literature also finds that CEOs also prefer to receive optimistic recommendations issued by analysts since it is associated with their interests (Malmendier and Shanthikumar 2014). 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 expectation of a firm's performance is poor. This, in turn, may positively (negatively) affect CEOs' *ACOMP* as a benchmark of ability and effort. Therefore, analysts' recommendations are considered when evaluating CEOs' performance, which could lead to an effect on their *ACOMP* level.

As a result, I use four different measures of recommendation and test their association with CEOs' *ACOMP*. Specifically, I use Average Analyst Recommendation *(RAVG)*, Changes in Average Analyst Recommendation *(RCHG)*, Buy Analyst Recommendation *(RBUY)*, and Sell Analyst Recommendation *(RSELL)* to investigate this relation. I expect that there should be a positive (negative) relation between optimistic (pessimistic) analysts' recommendations and CEOs' *ACOMP*. Our hypothesis is the following:

H1b: *Negative (Positive) analysts' recommendations are negatively (positively) associated with CEOs' ACOMP.*

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

Monitoring mechanisms are generally applied to align the interest of top executives with that of shareholders. Corporate governance has been suggested as the most prevalent mechanism for aligning the interests of stakeholders and CEOs (Sauerwald *et al.* 2019; Anderson *et al.* 2009). Firms facing strong monitoring mechanisms are more likely to provide transparent financial disclosure and reduce managers' discretionary behaviour, which contributes to the quality of analysts' forecasts and recommendations, and also decreases the information asymmetry between firms and investors (Burgstahler and Eames 2006; Adut *et al.* 2011; El Diri *et al.* 2020; Elyasiani *et al.* 2017). Therefore, the relation between analysts' forecasts or recommendations and *ACOMP* is likely to be exacerbated in firms facing stronger external monitoring mechanisms.

We employ three proxies for external monitoring mechanisms.[4] First, the *CGOV Score* is the corporate governance score from Refinitiv's database, which reflect firms' level of corporate governance directly. A higher value of *CGOV Score* indicates stronger monitoring. Second, the *Takeover index* developed by Cain *et al.* (2017) indicates the susceptibility to takeovers. Firms with a higher *Takeover Index* face higher monitoring than their peers (Cain *et al.* 2017). Finally, I 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*

[4] There are also other corporate governance proxies that received attention in the literature, i.e., board characteristics and CEO characteristics. I have tested these characteristics in our empirical model, however, I do not find conclusive evidence.

are likely to be under greater scrutiny by external stakeholders (Ebrahimi *et al.* 2021). Together, I expect that firms under higher scrutiny, i.e., with susceptibility to stricter monitoring mechanisms, will experience a stronger negative association between short-term analysts' earnings forecast metrics and CEOs' *ACOMP*. As a result, I propose the following hypotheses:

H2a: *Stronger external monitoring mechanisms drive the negative association between analysts' earnings forecast metrics and CEOs' ACOMP.*

The effect of monitoring mechanisms on the relation between analysts' recommendations and CEOs' *ACOMP*, however, is not straightforward. Monitoring mechanisms might drive CEOs' *ACOMP* with short-term analysts' metrics, but recommendations are long-term oriented to reflect analysts' opinions (Bradshaw 2004). That is, they focus on an extensive evaluation of firms' strategy and future cash flows that supports analysts' decision to issue a long-term-oriented buy or a sell recommendation (Jung *et al*. 2012). In addition, compared to earnings forecasts, the accuracy of analyst recommendations is hard to be evaluated due to the ambiguous benchmark (Hirshleifer *et al.* 2021). Previous academic literature finds that analysts are more likely to issue *RBUY* to firms that have overvalued stocks (Mohanram *et al.* 2020). The over-optimistic recommendations contribute to mispricing in the market if investors tend to follow the recommendations (Engelberg *et al.* 2020; Guo *et al.* 2020), which further increases the difficulty of evaluating the accuracy of recommendations. Therefore, it is not clear ex-ante whether stronger external monitoring mechanisms drive this relation. Our hypothesis in the null form is the following:

H2b: *Stronger external monitoring mechanisms do not drive the negative association between analysts' recommendation metrics and CEOs' ACOMP.*

3.3 Data, variables and descriptive statistics

Our sample includes all non-financial listed U.S. firms with available data for CEOs' compensation from ExecuComp, analysts' earnings forecast and recommendations 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 from 1993 to 2020. The Appendix lists and explains all variables used in our empirical analyses.

3.3.1 Measurement of *ACOMP*

Following prior literature (Core *et al.* 2008; Robinson *et al.* 2011; Alissa 2015), I 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, and all variables are defined in the Appendix. I include fixed effects for year and 2-digit SIC codes in the above OLS model.

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

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

3.3.2 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, I 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:

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

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 I 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

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[5] In I/B/E/S database, Forecast Period End Date (FPEDATS) correspond to financial year end date of 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 I focus only on FY1, the 1st one-year ahead forecast issued by the analyst. Further, for same firms, 1st forecast announcement dates are different for different analysts for the same FPEDATS, and many analysts issue 1st 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 one-year horizon, I include only those analysts who issues 1st forecast within the first 90 days. I.e., I consider only those 1st 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. I 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.

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 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:

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

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 I 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 I use is a dummy variable *NSURP*, which equals one if the earnings surprise (*SURP*) is negative, and zero otherwise. I 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.

3.3.3 Analysts' recommendation metrics

Our study uses four measures of analyst stock recommendations: *RAVG*, *RCHG*, *RBUY* and *RSELL*. The information provided by I/B/E/S uses a five-point recommendation scale. Specifically, a recommendation with the value of 1 means 'strong buy', 2 means 'buy', 3 means 'hold', 4 means 'underperform', and 5 means 'sell'. Therefore, a higher score means a lower recommendation in I/B/E/S. To facilitate interpretation and understanding, I reverse coded I/B/E/S five-point scale so that a higher score indicates a higher buy recommendation.

We calculate *RAVG* as the mean analyst recommendation for all analysts who cover a firm over a year following Wiersema and Zhang (2011). For *RCHG, I* measure it as the difference between the *RAVG* in the next year *(t + 1)* and the *RAVG* in the current period *(t)*. A negative value of *RCHG* means a downgrade in *RAVG*, a positive value would mean an upgrade in *RAVG.* A zero value would mean there has been no change in *RAVG. RBUY* is an indicator which equals one if a firm's *RAVG* is greater than three, and zero otherwise.[8] *RSELL* is also an indicator variable that equals one if the value of firms' *RAVG* is smaller than three, which means the firm has been recommended as 'Underperformance' or 'Sell'.

3.3.4 Measures of external monitoring mechanism

We use *CGOV Score*, *Takeover Index*, and firm-level political risk (*FLPR*) to proxy a firm's external monitoring environment. *CGOV Score* is obtained from the Refinitiv database. Following Cain *et al.* (2017), the firm-level *Takeover Index* indicates the hostile takeover hazard and susceptibility to takeovers. *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.[9]

3.3.5 Measurement of control variables

Besides the variables of primary interest discussed above, I include several firm-level control variables in our multivariate regression models. Consistent with prior studies, I include firm-level control variables: *Leverage (LVG), SIZE, R&D expenditure (RDEXP), Advertising expense (ADEXP), Total Q (TQ)*, and *Volatility (VOL)* (Chaney *et al.* 2011; Zang 2012; Dah

[8] As I reverse coded the analysts' recommendations, value 4 and 5 means 'Buy' and 'Strong Buy', respectively.

[9] The *FLPR* data obtained from Hassan *et al.* (2019) is quarterly instead of annual.

and Frye, 2017). All variables are defined in the Appendix. I also include industry (2-digit SIC codes) and year dummies to control for the industrial sector and time-specific fixed effects.

3.3.6 Descriptive statistics

We report descriptive statistics of all main variables used in our model in Table 3.1. All continuous variables are winsorized at their 1st and 99th percentiles. Column (1) shows the list of variables used in our subsequent regression models. The mean (Column (2)) and standard deviation (Column (3)) values of all variables are as expected, with no extreme values and comparable with the previous literature. Descriptive statistics of other control variables are also comparable to previous literature with some differences in reasonable range due to the variations of the sample (Core *et al.* 2008; Bugeja *et al.* 2016; Dah and Frye 2017).

Regarding Table 3.1, by construction *ACOMP* has a mean close to zero, with a value of 0.002. The mean of *FEEPS* is 0.023, and the mean of *WLKDN* is 0.102. The positive value suggests analysts initially issue optimistic forecasts and then adjust their estimations to a lower level due to firms' unpleasant performance. The mean of *NSURP* is 0.491, implying that analysts issue relatively optimistic forecasts roughly 50% of the time. Turning to the recommendation-related variables, *RAVG* has a mean of 3.658. *RCHG* has a mean of -0.069 with a range of -4 to 4, which indicates a downgrade in *RAVG*. The mean of *RBUY* is 0.596, indicating that analysts issue 'Buy' or 'Strong Buy' recommendations roughly 60% of the time. On the other hand, *RSELL* has a mean of around 0.071, implying that analysts issue 'Underperformance' or 'Strong Sell' recommendations roughly 7.1% of the time. The descriptive statistics indicate that positive recommendations are issued more frequently than negative recommendations.

We further check the correlation among those variables, and all major variables show low or moderate correlation with each other in untabulated results. I expect these variables to control for the variation in CEOs' compensation, reflective of their efforts, ability, risk premium, and other general economic determinants based upon firms' performance. Therefore, leaving us to test the unexplained variation in their compensation (CEOs' *ACOMP*) on analysts' earnings forecast and recommendation metrics.

Table 3.1: Summary Statistics

This table reports summary statistics for all continuous variables used in the multivariate analysis. All variables are winsorized at their 1st and 99th percentiles. The sample is based on the annual data of U.S. firms from 1993 to 2020.

Variables	Mean	Standard Deviation	Median	Min	Max
(1)	(2)	(3)	(4)	(5)	(6)
ACOMP	0.002	0.606	0.000	-4.883	5.601
FEEPS	0.023	0.063	0.006	0.000	0.492
WLKDN	0.102	0.796	0.001	-2.845	4.473
DISP	0.007	0.020	0.002	0.000	0.155
RAVG	3.658	0.841	3.667	1.000	5.000
RCHG	-0.069	1.058	0.000	-4.000	4.000
LVG	0.220	0.185	0.203	0.000	0.823
SIZE	7.305	1.556	7.205	4.077	11.384
RDEXP	0.037	0.060	0.008	0.000	0.315
ADEXP	0.013	0.030	0.000	0.000	0.179
TQ	1.431	1.780	0.893	-0.283	11.209
VOL	11.526	1.914	11.849	5.843	15.436

3.4 Empirical results and discussions

3.4.1 Empirical model

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

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

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. As for $Analyst\ Recommendations$, I use the one-year lag period recommendations from I/B/E/S, which can be directly employed in our regression model. $Year_t$ indicates year fixed effects, and $Industry_j$ indicates industry fixed effects based on 2-digit SIC codes. Detailed definitions of all variables are in the Appendix. I estimate our regressions using pooled cross-section ordinary least squares regressions with standard errors clustered at the firm level.

3.4.2 Effect of analysts' forecast on *ACOMP* (Test of H1a)

We start by examining the relation between analysts' earnings forecast metrics and *ACOMP*. Empirical results in support of H1a are reported in Table 3.2. Table 3.2 presents the main regression result with different analysts' relevant variables using Eq. (5). In Columns (2) to (5), I report the effect of *FEEPS*, *WLKDN*, *DISP*, and *NSURP* on *ACOMP*, respectively.

Table 3.2: Effect of analysts' forecast on abnormal compensation of CEOs

This table reports multivariate regression results employing abnormal compensation (*ACOMP*) as dependent variable and the variable of interest, analysts' earnings forecast error (*FEEPS*), analysts' walk down of earnings forecast (*WLKDN*), analysts' earnings forecast dispersion (*DISP*), and a dummy variable indicating the negative forecast surprise (*NSURP*). Columns (2) to (5) show the results of our baseline model using OLS regression. Columns (6) to (9) show the results of our baseline model including the regressors used to derive ACOMP following Chen et al. (2018). Control variables include Leverage (*LVG*), Firm size (*SIZE*), R&D expenditure (*RDEXP*), Advertising expenditure (*ADEXP*), Total Q (*TQ*), and Volatility (*VOL*). All analysts' earnings forecast related variables and control variables (except *VOL*) are lagged in the regressions. All variables are winsorized at their 1st and 99th percentiles. The sample is based on annual data of U.S. firms from 1993 to 2020. ***, **, * indicate significance at the 1, 5, and 10 percent level of a two-tailed t-test, ###, ##, # indicate significance at the 1, 5, and 10 percent level of a one-tailed t-test respectively. t-statistics in parentheses, F statistics in brackets.

Variables	*ACOMP*							
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FEEPS	-0.307***				-0.415***			
	(-2.975)				(-4.021)			
WLKDN		-0.021***				-0.023***		
		(-2.969)				(-3.117)		
DISP			-0.790**				-1.159***	
			(-2.292)				(-3.316)	
NSURP				-0.050***				-0.059***
				(-4.994)				(-5.565)
LVG	0.219***	0.205***	0.212***	0.208***	0.201***	0.184***	0.195***	0.188***
	(4.041)	(3.823)	(3.839)	(3.871)	(3.732)	(3.455)	(3.523)	(3.515)
SIZE	0.014	0.015	0.011	0.015	0.028***	0.028**	0.025**	0.029***
	(1.423)	(1.467)	(1.030)	(1.490)	(2.591)	(2.559)	(2.148)	(2.607)
RDEXP	1.065***	1.045***	1.086***	1.032***	1.164***	1.126***	1.176***	1.119***
	(5.015)	(4.911)	(5.127)	(4.857)	(4.631)	(4.456)	(4.675)	(4.423)
ADEXP	-0.752**	-0.758**	-0.816**	-0.762**	-0.584	-0.608	-0.656*	-0.605
	(-2.043)	(-2.057)	(-2.155)	(-2.075)	(-1.577)	(-1.641)	(-1.718)	(-1.638)
TQ	0.004	0.003	0.004	0.003	0.014	0.014	0.012	0.014
	(0.445)	(0.398)	(0.403)	(0.292)	(1.254)	(1.250)	(1.062)	(1.268)
VOL	0.008*	0.009**	0.009**	0.008*	0.010**	0.011***	0.010**	0.011**
	(1.847)	(2.072)	(1.967)	(1.915)	(2.209)	(2.579)	(2.294)	(2.516)
TENURE					-0.018	-0.015	-0.014	-0.015
					(-1.510)	(-1.328)	(-1.270)	(-1.330)
SP500					-0.069***	-0.066**	-0.068**	-0.068***
					(-2.598)	(-2.491)	(-2.570)	(-2.579)
BM					0.096*	0.085	0.082	0.092*
					(1.884)	(1.644)	(1.581)	(1.785)
ARET					0.008	0.007	0.006	0.005
					(0.577)	(0.471)	(0.414)	(0.376)
LARET					0.021*	0.004	0.028**	-0.006
					(1.657)	(0.281)	(1.990)	(-0.501)
ROA					-0.098	-0.082	-0.098	-0.085
					(-1.176)	(-0.983)	(-1.133)	(-1.033)
LROA					0.023	0.020	0.005	0.022
					(0.275)	(0.237)	(0.065)	(0.270)
Industry-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.152	-0.156	-0.195	-0.126	-0.323**	-0.324**	-0.357**	-0.299**
	(-1.253)	(-1.334)	(-1.614)	(-1.062)	(-2.395)	(-2.451)	(-2.544)	(-2.267)
Observations	19,749	19,749	18,390	19,749	19,749	19,749	18,390	19,749
Pseudo R-squared	0.015	0.015	0.015	0.016	0.018	0.018	0.018	0.019

We expect CEO's *ACOMP* to be negatively associated with *FEEPS, WLKDN*, *DISP* and *NSURP*, and *I* find strong support for our hypothesis. 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, I measure the economic significance of a variable by multiplying its standard deviation with its regression coefficient.[10] I 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 1.93% (-0.307×0.063).

We also find significantly negative coefficients of *WLKDN*, *DISP*, and *NSURP* at the 1% level, 5% level, and 1% level, respectively (see Columns (3) – (5)). The regression estimate suggests that when there is one standard deviation increase in *WLKDN*, *DISP*, and *NSURP* from the mean, the expected decrease in *ACOMP* is 1.67% (-0.021×0.796), 1.58% (-0.790×0.020) and 2.50% (-0.050×0.500), respectively. Therefore, as predicted by our hypothesis, *ACOMP* is likely to reduce when the accuracy or the expectation of analysts' forecasts decreases. The finding is largely in line with the discussions that analysts' forecast indicates the firm's disclosure quality and performance which should be managed by CEOs.

Furthermore, to reduce the potential Type I and Type II classification errors, I also follow the procedure of Chen *et al.* (2018) by including the regressors used to derive *ACOMP*

[10] If a regressor X is normally distributed, replacing x with its standardized 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).

in our test equation.[11] 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, I re-estimate our baseline model. However, prior to including all controls again in the second-stage regression, I check the correlation among all covariates and find that the correlation between *LNSALE* and *SIZE* is relatively high, about 0.9. Therefore, I add all covariates in Eq. (1) as additional control variables to Eq. (5), but I exclude *LNSALE.* Table 3.2, Columns (6) to (9) present the results.

We find the coefficients of *FEEPS*, *WLKDN*, *DISP*, and *NSURP* are negative and significant at the 1% level. In addition, the economic significance persists. The regression estimates suggest that when there is one standard deviation increase in *FEEPS*, *WLKDN*, *DISP* and *NSURP* from the mean, the expected decreases in *ACOMP* are 2.61% (-0.415×0.063), 1.83% (-0.023×0.796), 2.32% (-1.159×0.020) and 2.95% (-0.059×0.500), respectively. Compared to the economic significance of variables using the original baseline model, the effect of *FEEPS*, *WLKDN*, *DISP*, and *NSURP* on *ACOMP* is higher after including the regressors in Eq. (1). Such results further suggest that CEOs are likely to be penalized by reduced *ACOMP* when the accuracy of analysts' forecast and the expectation of firm's earning decreases, and the volatility of forecasts and negative *SURP* increases. The broadly qualitatively similar results indicate that our results retain their interpretation after considering the correction suggested by Chen *et al.* (2018).

[11] 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.

3.4.3 Effect of analysts' recommendation on *ACOMP* (Test of H1b)

Next, I investigate the effects of analysts' recommendations on CEOs' *ACOMP*. Table 3.3 reports the results. In Columns (2) to (5), I report the effect of *RAVG, RCHG*, *RBUY*, and *RSELL* on *ACOMP*, respectively. I find that the coefficient of *RAVG* is positive and significant at the 1% level (see Column (2)). It is also economically significant. When there is one standard deviation increase in *RAVG*, the expected increase in *ACOMP* is 1.85% (0.022×0.841). The result indicates that CEOs are likely to be rewarded by a higher *ACOMP* when analysts issue higher recommendations as predicted by agency theory.

Table 3.3: Effect of analysts' recommendation on abnormal compensation of CEOs

This table reports multivariate regression results employing abnormal compensation (*ACOMP*) as dependent variable and the variable of interest, average of recommendation (*RAVG*), change of recommendation (*RCHG*), buy recommendation (*RBUY*), and sell recommendation (*RSELL*). Columns (2) to (5) show the results of our baseline model using OLS regression. Columns (6) to (9) show the results of our baseline model including the regressors used to derive ACOMP following Chen et al. (2018). Control variables include Leverage (*LVG*), Firm size (*SIZE*), R&D expenditure (*RDEXP*), Advertising expenditure (*ADEXP*), Total Q (*TQ*), and Volatility (*VOL*). All analysts' earnings forecast related variables and control variables (except *VOL*) lagged in the regressions. All variables are winsorized at their 1st and 99th percentiles. The sample is based on annual data of U.S. firms from 1993 to 2020. ***, **, * indicate significance at the 1, 5, and 10 percent level of a two-tailed t-test, ###, ##, # indicate significance at the 1, 5, and 10 percent level of a one-tailed t-test respectively. t-statistics in parentheses, F-statistics in brackets.

Variables				*ACOMP*				
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RAVG	0.021***				0.022***			
	(2.598)				(2.760)			
RCHG		0.013##				0.014##		
		{3.020}				{3.180}		
RBUY			0.033**				0.035***	
			(2.560)				(2.740)	
RSELL				-0.055**				-0.060**
				(-2.230)				(-2.434)
LVG	0.097	0.019	0.099	0.098	0.077	-0.021	0.079	0.078
	(1.512)	(0.234)	(1.543)	(1.523)	(1.205)	(-0.260)	(1.241)	(1.219)
SIZE	0.008	-0.014	0.007	0.007	0.020	-0.001	0.019	0.020
	(0.642)	(-0.763)	(0.556)	(0.604)	(1.521)	(-0.031)	(1.441)	(1.500)
RDEXP	0.822***	0.483	0.810***	0.816***	0.960***	0.572	0.948***	0.954***
	(3.430)	(1.394)	(3.373)	(3.411)	(3.512)	(1.390)	(3.464)	(3.497)
ADEXP	-0.939**	-0.967*	-0.945**	-0.947**	-0.743*	-0.726	-0.749*	-0.753*
	(-2.310)	(-1.886)	(-2.328)	(-2.331)	(-1.805)	(-1.408)	(-1.824)	(-1.833)
TQ	0.003	-0.002	0.003	0.004	0.013	0.013	0.013	0.013
	(0.314)	(-0.150)	(0.312)	(0.371)	(1.018)	(0.815)	(1.011)	(1.036)
VOL	0.011*	0.007	0.011*	0.011*	0.015**	0.011	0.015**	0.015**
	(1.737)	(0.734)	(1.733)	(1.754)	(2.441)	(1.130)	(2.430)	(2.435)
TENURE					0.005	-0.009	0.005	0.005
					(0.354)	(-0.444)	(0.359)	(0.350)
SP500					-0.073**	-0.059	-0.073**	-0.074**
					(-2.511)	(-1.614)	(-2.509)	(-2.539)
BM					0.105*	0.125	0.106*	0.104
					(1.664)	(1.345)	(1.676)	(1.639)
ARET					-0.017	0.033	-0.016	-0.016
					(-0.828)	(1.140)	(-0.820)	(-0.823)
LARET					0.000	-0.024	0.002	0.003
					(0.014)	(-0.761)	(0.096)	(0.169)
ROA					0.081	-0.156	0.081	0.085
					(0.714)	(-0.814)	(0.714)	(0.746)
LROA					-0.082	-0.054	-0.080	-0.082
					(-0.787)	(-0.300)	(-0.771)	(-0.788)
Industry-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.090	0.512	-0.027	-0.006	-0.301	0.286	-0.233	-0.209
	(-0.518)	(1.208)	(-0.156)	(-0.035)	(-1.573)	(0.684)	(-1.225)	(-1.096)
Observations	9,969	4,108	9,969	9,969	9,969	4,108	9,969	9,969
Pseudo R-squared	0.013	0.020	0.013	0.013	0.017	0.024	0.016	0.016

Column (3) shows that the coefficient of *RCHG* is positive and significant at 5% level (one-tailed test). The regression result indicates that one standard deviation increase in *RCHG* from the mean increases *ACOMP* by 1.38% (0.013×1.058). The positive and significant coefficient indicates that CEOs are likely to receive more *ACOMP* if the analysts issue an upgrade in *RCHG*. Columns (4) and (5) show the significant positive and negative coefficients of *RBUY* and *RSELL* at 5% level, respectively. Similarly, I find that a one standard deviation increase in *RBUY* (*RSELL*) increases (decreases) *ACOMP* by 1.62% (0.033×0.491) or 1.41% (-0.055×0.256), respectively. Such results suggest that when firms receive buy recommendations from analysts, CEOs are rewarded, and therefore they are interested in managing analysts' expectations about their firms.

In addition, I also re-estimate our baseline model by including the regressors used to derive *ACOMP*, according to Chen *et al.* (2018). Columns (6) to (9) present the results. I find the coefficients of *RAVG, RCHG, RBUY,* and *RSELL* retain their expected sign and significance. Similarly, I calculate their economic significance. The regression estimate suggests that when there is one standard deviation increase in *RAVG, RCHG*, *RBUY*, and *RSELL* from the mean, the expected increases in *ACOMP* are 1.85% (0.022×0.841), 1.48% (0.014×1.058), 1.72% (0.035×0.491) and -1.54% (-0.060×0.256), respectively. The results remain broadly qualitatively unchanged. Together, our empirical results support that when analysts issue favourable recommendations for a firm, the signal is well received by investors leading to a higher stock price, indicating a better firm's performance. Thus, CEOs are likely to be rewarded with *ACOMP*. Our empirical results are consistent with our hypothesis that analysts' recommendations provide valuable information to investors and outsiders so that they are considered important indicators for firms' financial disclosure environment and performance, reflecting CEOs' managerial ability, resulting in an effect on *ACOMP*.

In addition, to address the potential endogeneity problem, I re-estimate our multivariate regression models with the instrumental variable approach. Following prior literature, I first test whether there is an endogeneity problem or not (Bascle 2008). Then, I employ the Jackknife method by using instrumental variables 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, I 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. I find that the hypothesis of endogeneity is rejected well above the 10% level for all recommendation variables (*RAVG*, *RCHG* and *RBUY*, and *RSELL*), and it is also rejected a little over the 10% level for *NSURP*. The other analysts' forecast metrics, however, show the presence of endogeneity. This might be because analysts' recommendations are designed to provide a long-term forecast of the future of the firm, whereas the analysts' forecast metrics I use to focus on a short-term period (one year ahead), and therefore, may be endogenous to CEOs' *ACOMP*. Therefore, I show in Table 3.4 the results for analysts' forecasts metrics only, as there is evidence of endogeneity for most of them, but not for the recommendation metrics as our previous results in Table 3.2 hold. Table 3.4 shows that the results with instrumental variables are consistent with our baseline model in Table 3.2. I find that the coefficients of *FEEPS*, *WLKDN*, *DISP*, and *NSURP* remain negative and significant. This further supports that our findings are robust to endogeneity concerns.

Table 3.4: IV regression for the effect of analysts' forecast on abnormal compensation of CEOs

This table reports multivariate regression results of instrument variable estimates employing abnormal compensation (*ACOMP*) as dependent variable and the variable of interest, analysts' earnings forecast error (*FEEPS*), analysts' walk down of earnings forecast (*WLKDN*), analysts' earnings forecast dispersion (*DISP*), and a dummy variable indicating the negative forecast surprise (*NSURP*). The instrument variable is the mean of the respective variable in a given year, industry and firm size, excluding the firm itself (jackknife average). Control variables include Leverage (*LVG*), Firm size (*SIZE*), R&D expenditure (*RDEXP*), Advertising expenditure (*ADEXP*), Total Q (*TQ*), and Volatility (*VOL*). The underidentification test (Kleibergen-Paap rk LM statistic) and the weak identification test (Kleibergen-Paap rk Wald F statistic) are reported. All analysts' earnings forecast related variables and control variables (except *VOL*) lagged in the regressions. All variables are winsorized at their 1st and 99th percentiles. The sample is based on annual data of U.S. firms from 1993 to 2020. ***, **, * indicate significance at the 1, 5, and 10 percent level of a two-tailed t-test.

Variables				*ACOMP*				
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Endogeneity test (p-value)					0.003***	0.008***	0.000***	0.123
MFEEPS	0.243***							
	(5.761)							
MWLKDN		0.264***						
		(8.172)						
MDISP			0.283***					
			(5.211)					
MNSURP				0.216***				
				(11.664)				
FEEPS					-2.937***			
					(-2.900)			
WLKDN						-0.257***		
						(-3.815)		
DISP							-7.908**	
							(-2.531)	
NSURP								-0.194**
								(-2.047)
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
Constant	0.053	1.245	0.0111	1.040	-0.067	0.038	-0.120	-0.087
	(3.243***)	(1.832*)	(2.390**)	(5.252***)	(-0.383)	(0.160)	(-0.676)	(-0.420)
Kleibergen-Paap rk Wald F statistic	33.167***	66.725***	27.167***	135.841***				
Kleibergen-Paap rk LM statistic					27.047***	54.230***	21.620***	117.036***
Observations	19,316	19,316	17,913	19,316	19,316	19,316	17,913	19,316
Pseudo R-squared	0.013	0.013	0.014	0.014	0.013	0.014	0.013	0.016

Overall, the main empirical results support the hypothesis that CEOs' *ACOMP* is affected by analysts' forecasts and recommendations. Specifically, a higher *FEEPS, WLKDN, DISP*, and *NSURP* lead to a lower *ACOMP*. A higher value of *RAVG*, *RCHG*, and *RBUY*, indicating positive recommendations, leads to a higher *ACOMP*. However, a higher value of *RSELL*, indicating negative recommendations, results in a lower *ACOMP*. This is consistent with our expectation, showing that the information provided by analysts is an important channel considered by investors to evaluate firms' performance and CEOs' managerial ability.

3.4.4 Channel analyses (Test of H2)

In this section, I classify our sample into different sub-samples based on external monitoring metrics such as *CGOV Score*, *Takeover Index*, and *FLPR*. 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-sample.

Table 3.5: Channel analysis of the effect of analysts' forecast and recommendation on *ACOMP* of CEOs

This table reports multivariate regression results employing abnormal compensation (*ACOMP*) as dependent variable and the variable of interest, analysts' earnings forecast error (*FEEPS*), analysts' walk down of earnings forecast (*WLKDN*), analysts' earnings forecast dispersion (*DISP*), and a dummy variable indicating the negative forecast surprise (*NSURP*), average of recommendation (*RAVG*), change of recommendation (*RCHG*), buy recommendation (*RBUY*), and sell recommendation (*RSELL*). Our sample is classified based on three monitoring proxies: *CGOV Score*, *Takeover Index*, and *FLPR*. Control variables include Leverage (*LVG*), Firm size (*SIZE*), R&D expenditure (*RDEXP*), Advertising expenditure (*ADEXP*), Total Q (*TQ*), and Volatility (*VOL*). The untabulated control variables remain their expected sign and significance. All analysts' earnings forecast related variables and control variables (except *VOL*) lagged in the regressions. All variables are winsorized at their 1st and 99th percentiles. The sample is based on annual data of U.S. firms from 1993 to 2020. ***, **, * indicate significance at the 1, 5, and 10 percent level of a two-tailed t-test.

Variables	Low	High	Variables	Low	High
(1)	(2)	(3)	(4)	(5)	(6)
Monitoring Mechanism	*CGOV Score*			*CGOV Score*	
FEEPS	-0.155	-0.372***	*RAVG*	0.033*	0.007
	(-0.801)	(-3.054)		(1.960)	(0.665)
WLKDN	-0.038**	-0.019**	*RCHG*	0.011	-0.000
	(-2.168)	(-2.380)		(0.708)	(-0.031)
DISP	-0.125	-1.033***	*RBUY*	0.039	0.014
	(-0.189)	(-2.656)		(1.461)	(0.870)
NSURP	-0.025	-0.061***	*RSELL*	-0.049	-0.049*
	(-1.328)	(-4.728)		(-0.937)	(-1.718)
Monitoring Mechanism	*Takeover Index*			*Takeover Index*	
FEEPS	-0.108	-0.641***	*RAVG*	-0.000	0.035***
	(-0.734)	(-3.699)		(-0.023)	(3.009)
WLKDN	0.003	-0.052***	*RCHG*	0.006	0.011
	(0.312)	(-3.539)		(0.374)	(0.786)
DISP	-0.329	-2.030***	*RBUY*	-0.001	0.058***
	(-0.638)	(-3.660)		(-0.050)	(3.012)
NSURP	-0.050***	-0.048***	*RSELL*	-0.075*	-0.038
	(-3.172)	(-3.113)		(-1.708)	(-1.156)
Monitoring Mechanism	*FLPR*			*FLPR*	
FEEPS	-0.204	-0.361***	*RAVG*	0.014	0.016
	(-1.426)	(-2.727)		(1.087)	(1.434)
WLKDN	-0.017	-0.024**	*RCHG*	-0.004	0.014
	(-1.500)	(-2.520)		(-0.269)	(1.027)
DISP	-0.625	-0.963*	*RBUY*	0.016	0.025
	(-1.431)	(-1.920)		(0.777)	(1.335)
NSURP	-0.046***	-0.062***	*RSELL*	-0.085**	-0.014
	(-3.261)	(-4.081)		(-1.988)	(-0.449)

Table 3.5 reports the results. I find that the results reported in Table 3.2 for earnings forecast metrics are significant only for firms with high *CGOV Score*. I find a negative and significant association between most of the analysts' forecast-related metrics and *ACOMP* in high *CGOV Score* firms but not in low *CGOV Score* firms. The coefficients of *FEEPS*, *WLKDN*, *DISP*, and *NSURP* are negative and significant with values of -0.372, -0.019, -1.033, and -0.061, respectively. I find most of the coefficients in low *CGOV Score* firms are insignificant, except *WLKDN*. Similarly, for *Takeover Index,* the estimated coefficients of *FEEPS*, *WLKDN*, *DISP*, and *NSURP* are negative and significant, with values of -0.641, -0.052, -2.030 and -0.048 only in the high subsample, except *NSURP*, that is also negative and significant in the low subsample. Finally, for *FLPR,* the findings closely mirror the previous discussions. The negative effect of analysts' forecast-related metrics is limited to the firms with high *FLPR*. I find that the coefficients of *FEEPS*, *WLKDN*, *DISP* and *NSURP* are negative and significant, with values of -0.361, -0.024, -0.963 and -0.062, respectively. For firms with low *FLPR,* most of the coefficients are insignificant, except *NSURP*. Together, these results suggest that the relation between analysts' forecast metrics and *ACOMP* is primarily driven by firms facing a high level of external monitoring.

Turning to recommendation-related metrics (H2b), I find that the coefficients on *RAVG* and *RBUY* are positive and significant in the sub-sample of firms with high *Takeover Index,* but *RCHG* and *RSELL* are insignificant. Further, I do not find consistent results when partitioning is based on *CGOV Score* and *FLPR*. Recommendations, therefore, are not affected by external monitoring mechanisms due to their long-term nature, supporting H2b. Rather, the results I find regarding the negative relation between short-term analysts' earnings forecast metrics and *ACOMP* are channelled through stronger monitoring mechanisms.

3.5 Additional tests

We conduct several additional tests. First, I focus on whether bad macro times play a role in moderating the relation between analysts' forecasts or recommendations and *ACOMP*. Prior literature suggests that investors may rely more on analysts due to the high uncertainty in bad times (Loh and Stulz, 2018). It is difficult for investors to assess firms' prospects during the bad time, and hence, they will rely more on information issued by analysts (Kacperczyk and Seru, 2007; Loh and Stulz 2018). Specifically, I include the Long-Term Capital Management *(LTCM)* crisis of 1998, the credit crisis of 2007 to 2009, and the recessions defined by the National Bureau of Economic Research *(NBER)* in 2001. I find broadly insignificant effects of bad times in moderating the relation between analysts' forecasts or recommendations and *ACOMP*. Also, I find no significant difference in the association between bad and normal times when employing the channel analyses. This indicates that our results are robust to specific events, i.e., financial crises and recessions.

Second, I focus on whether individual characteristics of the board or CEOs moderate the relation between analysts' forecasts or recommendations and *ACOMP*. Prior literature shows that the board characteristics or CEO characteristics are likely to affect the level of corporate governance, and hence the quality of earnings forecasts and recommendations (Byard *et al.* 2006; Francoeur *et al.* 2022; Hsu *et al.* 2021). Therefore, I re-estimate our main multivariate regressions with different CEO and board characteristics. Specifically, I use several metrics such as board independence, board tenure, board size, board gender, CEO gender, and CEO overconfidence. Broadly, I do not find significant differences between the subsamples classified based on these proxies. The plausible explanation may be that compared to the monitoring mechanisms I use, these individual firm or CEO characteristics are not effective monitors on a stand-alone basis. Therefore, the monitoring effect I observe is due to broader monitoring from outsiders, which has a much stronger effect than individual internal monitoring mechanisms.

3.6 Conclusion and future direction

We provide persistent empirical evidence that analysts' forecast metrics, *FEEPS*, *WLKDN*, *DISP*, and *NSURP* are negatively associated with CEOs' *ACOMP*. In addition, I demonstrate that higher average recommendations, positive changes in recommendations and buy recommendations are related to higher *ACOMP.* 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 compensation positively, as predicted by the agency theory. 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 can discipline CEOs effectively in strong monitoring environments. Overall, I expect our results to shed light on the mixed results found in the previous literature regarding the relation between CEOs' compensation and the information issued by analysts. In addition, I supplement this literature on which factors moderate or drive this association.

We suggest future studies to investigate what is the specific monitoring channel that has a more pronounced effect on CEOs' *ACOMP*, so I can advance this literature that studies what affects CEOs' compensation. In addition, I suggest further studies focus on the characteristics of analysts and investigate the factors that drive the difference between recommendations and earnings forecasts. A research agenda that is, for certain, far from over.

Appendix for Chapter 3

Appendix 3.1: Variable definition	
Variable	Description
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 firm's earnings forecasts during a fiscal year and is 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
Recommendation	Categorical variable with the value of 1, 2, 3, 4, 5, which indicates the analyst issues "strong sell", "sell", "still", "buy", "strong buy" recommendations.
RAVG	Mean of analyst *recommendation* for all analysts who cover a firm over a year
RCHG	The difference between the *RAVG* in the next year (*t + 1*) and the *RAVG* in the current period (*t*)
RBUY	An indicator which equals one (and zero otherwise) if firm's *RAVG* is greater than three
RSELL	An indicator which equals one (and zero otherwise) if firm's *RAVG* is smaller than three.
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.
$\boldsymbol{Log\ Tenure}$	The logarithm of the CEO's tenure (in years).
$\boldsymbol{S\&P500}$	Indicator variable equal to one (and zero otherwise) for firms in the S&P500 index at the end of this fiscal year.
$\boldsymbol{Log\ Sale}$	The 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	$$\mathrm{Log}(\mathrm{Total\ Compensation}_{i,t}) = \beta_0 + \beta_1 \mathrm{Log}(\mathrm{Tenure}_{i,t}) + \beta_2(\mathrm{S\&P500}_{i,t-1}) + \beta_3 \mathrm{Log}(\mathrm{Sales}_{i,t-1}) + \beta_4(\mathrm{BM}_{i,t-1}) + \beta_5(\mathrm{RET}_{i,t}) + \beta_6(\mathrm{RET}_{i,t-1}) + \beta_7(\mathrm{ROA}_{i,t}) + \beta_8(\mathrm{ROA}_{i,t-1}) + u_{i,t}$$
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 R&D 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 (item *corpgov_score*)
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

Chapter 4:

EFFECT OF CASH FLOW RISK ON CORPORATE FAILURES, AND THE MODERATING ROLE OF EARNINGS MANAGEMENT AND ABNORMAL COMPENSATION

4.1 Introduction

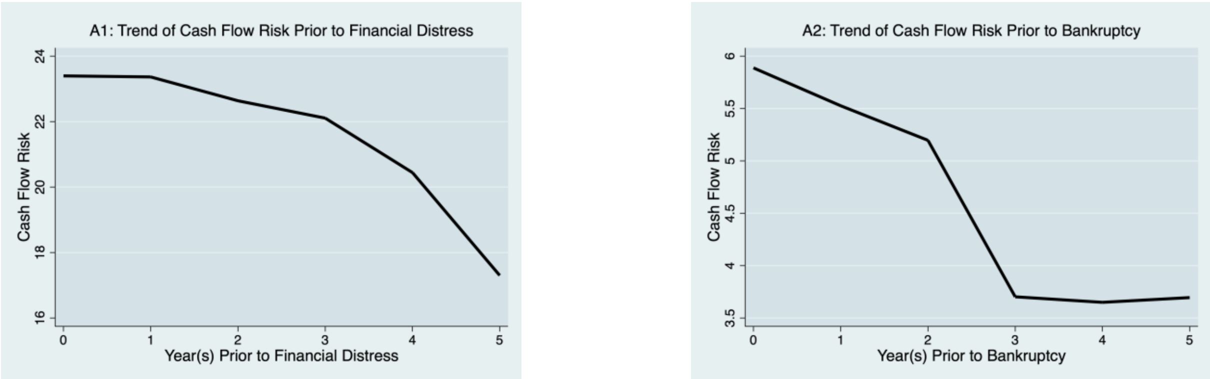
Financial economists, in general, agree that cash flows help investors to assess firms' going concern status by providing information about their solvency position. In recent years, the importance of cash flow risk (*CFR*) is realised by credit rating agencies as well. For example, Fitch retained the rating of Wyndham Worldwide Corp. at BBB - even though its business surrounding was fickle. The reason is that Fitch affirmed Wyndham's effort that "Wyndham has modified its business model to decrease cash flow volatility".[12]

Intuitively, a firm's financial health is fundamentally driven by the stability of its cash flows. Thus, volatile cash flows should adversely affect its survival likelihood. Our empirical investigation shows that *CFR* of non-financial firms in the United States (U.S.) increase steeply as firms approach financial distress or bankruptcy, thus providing a perceivable and reliable signal in predicting a firm's failure (see Fig. 4.1). Moreover, Fig. 4.2 shows that the average *CFR* increased steadily and persistently over the past four decades or so, from about 0.2 in 1980 to about 9.5 in 2021. This upward trend of *CFR* is notable and contains time-varying information, which may help us to estimate firm failures more effectively. Firms with higher

[12] The report is available at https://www.fitchratings.com/research/corporate-finance/fitch-maintains-rating-watch-negative-on-wyndham-worldwide-corp-29-03-2018.

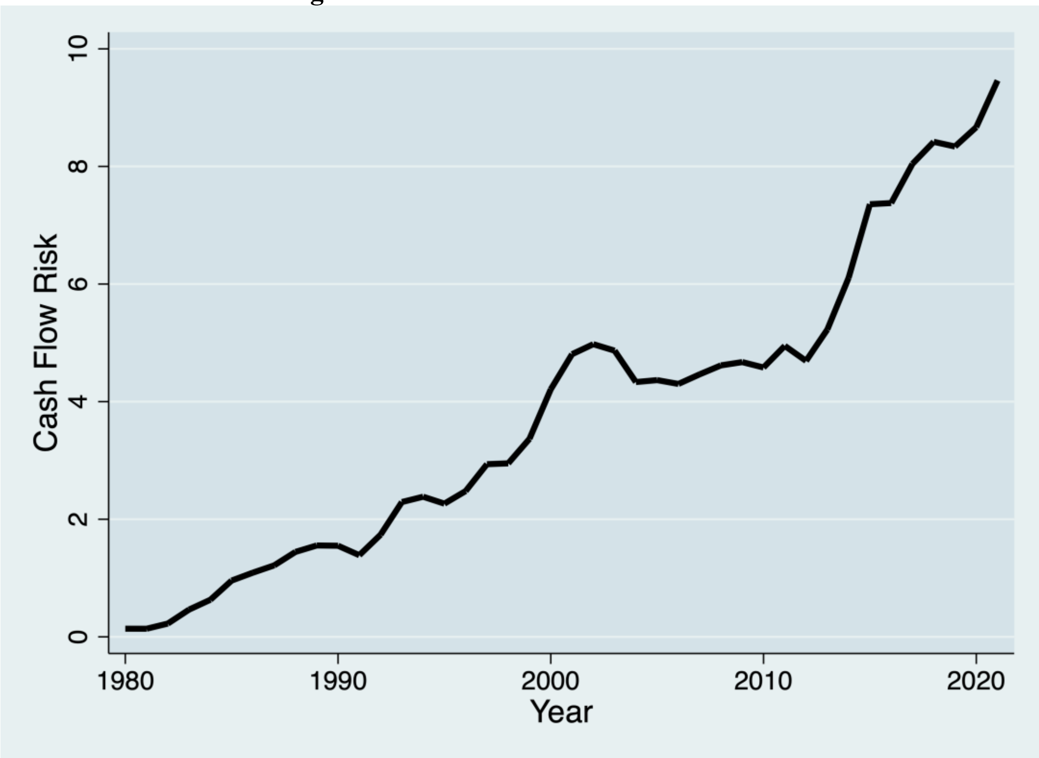
cash flow volatility are more likely to experience internal cash flow shortfall (Minton and Schrand 1999; Minton *et al.* 2002), which often leads to financial distress, thus threatening its going concern status. As such, *CFR* is a noteworthy contender in predicting corporate bankruptcy or firm failures.

Figure 4.1: Time trend of cash flow risk 5 years prior to financial distress and bankruptcy



Notes: This figure exhibits the annual average of cash flow risk (*CFR*) over the 5-year periods prior to financial distress and bankruptcy filings for U.S. firms.

Figure 4.2: Time trend of cash flow risk



Notes: This figure exhibits the annual average of cash flow risk (*CFR*) over the period 1980 to 2021 for U.S. firms.

In light of the above discussion, I explore the explanatory power of *CFR* in predicting corporate failures using a sample of publicly traded U.S. firms over the period 1980 to 2021. Considering the limitations of bankruptcy as a failure indicator (see Gupta and Chaudhry 2019), I use the definition of financial distress proposed by Gupta and Chaudhry (2019) as the dependent variable to perform our empirical analysis.[13] In line with the existing literature (Huang 2009; Douglas *et al.* 2014; Hong *et al.* 2017), I employ a backward-looking estimate of *CFR*, the standard deviation of the ratio of operating cash flow to sales over the past sixteen quarters with at least eight non-missing observations as a suitable predictor. Test results confirm that *CFR* is consistent and economically significant in predicting financial distress.

[13] Our results are also robust to alternative measures of firms' failure indicators including financial constraints, presumed covenant violation and legal bankruptcy. The test results are presented in section 3.4.5.

Although I find a positive, robust, and statistically significant relation between a continuous measure of *CFR* and the likelihood of firms experiencing financial distress, the coefficients of *CFR* remain relatively small, and its average marginal effects are relatively small as well. Thus, to improve its discriminatory power, I re-estimate our regression model with a transformed version of the *CFR* measure. Specifically, I employ a dummy variable *CFRH* which equals one, if a firm's *CFR* is above the median in a given year and industry and zero otherwise. The use of *CFRH* led to a dramatic rise in its discriminatory power, the magnitude of its coefficients, average marginal effects, and, hence, the economic significance. The explanatory power of our model also improved by around 7%.

Next, I investigate what firms do to minimize the adverse impact of high *CFR* on their failure likelihood. The firm's reaction to elevated risk can be assessed from two distinct viewpoints. First, due to career concerns and to avoid the likelihood of violating debt covenants (Habib *et al.* 2013), managers may engage in earnings management to reduce agency costs. In terms of the upper echelons theory, managers who face heavy job demands as a result of the firm's performance challenges are prone to utilizing heuristics (Hambrick 2007), thereby exhibiting a greater inclination towards income-seeking behaviour (Hambrick and Mason 1982).

Thus, to investigate the theoretical prediction of the upper echelons theory, I investigate whether managers employ accrual and real earnings management (*AEM*, *REM*) to reduce the effect of *CFRH* on financial distress. Executives' choices in financial decisions are also significantly affected by their experiences, values, and personalities (Hambrick 2007). Due to the differences in managers' risk aversion, one may expect executives to undertake varying earnings management activities when they face high *CFR*. However, executives who are less risk-averse may engage in *AEM* and *REM* (Deng *et al.* 2018; Cai *et al.* 2019; Cai *et al.* 2020), to reduce financial distress likelihood. While, aggressive executives are also likely to engage in *AEM* or *REM* to smooth income or operating cash flows, and hide their unhealthy financial health, thereby reducing the probability of financial distress (Cai *et al.* 2019; Khuong 2020). Also, firms with high *CFR* may have stronger precautionary motivations to manipulate earnings (Sha *et al.* 2021) since they want to avoid future underinvestment problems and financial distress.

Second, in accordance with the agency theory, efficient boards may employ appropriate compensation incentives to align the interests of managers with those of the firm, thereby enabling managers to act as "good" stewards and mitigate high risk (Velte 2020). Accordingly, firms with efficient boards may adjust managers' compensation levels in response to high *CFR*, as monetary incentives are an effective means of aligning the interests of managers and shareholders. Thus, to investigate the theoretical prediction of the agency theory, I investigate whether abnormal compensation (*ACOMP*) of CEOs negatively moderates the relation between *CFRH* and financial distress. As boards in firms with high *CFR* are more likely to take preventive measures to manage the risk. Due to the interest alignment effect, managers with a higher or positive *ACOMP* are expected to pay more effort into managing the volatile cash flow.

In line with the predictions of the upper echelons theory, test results confirm that *AEM* and *REM* negatively moderate the relation between *CFRH* and financial distress. Suggesting that managers use earnings management successfully to reduce the impact of high *CFR* on firms' failure likelihood. Also confirming the predictions of the agency theory, I observe a negative moderating effect of *ACOMP*. Suggesting that compensation packages designed by boards that incentivize superior risk management help firms in reducing their failure likelihood, thereby, making managers act as good stewards of firms (Velte 2020).

Finally, as robustness checks, I explore the effect of *CFR* on alternative measures of financial distress (financial constraints and presumed covenant violation) and Chapter 11/7 bankruptcy filings, and find broadly similar results. Overall, our investigation suggests that the superior performance of *CFR* in predicting financial distress is robust to various definitions of firm failure or distress.

Overall, our contribution lies in providing a reliable, robust and stable predictor of financial distress, *CFR*, and what firms do to minimize its adverse impact on their financial health. The evidence reported in this study is expected to encourage managers and shareholders to pay attention to *CFR* when evaluating a firm's financial health. In addition, creditors and analysts may also benefit from paying more attention to executives' activities in firms facing higher levels of *CFR*. As I confirm that an efficient board and proper compensation levels do improve a firm's risk management practices, eventually leading to a reduced likelihood of a firm's failure.

4.2 Literature review and hypothesis development

This section presents the rationale behind our choice of a firm's failure definition and *CFR* measure, and develops related hypotheses.

4.2.1 Defining firm failures

A firm's exit as a repercussion of underperformance is generally regarded as its failure/exit in the bankruptcy or firm failure literature (Chava and Jarrow 2004; Campbell *et al.* 2008). Firms that struggle to compete with their peers and sink into financial difficulties will eventually exit the market. The existing literature on bankruptcy or distress risk is extensive and concentrates particularly on modelling methodologies (Neves and Vieira 2006) and the selection of explanatory variables (Shumway 2001; Campbell *et al.* 2008). However, defining firm failures constitutes the premise of all empirical analyses.

Previous studies primarily adopt legal bankruptcy events in conformity with related bankruptcy codes such as U.S. Chapter 7 or 11 fillings. Considering the declined number of legal bankruptcy filings and the significant number of out-of-court settlements, some studies employ other relevant events such as acquisition or delisting (Shumway 2001), or in-default credit ratings (Campbell *et al.* 2008) to supplement bankruptcy filings. However, the problem of these definitions of bankruptcy cannot be neglected. First, the number of U.S. firms filing for bankruptcy under Chapter 7 or Chapter 11 has decreased significantly in recent years. Thus, this gives misleading signals to investors regarding bankruptcy likelihood. Second, it is inappropriate to predict a combination of heterogeneous outcome variables, bankruptcy filings and other default events to proxy bankruptcy. Third, typically a long time lag exists between the legal default date and the real default moment due to the lengthy bankruptcy resolution process (Gupta and Chaudhry 2019). Stakeholders require a visible signal to recognize a firm's financial difficulties well in advance, since waiting until legal bankruptcy filings cause significant erosion in firm value. They may suffer huge losses if they are unable to identify and prepare for the forthcoming crisis. In this regard, an alternative measure to identify firms in financial distress/difficulties is appropriate.

Debt covenant violation is identified as an outstanding indicator of financial difficulties by auditing standards. Violations are technical defaults of financial debt covenants and signal increased financial difficulties (Bhaskar *et al.* 2017). Debt covenants state the restrictions based on accounting information such as interest coverage, leverage, current ratio, or net worth. Bhaskar *et al.* (2017) describe debt covenant violations as "trip wires". Although the restrictions in covenants do not imply that firms face financial difficulties (Dichev and Skinner

2002), firms are likely to experience financial difficulties when lenders react to the "tripped wire" by terminating the loan or restructuring. In this case, firms with violated covenants may suffer higher costs (Kim 2020) and experience financial difficulties or even declare bankruptcy (Bhaskar *et al.* 2017). Similarly, Jaggi and Lee (2002) use debt covenant violations to indicate the severity of financial distress.

Debt covenants state that firms are required to maintain threshold levels, specifically, the level of accounting-based metrics (Demerjian *et al.* 2020), to avoid increased credit risk. The violation of these metrics causes a negative impact on the firm's credit ratings due to inconsistencies in the performance (Graham *et al.* 2005), which further leads to riskier debts and worse future financial health. Therefore, firms that fail to maintain the thresholds are more likely to experience financial distress. Christensen and Nikolaev (2012) classify metrics of debt covenants into performance covenants (P-covenants) and capital covenants (C-covenants). Firms that fail to maintain both P-covenants and C-covenants are likely to experience persistent poor performance and be unable to maintain sufficient capital, which could potentially deteriorate their financial health.

Therefore, to examine firms' degree of financial distress, literature relies on the presumed violation of interest coverage ratio level (from P-covenants) and leverage ratio level (from C-covenants), since those metrics are broadly related to covenant contracts (Demerjian and Owens 2016). Firms with low-interest coverage levels and high leverage ratio levels are more likely to experience financial difficulties and find it harder to access external financing as they confront more difficulties in accessing new borrowing. As such, financial covenants used for estimating financial distress are minimum interest coverage covenants and maximum leverage ratio covenants (Demerjian and Owens 2016). However, the presumed covenants violation measure has an arguable problem that there is no consistent definition for "minimum" or "maximum" thresholds. The value of the threshold is changeable and customised in contracts. Therefore, studies using covenant violations have to customise the appropriate threshold under different requirements.

Another strand of literature uses a series of variations of firms' financial status and financial constraints, which are reflections of fundamental information, to predict financial distress. Such literature uses a firm's fundamental statements to infer its financial constraints, a measure of financial health (e.g. Farre-Mensa and Ljungqvist 2016). *KZ* index (Kaplan and Zingales 1997) is the most prominent measure of such financial constraints. Using five accounting variables, this index loads positively on leverage and market-to-book (*MB*) ratio and negatively on cash flow, dividends and cash. Therefore, the higher value indicates a firm is more constrained and facing higher financial stress. Similarly, Whited and Wu (2006) use another approach (*WW* index) including different accounting variables to reflect a firm's financial constraints. Firms with higher *WW* index values are classified as financially constrained and are more likely to be in distress.

Flagg *et al.* (1991) argue that a firm starts the failure process when it experiences a decline in "health". Financially distressed firms tend to have negative cash flows, reduced dividend payments, or loan defaults (Lau 1987; Flagg *et al.* 1991; Ward 1994), and those events signal a decline in "health". Many studies define financial distress following this framework. Turetsky and McEwen (2001) describe financial distress as a series of stages with a starting point which is the abnormal reduction of cash flow from operating activities. After this decline in financial health, they track different accounting characteristics such as decreasing dividends payment, loan default, or debt restructuring as subsequent distress processes. Franzen *et al.* (2007) also use accounting-based measures to evaluate the distress risk and highlight the popularity of using accounting information in the literature to proxy financial distress.

Similarly, Bhaskar *et al.* (2017) use negative net incomes and operating cash flows to identify financially distressed firms. Due to deficient cash flows, firms are likely to suffer agency costs while seeking external capital, which leads to underinvestment (Hong *et al.* 2019) and further deteriorates the firm's "health". Gupta and Chaudhry (2019) also depict a series of financial characteristics variations to predict financial distress.

As a consequence, I select a dynamic definition conditioned upon accounting and market information, which is proposed by Gupta and Chaudhry (2019), as the main definition of financial distress. Relying on financial fundamentals, a firm is supposed to be financially distressed in the year *t* if the following three conditions are satisfied:

Condition 1: Average market value declines in the years *t–1* and *t–2*.

Condition 2: Earnings before interest tax depreciation and amortisation are less than financial expenses in the years *t–1* and *t–2*.

Condition 3: Operating cash flow is less than financial expenses in the years *t–1* and *t–2*.

This financial distress measure outperforms from the following perspectives. First, Gupta and Chaudhry (2019) use average market value instead of market value on a given date to indicate a firm's average state. They also impose geometrically declining weights on a firm's market values to emphasise the importance of recent observations. Second, this measure comprehensively captures a firm's financial health from both the ability to meet financial commitment and the ability to repay the debts timely. A few studies pay less attention to the timing of cash inflows and outflows, which actually affects the on-time debt repayment (Pindado *et al.* 2008; Keasey *et al.* 2015). In this regard, the financial distress measure proposed by Gupta and Chaudhry (2019) overcomes the limitations I stated earlier and is more appropriate in estimating financial distress for our study.

In light of the above discussion, I employ the measure of financial distress proposed by Gupta and Chaudhry (2019) as a proxy to capture firms' failure or default to perform our empirical analysis. In addition, to establish the robustness of our findings, I also present our results employing alternative definitions of firm failure, namely, financial stress, presumed covenants violation, and legal bankruptcy filings, in Section 4.4.5.

4.2.2 Defining *CFR*

According to bankruptcy laws in several countries, a firm is likely to go bankrupt or experience financial distress if one of the following two statuses is fulfilled. First, the firm confronts insufficient cash flows to pay the creditors, called cash flow shortage. Second, the firm is "overindebted" so that the value of its liabilities exceeds the assets value (Uhrig-Homburg 2005). Over-indebtedness is mentioned only in a few countries, such as Germany and Japan; however, cash flow shortage is required in almost all bankruptcy codes. Charitou *et al.* (2004) emphasize the importance of operating cash flow in estimating financial distress. Additionally, Minton *et al.* (2002) find that higher fundamental volatility results in lower future cash flows and earnings, leading to a high probability of cash flow shortage caused by poor information quality (Su 2013). Such a link implies that firms with higher *CFR* are perceived to experience cash flow shortfalls, which increases the probability of financial distress or bankruptcy. Moreover, Froot *et al.* (1993) illustrate that future cash flow performance is negatively related to *CFR*. A higher cost of capital may be generated based on the analysts' forecast of the firm's future unsatisfactory performance. Minton *et al.* (2002) supplement this argument and assert that cash flow volatility is positively associated with the cost of accessing external capital. In their investigation, *CFR* is measured as the coefficient of variation of a firm's quarterly operating cash flows. As such, high cash flow volatility not only causes internal insufficient cash flows over time but also increases the cost of capital, which, in turn, deteriorates the firm's cash flow shortage and exacerbates its financial distress.

CFR is also broadly used as a determinant of firms' yield spreads (Güntay and Hackbarth 2010; Tang and Yan 2010; Douglas *et al.* 2014; Molina 2015) due to the importance of fundamental information, which further influences firms' financial health. The intuition is that cash shortfall caused by *CFR* leads to lower payoffs to investors, which results in unexpected forecasts and a higher likelihood of financial distress. Tang and Yan (2010) find that *CFR* has a statistically significant relationship with spreads; this study measures *CFR* using the coefficient of variations of operating cash flows. Similarly, Molina (2015) shows a significant positive association between yield spreads and cash flow volatility calculated as the coefficient of variation of operating incomes. Douglas *et al.* (2014) document a strong economic effect of *CFR* on bond yield spreads especially for firms that are closer to default. In this investigation, *CFR* is measured as the standard deviation of operating cash flows scaled by different variables to proxy firm value. Based on these empirical results, I expect *CFR* to be positively associated with financial distress.

There are also alternative explanations for the expected positive relation between *CFR* and financial distress. Some academic studies empirically document the impact of *CFR* on credit ratings. Credit ratings indicate a firm's financial health. Rating agencies provide different levels of ratings to reduce the information asymmetry between investors and corporations. Higher credit ratings enhance a firm's reputation, thereby, affecting the cost of capital. In contrast, for lower-rated firms, debts are risky and vary with future cash flows (Güntay and Hackbarth 2010), which further increases the likelihood of experiencing financial distress as discussed above. Güntay and Hackbarth (2010) report that *CFR* (proxies by forecast dispersion) is related to credit rating downgrades, which, in turn, leads to credit risk along with higher bond credit spreads and influences the probability of financial distress.

Based on the above discussions, previous studies that investigate a firm's financial health and *CFR* generally employ two categories of measure: (i) studies directly using cash flow-related accounting information to measure *CFR*, or (i) studies applying a potential proxy for *CFR*. Alnahedh *et al.* (2019) state that direct cash flow information contributes more accuracy when capturing uncertainty. Accordingly, I employ the direct measure of *CFR* to predict the likelihood of financial distress. The prevalent direct measure employs the standard deviation of cash flows to a scalar, such as book assets, sales, or book equity (Huang 2009; Douglas *et al.* 2014; Hong *et al.* 2017). To standardise firms' cash flows, I use sales as the proxy for firm size (Berk 1997) based on the following reason: first, recent studies (Huang 2009; Hong *et al.* 2017) use the ratio of cash flow to sales in their study and report significant results; second, Huang (2009) confirms that using sales as scalar can effectively reduce the autocorrelation in cash flows.

Overall, I expect *CFR* to have a positive effect on the probability of financial distress. Therefore, our hypothesis is as follows:

H1: *There is a positive association between CFR and financial distress.*

4.2.3 Moderating effects of *EM* and *ACOMP*

4.2.3.1 Moderating effects of EM

Managers in firms facing high *CFR* are likely to take preventive measures to reduce the impact of volatile cash flows on the failure likelihood. Analysts and related stakeholders rely on this information to evaluate a firm's performance (Givoly *et al.* 2009), especially when firms are facing bankruptcy risks (Yoo and Pae 2017). Due to the greater scrutiny from outsiders and career concerns, managers may opportunistically exercise discretion over earnings to minimize the agency cost (Jiraporn *et al.* 2008) and satisfy the outsiders (Burgstahler and Dichev 1997). The managers will disseminate new reports aimed at enhancing and updating investors' perceptions regarding the financial well-being of the organization (Beyers *et al.* 2019). This resonates with the predictions of the upper echelons theory which posits that executives facing heavy challenges or performance difficulties are subjected to high job demands (Hambrick 2007). This can lead to non-rational decisions making by managers, including the utilization of opportunistic behaviours (Hambrick and Mason 1982; Ronen and Yaari 2008). This phenomenon is attributed to the fact that such managers may be more heavily influenced by their characteristics and experience (e.g. Arun *et al.* 2015; Harris *et al.* 2019; Cai *et al.* 2019).

Therefore, some risk-taking managers may intervene in financial statements to maintain the volatility of cash flow within a rational range in order to avoid its negative influence on the firm value. Managers of unhealthy firms or low growth potential (Li and Kuo 2017) may also have higher incentives to manipulate their financial performance, such as earnings (Saleh and Ahmed 2005; Charitou *et al.* 2011). Indeed, a manager's managerial risk aversion is associated with *AEM* (Faccio *et al.* 2016; Deng *et al.* 2018; Cai *et al.* 2019; Bouaziz *et al.* 2020), as well as *REM*. Executives who are less risk-averse are also likely to engage in *AEM* (Deng *et al.* 2018) to smooth income and reduce *CFR* (Cai *et al.* 2019). For risk-taking managers, they are likely to use *AEM* to reduce *CFR* instead of financial derivatives for hedging purposes (Barton 2001). Such activities decrease earnings and cash volatility, leading to a reduced level of bankruptcy probability (Sha *et al.* 2021). In addition, previous literature shows that *REM* has a direct effect on cash flow (Braam *et al.* 2015). Aggressive managers are likely to engage in *REM* when a firm has unpredictable volatility of cash flows, to help firms hide the worsening state of financial health (Khuong 2020). Additionally, managers in firms with weak internal governance are more susceptible to engaging in *REM* (Cheng *et al.* 2016) due to their stronger entrenchment power. Using *REM*, managers also try to smooth the earnings and firms' operating cash flows (Cai *et al.* 2020), which further decreases the probability of distress.

In addition, firms with high *CFR* may have stronger precautionary motivations to avoid future underinvestment problems and financial distress (Han and Qiu 2007; Sha *et al.* 2021). Prior literature documents that when firms face high *CFR*, they are more likely to reduce innovative investment to avoid strong financial constraints (Liu *et al.* 2017; Beladi *et al.* 2021) due to the precautionary motives. Therefore, these firms are more likely to undertake *AEM* to avoid unexpected changes to earnings and cash flow in financial statements (Sha *et al.* 2021) or undertake *REM* to directly affect their cash flows (Braam *et al.* 2015), expecting to reduce their default likelihood.

Thus, guided by the predictions of the upper echelons theory and the above discussion, our hypothesis is as follows:

H2: *EM negatively moderates the relation between CFRH and financial distress.*

4.2.3.2 Moderating effects of ACOMP

In addition to *EM* activities, firms with efficient boards may also try to adjust compensation incentives in response to firms' high risk (Gormley *et al.* 2013). A firm's risk environment affects the structure of its executive's compensation level, which in turn alters the manager's incentives and corporate investments to manage the firm's risk (Gormley and Matsa, 2011). When firms face high risk, shareholders' interests and benefits may be negatively affected. Agency theory posits that monetary incentives are an effective means of aligning the interests of managers and shareholders. In this manner, the use of monetary incentives serves as a mechanism for mitigating the agency problem that arises from the inherent misalignment of interest between managers and shareholders. The value-maximizing financial decisions are therefore tied to the manager's compensation level, and board members may intervene when necessary to minimize value erosion.

Thus, boards may react by adjusting compensation levels in light of the increased risk to motivate managers to reduce the volatility and probability of financial distress (Gormley *et al.* 2013). Additionally, efficient internal governance is also reported to be an important determinant of a firm's cash flows (Cheng *et al.* 2016). Thus, managers are more likely to be encouraged to undertake active actions in managing *CFR* if their compensation structures incentivise them to do so. Accordingly, I expect firms with efficient boards to adjust compensation levels in response to high *CFR*. This alignment of interests is expected to result in managers making greater efforts to manage volatile cash flow, especially when they have a higher or positive *ACOMP*. To test this assertion, I examine whether the negative relation between *CFR* and financial distress is moderated by CEOs abnormal compensation (*ACOMP*).

Thus, guided by the predictions of the agency theory and the discussion above, our hypothesis is as follows:

H3: *ACOMP negatively moderates the relation between CFRH and financial distress.*

4.3 Data, covariates and summary statistics

Our sample includes all U.S. domestic firms listed on NYSE, AMEX, and NASDAQ with available accounting and stock returns data. Accounting data are obtained from Compustat, and stock returns data from the Center for Research in Security Prices (CRSP). The sample is from 1980 to 2021. I exclude firms in financial services, transportation, community, public utilities, public administration and non-classifiable industrial sectors to maintain broad homogeneity in financial reporting and market competition within our sample.

4.3.1 Dependent variable

As discussed in section 4.2.1, I employ the definition of financial distress proposed by Gupta and Chaudhry (2019) as the dependent variable.

4.3.2 Independent variables

This section discusses all covariates employed in the subsequent empirical analysis.

4.3.2.1 Cash flow risk

As a predictor variable, *CFR* incorporates more historical time series information. I measure *CFR* as the standard deviation of the ratio of operating cash flow to sales (as discussed in section 4.2.2) over the last sixteen quarters with a minimum of eight non-missing observations (Huang 2009; Hong *et al.* 2017). Cash flow from operations (*CFO*) is defined as the sum of earnings before extraordinary items, depreciation and amortisation, and change in working capital (Huang 2009). This definition examines the fluctuation of cash flow without the camouflage of other accounting variables documented in the accounting statements (Huang 2009). Consistent with the previous literature, I scale it by sales, which are used as a proxy for firm size (Berk 1997; Huang 2009). In order to match with other variables, I calculate the annual *CFR* based on the average of the calculated quarterly data.

Additionally, to assess the explanatory power and economic significance of *CFR*, I re-estimate our results with its transformed version. Specifically, I use a dummy variable *CFRH* that equals one if the firm's *CFR* exceeds the median level in a given year and industry, and zero otherwise. A firm having *CFRH* indicates a relatively high *CFR* than its industry peers.

3.3.2.2 EM and ACOMP

Following prior literature (Huang *et al.* 2017; Ferri *et al.* 2018), I use Collins *et al.* (2017) model to measure *AEM*. Specifically, I estimate the following equation:

$$\frac{ACC_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{ACC_{i,t-1}}{Assets_{i,t-1}} + \beta_2 \frac{(\Delta Sales - \Delta AR)_{i,t}}{Assets_{i,t-1}} + \sum_k \beta_{3,k} \frac{ROA_{Dum_{k,i,t}}}{Assets_{i,t-1}} + \sum_k \beta_{4,k} \frac{SG_{Dum_{k,i,t-1}}}{Assets_{i,t-1}} + \sum_k \beta_{5,k} \frac{MB_{Dum_{k,i,t-1}}}{Assets_{i,t-1}} + u_{i,t} \quad (1)$$

where *ACC* is total accruals, calculated as the sum of the change in accounts receivable, inventories, accounts payable, taxes, and other items from the cash flow statement, and *i* indexes firm and *t* indexes year. *Assets* is the book value of total assets, $\Delta Sales$ denotes the changes in sales, ΔAR denotes the changes in account receivables, dummy variables $ROA_{Dum_{k,i,t}}$, $SG_{Dum_{k,i,t-1}}$, $MB_{Dum_{k,i,t-1}}$ equals one if the variable belongs to the k_{th} quintile in the aggregate data, and zero otherwise. Using Eq. (1), discretionary accruals are calculated as the residual from the regression estimated in a given year and industry. Each industry-year group has at least 20 observations, otherwise discarded.

For *REM*, I use the model proposed by Roychowdhury (2006). Specifically, I use the sum of three components including *Abnormal production costs*, *Abnormal discretionary expenses* times minus one, and *Abnormal operating cash flow* times minus one, to measure *REM.* And the three components are estimated using the following equations:

$$\frac{PROD_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{i,t-1}} + \beta_2 \frac{\Delta Sales_{i,t}}{Assets_{i,t-1}} + \beta_3 \frac{\Delta Sales_{i,t-1}}{Assets_{i,t-1}} + u_{i,t} \quad (2)$$

$$\frac{DISX_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{i,t-1}} + \beta_2 \frac{Sales_{i,t}}{Assets_{i,t-1}} + u_{i,t} \quad (3)$$

$$\frac{CFO_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{i,t-1}} + \beta_2 \frac{Sales_{i,t}}{Assets_{i,t-1}} + \beta_3 \frac{\Delta Sales_{i,t}}{Assets_{i,t-1}} + u_{i,t} \quad (4)$$

Prior literature shows that CEOs' compensation can be explained by their ability, effort, risk premium, and other economic determinants. The amount of pay that cannot be explained by these determinants is regarded as *ACOMP*. I follow prior research in developing a benchmark model to estimate expected and unexplained *ACOMP* (Core *et al.* 2008; Robinson *et al.* 2011; Alissa 2015). I estimate the expected compensation of the CEO by regressing the CEO's total compensation, which is the sum of salary, bonus, the value of restricted stock grants, the value of options granted during the year, and other annual pay (Core *et al.* 2008), on proxies for several economic determinants in a given year and industry, as follows:

$$Log(Total\ Compensation_{i,t}) = \beta_0 + \beta_1 Log(Tenure_{i,t}) + \beta_2(S\&P500_{i,t-1}) + \beta_3 Log(Sales_{i,t-1}) + \beta_4(BM_{i,t-1}) + \beta_5(RET_{i,t}) + \beta_6(RET_{i,t-1}) + \beta_7(ROA_{i,t}) + \beta_8(ROA_{i,t-1}) + u_{i,t} \quad (5)$$

where *i* indexes firm and *t* indexes year. *Total Compensation* is described above. $Log(Tenure)$ is the logarithm of the CEO's tenure (in years). $S\&P500$ is a dummy variable that equals one for firms in the S&P500 index at the end of this year, and zero otherwise. $Log(Sale)$ is the logarithm of the firm's sales. *BM* is the book-to-market ratio at the end of year. *RET* is the firm's buy-and-hold return. *ROA* is the return on assets. The above OLS model includes fixed effects for years and 2-digit SIC codes of industries. I separate the actual total compensation of CEOs into two parts: the *Expected Compensation* estimated from Eq. (5), and the *ACOMP* (the residual obtained from the same equation). Therefore, I compute the *ACOMP* as:

$$ACOMP_{i,t} = Total\ Compensation_{i,t} - Expected\ Compensation_{i,t} \quad (6)$$

3.3.2.3 Control variables

Prior academic studies have shown that many variables affect the likelihood of firms experiencing financial distress. Campbell *et al.* (2008) employ a fairly broad collection of explanatory variables, including both accounting and equity market variables, to predict the likelihood of firm failures. Indeed, models consisting of both accounting and market metrics outperform either accounting-based or market-based models (Das *et al.* 2009). Gupta and Chaudhry (2019) also address the complementary effect between accounting variables and market variables. In the investigation, they extend the set of covariates employed by Campbell *et al.* (2008) with two additional variables, financial expenses to sales and tax to market valued total assets. Moreover, to construct the parsimonious multivariate prediction model, they evaluate respective variables' average marginal effects and find five highly significant variables in predicting financial distress. In light of this, I employ the covariates suggested by Gupta and Chaudhry (2019) to proceed with our empirical analysis. In addition, considering the macroeconomic variation in specific industrial sectors and the duration dependency, I adopt two more control variables as well. Detailed definitions of firm-level explanatory variables and the two additional control variables are as follows:

i. *NIMTAAVG* – Weighted average of net income to market-valued total assets (*NIMTA*) over the previous 3 years:

$$NIMTAAVG_{i,t} = \frac{1}{1.75}NIMTA_{i,t-1} + \frac{0.5}{1.75}NIMTA_{i,t-2} + \frac{0.25}{1.75}NIMTA_{i,t-3}$$

$$where, \qquad NIMTA_{i,t} = \frac{Net\ Income_{i,t}}{(Market\ Value\ of\ Equity_{i,t} + Total\ Liabilities_{i,t})}$$

ii. $EXRETAVG$ – The weighted average of monthly log excess returns relative to S&P 500 index:

$$EXRETAVG_{i,t-1,t-12} = \frac{1-\phi}{1-\phi^{12}}\left(EXRET_{i,t-1} + \cdots + \phi^{11}EXRET_{i,t-12}\right)$$

$$where, \qquad EXRET_{i,t} = Log\left(1 + Equity\ Return_{i,t}\right) - Log\left(1 + Equity\ Return_{S\&P\ 500,t}\right)$$

iii. *FES* – Ratio of financial expense to sales:

$$FES_{i,t} = \frac{Financial\ Expense_{i,t}}{Sales_{i,t}}$$

iv. *TMTA* – Ratio of income tax to market-valued total assets:

$$TMTA_{i,t} = \frac{Tax\ of\ Total\ Income_{\ i,t}}{Market\ Value\ of\ Equity_{i,t} + Total\ liabilities_{i,t}}$$

v. *CASHMTA* – Ratio of cash and short-term investments scaled by market value of total assets:

$$CASHMTA_{i,t} = \frac{Cash\ and\ Short\text{–}term\ Investments_{\ i,t}}{Market\ Value\ of\ Equity_{i,t} + Total\ Liabilities_{i,t}}$$

vi. *INDRISK* – Industry risk:

$$INDRISK_{i,t} = \frac{Number\ of\ firms\ with\ the\ interest\ event\ in\ each\ industry_{\ i,t}}{Total\ number\ of\ firm\ in\ each\ industry_{i,t}}$$

vii. *LNAGE* – The logarithm of firm's annual age[14]:

$$LNAGE_{i,t} = Log\left(age_{i,t}\right)$$

We expect *NIMTAAVG*, *EXRETAVG*, *TMTA* and *CASHMTA* to have a negative effect on the likelihood of financial distress, in contrast, *FES, INDRISK* and *LNAGE* are expected to

[14] The firm's age is measured as the duration of current year and first year in which firm has valid data in Compustat.

be positively related to the likelihood of financial distress. *NIMTAAVG* represents a firm's profitability; firms with high profitability are related to lower insolvency probability. The market variable *EXRETAVG* is expected to affect the likelihood of financial distress negatively since distressed firms typically have lower returns compared to healthy ones. Firms with healthy financial status usually have a higher frequency and larger volume of business leading to more tax payments; therefore, *TMTA* is negatively associated with firm failures. As a proxy for liquidity, *CASHMTA* indicates a firm's liquid assets level, as the default probability increases if the firm holds fewer liquid assets. All variables are winsorised at their 1^{st} and 99^{th} percentiles to minimize the influence of outliers.

4.3.3 Summary statistics

We report the summary statistics of all variables in Table 4.1 for financially distressed and healthy groups of firms to get a preliminary understanding of the differences among the firms' characteristics.

Table 4.1: Sample description

This table reports summary statistics for all covariates used in the multivariate analysis. To facilitate comparison, summary statistics are reported separately for healthy and financially distressed groups of firms. All variables are winsorised at their 1st and 99th percentile values. The sample is based on the annual data of U.S. firms from 1980 to 2021.

Variable	Status	Obs	Mean	Standard Deviation	Minimum	Median	Maximum
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CFR	Healthy	87,718	3.601	18.895	0.012	0.200	166.697
	Distressed	1,543	26.849	49.876	0.014	3.454	166.697
NIMTAAVG	Healthy	87,718	-0.073	0.226	-1.286	0.006	0.197
	Distressed	1,543	-0.271	0.265	-1.286	-0.191	0.197
EXRETAVG	Healthy	87,718	-0.009	0.051	-0.180	-0.006	0.132
	Distressed	1,543	-0.011	0.081	-0.180	-0.011	0.132
FES	Healthy	87,718	0.089	0.336	0.000	0.016	2.672
	Distressed	1,543	0.242	0.598	0.000	0.023	2.672
TMTA	Healthy	87,718	0.018	0.036	-0.086	0.005	0.166
	Distressed	1,543	-0.001	0.019	-0.086	0.000	0.166
CASHMTA	Healthy	87,718	0.118	0.172	0.000	0.054	0.920
	Distressed	1,543	0.237	0.233	0.000	0.166	0.920
LNAGE	Healthy	87,718	2.137	1.002	0.000	2.197	4.357
	Distressed	1,543	2.427	0.561	1.386	2.303	4.007
INDRISK	Healthy	87,718	0.008	0.011	0.000	0.004	0.067
	Distressed	1,543	0.024	0.015	0.000	0.020	0.067
AEM	Healthy	87,718	-0.007	0.080	-2.185	-0.007	1.186
	Distressed	1,543	0.029	0.021	-2.108	0.030	0.703
REM	Healthy	87,718	0.027	0.716	-1.515	-0.063	2.821
	Distressed	1,543	-0.090	0.709	-1.515	-0.173	2.822
ACOMP	Healthy	87,718	-0.002	0.604	-4.883	0.000	5.601
	Distressed	1,543	-0.028	0.720	-2.550	0.001	1.956

We report mean, median, standard deviation, minimum value and maximum value of all covariates. Column 1 shows the list of variables used in our subsequent regression models, Column 2 states the healthy/distressed status of firms, and the remaining columns report descriptive statistics, which are comparable to previous literature (Campbell *et al.* 2008; Huang 2009; Gupta and Chaudhry 2019), with some differences in reasonable range due to the variations in samples.

Most notably, *CFR* exhibits a distinctly high mean value in the financially distressed group at 26.8, which is almost 8 times higher than their healthy counterparts (3.6), indicating that distressed firms have higher levels of volatile cash flows. Other covariates' descriptive statistics are similar to those reported by Gupta and Chaudhry (2019). Table 4.1 reports a distinct comparison of distressed and healthy firms' characteristics. For the distressed group, firms typically make losses (the mean of loss is about 27%, and the median loss is 19%), and have a relatively lower return as well as tax payment compared to healthy firms. Similar to Gupta and Chaudhry (2019), the mean of *FES* (0.242) and *INDRISK* (0.024) are slightly higher for the distressed group than for the healthy group. I check the correlation among those variables as well, and all covariates show low or moderate correlation with each other in untabulated results. The mean of *AEM*, *REM* and *ACOMP* are around zero since they are calculated as a residual of the regression model. I find that distressed firms are more likely to engage in upward *AEM* (0.029) and downward *REM* (-0.090).

4.4 Role of *CFR* in predicting financial distress

4.4.1 Panel logit regression

In line with the existing literature, I examine the probability of a firm's failure using panel logistic regression with random effects. Although hazard models are popular in previous academic studies, the discrete hazard model with logit link is actually a panel logistic model controlling for a firm's age (Gupta *et al.* 2018). Moreover, the panel logistic model achieves the essential required functions in empirical validation and is easier to understand. Thus, following Campbell *et al.* (2008) and Gupta and Chaudhry (2019), the marginal probability of a firm's financial distress over the next period is assumed to follow a logistic distribution:

$$P(Y_{it} = 1) = \frac{1}{1 + \exp\left(-\alpha - \beta x_{i,t-1}\right)} \tag{7}$$

where Y_{it} is an indicator that equals one if the firm is financially distressed in time *t*, and $X_{i,t-1}$ is a vector of explanatory variables known at the end of the previous year. In addition, the higher value of $\alpha + \beta x_{i,t-1}$ suggests the higher likelihood of financial distress.

4.4.2 Baseline multivariate regression model

The main objective of our empirical analysis is to investigate the effect of *CFR* on financial distress. Thus, I start with a baseline model that includes *NIMTAAVG*, *EXTRETAVG*, *FES*, *TMTA*, *CASHMTA*, *LNAGE* and *INDRISK* as explanatory variables, along with our variable of interest, *CFR*. Results are reported in Table 4.2. Model 1 presents the impact of *CFR* on financial distress. I find that the estimated coefficient of *CFR* is positive and significant at the 1% level. In addition, the average marginal effects (*AME*)[15] of *CFR* is 0.003 and significant. Consistent with our expectation, firm profitability, excess stock return and tax payment are negatively related to the distress risk, in contrast, a firm's financial expenses increase its probability of financial distress. All financial covariates are jointly significant in predicting the likelihood of financial distress of U.S. firms. In addition, Model 1 exhibits a classification

[15] Average marginal effects are multiplied by 100 for expositional reasons.

performance of around 91% (measured using the area under the ROC curve)[16]. The result, therefore, implies that firms with high *CFR* are more likely to experience financial distress.

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[16] I evaluate the classification performance using a non-parametric classification measure, namely Area Under Receiver Operating Characteristic Curve (AUROC). The higher value of AUROC indicates the better performance of prediction model. For out-of-sample validation, I use observations from 1980 until 2017 to estimate our model, with the estimates, I predict the likelihood of financial distress for the year 2018; then I extend the observations from 1980 until 2018 to estimate our model and predict the likelihood of financial distress for the year 2019, and so on until 2021. I estimate the out-of-sample AUROC with these predicted likelihoods value from 2017 to 2021.

Table 4.2: Baseline multivariate regression of financial distress

This table reports multivariate regression estimates employing financial distress as the dependent variable and covariates including *CFR, NIMTAAVG, EXTRETAVG, FES, TMTA, CASHMTA*, *LNAGE* and *INDRISK*. All variables are winsorised at their 1st and 99th percentile values. Model 1 is the multivariate model with *CFR*, Model 2 is the multivariate model of instrumental variable estimates. The instrumental variable is the mean of the *CFR* in a given year, industry and firm size, excluding the firm itself (jackknife average). Model 3 is the multivariate model with a dummy variable *CFRH*, which equals one if a firm's *CFR* is above the median in a given year and industry. The coefficient of average marginal effect (*AME*) is multiplied by 100 for expositional purposes. N = 0 represents the number of healthy firms. N = 1 represents the number of financially distressed firms. AUROC-W is the within-sample area under the ROC curve and AUROC-H is the out-of-sample area under the ROC curve. The sample is based on annual data of U.S. firms from 1980 to 2021. ***, **, * indicate significance at the 1, 5, and 10 % levels, respectively.

Variable	*Financial Distress*		
(1)	(2)	(3)	(4)
	Model 1	Model 2	Model 3
CFR	**0.004******	**0.020******	
	(3.872)	(8.210)	
CFRH			**1.393******
			(14.242)
AME × 100	0.003***	-	1.195***
	(3.988)		(10.320)
NIMTAAVG	-2.725***	-1.245***	-2.415***
	(-18.692)	(-9.703)	(-17.482)
EXTRETAVG	-10.844***	2.204***	-10.688***
	(-21.149)	(9.343)	(-21.476)
FES	0.355***	-0.563***	0.321***
	(4.629)	(-4.797)	(5.066)
TMTA	-10.632***	-5.448***	-9.007***
	(-9.954)	(-12.329)	(-8.642)
CASHMTA	2.694***	0.706***	2.489***
	(16.811)	(7.960)	(16.218)
LNAGE	-0.020	0.074***	0.210***
	(-0.369)	(3.842)	(4.072)
INDRISK	27.803***	6.435***	28.539***
	(12.826)	(6.331)	(13.597)
Model's goodness of fit and prediction performance measure			
Chi2	2433.120	1751.210	2569.441
Log likelihood	-5595.167	-378882.180	-5669.862
R-square	0.212	-	0.284
AUROC-W	0.913	-	0.915
AUROC-H	0.900	-	0.887
N = 0	84,852	87,718	84,852
N = 1	1,543	1,543	1,543

In addition, to address the potential endogeneity issue, I re-estimate our baseline model with the instrumental variable approach. I employ the Jackknife method by using the instrumental variable calculated as the mean of *CFR* in a given year, industry, and size excluding the firm itself. Model 2 in Table 4.2 reports the results and I find that the coefficient of *CFR* remains positive and significant. This further supports that our findings are robust to endogeneity concerns.

Although *CFR* and its *AME* are statistically significant in Model 1, the magnitude of its coefficients and *AME* are relatively small, implying a relatively low change in the predicted probability due to a unit change in *CFR*. Therefore, I propose another version of *CFR* to improve Model 1's performance, a dummy variable capturing firms with high *CFR*, *CFRH*. Specifically, the new dummy variable *CFRH* equals one if the firm's *CFR* is higher than the median in a given year and industry, and zero otherwise. *CFRH* focuses more on the group with relatively high *CFR*. Column 3 in Table 4.2 presents the results. I find that *CFRH* has much higher magnitudes of coefficients and also much larger *AME* compared to the continuous *CFR* in Column 1. Therefore, *CFRH* is significant in predicting the likelihood of financial distress as expected. The coefficient of *CFRH* is positive and significant at the 1% level with a magnitude of 1.393. The *AME* (in percentages) of *CFRH* is 1.195, which is much higher than the one in Model 1. The high value of *AME* suggests considerable economic significance.

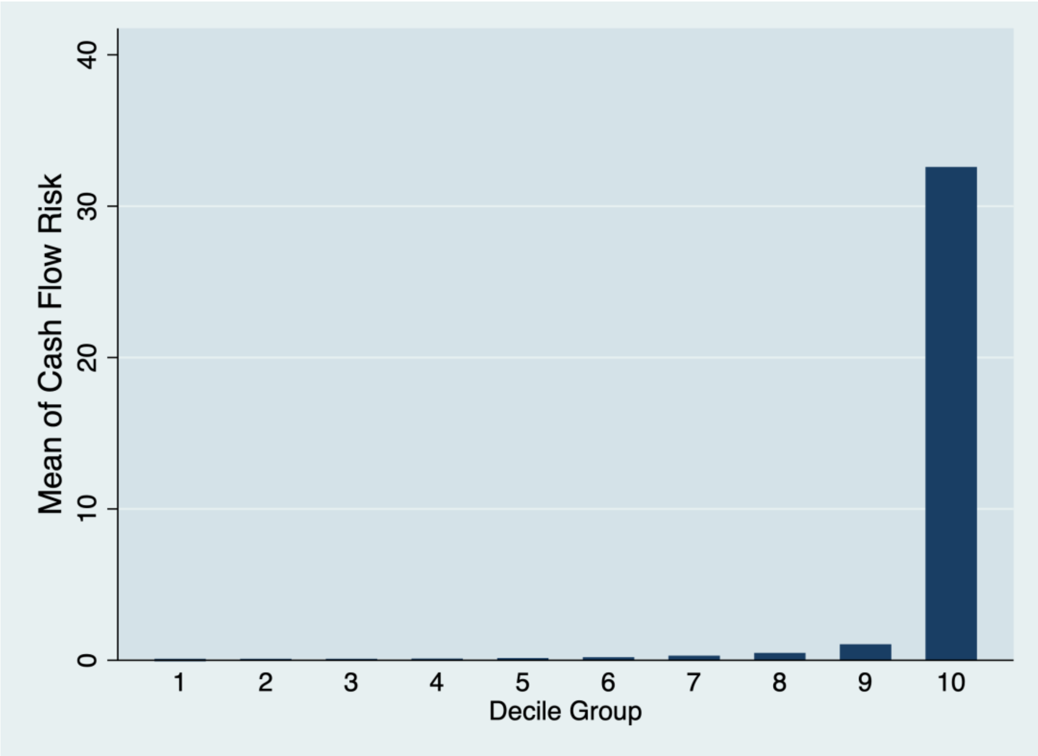
In addition to the increased economic significance, our proposed multivariate regression delivers a noticeable improvement in explanatory power over the models discussed in the previous section. I report McFadden's pseudo-*R–squared* to make the comparison. The *R–squared* increased from 0.212 to 0.284, which is about 7% improvement in the explanatory power. The high value of AUROC, around 92%, indicates excellent classification performance. Therefore, our final baseline model (with *CFRH*) to predict financial distress is as follows:

$$\boldsymbol{Financial\ Distress_{i,t}} = \beta_0 + \boldsymbol{\beta_1} \times \boldsymbol{CFRH_{i,t}} + \beta_2 \times NIMTAAVG_{i,t} + \beta_3 \times EXRETAVG_{i,t-1} + \beta_4 \times FES_{i,t-1} + \beta_5 \times TMTA_{i,t-1} + \beta_6 \times CASHMTA_{i,t-1} + \beta_7 \times LNAGE_{i,t-1} + \beta_8 \times INDRISK_{i,t-1} \quad (8)$$

4.4.3 Moderating role of *EM* (Test of H2)

In this section, I investigate the moderating effect of *AEM* and *REM* on the relation between *CFRH* and financial distress. In addition, I also test the moderating role of *EM* using another version of *CFR*. Specifically, *CFRD* is a dummy variable which equals one if a firm is in the top decile of *CFR* in a given year and industry. Fig. 4.3 shows the mean of different decile groups. I find that the top decile has the highest value, around 32, of average *CFR*, however, the value of other groups' average *CFR* range within 2. Therefore, to account for this extreme skewness in the distribution of *CFR*, besides *CFRH* I also use *CFRD* in our moderation analysis.

Figure 4.3: Mean of cash flow risk over decile groups



Notes: This figure exhibits the average cash flow risk (*CFR*) of different decile groups the over period 1980 to 2021 for U.S. firms.

Table 4.3: Multivariate regression of financial distress with earnings management as moderator

This table reports multivariate regression estimates employing financial distress as the dependent variable. The regression employs different variables including *PAEM*, *HAEM*, *PREM*, and *HREM* with *CFRH* as interaction terms. Panel A is the multivariate regression with a dummy variable *CFRH*, which equals one if a firm's *CFR* is above the median in a given year and industry. Panel B is the multivariate regression with a dummy variable *CFRD,* which equals one if a firm is in the top decile of *CFR* in a given year and industry. N = 0 represents the number of healthy firms. N = 1 represents the number of financially distressed firms. The sample is based on annual data of U.S. firms from 1980 to 2021. ***, **, * indicate significance at the 1, 5, and 10 % levels, respectively.

Variables	*Financial Distress*			
(1)	(2)	(3)	(4)	(5)
Panel A: Multivariate regression of financial distress with *CFRH*				
CFRH	2.541***	2.437***	2.037***	2.306***
	(5.271)	(5.902)	(5.346)	(5.348)
HAEM	2.242***			
	(4.888)			
CFRH× HAEM	**-1.094****			
	(-2.231)			
PAEM		1.878***		
		(4.798)		
CFRH× PAEM		**-0.997****		
		(-2.365)		
HREM			1.478***	
			(3.977)	
CFRH× HREM			**-0.469**	
			(-1.195)	
PREM				1.587***
				(3.753)
CFRH× PREM				**-0.766***
				(-1.738)
Controls	Yes	Yes	Yes	Yes
Model's goodness of fit and prediction performance measure				
Chi2	1793.293	2230.320	1867.54	2237.31
Log likelihood	-5305.397	-5947.015	-5392.415	-5953.065
R-square	0.347	0.299	0.297	0.289
N = 0	63,997	93,433	66,222	93,433
N = 1	1,469	1,584	1,484	1,584
Panel B: Multivariate regression of financial distress with *CFRD*				
CFRD	2.802***	2.803***	2.630***	2.743***
	(7.876)	(8.817)	(9.800)	(10.293)
HAEM	1.656***			
	(7.860)			
CFRD× HAEM	**-1.479*****			

	(-4.138)			
PAEM		1.458***		
		(7.522)		
CFRD× PAEM		**-1.471*****		
		(-4.595)		
HREM			1.378***	
			(7.410)	
CFRD× HREM			**-1.327*****	
			(-4.841)	
PREM				1.243***
				(6.845)
CFRD× PREM				**-1.431*****
				(-5.276)
Controls	Yes	Yes	Yes	Yes
Model's goodness of fit and prediction performance measure				
Chi2	1922.66	2341.75	1968.39	2323.760
Log likelihood	-5057.129	-5677.359	-5145.790	-5686.696
R-square	0.276	0.243	0.255	0.234
N = 0	61,577	87,813	63,624	87,813
N = 1	1,423	1.537	1,438	1.537

To analyse the moderating effect of *AEM* or *REM*, I employ dummy variables, *HAEM*, *PAEM*, *HREM* and *PREM*. *HAEM* (*HREM*) equals one if the *AEM* (*REM*) is above the median of industry-year, and zero otherwise. *PAEM* (*PREM*) equals one if the *AEM* (*REM*) is nonnegative, and zero otherwise. Panel A of Table 4.3 reports the results using *CFRH*. I find that the coefficient of interaction terms $CFRH \times HAEM$ and $CFRH \times PAEM$ are negative and significant at 0.01 level with values -1.094 and -0.997, respectively. The results indicate that executives in firms facing high *CFR* may engage in *AEM* to reduce the probability of financial distress. Thus, the empirical results support the hypothesis predicted by the upper echelons theory that managers who are facing high job demands, such as the challenge of firm performance, are more susceptible to being affected by their personal characteristics when making financial decisions (Hambrick 2007). However, for *REM*, I find that the coefficient of interaction terms $CFRH \times HREM$ and $CFRH \times PREM$ are insignificant or weakly significant at 0.1 level. The plausible explanation is that managers exhibit a greater tendency towards inflating earnings or strategically timing a firm's information releases, with the aim of manipulating firm's performance through *AEM* than *REM* as *AEM* is timelier (Edmans et al. 2017). In addition, there might not be much room or time left to do *REM* for managers in firms with high *CFR*.

Panel B reports the results using *CFRD* in our baseline model. I find that the coefficient of interaction terms $CFRD \times HAEM$ and $CFRD \times PAEM$ are negative and significant at 0.01 level with values -1.479 and -1.471, respectively. In addition, the coefficient of interaction terms $CFRD \times HREM$ and $CFRD \times PREM$ are negative and significant at 0.01 level (-1.327 and -1.431, respectively). The results indicate that, for firms facing extremely high *CFR*, the managers are more likely to be more aggressive and engage in accruals and real earnings management to reduce the likelihood of financial distress, since they face greater job demand suggested by upper echelons theory. Thus, overall I find convincing evidence that earnings management negatively moderates the relation between *CFR* and financial distress. Thereby affirming the upper echelons theory's prediction that when top managers are faced with intense job demands, such as the need to improve company performance, they are prone to utilizing heuristics in their financial decision-making.

4.4.4 Moderating role of *ACOMP* (Test of H3)

In this section, I investigate the moderating effect of *ACOMP* on the relation between *CFRH* and *CFRD*, and financial distress. I employ the model proposed by Core *et al.* (2008) to measure *ACOMP*. Similarly, I employ two dummy variables to analyse the moderating effect, *HACOMP* and *PACOMP*. *HACOMP* equals one if *ACOMP* is above the median in a given year and industry, and zero otherwise. *PACOMP* equals one if *ACOMP* is non-negative, and zero otherwise. Panel A of Table 4.4 reports the results using *CFRH*, while Panel B of Table 4.4 reports the results using *CFRD*. The coefficients of interaction terms $CFRH \times HACOMP$ and $CFRH \times PACOMP$ are negative and significant (-1.071, -1.190) at 0.01 level. Similarly, the coefficients of interaction terms $CFRD \times HACOMP$ and $CFRD \times PACOMP$ are negative and significant at 0.01 level with values -1.561 and -1.577, respectively.

Table 4.4: Multivariate regression of financial distress with abnormal compensation as moderator

This table reports multivariate regression estimates employing financial distress as the dependent variable. The regression employs different variables including *PACOMP* and *HACOMP* with *CFRH* as interaction terms. Panel A is the multivariate regression with a dummy variable *CFRH*, which equals one if a firm's *CFR* is above the median in a given year and industry. Panel B is the multivariate regression with a dummy variable *CFRD,* which equals one if a firm is in the top decile of *CFR* in a given year and industry. N = 0 represents the number of healthy firms, and N = 1 represents the number of financially distressed firms. The sample is based on annual data of U.S. firms from 1980 to 2021. ***, **, * indicate significance at the 1, 5, and 10 % levels, respectively.

Variables	*Financial Distress*	
(1)	(2)	(3)
Panel A: Multivariate regression of financial distress with *CFRH*		
CFRH	2.503***	2.633***
	(6.409)	(5.930)
HACOMP	1.770***	
	(4.780)	
CFRH× HACOMP	**-1.071*****	
	(-2.670)	
PACOMP		1.826***
		(4.326)
CFRH× PACOMP		**-1.190*****
		(-2.632)
Controls	Yes	Yes
Model's goodness of fit and prediction performance measure		
Chi2	1793.293	2230.320
Log likelihood	-5305.397	-5947.015
R-square	0.347	0.299
N = 0	63,997	93,433
N = 1	1,469	1,584
Panel B: Multivariate regression of financial distress with *CFRD*		
CFRD	2.896***	2.924***
	(8.792)	(8.458)
HACOMP	1.185***	
	(6.692)	
CFRD× HACOMP	**-1.561*****	
	(-4.702)	
PACOMP		1.150***
		(6.131)
CFRD× PACOMP		**-1.577*****
		(-4.535)
Controls	Yes	Yes
Model's goodness of fit and prediction performance measure		
Chi2	1924.031	2326.160
Log likelihood	-5053.379	-5692.588
R-square	0.242	0.229
N = 0	61,184	87,813
N = 1	1,420	1,537

Such results suggest that when firms face high or extremely high *CFR*, some boards may respond effectively by adjusting compensation structures to motivate executives to put more effort into managing the high *CFR*. Considering the interest alignment effect, board members adjust executives' *ACOMP* to a higher level to align managers' interests with firms' interests. Therefore, executives with high and positive *ACOMP* may have higher incentives to reduce the risk and thereby reducing the probability of financial distress. Overall, in line with the predictions of the agency theory, I find that boards are effective in adjusting compensation levels in response to higher *CFR*. This alignment of interests encourages managers to put more effort into managing volatile cash flows.

4.4.5 Alternative definitions of firm failure

Besides the main results reported above, I also conduct several robustness checks to gain deeper insight into the effect of *CFR* on the likelihood of firms facing financial distress. To further provide evidence of the extent to which our results are robust, I use four alternative definitions to identify a firm's financial difficulties. First, I use two definitions for financial constraints, the *KZ* index and the *WW* index. Using *KZ* index, a firm's degree of financial constraints is estimated by five variables: cash flow, market-to-book, leverage, dividends, and cash holdings (Lamont *et al.* 2001; Kothari *et al.* 2016). A higher index value indicates a firm is more likely to be in financial distress. I use a dummy variable *FSKZ* which equals one if a firm is in the top quartile based on the *KZ* index in a given year and industry indicating the financial stress, and zero otherwise. *WW* index is another measure of the financial stress which uses several variables as well: cash flow to assets, dividend, long-term debt to assets, total assets, sales growth, and industry sales growth (Whited and Wu 2006). Similarly, I use a dummy variable *FSWW* which equals one if a firm is in the top quartile based upon the *WW* index in an industry-year group, indicating that the firm is more likely to be financially stressed, and zero otherwise.

Second, I proxy firms that are financially distressed if they are presumed to violate debt covenant conditions. Considering the discussion before, firms with either a high leverage ratio or low-interest coverage are more likely to experience financial difficulties and hardship in accessing external financing. These two violated metrics indicate firms have persistent poor performance and insufficient capital level, which may lead to financial distress or bankruptcy. Therefore, firms with low-interest coverage and high leverage ratios are supposed to have covenant violations. Specifically, I classify firms in the bottom quartile of the interest coverage ratio and the top quartile of the leverage ratio in a given year as covenant-violation groups of firms. The leverage ratio is defined as the sum of short-term debt and long-term debt to total assets, and the interest coverage ratio is calculated as earnings before interest and taxes (*EBIT*) to interest expenses.

We also employ legal bankruptcy as a failure definition by identifying firms that filed for Chapter 11/7 bankruptcy in the Compustat[17] database. I separately estimate our prediction models for these four alternative definitions of firm failures using Eq. (8). The response variable in both models has binary outcomes. Table 4.5 reports the estimation results with these alternative measures for a 1-year prediction horizon.

[17] I use code "*TL*" in *"Status Alert"* variable in Compustat to identify whether the firms filed for bankruptcy.

Table 4.5: Multivariate regression of financial distress with alternative definitions of firm failure

This table reports multivariate regression estimates employing alternative definitions of firm failures: financial stress (*FSKZ* and *FSWW*), presumed covenant violation (*DC*) and legal bankruptcy filings (*Bankrupt*). All variables are winsorised at their 1st and 99th percentile values. N = 0 represents the number of healthy firms. N = 1 represents the number of financially distressed firms. The sample is based on annual data of U.S. firms from 1980 to 2021. ***, **, * indicate significance at the 1, 5, and 10 % levels, respectively.

Variable	*FSKZ*	*FSWW*	*DC*	*Bankrupt*
(1)	(2)	(3)	(4)	(5)
CFRH	**0.116*** **	**0.900*** **	**0.348*** **	**1.137*** **
	(3.289)	(18.695)	(7.266)	(3.940)
Controls	Yes	Yes	Yes	Yes
Model's goodness of fit and prediction performance measure				
Chi2	4302.732	4490.350	926.151	121.972
Log likelihood	-24843.605	-18276.820	-14125.281	-767.919
R-square	0.171	0.167	0.046	0.056
N = 0	83,348	85,023	89,521	94,857
N = 1	11,669	9,994	5,496	160

Columns 2 and 3 in Table 4.5 report the result for *FSKZ* and *FSWW* as failure definitions, respectively. As I see, *CFRH* remains significant at 1% level with values of 0.116 and 0.900, respectively. Column 4 presents the results for presumed covenant violation as failure definition. Similarly, the key variable *CFRH* is positive and significant with a value of 0.348. Turning to firms that filed for bankruptcy, I find the result is qualitatively unchanged and the coefficient of *CFRH* is also positive and significant at 1% level, 1.137. Such results suggest that firms that filed for bankruptcy have suffered high *CFR* and significant erosion in firm value already. However, I find that the value of *R-squared* is lower compared to the models employing the financial distress definition in our main results, which indicates that our model performs better in predicting financial distress.

In view of our empirical findings, I have a strong motivation to believe in the superior performance of *CFRH* in predicting firm failures; the overall explanatory power of our model is robust to alternative failure definitions.

4.5 Additional tests

We also conduct a few additional tests. I focus on whether corporate governance mechanisms play a role in moderating the relation between *CFR* and financial distress. Prior literature shows that firms' risk is more likely to be reduced or controlled in firms with a strong governance structure (Ahmad *et al.* 2021; Boachie and Mensah 2022), therefore, I re-estimate our baseline model with different variables indicating the level of firm's corporate governance mechanisms. Specifically, I have tried the corporate governance score from Refinitiv and MSCI (KLD), takeover index (Cain *et al.* 2017), board co-option (Coles *et al.* 2014) and different board characteristics including board independence, board size, and board tenure, etc. However, I fail to find consistent and significant effects of corporate governance in moderating the association between *CFR* and financial distress.

4.6 Conclusion

In this study, I explore the association between *CFR* and financial distress of U.S. listed firms. Our principal results make three main contributions to the literature on corporate failure and *CFR*. First, our test results show a positive significant effect of *CFR* on financial distress. Second, although I find a superior and statistically significant role of *CFR* in predicting the likelihood of financial distress, the magnitude of its *AME* remains relatively small. Therefore, I improve our model with *CFRH*. Such binary transformation raises the discriminatory power of *CFR* and the explanatory power of our model dramatically. Third, I find that the effect of *CFRH* on financial distress is moderated negatively in firms with higher and positive *AEM*, *REM* and *ACOMP*. The results suggest that managers in companies with a high level of *CFR* tend to rely more on heuristics in the form of earnings management. This aligns with the upper echelons theory, which posits that managers facing significant performance pressure are more likely to be influenced by their personal characteristics in their decision-making. On the other hand, boards may offer compensation packages to encourage better risk management practices, as agency theory argues that financial incentives are effective in serving as a monitoring tool.

We also document that the significance of *CFR* is robust to alternative definitions of firm failure such as financial constraints, presumed covenant violation and legal bankruptcy filings. In addition, I argue that our definition to identify a firm's financial difficulties outperforms legal bankruptcy filings, since waiting until bankruptcy filing may lead to significant losses to stakeholders and unexpected erosion in the firm value. Also, some cases of "strategic bankruptcy" may mislead stakeholders and conceal the real financial health of firms (Gupta *et al.* 2019). In general, these results provide strong empirical support for the significance of *CFR* as a financial distress predictor.

The findings of this study have some limitations that should be considered. First, as the agency theory suggests, internal and external corporate governance should serve as an effective mechanism for mitigating agency conflicts. Therefore, the effect of *CFRH* on financial distress should be moderated by corporate governance metrics. Nonetheless, our findings do not consistently support this hypothesis, and further studies are needed to gain a deeper insight into this matter. Second, while our findings are generalizable to U.S. firms, caution should be taken in applying the results to non-U.S. firms. Given the substantial variations in corporate governance, regulatory authority, and information ecosystems across countries (La Porta et al. 1997; La Porta et al. 1998), researchers may consider those factors as potential moderators when exploring the effect of *CFR* on firm failures across different countries.

Chapter 5:

CONCLUSION

I conduct three different empirical studies in this thesis. In Chapters 2, 3, and 4 of this thesis, I explore the impact of earnings management activities and analysts' information environment on the abnormal compensation of CEOs, along with the role of CEOs' abnormal compensation and earnings management in reducing the likelihood of the firm's failure. Based on agency theory, I aim to explore three unresolved questions that previous research has not fully examined. First, are CEOs punished for managing earnings? Second, can analysts discipline CEOs? Lastly, how do managers and firms respond to the persistent rise in cash flow risk observed over the last forty years?

The three empirical studies in this thesis are grounded in the agency theory's monitoring mechanisms. Based on this perspective, I developed various hypotheses which are closely related to the above three questions. Our hypotheses were tested using data sourced from the U.S. market. The empirical chapters in this thesis focus on the most recent years for which complete information was available to determine our variables.

This chapter is organized as follows. Section 5.1 provides a summary of the findings and implications of our three empirical studies. In section 5.2, I outline the limitations of our studies and propose potential avenues for future research.

5.1 Findings and implications

5.1.1 Are CEOs punished for managing earnings?

In Chapter 2, I investigate whether CEOs are penalized for engaging in earnings management activities. Our empirical evidence shows a significant negative relation between *EM* and

ACOMP. Notably, this study documents that the adverse impact of *REM* on *ACOMP* is more pronounced, leading to further deterioration in a firm's long-term value. Our findings suggest that executives involved in *EM* face the penalty of reduced excess compensation. Furthermore, the results indicate that the adverse effect of *AEM* on *ACOMP* is amplified in firms experiencing financial distress. Our findings have important implications for firms' governance practices and emphasize the need for effective monitoring mechanisms to detect *EM* activities and mitigate the negative consequences of *EM* on firm performance.

This study presents potential implications for a range of stakeholders. The findings demonstrate that CEOs engaging in *EM* are likely to receive lower *ACOMP*, which supports the effectiveness of compensation-based monitoring mechanisms in U.S. firms. Moreover, CEOs in financially stressed firms engaging in *AEM* also receive lower *ACOMP*. However, this study reveals that CEOs in high political risk firms who engage in *AEM* receive higher *ACOMP*, indicating that the existing monitoring mechanisms may not be identifying and addressing such behaviour effectively. Thus, caution is advised, and greater attention should be paid to potential *EM* activities by analysts and stakeholders of these firms. Overall, I expect our results to contribute to shaping future regulations governing executives' pay structure by providing additional insight into the mixed findings in the literature on the connection between CEOs' compensation and *EM*. Moreover, our research contributes to this literature by identifying the factors that moderate this relation.

5.1.2 Can analysts discipline CEOs?

In Chapter 3, I find that analysts' forecast metrics, *FEEPS, WLKDN, DISP*, and *NSURP* have a negative impact on CEOs' *ACOMP*. In addition, I find that higher average recommendations, positive changes in recommendations, and buy recommendations are significantly and positively associated with CEOs' *ACOMP*. These results suggest that CEOs are likely to receive increased compensation when the analysts' information environment is favourable, indicating that CEOs contribute to the disclosure of high-quality information, which aligns with the predictions of agency theory. Additionally, our results also indicate that this relation is particularly evident in firms subject to stronger external monitoring mechanisms. Therefore, in summary, our findings suggest that analysts can effectively discipline CEOs in strong monitoring environments.

This study contributes to the literature on the association between CEO compensation and the information disseminated by analysts by providing additional clarity on previously inconsistent findings. Specifically, our results identify the factors that moderate or drive this relation. This research enhances our understanding of the role of analysts in shaping CEOs' compensation and the impact of external monitoring mechanisms on this relation.

5.1.3 Effect of cash flow risk on corporate failures, and the moderating role of earnings management and abnormal compensation

In Chapter 4, I investigate the association between *CFR* and financial distress of U.S. listed firms. This study makes three primary contributions to the literature on corporate failure and the *CFR*. First, our test results demonstrate a significant positive effect of *CFR* on financial distress. Second, while I find a superior and statistically significant role of *CFR* in predicting the likelihood of financial distress, the magnitude of its *AME* is relatively small. Therefore, I improve our model by incorporating a binary transformation of *CFR*, referred to as *CFRH*. This transformation enhances the discriminatory power of *CFR* and the explanatory power of our model considerably. Third, our study reveals that the impact of *CFRH* on financial distress is moderated negatively in firms exhibiting higher and positive *EM* and *ACOMP*. Overall, our study contributes to the literature on corporate failure by enhancing our understanding of the role of *CFR* and the factors that moderate its impact on financial distress.

This study also demonstrates the robustness of the *CFR* as a predictor of financial distress across alternative definitions of firm failure. Specifically, I find that *CFR* remains a significant predictor of financial distress when using alternative definitions such as financial constraints, presumed covenant violation, and legal bankruptcy filings. I argue that our definition for identifying a firm's financial difficulties outperforms legal bankruptcy filings as waiting until bankruptcy filing may result in significant losses to stakeholders and unexpected erosion in firm value. Therefore, our definition is a more effective option for identifying financial distress and reducing the likelihood of unexpected losses for stakeholders. Overall, our study highlights the importance of a robust definition for identifying financial distress in firms and supports the use of *CFR* as a predictor of such distress.

The findings of our study suggest that managers in firms with a high level of *CFR* tend to rely more on heuristics in the form of earnings management. This result is consistent with the upper echelons theory, which posits that managers under significant performance pressure are more likely to be influenced by their personal characteristics in their decision-making. In contrast, boards may design compensation packages that incentivize better risk management practices, as suggested by agency theory. This theory proposes that financial incentives serve as an effective monitoring tool. By aligning the interests of managers with those of the firm, compensation packages can encourage better risk management practices and reduce the reliance on heuristics in decision-making. Overall, our study highlights the importance of both personal characteristics and financial incentives in shaping managerial behaviour and provides insights for boards and managers to improve risk management practices in firms.

5.2 Limitations and future studies

In the summary and conclusion, it is necessary to highlight both the limitations and potential avenues for future studies. In Chapter 2, I find a negative relation between *EM* and *ACOMP*. Specifically, I find a more pronounced negative impact on *ACOMP* resulting from *REM.* Considering the agency theory, corporate governance should serve as an effective mechanism for monitoring managers' behaviour. Nevertheless, our empirical analysis fails to reveal consistent and statistically significant findings when utilizing other frequently employed indicators as proxies for corporate governance. Therefore, further investigation is required to obtain a more refined comprehension of the impact.

In Chapter 3, I suggest future studies to investigate what is the specific monitoring channel that has a more pronounced effect on CEOs' *ACOMP*. In addition, I suggest further studies focus on the characteristics of analysts and investigate the factors that drive the difference between recommendations and earnings forecasts. It is imperative to note that this research agenda remains far from complete, and additional studies are necessary to further elucidate these complex dynamics.

The findings of Chapter 4 also have some limitations that should be considered. Specifically, the agency theory proposes that internal and external corporate governance should function as a robust mechanism for mitigating agency conflicts, thereby moderating the effect of *CFRH* on financial distress. However, our results do not consistently support this hypothesis, suggesting the need for further research to deepen our understanding of this matter. In addition, while our findings are applicable to U.S. firms, caution should be exercised in generalizing these results to non-U.S. firms. Variations in corporate governance, regulatory authority, and information ecosystems across different countries may require researchers to consider these factors as potential moderators when investigating the effect of *CFR* on firm failures in international settings.

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