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Three Essays on CEO Behavior and Corporate Performance: Evidence from IPO Survival, Organizational Capital, and Executive Pay

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Abstract

The thesis consists of three independent empirical chapters that examine the effects of executive characteristics on corporate outcomes, corporate governance, and managerial compensations. Specifically, the first chapter empirically examines the impact of the use of optimistic tone in IPO prospectuses on IPO survival. The results suggest that net positive tone has strong positive predictive power for IPO survival. The second chapter investigates how CEO turnover affects the accumulation of organizational capital and the results suggest that CEO turnover increase the accumulation of organizational capital. The third chapter[1] analyzes the impact of managerial overconfidence on pay-for-luck compensation. The introduction chapter provides an overview and main findings of the thesis.

The first empirical chapter examines how the use of optimistic language in IPO prospectuses (S-1 filings) influences IPO survival. First, to address the issue of negative phrases being wrapped in positive words, I use FinBERT to detect positive and negative sentences and construct a measure of relative optimism. Second, I use Loughran and McDonald (2016)'s financial dictionary to build an alternative measure of managerial optimism based on the relative frequency of positive word counts. The findings show that the use of optimistic language serves as a positive signal for IPO survival in both FinBERT-based and Loughran and McDonald (ibid.)-based measures. This optimistic tone retains strong predictive power even after controlling for other determinants identified in prior studies. Robustness checks confirm that optimistic tone consistently predicts IPO survival across various survival models. The results remain robust across several additional

1. This chapter is accepted by International Review of Financial Analysis (Wei 2025)

specifications, including entropy balancing and the internal instrumental variable (IV) approach of Lewbel (2012). Specifically, optimistic tone is associated with a 50% to 60% lower IPO failure hazard. Furthermore, the analysis shows that underwriter quality and venture capital (VC) backing strengthen this relationship, amplifying the positive effect of optimistic tone on IPO survival.

This study empirically examines the determinants of organizational capital, with a particular focus on the impact of CEO turnover. I find that the appointment of a new CEO significantly stimulates the accumulation of organizational capital, increasing its stock by approximately 15%. Furthermore, a one standard deviation increase in managerial ability corresponds to an estimated 7%-8% increase in the standard deviation of organizational capital. Our findings further show that the positive association between CEO turnover and organizational capital is stronger when successor CEOs have higher managerial ability and stronger long-horizon incentive alignment. These patterns are consistent with the view that CEO quality and incentive design shape post-turnover organizational capital accumulation. However, because the chapter does not directly observe internal organizational changes such as hiring, training, management-system adoption, or process redesign, these results are interpreted as heterogeneity evidence rather than definitive proof of specific mechanisms. Furthermore, the post-turnover increase in organizational capital is more pronounced when successor CEOs have higher measured managerial ability. By contrast, the estimated post-turnover response is weaker when successor CEOs score lower on ability-related measures. These results describe average differences across turnover events and should not be interpreted as direct evidence of individual CEOs' intentions or strategic motives. Our results remain robust across subsamples defined by different turnover reasons, including voluntary, involuntary, and forced turnover. These estimates are consistent with a causal interpretation under standard difference-in-differences assumptions, but the chapter does not claim that the DiD designs fully eliminate all threats to identification. Additionally, I observe that the CEO compensation structure—including performance-based pay and the CEO pay gap-is associated with a stronger post-turnover response to the positive effect of CEO ability on organizational capital. Finally, the presence of outside CEOs and highly capable CEOs further strengthens the positive effects of CEO turnover on organizational capital.

The third chapter examines how CEO overconfidence amplifies the "pay-for-luck" phenomenon in executive compensation. Using a decomposition of firm performance into exogenous "luck" and firm-specific "skill" components, we find that overconfident CEOs receive disproportionately higher rewards for positive market shocks while avoiding equivalent penalties for negative shocks. To address endogeneity concerns, we instrument CEO overconfidence using the industry-level density of overconfident CEOs and Lewbel (2012)'s internal IV approach. Our results remain robust across alternative overconfidence measures, empirical specifications, and governance conditions. Further analysis suggests that overconfident CEOs engage in greater risk-taking behaviors and higher R&D investments which reinforce the effects of CEO overconfidence on pay-for-luck. Additionally, we find that stronger corporate governance and DoDD-Frank Act mitigates the extent of overconfident CEOs' pay-for-luck. These findings contribute to the literature on executive compensation and behavioral corporate finance, offering implications for incentive design and governance reforms.

Contents

List of Tables

List of Figures

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Declaration

“I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.”

Printed Name: Xiaoqin Wei   19th March 2026

Chapter 1

Introduction

This thesis comprises three independent chapters on three topics of corporate governance and corporate finance. The first chapter examines the effects of net positive tones in IPO prospectuses on IPO survival by exploiting Loughran and McDonald (2016)'s financial dictionary and Liu et al. (2021) and Huang et al. (2023)'s state-of-art FinBERT model to construct the tones of S-1 fillings. The second chapter examines the determinants of organizational capital from the views of managerial characteristics, providing empirical evidence supporting Dessein and Prat (2022)'s theoretical prediction, and the third chapter analyzes the effects of CEO overconfidence on pay-for-luck from the views of fairness concerns of executives (Liu and Sun 2023; Chaigneau et al. 2022). Corporate leadership, particularly the role of the CEO, has long been recognized as a crucial determinant of firm performance and survival started from the study of Bertrand and Schoar (2003), especially during critical transitional phases such as Initial Public Offerings (IPOs) (Boulton and Campbell 2016). This thesis contributes to the extensive yet continually evolving literature on corporate finance and corporate governance by examining how specific CEO characteristics and corporate behaviors, including use of net positive tones, managerial ability, CEO turnover, and overconfidence, influence corporate outcomes and corporate governance, with particularly focus on IPO survival, accumulation of organizational capital, and executive compensation structures.

While prior research extensively explores firm-level predictors of IPO survival such as financial ratios, accounting quality, venture capital backing, and audit quality (Krishnan et al. 2011; Jain and Kini 2000; Demers and Joos 2007; Espenlaub et al. 2012; Colak et al. 2021; Anagnostopoulou et al. 2021), relatively few studies examine how use of language in S-1 fillings affect IPO survival. Colak et al. (2022) present a prediction model that incorporates market, financial, and pricing risk factors. Our research builds upon the studies of Anagnostopoulou et al. (2021) and Gounopoulos and Pham (2018) and Colak et al. (2022), exploring the effect of the use of optimistic language in IPO prospectuses on IPO survival. Our findings suggest that the use of optimistic language in IPO prospectuses positively affect IPO survival and demonstrate strong predictive power based on the models proposed by Anagnostopoulou et al. (2021) and Gounopoulos and Pham (2018) and Colak et al. (2022).

Despite extensive analysis of the tone in SEC filings, its effects on IPO performance remain unclear due to data limitations. Prior work in textual analysis suggests that positive tone is difficult to measure accurately, as positive words are often negated in ways that are challenging to detect programmatically. Both Tetlock (2007) and Loughran and McDonald (2011) note that results related to positive words are mixed because negative phrases are frequently wrapped in positive language[1]. To address this issue, I follow the state-of-the-art pre-trained FinBERT model developed by Huang et al. (2023), a deep learning approach to extracting textual information. The main benefit of FinBERT is its focus on sentences rather than individual words. It addresses the concerns raised by Loughran and McDonald (2011) that negative phrases are often embedded in positive wording.

I construct the optimism tone using the ex ante relative positive tone in IPO prospectuses. While top managers often exhibit excessive optimism (Malmendier and Tate 2008), which may be reflected in their writing style, I argue that tone also has predictive power and signals future IPO survival. This is because the IPO prospectus is not prepared solely by

1. For example, as noted by managers of VA Linux Systems in their S-1: “Our business strategy may not be successful and we may not successfully manage these risks.”

executives but also involves auditors, underwriters, and venture capital firms. As such, the document may reflect not just managerial confidence but the collective confidence of all involved parties, thereby signaling strong future performance to the market, given their superior information about the firm. Although Loughran and McDonald (2013) finds that the tone of S-1 filings affects IPO underpricing, my study contributes further by showing that optimism tone, proxied by the ex ante relative positive tone in S-1 filings, exhibits strong predictability for IPO survival.

The study introduces the FinBERT, a pre-trained deep learning language model, developed by Huang et al. (2023) and Liu et al. (2021). An important advantage of FinBERT is that it leverages contextual embeddings and a transformer-based architecture trained on financial corpora, which allows it to capture the meaning of sentences beyond simple word counts (ibid.). Unlike dictionary-based methods, which treat words independently, FinBERT accounts for linguistic nuances such as negations, modifiers, and context-specific semantics. This feature is particularly relevant in S-1 filings, where cautious or risk-related statements may include positive words that actually convey negative implications. By operating at the sentence level, FinBERT reduces misclassification errors inherent in bag-of-words approaches.

While previous studies have analyzed the effects of strategic IPO prospectus disclosure on underpricing (Hanley and Hoberg 2010, 2012) and the effects of S-1 tone on underpricing and volatility (Loughran and McDonald 2013, 2016), whether language can signal IPO performance remains unclear. Existing research on SEC filings relies heavily on the LM dictionary, yet dictionary-based methods struggle to identify cases where negative phrases are embedded in positive wording. Thus, Loughran and McDonald (2016) argue that, unless a study can convincingly resolve the problem of negation, positive sentiment is best left untested.

Using the Cox hazard model, I find that optimism tone (net positive) calculated by both LM's method and FinBERT method is associated with a 50% to 60% lower IPO failure hazard, highlighting both its economic significance and strong predictive power. Our results of optimistic tone on IPO survival remain consistent across various types of survival models, including the Accelerated Failure Time (AFT) model and the logit model. The main variables continue to show strong predictability when controlling for predictors in Colak et al. (2022), Anagnostopoulou et al. (2021),and Gounopoulos and Pham (2018). Moreover, our findings are robust when employing an entropy-balanced sample and Lewbel (2012)'s internal instrumental variable (IV) method to address endogeneity concerns.

Furthermore, I find that the association is stronger among VC-backed IPOs. Moreover, the association is stronger when underwriter quality is higher. This finding aligns with the information asymmetry view that investors view the positive tone written by managers and underwriters, who face legal penalties for misstatements,as a credible signal concerning the riskiness of the offering (Hanley and Hoberg 2010).

This empirical chapter makes three main contributions to the literature on IPO performance, IPO prospectus tone, and text-based analysis in financial disclosures. First, I provide novel evidence on the predictive power of optimistic language in IPO prospectuses for long-run IPO survival. While prior research has primarily focused on short-run IPO outcomes such as underpricing (Loughran and McDonald 2013; Boulton and Campbell 2016), I show that optimistic tone—measured ex ante from the S-1 filing—is a strong and robust predictor of whether a firm remains listed in the years following its IPO. The results reveal that firms with higher optimism tone experience approximately 50% lower failure risk, even after controlling for firm fundamentals, financial quality, and other standard predictors from the survival literature (Colak et al. 2022; Gounopoulos and Pham 2018;

Anagnostopoulou et al. 2021). These findings offer empirical support for the theoretical frameworks of Hanley and Hoberg (2010), who argue that investors view the positive tone written by managers and underwriters, who face legal penalties for misstatements,as a credible signal concerning the riskiness of the offering.

Second, this study contributes methodologically by applying FinBERT, a deep learning-based sentiment model fine-tuned on financial text, to IPO prospectus analysis. While most existing studies rely on dictionary-based methods such as the LM financial dictionary (Loughran and McDonald 2011), these approaches struggle with context-specific negations and word ambiguity. FinBERT addresses these limitations by performing sentence-level classification using a transformer architecture trained on financial corpora, allowing for more accurate identification of positive and negative tones. To the best of my knowledge, this study applies FinBERT to fill the gap in the analysis of positive sentiments in IPO prospectuses. I construct two FinBERT-based optimism measures and demonstrate that both exhibit strong predictive power for IPO survival. The FinBERT results are consistent with, and complementary to, traditional dictionary-based measures.

Third, I identify two key moderators that amplify the relationship between optimism tone and IPO survival: underwriter quality and VC backing. These findings are consistent with the information asymmetry view, suggesting that when optimistic language is endorsed by reputable market participants, who are themselves liable for the content of the prospectus, it serves as a credible signal of firm quality. This result aligns with prior work on the certification role of intermediaries in IPOs (Hanley and Hoberg 2010) and highlights the importance of contextualizing managerial tone within the broader IPO ecosystem.

The second empirical chapter analyses the impact of CEO turnover and managerial ability on organizational capital accumulation. Despite numerous studies on the CEO's impact on corporate behavior and performance (e.g., (Demerjian et al. 2012; Custódio et al. 2019; Shang 2021; Dessein and Prat 2022)) since Bertrand and Schoar (2003) demonstrated that CEO fixed effects significantly influence corporate outcomes, understanding why and how CEOs affect corporate outcomes remains essential for both academics and regulators. Huson et al. (2004) document positive corporate performance following CEO turnover; however, although CEO transitions bring shifts in management style and strategy, most studies focus on turnover determinants (e.g., Bushman et al. (2010), DeFond and Park (1999), Fiordelisi and Ricci (2014) and Jenter and Lewellen (2021)), with limited research on turnover consequences and the mechanisms behind Huson et al. (2004)'s findings.

While studies have examined the influence of organizational capital on various corporate behaviors and outcomes, such as M&A results, tax avoidance, and investment policies (Gao et al. 2021; Hasan et al. 2018; Carlin et al. 2012; Li et al. 2018; Leung et al. 2018; Hasan and Uddin 2022; Francis et al. 2021), limited research focuses on the determinants of organizational capital. Notably, recent theoretical models predict that CEO transitions, managerial ability, and other CEO characteristics (e.g., compensation structure) play significant roles in determining the stock of organizational capital (Dessein and Prat 2022). Dessein and Prat (ibid.) predict that talented managers prioritize long-term benefits, while managerial short-termism hinders the accumulation of organizational capital. Although Dessein and Prat (ibid.) theoretically propose CEO turnover and other CEO-related variables as determinants of organizational capital, empirical evidence remains limited.

This empirical chapter seeks to answer what the determinants of organizational capital are and provide empirical evidence for Dessein and Prat (ibid.)'s theory paper. I follow the Eisfeldt and Papanikolaou (2013)'s method, utilizing selling, general, and administration expense (SG&A) as a proxy of organizational capital. CEO turnover data is sourced from Compustat and I validate turnover data using Gentry et al. (2021)'s database, which includes detailed, hand-collected reasons for CEO departures.

The results demonstrate that CEOs turnover is positively associated with the growth of organizational capital, with the association being more significant in a group of CEOs with higher managerial ability. Moreover, the results underscore the moderating role of CEO compensation structure, highlighting that performance-based incentives and external CEO appointments strengthen the positive impact of managerial ability on organizational capital. Furthermore, CEO ability also serves as a moderator in the relationship between CEO turnover and organizational capital.

This study contributes to both CEO turnover and organizational literature. Organizational capital, a form of special intangible asset embedded in a company's key talent, such as experts and executives, becomes becoming increasingly important. While studies have extensively analyzed the effects of organizational capital on various corporate outcomes and corporate governance (Hasan et al. 2018; Carlin et al. 2012; Li et al. 2018; Leung et al. 2018; Hasan and Uddin 2022; Attig and Cleary 2014; Marwick et al. 2020; Francis et al. 2021). However, the determinants of organizational capital have yet to be established.

This study highlights that CEO turnover increases organizational capital by approximately 15% in post-turnover periods, while organizational capital levels remain stable in pre-turnover periods. Utilizing a difference-in-differences (DiD) analytical framework, I confirm the robustness of our results through various DiD models, including two-way fixed effects (TWFE) estimators, staggered DiD estimators, and doubly robust estimators[2]. The positive effects of CEO transitions are consistent across sub-samples categorized by turnover type, with more pronounced effects following performance-related or misconduct-related dismissals.

2. See Sant'Anna and Zhao (2020), where it is argued that TWFE estimators may be biased when event dates vary across the treatment group. The doubly robust DiD framework provides more reliable results.

Furthermore, I investigate mechanisms through which CEO characteristics enhance organizational capital accumulation. Using a triple-difference (DDD) framework, I find that interaction terms between CEO ability [3] and CEO turnover are significantly positive, suggesting that capable CEOs invest more in organizational capital. Additionally, our analysis reveals that CEOs with higher compensation relative to industry peers invest significantly more in organizational capital, supporting the hypothesis that higher-paid CEOs possess greater abilities.

Next, I find that managerial ability has a positive effect on organizational capital. Economically significant, our results suggest that a one standard deviation increase in managerial ability leads to a 7%-8% change in the standard deviation of organizational capital. I use peer-group average value[4] of managerial ability as an instrumental variable and adopt a cutting-edge double robust machine learning (DDML) approach to mitigate endogeneity.

This chapter makes the following contributions. First, it contributes to the organizational capital literature [5]. While recent empirical studies examine organizational capital's effects on corporate behavior, policies, and performance[6], fewer studies address organizational capital's determinants. Dessein and Prat (2022) highlight leadership's critical role in organizational capital accumulation, developing a model that reveals the influence of CEO characteristics and transitions on organizational capital. This chapter advances OC literature by empirically examining CEO transitions and variables as organizational capital determinants. I find that CEO transitions positively affect organizational capital accumulation, with managerial ability and relative compensation serving as moderating

3. I adopt Demerjian et al. (2012)'s well-established measure of CEO ability (or managerial ability) in the management, accounting, and finance fields.
4. I acknowledge that peer-group average IVs are sometimes limited in mitigating omitted variable bias (Gormley and Matsa 2014); therefore, I employ double robust machine learning (DDML) to address endogeneity issues.
5. After Prescott and Visscher (1980) emphasized organizational capital's importance, empirical research was limited due to data challenges. Eisfeldt and Papanikolaou (2013) suggested using selling, general, and administration expense (SG&A) as a proxy for organizational capital, enabling further empirical research.
6. See: Gao et al. (2021), Hasan et al. (2018), Carlin et al. (2012), Li et al. (2018), Leung et al. (2018), Hasan and Uddin (2022), Francis et al. (2021) and Eisfeldt and Papanikolaou (2013)

factors, refining the impact of CEO transitions on organizational capital accumulation. These findings address Dessein and Prat (2022)'s call for empirical studies on CEO influences on organizational capital, enhancing the understanding of executive dynamics on organizational capital.

Second, this study contributes to CEO turnover literature. Previous studies focus on turnover determinants[7], with fewer addressing the consequences of CEO transitions[8]. The chapter enriches this literature by providing empirical evidence on how CEO transitions influence organizational capital, offering new perspectives on the strategic implications of executive changes and CEO characteristics. Third, the chapter also contributes to the literature on CEO ability and industry tournament incentives.

In the third empirical chapter, I explore the link between managerial overconfidence and pay-for-luck phenomena in executive compensation. Executive compensation remains a central topic in corporate finance, particularly concerning whether changes in CEO pay are aligned with firm performance or reflect managerial influence over the pay-setting process. Traditional agency theory posits that compensation contracts are designed to align executive incentives with shareholder interests (Holmström 1979). However, the rent-extraction view suggests that powerful CEOs can influence their own pay structures, extracting undue compensation beyond their firm-specific contributions (Bertrand and Mullainathan 2001). A key manifestation of this is the phenomenon of pay-for-luck, where CEOs receive compensation increases due to favorable external market conditions rather than their own skill.

7. E.g., Bushman et al. (2010), DeFond and Park (1999), Fiordelisi and Ricci (2014) and Jenter and Lewellen (2021)

8. E.g., **Iisbach1995ceo**; Intintoli et al. (2017) and Huson et al. (2004)

Empirical studies document substantial evidence of pay-for-luck in executive compensation. Bertrand and Mullainathan (2001) find that CEOs in the oil and gas industry receive higher pay when oil prices rise, even though they exert little control over commodity markets. Similarly, Garvey and Milbourn (2006) show that CEO compensation structures reward executives for industry-wide booms but do not penalize them symmetrically for downturns. More recently, Andreani et al. (2025) exploit the U.S. Tax Cuts and Jobs Act (TCJA) of 2017 as an exogenous event and find thatIakly monitored CEOs secured significant pay raises following tax windfalls butIre not penalized for corresponding tax losses. These findings challenge the notion that executive compensation contracts are purely incentive-driven and raise concerns that pay-for-luck may reflect inefficient rent-seeking behavior.

Despite extensive research on pay-for-luck, relatively little is known about the individual-level determinants that shape its magnitude. Specifically, why do some CEOs receive greater pay-for-luck than others? One potential explanation lies in CEO overconfidence, a behavioral trait that affects risk-taking, corporate decision-making, and executive compensation (Malmendier and Tate 2005a, 2008; Humphery-Jenner et al. 2016). Overconfident CEOs tend to attribute good firm outcomes to their own ability while blaming negative outcomes on external factors—a cognitive bias known as self-attribution bias (Kim 2013; Billett and Qian 2008). This bias may lead them to demand higher compensation increases when performance is boosted by luck while resisting pay cuts when market conditions deteriorate.

This chapter examines whether CEO overconfidence amplifies the pay-for-luck phenomenon in executive compensation. I test three key hypotheses: (1) overconfident CEOs exhibit stronger pay-for-luck sensitivity, receiving greater compensation increases in response to external, market-driven performance shocks. Overconfident CEOs are more likely to attribute corporate performance related to external conditions to their own managerial ability and managerial effort; (2)Iak corporate governance exacerbates this relationship, as firms with ineffective monitoring allow overconfident CEOs to negotiate favorable pay structures; and (3) overconfident CEOs' risk-taking behavior amplifies pay-for-luck effects, as they are more likely to pursue volatile investment strategies that heighten firm exposure to external shocks. CEOs who have a higher level of fairness concerns are more likely to have risk-taking behaviors (Liu and Sun 2023) to catch up with their peers and satisfy their fairness concerns.

To empirically examine these hypotheses, I decompose firm performance into luck, representing external market and industry shocks, and skill, representing firm-specific performance, following the methodologies of Garvey and Milbourn (2006) and Daniel et al. (2020). I measure CEO overconfidence using both the option-based proxy (Malmendier and Tate 2005a) and a text-based sentiment measure from 10-K filings (Hirshleifer et al. 2012). To address endogeneity concerns, I employ an IV approach, leveraging the industry-wide density of overconfident CEOs as an exogenous instrument (Deshmukh et al. 2021). I also use Lewbel (2012)'s internal IV approach to further isolate the endogenous issues.

Our results reveal several key insights. Firstly, overconfident CEOs receive significantly larger pay-for-luck adjustments than their non-overconfident counterparts. A one-standard-deviation increase in luck leads to a 21% higher compensation increase for overconfident CEOs relative to less confident executives. Secondly, I findIak corporate governance intensifies these effects. In firms with low board independence and high institutional investors, the pay-for-luck gap between overconfident and non-overconfident CEOs is 40% larger. Thirdly, overconfident CEOs' higher risk-taking behavior contributes to stronger pay-for-luck effects, as they pursue volatile strategies that magnify external shocks to firm performance. Fourthly, I find board rewards overconfident CEOs through pay-for-luck for their higher investment in research and development expense (R&D), which aligns with Hirshleifer et al. (2012)'s argument that overconfident CEOs are willing to invest more time and more managerial efforts to understand innovative projects. Fifthly, I find that Dodd-Frank and Say-on-Pay Rule decrease the pay-for-luck behaviors in both overconfident groups and non-overconfident groups.

Our research builds on the foundational work of Gervais et al. (2011), who argue that overconfident managers are willing to exert greater effort in high-risk, high-return projects, enabling firms to design incentive-compatible contracts that offer below-market compensation. It also draws on the empirical findings of Kim and Park (2024), who show that boards tend to adjust performance targets more aggressively and asymmetrically for overconfident CEOs. Although prior studies suggest that overconfident CEOs may face disadvantages in compensation design, our study contributes to this literature by providing new evidence that these CEOs extract greater benefits from pay-for-luck due to fairness concerns rooted in self-attribution bias (Liu and Sun 2023; Billett and Qian 2008). Specifically, I show that overconfident CEOs are more likely to interpret positive performance outcomes as self-driven and are therefore particularly sensitive to perceived under-compensation. This sensitivity amplifies their tendency to seek compensation through luck-sensitive mechanisms, especially underIak corporate governance.

This study also contributes to the growing literature on fairness concerns in executive compensation, particularly by providing empirical evidence on how these concerns interact with CEO overconfidence to distort pay outcomes. Overconfident CEOs represent an ideal context for examining fairness-driven rent extraction. As shown by Gervais et al. (2011), such CEOs are willing to accept below-market pay packages ex ante, driven by their optimism and risk-seeking behavior. However, this initial pay disadvantage, when combined with self-attribution bias (Billett and Qian 2008), heightens their sensitivity to perceived unfairness in ex post reward allocations. Our findings suggest that these fairness concerns manifest in the form of asymmetric pay-for-luck, where overconfident CEOs receive greater rewards for favorable external shocks while facingIaker penalties for unfavorable ones. This behavior is particularly pronounced underIaker governance conditions. In doing so, this chapter complements and extends recent behavioral models such as Liu and Sun (2023), DeMarzo and Kaniel (2023), Edmans et al. (2023), and Chaigneau et al. (2022), offering empirical support for the fairness channel in shaping pay-for-luck phenomenon.

Moreover, our findings highlight that both firm-level governance mechanisms and external regulatory oversight can mitigate the opportunistic compensation outcomes associated with CEO overconfidence. I further contribute to the theoretical literature by offering empirical support for the rat-racing channel proposed by Liu and Sun (2023), whereby overconfident CEOs pursue higher-risk projects to increase the probability of extreme performance outcomes, thereby amplifying pay-for-luck. Collectively, our results refine the understanding of how CEO overconfidence interacts with fairness concerns to distort compensation dynamics and demonstrate how institutional constraints can help realign managerial incentives.

These findings contribute to three strands of literature. First, I extend the executive compensation literature (Jensen and Murphy 1990; Bertrand and Mullainathan 2001; Chaigneau et al. 2022; Daniel et al. 2020; Campbell and Thompson 2015a; Andreani et al. 2025) by demonstrating that individual CEO traits shape pay-for-luck sensitivity. Second, I contribute to the behavioral corporate finance literature (Malmendier and Tate 2005a; Hirshleifer et al. 2012; Humphery-Jenner et al. 2016), showing that self-attribution bias influences compensation structures. Third, our results inform corporate governance debates, emphasizing the role of board oversight in mitigating excessive pay-for-luck Andreani et al. (2025).

While the behavioral traits of overconfident CEOs have been extensively studied, their interplay with fairness concerns and compensation responses remains under-theorized. Our study integrates insights from Gervais et al. (2011) and Liu and Sun (2023)[9] to propose a conceptual bridge: overconfidence leads to higher subjective ownership of outcomes, which heightens fairness concerns when compensation lags performance. These dynamics, when reinforced by managerial power orIak governance, create fertile ground for asymmetric pay-for-luck outcomes.

9. Also see: Chaigneau et al. (2022), Edmans et al. (2023) and DeMarzo and Kaniel (2023)

Beyond academic contributions, our findings have significant policy implications. Given increasing regulatory scrutiny on executive pay fairness, such as the Dodd-Frank Say-on-Pay Rule, our results suggest that strengthening board independence and shareholder oversight could mitigate excessive pay-for-luck among overconfident executives. Implementing governance reforms that tie pay more closely to firm-specific skill rather than external factors could improve compensation efficiency and shareholder alignment.

Collectively, these chapters contribute to the literature on corporate governance and behavioral finance by analyses of how CEO traits shape strategic corporate behaviors and outcomes. This thesis highlights the effects of managerial characteristics on IPO survival, organizational capital, and compensation structure, providing valuable insights for boards, investors, and policy-makers aiming to optimize governance structures and managerial incentives to enhance firm performance and stability.

The remainder of the thesis proceeds as follows: Chapter 2 provides an in-depth empirical analysis of managerial tone and IPO survival. Chapter 3 examines CEO turnover and its implications for organizational capital accumulation. Chapter 4 investigates managerial overconfidence in the context of executive compensation. Chapter 5 concludes by summarizing the findings and discussing their implications for theory and practice.

Chapter 2

The Use of Optimistic Language in the Prospectus and IPO Survival

Key words: IPO survival, Text analysis, FinBERT, IPO prospectus language

2.1 Introduction

The long-run performance of Initial Public Offerings (IPOs) is poor, regardless of whether the IPOs originate from the U.S. or the international IPO market. More than 30% of IPOs are delisted within five years, as documented by Ritter (1991) [1]. While newly listed firms that choose to go private again or change markets (e.g., from a domestic market to foreign markets) [2] may benefit both firms and investors, IPO delistings driven by negative exit reasons—such as bankruptcy, unfavorable mergers and acquisitions, poor financial conditions, failure to meet exchange regulations, or other adverse outcomes—can harm both firms and investors. Hence, understanding and predicting IPO delisting events are crucial for regulators and corporate stakeholders.

While most of the IPO survival literature focuses on firm-level factors, such as VC background, audit quality, financial ratios, accounting integrity, stakeholder welfare, and firms' fundamental conditions [3], relatively few studies examine how use of language in S-1 fillings affect IPO survival. Colak et al. (2022) present a prediction model that incorporates market, financial, and pricing risk factors. Our research builds upon the studies of Anagnostopoulou et al. (2021) and Gounopoulos and Pham (2018) and Colak et al. (2022), exploring the effect of the use of optimistic language in IPO prospectuses on IPO survival. Our findings demonstrate strong predictive power based on the models proposed by Anagnostopoulou et al. (2021) and Gounopoulos and Pham (2018) and Colak et al. (2022).

1. Current studies on IPOs also emphasize the ongoing trend of poor post-IPO performance and low survival rate (e.g., see Colak et al. (2021), Gounopoulos and Pham (2018), Amini et al. (2023), Alhadab et al. (2015) and Espenlaub et al. (2016)).
2. These positive reasons for IPO delisting are also referred to as "voluntary delisting"
3. See: Krishnan et al. (2011), Jain and Kini (2000), Demers and Joos (2007), Espenlaub et al. (2012), Anagnostopoulou et al. (2021) and Amini et al. (2023)

Despite extensive analysis of the tone in SEC filings, its effects on IPO performance remain unclear due to data limitations. Prior work in textual analysis suggests that positive tone is difficult to measure accurately, as positive words are often negated in ways that are challenging to detect programmatically. Both Tetlock (2007) and Loughran and McDonald (2011) note that results related to positive words are mixed because negative phrases are frequently wrapped in positive language[4]. To address this issue, I follow the state-of-the-art pre-trained FinBERT model developed by Huang et al. (2023), a deep learning approach to extracting textual information. The main benefit of FinBERT is its focus on sentences rather than individual words. It addresses the concerns raised by Loughran and McDonald (2011) that negative phrases are often embedded in positive wording.

I construct the optimism tone using the ex ante relative positive tone in IPO prospectuses. While top managers often exhibit excessive optimism (Malmendier and Tate 2008), which may be reflected in their writing style, I argue that tone also has predictive power and signals future IPO survival. This is because the IPO prospectus is not prepared solely by executives but also involves auditors, underwriters, and venture capital firms. As such, the document may reflect not just managerial confidence but the collective confidence of all involved parties, thereby signaling strong future performance to the market, given their superior information about the firm. Although Loughran and McDonald (2013) finds that the tone of S-1 filings affects IPO underpricing, my study contributes further by showing that optimism tone—proxied by the ex ante relative positive tone in S-1 filings—exhibits strong predictability for IPO survival.

An important alternative interpretation is strategic disclosure. Because the S-1 filing is prepared by managers together with underwriters, auditors, and other IPO participants who possess superior private information, a more optimistic tone may partly reflect insiders' ex ante expectation that the firm is more likely to survive after listing. Under this view, tone is not necessarily a purely exogenous driver of survival; rather, it may sum-

4. For example, as noted by managers of VA Linux Systems in their S-1: "Our business strategy may not be successful and I may not successfully manage these risks."

marize private assessments of firm quality and future viability. This possibility does not diminish the economic relevance of tone, but it changes the interpretation of the estimates. Accordingly, throughout this chapter, I interpret optimistic language primarily as an ex ante disclosure signal and examine whether it retains incremental predictive power after controlling for a rich set of observable determinants of IPO survival. Because tone is measured from the prospectus before post-IPO outcomes are realized, it is informative from an ex ante perspective; however, the empirical design cannot fully rule out the possibility that tone is strategically chosen in anticipation of future survival prospects.

I use a text-based method[5] derived from Loughran and McDonald (2011, 2016)'s (LM) word lists to construct a confidence variable for the management team. Acknowledging that S-1 filings are prepared by various IPO participants (e.g., venture capitalists, bookrunners, and audit teams), I also calculate the word ratio by focusing exclusively on the Management Discussion and Analysis (MD&A) section of the S-1 filings, which is more likely authored by the management team, to capture managerial confidence. This study also distinguishes the optimistic language from IPO prospectus tones and managerial overconfidence; managerial overconfidence is a psychological trait Malmendier and Tate (2008) that may influence the corporate outcome while IPO prospectus tones is a writing style that incorporate hidden information signaling corporate performance to the markets (Loughran and McDonald 2016).

The study introduces the FinBERT, a pre-trained deep learning language model, developed by Huang et al. (2023) and Liu et al. (2021). An important advantage of FinBERT is that it leverages contextual embeddings and a transformer-based architecture trained on financial corpora, which allows it to capture the meaning of sentences beyond simple word counts (ibid.). Unlike dictionary-based methods, which treat words independently, FinBERT accounts for linguistic nuances such as negations, modifiers, and

5. This method is also referred to as "BOW" (Bag of Words), which involves extracting words relevant to different sentiments, including positive, negative, weak uncertainty, and strong uncertainty, based on a pre-specified bag of words.

context-specific semantics. This feature is particularly relevant in S-1 filings, where cautious or risk-related statements may include positive words that actually convey negative implications. By operating at the sentence level, FinBERT reduces misclassification errors inherent in bag-of-words approaches.

While previous studies have analyzed the effects of strategic IPO prospectus disclosure on underpricing (Hanley and Hoberg 2010, 2012) and the effects of S-1 tone on underpricing and volatility (Loughran and McDonald 2013, 2016), whether language can signal IPO performance remains unclear. Existing research on SEC filings relies heavily on the LM dictionary, yet dictionary-based methods struggle to identify cases where negative phrases are embedded in positive wording. Thus, Loughran and McDonald (2016) argue that, unless a study can convincingly resolve the problem of negation, positive sentiment is best left untested.

Using the Cox hazard model, I find that optimism tone (net positive) calculated by both LM's method and FinBERT method is associated with a 50% to 60% lower IPO failure hazard, highlighting both its economic significance and strong predictive power. Our results of optimistic tone on IPO survival remain consistent across various types of survival models, including the Accelerated Failure Time (AFT) model and the logit model. The confidence variables keep showing strong predictability when controlling predictors in Colak et al. (2022), Anagnostopoulou et al. (2021),and Gounopoulos and Pham (2018). Moreover, our findings are robust when employing an entropy-balanced sample and Lewbel (2012)'s internal instrumental variable (IV) method to address endogeneity concerns.

Furthermore, I find that the VC involvement serves as an important moderator amplifying the positive effects of optimism tone on IPO survival. Moreover, the effects of optimism tone are more pronounced when IPO firms have higher underwriter quality. This finding aligns with the information asymmetry view that investors view the positive tone written by managers and underwriters, who face legal penalties for misstatements,as a credible signal concerning the riskiness of the offering (Hanley and Hoberg 2010).

This paper makes three main contributions to the literature on IPO performance, IPO prospectus tone, and text-based analysis in financial disclosures. First, I provide novel evidence on the predictive power of optimistic language in IPO prospectuses for long-run IPO survival. While prior research has primarily focused on short-run IPO outcomes such as underpricing (Loughran and McDonald 2013; Boulton and Campbell 2016), I show that optimistic tone—measured ex ante from the S-1 filing—is a strong and robust predictor of whether a firm remains listed in the years following its IPO. The results reveal that firms with higher optimism tone is associated with a 50% to 60% lower IPO failure hazard, even after controlling for firm fundamentals, financial quality, and other standard predictors from the survival literature (Colak et al. 2022; Gounopoulos and Pham 2018; Anagnostopoulou et al. 2021). These findings offer empirical support for the theoretical frameworks of Hanley and Hoberg (2010), who argue that investors view the positive tone written by managers and underwriters, who face legal penalties for misstatements,as a credible signal concerning the riskiness of the offering.

Second, this study contributes methodologically by applying FinBERT—a deep learning-based sentiment model fine-tuned on financial text—to IPO prospectus analysis. While most existing studies rely on dictionary-based methods such as the LM financial dictionary (Loughran and McDonald 2011), these approaches struggle with context-specific negations and word ambiguity. FinBERT addresses these limitations by performing sentence-level classification using a transformer architecture trained on financial corpora, allowing for more accurate identification of positive and negative tone. To the best of knowledge, this study applies FinBERT to fill the gap of analysis of positive sentiments of IPO prospectuses. I construct two FinBERT-based optimism measures and demonstrate that both exhibit strong predictive power for IPO survival. The FinBERT results are consistent with, and complementary to, traditional word-count-based measures.

Third, I identify two key moderators that amplify the relationship between optimism tone and IPO survival: underwriter quality and VC backing. These findings are consistent with the information asymmetry view, suggesting that when optimistic language is endorsed by reputable market participants—who are themselves liable for the content of the prospectus—it serves as a credible signal of firm quality. This result aligns with prior work on the certification role of intermediaries in IPOs (Hanley and Hoberg 2010) and highlights the importance of contextualizing managerial tone within the broader IPO ecosystem.

Collectively, these contributions extend the IPO literature by shifting the focus from firm-level characteristics to communication-based managerial signals, and by introducing advanced natural language processing techniques to measure optimism in a more context-aware and economically meaningful way.

The rest of the paper is organized as follows. Section 2 discusses the related literature and develops the hypotheses. Sections 3 and 4 describe the sample and explain the survival analysis methodology. Section 5 reports the empirical findings on the impact of optimistic tone on the probability of failure and the time to survival of IPO firms. Sections 6 and 7 present robustness checks of the results and additional tests addressing endogeneity. Section 8 provides a discussion and analysis of the potential channels through which optimistic tone affects IPO survival. Finally, Section 9 offers concluding remarks.

2.2 Literature review and hypothesis development

2.2.1 IPO survival review

While the long-run performance of IPOs is generally poor, it is crucial to understand the fundamental reasons behind IPO survival and predict failure risk. Numerous studies have analyzed various determinants of IPO survival, including firm age and VC backing (Krishnan et al. 2011; Jain and Kini 2000), auditor quality (Jain and Martin Jr 2005), intangibility, leverage, operating performance (Demers and Joos 2007), market conditions (Espenlaub et al. 2012), and earnings management (Anagnostopoulou et al. 2021). Notably, Colak et al. (2022) developed a machine learning model incorporating a wide range of financial ratios to predict IPO survival with a high degree of accuracy.

However, previous studies have primarily focused on corporate characteristics (e.g., corporate fundamentals and accounting ratios). Following Bertrand and Schoar (2003), who highlight the significant role of management style in shaping corporate policies, recent research has begun examining the impact of management teams on IPO survival. For example, Gounopoulos and Pham (2018) argue that specialist CEOs enhance IPO survival, while Colak et al. (2021) suggest that a greater pay gap between the CEO and other executives also improves IPO survival. Additionally, Amini et al. (2023) find that employee welfare and social capital positively influence IPO survival. Remarkably, Boulton and Campbell (2016) show that managerial confidence is positively correlated with IPO underpricing.

2.2.2 IPO prospectus language review

Building on Tetlock (2007), several studies use the Harvard IV-4 word lists to measure tone in financial media. For instance, Tetlock et al. (2008) analyze articles from the *Wall Street Journal* and *Dow Jones News Service* related to S&P 500 firms. They find that a higher frequency of negative words in firm-specific news is associated with lower future earnings, even after controlling for past accounting performance and analyst forecasts. Using over 900,000 Thomson-Reuters news articles, Heston and Sinha (2017) show that a positive net sentiment score—defined as the difference between positive and negative word frequencies—for articles mentioning a firm predicts higher stock returns over the next one to two days. In contrast, negative sentiment is linked with short-term declines in stock prices.

Hanley and Hoberg (2010) apply the Harvard IV-4 word lists to assess the tone of IPO prospectuses and find that a more positive net tone (percentage of positive words minus negative) corresponds with lower first-day returns and smaller offer price revisions. They argue that investors interpret optimistic language from managers and underwriters—who are legally liable for misstatements—as a credible signal about the firm's risk level. Similarly, Davis et al. (2012) use the Diction software to evaluate the tone in earnings press releases and show that firms using more optimistic language subsequently achieve higher return on assets (ROA). Their findings suggest that the language used to describe firm operations subtly communicates management's expectations about future performance. A greater use of Diction's optimism words relative to pessimism words is positively related to ROA over the next four quarters. In a related study, Davis and Tama-Sweet (2012) find that a more pessimistic tone in the Management Discussion and Analysis (MD&A) section of Form 10-K filings predicts lower future ROA.

2.2.3 Hypothesis development

2.2.3.1 Information asymmetry view

Our first hypothesis builds upon the theory of Hanley and Hoberg (2010) and Beatty and Ritter (1986). Hanley and Hoberg (2010) argues that investors perceive optimistic language from managers and underwriters—who bear legal liability for misstatements—as a credible signal of the firm's future performance. While Beatty and Ritter (1986) emphasizes the information asymmetry present at the time of going public, IPO firms tend to be relatively small and less known to the market. Therefore, a higher proportion of net positive sentences in IPO prospectuses may convey insider information and signal stronger prospects for post-IPO survival.

Hypothesis 1: Net positive sentiments is positively correlated with IPO survival

Loughran and Ritter (2002)'s theory of relative bargaining power suggests that stronger issuers are more capable of persuading underwriters to exert effort during the pre-market phase, even when underwriting fees may not fully compensate them. When underwriter quality is high, their involvement lends greater credibility to the disclosed information. As a result, the positive tone in the IPO prospectus is more likely to be perceived as informative rather than promotional, thereby amplifying the impact of net positive sentiment on IPO survival.

Hypothesis 2: The positive impact of net positive sentiments is enhanced by underwriter's quality.

IPO prospectuses are prepared by multiple parties, including the management team, auditors, underwriters, and VC firms. Although Jain and Kini (2000) show that VC involvement enhances IPO survival and Krishnan et al. (2011) and Carter and Manaster (1990) find that VC reputation positively affects post-IPO outcomes, not all IPOs are VC-backed. This paper argue that when a VC firm is involved, it not only provides certification but also contributes to the overall quality and credibility of the disclosed information. In such cases, a more optimistic tone in the prospectus can further reduce information

Hypothesis 3: The positive impact of net positive sentiments is enhanced by VC involvement.

2.2.3.2 Managerial optimism view

In this section, I provide alternative explaination from managerial optimism views. There are two opposing views on the effect of managerial confidence on shareholder value maximization and corporate outcomes. According to agency cost theory, optimistic managers are more likely to engage in rent extraction behavior, making investment decisions that maximize managerial benefits, such as over-investment aimed at reputation accumulation. In contrast, information asymmetry theory suggests that managers remain focused on shareholder value maximization but hold more inside information. Consequently, optimistic managers exhibit pecking order behavior, as external financing is costly (Heaton 2019).

Psychological theories of managerial overconfidence suggest that managers are more likely to underestimate the potential risks of corporate projects and overestimate their benefits. Two of the most significant features of overconfident managers are over-investment and a preference for internal financing, consistent with the pecking order theory (Huang et al.

2016; Malmendier and Tate 2005a; Heaton 2002). Prior studies suggest that overconfident ones are more likely to undertake sub-optimal investment decisions and capital structure policies because they make decisions to increase their own reputation which is consistent with agency cost theory.

The market reaction to managerial overconfidence is generally negative (Malmendier and Tate 2008; Kim et al. 2016). Malmendier and Tate (2008) find that overconfident managers tend to overpay for target companies, and the market reaction to mergers conducted by overconfident managers is negative compared to those led by non-overconfident managers. Furthermore, Kim et al. (2016) demonstrate that overconfident managers increase the stock price crash risk, as they have strong incentives to hoard bad news. These managers often believe that the current stock price is undervalued, leading them to withhold bad news to prevent further price declines, while issuing voluntary management forecasts (Hribar and Yang 2016). In addition, Hsieh et al. (2014) and Choi et al. (2024) find that overconfident managers are more likely to engage in accounting manipulation, such as classification shifting and real earnings management.

Taken together, this paper predicts that managerial optimism negatively affects IPO survival, as overconfident managers consistently make sub-optimal decisions, and markets tend to hold a negative attitude toward them.

Hypothesis 4: managerial optimism is negatively correlated with IPO survival

Despite the tendency of managerial overconfidence to lead to sub-optimal corporate decisions, why do firms frequently hire overconfident managers? Two distinctive theories provide explanations for this puzzle.

Gervais et al. (2011) develop a theoretical model showing that risk-averse yet optimistic CEOs are less conservative, allowing firms to motivate CEOs to pursue riskier and more valuable projects at a lower cost. Overconfident managers are also more attractive to firms than their rational counterparts because overconfidence commits them to exert effort to learn about projects. Similarly, Goel and Thakor (2008) present a theoretical model demonstrating that CEO overconfidence can promote firm value up to a certain point, even though overconfident CEOs are more likely to undertake riskier and potentially value-destroying projects compared to rational CEOs.

Both theories generate testable hypotheses; however, managers may adjust their corporate policies as firms mature and accumulate past management experience. Current studies on managerial optimism predominantly focus on mature firms and face significant concerns regarding path dependence. In contrast, IPOs generally make investment decisions shortly before going public (Baranchuk et al. 2014). This reduces concerns about path dependence and allows for clearer inferences about the effects of managerial overconfidence.

Based on the perspective of shareholder value maximization and the hypothesis that managerial optimism induces greater managerial effort to evaluate risky and valuable projects, I make our second prediction that managerial confidence is positively correlated with IPO survival.

Hypothesis 5: managerial optimism is positively correlated with IPO survival

2.3 Sample and methodology

To empirically test the effect of the use of positive language on IPO survival, I construct our key variables [6], ***Optimism LM***, ***Optimism FinBERT Total***, and ***Optimism FinBERT Net***, using language content from S-1 filings. IPO-related information, including issue date, proceeds, and offer price, is collected from Eikon's SDC New Issue Database. To ensure data quality, I impose the following restrictions [7]: (1) The offer price must be at least five dollars per share; (2) The IPO must not be a spin-off, privatization IPO, American Depositary Receipt (ADR), Real Estate Investment Trust (REIT), unit offering, rights issue, limited partnership, closed-end fund, or financial institution; (3) The sample is restricted to domestic operating companies. I exclude all financial firms whose two-digit SIC codes fall within the range 60 to 69.

I obtain underwriter quality, venture capital (VC) backing, and firm age data from Jay Ritter's IPO database [8]. CEO-level control variables, including CEO education, age, tenure, gender, and chairman duality, are collected from various sources such as BoardEx and ExecuComp. Since ExecuComp primarily covers S&P 1500 firms, I manually supplement missing CEO-level information using S-1 filings and BoardEx. Furthermore, I collect CEO past experience data from BoardEx to calculate the CEO general ability index. Firm-level financial data is obtained from the Compustat database.

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6. I also construct ***Optimism LM MDA***, ***Optimism FinBERT Total MDA***, and ***Optimism FinBERT Net MDA***, using language content from MD&A section of S-1 filings
7. The justification for these restrictions is that ADRs, penny stocks (offer prices below five dollars per share), and unit offerings frequently exhibit data quality issues in the SDC database (Ritter 2020).
8. Available at: `https://site.warrington.ufl.edu/ritter/ipo-data/`.

2.3.1 IPO prospectus tones measurements

One challenge of our research is constructing the optimism variable for IPO firms with the traditional dictionary-based method. Previous studies use Harvard IV-4 word lists (Hanley and Hoberg 2010) and Diction (Boulton and Campbell 2016; Davis et al. 2012) to assess the tone of IPO prospectuses. More recent studies use LM's financial dictionary to gauge positive and negative words (Loughran and McDonald 2011, 2016). However, both Tetlock (2007) and Loughran and McDonald (2011) note that results related to positive words are mixed because negative phrases are frequently wrapped in positive language. For example, as noted by managers of VA Linux Systems in their S-1: "Our business strategy may not be successful and I may not successfully manage these risks.". To address above issue, our paper use FinBERT to measure IPO prospectus sentiments.

2.3.1.1 FinBERT, a deep learning approach

FinBERT represents a notable advancement among transformer models for analyzing financial text. FinBERT utilizes the BERT architecture but is specifically trained on financial texts. There are two established versions of FinBERT. The first, developed by Huang et al. (2023), is trained on financial reports, analyst reports, and earnings conference call transcripts. The second, introduced by Liu et al. (2021), is trained on financial news and Reddit chatroom discussions. Both FinBERT models are pre-trained transformer models. Accounting studies such as Huang et al. (2023) and Liu et al. (2021) emphasize the accuracy of their respective FinBERT models rather than exploring the distribution of positive and negative tones. Our paper use Huang et al. (2023)'s model as our paper focus on IPO prospectus, a type of financial report.

Cheng and Golshan (2025) utilize FinBERT to measure CEO tone to measure CEO depression, coding positive tone as 1, neutral as 0, and negative as -1. Bianchi et al. (2024) adopt FinBERT as an alternative method to examine how congressional viewpoints influence asset pricing. Cao et al. (2023) construct their BERT-based sentiment measure by calculating the ratio of BERT-negative sentences to the total number of sentences (or words) in 10-K sections. Kanelis and Siklos (2025) apply FinBERT at the sentence level to analyze press conference statements made by the ECB president. Finally, Aldy et al. (2025) compute sentiment scores using the difference between positive and negative values, reflecting the relative likelihood that the overall input text sequence is predominantly positive rather than negative.

Cheng and Golshan (2025) introduce a novel approach using FinBERT to measure CEO depression by analyzing vocal acoustic features from CEOs' conference call recordings. They validate their measure by examining its association with firm risk, job demands, CEO age, and gender. Their findings indicate that higher firm risk increases CEO depression, while higher job demands and demographic characteristics such as being older or female decrease the likelihood of CEO depression. Additionally, their analysis explores the consequences of CEO depression on career outcomes, notably turnover and pay-performance sensitivity, highlighting nuanced implications of mental health in corporate leadership.

Bianchi et al. (2024) use FinBERT as an alternative method to evaluate how congressional viewpoints expressed through tweets affect asset prices. Utilizing high-frequency identification, they demonstrate that supportive tweets positively influence stock prices, whereas critical tweets lead to negative price reactions. Their study extends the observation window to several days post-tweet, identifying persistent and economically significant price impacts, confirming the effectiveness of sentiment analysis via FinBERT in capturing market reactions to political information disseminated on social media platforms.

Cao et al. (2023) construct their sentiment measure based on BERT by calculating the ratio of negatively classified sentences relative to total sentences (or total words) in firms' 10-K filings. They argue that firms actively adapt their disclosure tone to align with algorithmic expectations, driven by the growing prevalence of AI-driven investors who interpret financial disclosures. Their research highlights the feedback effect where increased AI readership influences firms to reduce negative linguistic tones and enhance machine readability, evidencing strategic adaptations by corporations to technology-driven investor sentiment analysis (ibid.).

Kanelis and Siklos (2025) apply FinBERT to ECB press conference introductory statements to derive a novel sentiment indicator capturing the euro area's monetary policy stance. Their analysis demonstrates that FinBERT effectively classifies sentiment based on economic outlook and macroeconomic conditions as communicated by ECB officials. They find that monetary policy sentiment extracted from these statements significantly influences subsequent market expectations, while sentiment regarding financial stability issues exhibits no substantial effect, underscoring the differentiated informational value embedded in ECB communications.

Finally, Aldy et al. (2025) use FinBERT to compute corporate climate messaging sentiment scores by taking the difference between positive and negative sentiment classifications. They analyze the impacts of corporate climate disclosures, emission commitments, and earnings call dialogues on firm valuations, finding significant market valuation improvements for firms transparent about their emissions. Positive sentiment in earnings call Q&A sessions, identified via FinBERT, also mitigates the valuation discount linked to carbon emissions, whereas decarbonization commitments alone have a statistically insignificant effect, highlighting investor preferences for actionable transparency over symbolic declarations (ibid.).

To address the limitations of LM dictionary approach, our paper employ the state-of-the-art pre-trained FinBERT model Huang et al. (2023), which classifies each sentence in the IPO prospectus as positive, negative, or neutral. I then aggregate these sentence-level predictions into two optimism measures: **Optimism FinBERT Net** and **Optimism FinBERT Total**.

Following Kanelis and Siklos (2025), the first captures the net balance among non-neutral sentences:

$$\text{Optimism FinBERT Net} \;=\; \frac{\text{positive sentence} - \text{negative sentence}}{\text{positive sentence} + \text{negative sentence}}. \tag{2.1}$$

The second measurement follows Cao et al. (2023), calculated as the same net balance by the total number of sentences in the filing:

$$\text{Optimism FinBERT Total} \;=\; \frac{\text{positive sentence} - \text{negative sentence}}{\text{total number of sentence}}. \tag{2.2}$$

Both indices lie in $[-1, 1]$, where higher values indicate a more optimistic tone, values near zero indicate balance, and negative values indicate a more negative tone. By working at the sentence level, these measures mitigate the concern that negative phrases are embedded within positive wording, a limitation of word-count methods.

2.3.1.2 LM's financial dictionary

Our second text-based method follows the Bag-of-Words (BOW) approach from Loughran and McDonald (2011, 2016) to construct sentiment variables suited to the financial context, which is more appropriate than Diction [9]. Our findings remain robust and align with our argument that optimistic tone signals stronger post-IPO survival prospects when using Diction's BOW measurement of optimism, as detailed in Appendix (Table 1).

I construct the traditional dictionary-based method's measurement ***Optimism LM*** by using Loughran and McDonald (2011)'s words lists to extract key words from full S-1 fillings [10].

$$\text{Optimism LM} = \left(\frac{\text{Positive} - \text{Negative}}{\text{Positive} + \text{Negative}} \right) \times 100 \tag{2.3}$$

In the above equations, positive is the number of positive words (e.g., *growth, profit, success*) in the LM financial dictionary, and negative is the number of negative words (e.g., *loss, decline, failure*). Weak uncertainty is the number of weak uncertainty words (e.g., *likely, possible, potential*) and strong uncertainty is the number of strong uncertainty words (e.g., *uncertain, risk, volatility*). The key variable Optimism LM is standardized to the range of 0 to 1.

---

9. Diction is not designed for financial report and 75% of words may be misclassified by Diction in context of finance and accounting. For example, frequently occurring Diction optimistic words such as "respect," "necessary," "power," and "trust" may not typically carry positive meanings when used by managers to describe future or current operations. Similarly, they question whether Diction pessimism words like "no," "not," "without," "gross," and "pain" convey negative meanings in the context of typical accounting disclosures (Loughran and McDonald 2011, 2016).
10. Before I extract key words from fillings, I use python and follow standard natural language process to clean financial reports and to exclude any noisy information (such as HTML, XBRL, XML etc.) following Loughran and McDonald (2016)'s method which is public for academic research [11] (https://sraf.nd.edu/sec-edgar-data/cleaned-10x-files/10x-stage-one-parsing-documentation).

2.3.2 IPO survival measurements

I collect the IPO issue date from Eikon's SDC New Issue Database and IPO delist information from the Center for Research in Security Prices (CRSP) stock event database. The sample period of this study spans from 1st January 1997 to 31st December 2019, as the definition of a surviving IPO requires the firm to operate successfully for at least five years, and the IPO event database in CRSP ends on 31st December 2023.

I include the IPO years from 1997 to 2000 because the early 21st century experienced the internet bubble. Including these years ensures that our sample does not suffer from bias due to crisis-specific IPO years Ljungqvist and Wilhelm Jr (2003). Additionally, I exclude firms that went public before 1997 due to the limited availability of CEO-related information for public firms in that period.

2.4 Research design

I follow the standard survival analysis (or duration analysis) framework to investigate the relationship between optimistic tone and IPO survival. This research employs the hazard function and survival function to estimate the failure rate and survival rate, respectively. Additionally, I use the Cox proportional hazards model, as adopted in numerous studies analyzing IPO survival (Jain and Kini 2000; Colak et al. 2021; Anagnostopoulou et al. 2021).

2.4.1 Nelson-Aalen estimator

Firstly, I employ the Nelson-Aalen estimator, which is defined as

$$\widehat{H}(t) = \sum_{t_i \leq t} \frac{f_i}{r_i} \tag{2.4}$$

where f_i is the number of failed firms at timet_i, and the r_i is the number of firms at risk at time t_i.

2.4.2 Kaplan-Meier estimator

The survival function of Kaplan-Meier estimator is defined as

$$\widehat{S}(t) = \prod_{t_i \leq t} \frac{f_i - f_i}{r_i} \tag{2.5}$$

where f_i is the number of failed firms at time t_i, and the r_i is the number of firms at risk at time t_i.

2.4.3 Logit model

The first groups of regressions in our empirical analysis are logit model, hence the dependent variable is IPO survival a binary choice where 0 presents survival 1 presents involuntary delist from the public, hence the logit model is suitable for our research.

$$
\begin{aligned}
Failure_{i,t} = {} & \alpha_0 + \beta_1 OptimismTone_{i,t} + \Gamma_1\, Firm\ Controls \\
& + \Gamma_2\, IPO\ Controls + \Gamma_3\, CEO\ Controls \\
Optimism\ \ & + \Gamma_4\, Industry\ Fixed + \Gamma_5\, Year\ Fixed + Error
\end{aligned} \tag{2.6}
$$

where β_i is the coefficient of independent variables X_i. The key to empirical research is building a correct model. Previous research of IPO survival uses different models to estimate the IPO survival, there are two major models have been widely used: logit model and Cox hazard model. Unlike survival analysis, logit and discriminant models are only capable of predicting whether an event will occur, and not when the event occurs. These methodologies are unable to distinguish between firms that fail within six months from those that fail after five years. However, survival analysis allows us to assess the conditional probability of failure given that the firm has survived up to the present time, hence our research also consider Cox hazard model as our second main model.

2.4.4 Accelerate failure time (AFT) model

The AFT model is defined as:

$$
\begin{aligned}
\ln(T) = {} & \alpha_0 + \beta_1 OptimismTone_{i,t} + \Gamma_1\, Firm\ Controls \\
& + \Gamma_2\, IPO\ Characteristics + \Gamma_3\, CEO\ Controls \\
& + \Gamma_4\, Industry\ Fixed + \Gamma_5\, Year\ Fixed + Error
\end{aligned} \tag{2.7}
$$

where T present the life time of survived firms. The economical meaning of β is one unit of increment of x_i will increase β % of the lifetime of the IPOs. This study employs rigorous methods to identify the most appropriate survival model by evaluating various models with differing assumptions about time distribution, including exponential, Weibull, Gompertz, log-logistic, log-normal, and gamma. The Akaike Information Criterion (AIC) guides the selection of the optimal model.[12]

2.4.5 Cox proportional hazards model

The Cox proportional hazards model is defined as:

$$\begin{aligned}\log\left(\frac{h(t;x)}{h_0(t)}\right) = {} & \alpha_0 + \beta_1 \mathit{OptimismTone}_{i,t} + \Gamma_1\, \mathit{Firm\ Controls} \\ & + \Gamma_2\, \mathit{IPO\ Controls} + \Gamma_3\, \mathit{CEO\ Controls} \\ & + \Gamma_4\, \mathit{Industry\ Fixed} + \Gamma_5\, \mathit{Year\ Fixed} + \mathit{Error}\end{aligned} \tag{2.8}$$

12. The analysis begins with an exponential regression, which yields a hazard ratio below 1. This result suggests that managerial confidence reduces the failure rate relative to non-confident management teams. Next, a Weibull regression is estimated, rejecting the exponential distribution and establishing the Weibull model as a better fit. The hazard ratio remains consistent with the exponential model. A subsequent Gompertz regression reinforces the rejection of the exponential model, with hazard ratios aligning with those from the previous models. Comparing the AIC values of the Weibull (1911) and Gompertz (1994) models confirms the superiority of the Weibull regression. Following this, the log-normal and log-logistic (accelerated failure time) models are estimated. The log-normal model achieves a higher log-likelihood than the log-logistic model, supporting its selection. Finally, a conditional hazard function is evaluated to account for frailty (unobserved heterogeneity) within the sample. While the test reveals evidence of unobserved heterogeneity, it does not materially affect the results.

where $h_0(t)$ is the baseline hazard and t are the time, $h_0(t)$ only depends on time (t) rather than x_i. The baseline hazard is the same for any individuals in the sample. The individual hazard functions depending on $e^{(b_1x_1+b_2x_2+...+b_nx_n)}$ are always positive and proportional regarding baseline hazard. e^bi is the hazard ratio (HR), the economical meaning of HR is one unit of increment of x_i will lead the new hazard rate become e^bi times compared the old hazard rate. The results of logit model and AFT mode can be found in appendix.

2.4.6 Control variables

To control for various firm-level and IPO-level characteristics that significantly influence IPO survival, as suggested by prior research, I incorporate the following control variables.

Firstly, I include control variables capturing pre-IPO firm characteristics, as identified in previous studies (Anagnostopoulou et al. 2021; Boulton and Campbell 2016; Gounopoulos and Pham 2018; Colak et al. 2021). Specifically, I include firm age and sales to account for the positive effects of firm age and firm size on IPO survival, as documented by Hensler et al. (1997). Next, I control for leverage, market-to-book ratio, profitability, and asset tangibility in the IPO year (Alhadab et al. 2015; Anagnostopoulou et al. 2021; Colak et al. 2021; Gounopoulos and Pham 2018). Then, Jain and Kini (2008) emphasize that managers' strategic investment choices at the time of the IPO can influence the post-issue performance of IPO firms. IPO survival is positively associated with R&D intensity; therefore, I account for strategic investment decisions by including R&D intensity, advertising intensity, and capital expenditure intensity. For firms with missing R&D data, I replace these missing values with 0, following Alti (2006). Next, Anagnostopoulou et al. (2021) identify a negative relationship between earnings management and IPO survival. I control for earnings management using the method proposed by McVay (2006).

Secondly, I control for IPO characteristics, including the quality of other financial participants in the IPO process and IPO outcomes (Anagnostopoulou et al. 2021; Boulton and Campbell 2016; Colak et al. 2021). I introduce *log (proceeds)*, share overhang, and initial return as proxies for proceeds, insider ownership (Demers and Joos 2007; Gounopoulos and Pham 2018; Anagnostopoulou et al. 2021), and underpricing, as documented by Hensler et al. (1997). Moreover, Schultz (1993) finds a positive relationship between reputable underwriters and IPO survival. Similarly, Jain and Kini (2000) indicate that venture capitalist involvement in the IPO process enhances the survival profiles of IPO firms, while Jain and Martin Jr (2005) document that IPO firms audited by high-quality accounting firms exhibit longer survival periods in subsequent years. To capture the impact of these financial intermediaries on IPO survival, I include indicator variables for top-tier underwriter, venture capitalist, and Big4 auditor. I obtain the quality of underwriter and VC data from Jay Ritter's database [13]. The variable *underwriter* equals 1 if the underwriter is ranked at the top with the highest score in a given IPO year, and 0 otherwise. The variable *VC* equals 1 if the firm is backed by a venture capitalist, and 0 otherwise. Similarly, *Big4* equals 1 if the firm is audited by one of the Big 4 auditing firms, and 0 otherwise. Many studies use the initial return to control for the positive impact of underpricing; however, the initial return is itself an outcome of the IPO process and may depend on several other control variables, such as firm age and size. To ensure robustness, I run separate regressions with and without the initial return.

Finally, I also control for CEO characteristics, including chairman duality and tenure, as these have a positive impact on IPO survival, as suggested by Colak et al. (2021) and Gounopoulos and Pham (2018). Specifically, I control for CEO duality, CEO tenure, and additional variables that may influence the CEO's risk attitude, such as CEO age, gender, and educational background (MBA and PhD).

13. See: https://site.warrington.ufl.edu/ritter/ipo-data/

2.5 Empirical results

Before empirically testing our hypotheses, I provide summary statistics for the sample. Table 2.1 categorizes IPO firms issued between 1997 and 2019 into survived and failed groups, and it highlights the distribution of these groups across years (Panel A) and industries (Panel B). *Survived firms* are defined as those still actively trading (delisting codes 100–199). *Voluntary delist firms* include those delisted for positive reasons, such as mergers (codes 200–299) or exchanges (codes 300–399), while *Involuntary delist firms* refer to those delisted for adverse reasons, including liquidations (codes 400–499) or being dropped (codes 500–599). The delisting status is tracked for five years following the IPO.

Panel A of Table 2.1 reveals that 62.24% of the IPOs survived five years after issuance, while 13.54% experienced involuntary delisting and 24.22% were voluntarily delisted. These findings are consistent with prior studies like Colak et al. (2021), Gounopoulos and Pham (2018), Amini et al. (2023), and Anagnostopoulou et al. (2021). The dot-com bubble years (1997–2000) exhibit a high number of IPOs, with varying survival rates: 46.92% in 1997, 51.12% in 1998, 47.37% in 1999, and 57.14% in 2000. After the bubble burst, IPO activity declined, but survival rates improved significantly, particularly in 2001 (67.21%) and 2002 (60.00%).

Panel B summarizes the distribution of IPOs by two-digit SIC codes. The highest number of IPOs is observed in the *Computer Equipment and Services* sector (SIC 35, 73), accounting for 944 IPOs. However, this sector also has the largest percentage of voluntary delistings (30.93%), reflecting the volatility of technology firms during the sample period.

Failed IPO firms are concentrated in *Chemical Products* (SIC 28), *Electronic Equipment* (SIC 36), and *Transportation & Public Utilities* (SIC 41, 42, 44–49), where failure rates range from 14.72% to 20.00%. Notably, the proportion of surviving firms is highest in the *Oil and Gas* (SIC 13), *Chemical Products* (SIC 28), and *Scientific Instruments* (SIC 38) industries, where survival rates exceed 68%. Overall, while survival rates remain strong across most industries, the results highlight significant heterogeneity in IPO outcomes, particularly during the dot-com bubble and in technology-intensive sectors. Hence, in the following regressions, I control for year and industry fixed effects.

Table 2.1: IPO distribution by issue year and two-digit SIC codes.
This table presents the distribution of IPO firms issued between 1997 and 2019, categorized into voluntary delistings (1), involuntary delistings (2), and survived (3). Detailed definition for Voluntary, Involuntary, and Survived are available in Appendix 2. Table 2.1 categorizes IPO firms issued between 1997 and 2019 into survived, voluntary delist, and involuntary delist IPOs, and it highlights the distribution of these groups across years (Panel A) and industries (Panel B)

	1: Voluntary		2: Involuntary		3: Survived		Total	
	No.	%	No.	%	No.	%	No.	%
Panel A: Distribution by issue year								
1997	108	28.95	90	24.13	175	46.92	373	100.00
1998	51	22.87	58	26.01	114	51.12	223	100.00
1999	120	30.08	90	22.56	189	47.37	399	100.00
2000	83	25.23	58	17.63	188	57.14	329	100.00
2001	14	22.95	6	9.84	41	67.21	61	100.00
2002	16	32.00	4	8.00	30	60.00	50	100.00
2003	14	31.82	5	11.36	25	56.82	44	100.00
2004	42	29.58	7	4.93	93	65.49	142	100.00
2005	22	17.89	11	8.94	90	73.17	123	100.00
2006	25	19.84	9	7.14	92	73.02	126	100.00
2007	32	24.43	11	8.40	88	67.18	131	100.00
2008	2	13.33	2	13.33	11	73.33	15	100.00
2009	9	25.00	3	8.33	24	66.67	36	100.00
2010	11	15.07	6	8.22	56	76.71	73	100.00
2011	12	16.67	8	11.11	52	72.22	72	100.00
2012	26	30.59	5	5.88	54	63.53	85	100.00
2013	35	27.56	7	5.51	85	66.93	127	100.00
2014	38	20.88	11	6.04	133	73.08	182	100.00
2015	25	21.93	4	3.51	85	74.56	114	100.00
2016	14	20.90	1	1.49	52	77.61	67	100.00
2017	14	15.38	5	5.49	72	79.12	91	100.00
2018	13	13.27	6	6.12	79	80.61	98	100.00
2019	13	14.44	6	6.67	71	78.89	90	100.00
Total	739	24.22	413	13.54	1,899	62.24	3,051	100.00
Panel B: Distribution by Industry								
Chemical products (28)	88	16.64	42	7.94	399	75.43	529	100.00
Computer equipment & services (35,73)	292	30.93	139	14.72	513	54.34	944	100.00
Electronic equipment (36)	56	24.14	23	9.91	153	65.95	232	100.00
Entertainment services (70,78,79)	10	19.61	11	21.57	30	58.82	51	100.00
Food products (20)	13	37.14	4	11.43	18	51.43	35	100.00
Health services (80)	16	30.77	5	9.62	31	59.62	52	100.00
Manufacturing (30–34)	12	19.67	10	16.39	39	63.93	61	100.00
Oil and gas (13)	14	18.18	9	11.69	54	70.13	77	100.00
Scientific instruments (38)	45	23.81	14	7.41	130	68.78	189	100.00
Transportation & public utilities (41,42,44–49)	48	21.33	45	20.00	132	58.67	225	100.00
Wholesale & retail trade (50–59)	50	18.18	50	18.18	175	63.64	275	100.00
All others	95	24.93	61	16.01	225	59.06	381	100.00
Total	739	24.22	413	13.54	1,899	62.24	3,051	100.00

Table 2.2 provides a detailed summary of the main variables, including tone measures, firm-level characteristics, CEO characteristics, and univariate test between failed and survival IPOs. Panel A of Table 2.2 reports the summary statistics for net positive tone in IPO prospectuses and MD&A sections of IPO prospectuses. Overall, optimism measures derived from FinBERT and the LM dictionary suggest that surviving IPOs consistently display stronger positive tone compared to failed IPOs. Specifically, the optimism measure based on the full S-1 forms (Optimism LM) is significantly higher for surviving IPOs (0.285) relative to failed IPOs (0.257), with a difference of 0.027 significant at the 1% level. Similarly, the FinBERT-based measures show that optimism is higher among surviving firms: Optimism FinBERT Net equals 0.411 for survivors versus 0.405 for failed firms, and Optimism FinBERT Total equals 0.454 for survivors versus 0.447 for failed firms. Although these differences are modest in magnitude, they consistently point to a more optimistic disclosure tone in the prospectuses of firms that remain listed after their IPO. Moreover, the MD&A sections have similar patterns like the full S-1 fillings. However, the difference in net optimism tone computed by FinBERT between failed and survival IPOs is insignificant. I further find that the difference is majorly driven by dot-com bubble period during 1997-2000.

Panel B summarizes firm-level characteristics. Surviving IPOs are associated with stronger financial fundamentals compared to failed IPOs. Surviving firms are older (17.58 vs. 9.85 years), raise more capital (148.66M USD vs. 77.69M USD), and have higher offer prices (14.42 USD vs. 11.53 USD), all statistically significant at the 1% level. Sales volume is also higher for surviving firms (569.31M USD vs. 190.42M USD), with a significant difference of 378.89M USD at the 10% level. Additionally, they show lower leverage ratios (0.263) compared to failed firms (0.641), although the test statistic is missing. Firms with VC backing, reputable underwriters, and Big 4 auditors tend to survive more, with VC backing and underwriter reputation showing significance at the 1% and 5% levels, respectively. Initial returns are marginally higher for surviving IPOs (0.287 vs. 0.255). The mean classification shifting value is 0.08, with failed IPOs showing higher tendencies (0.126

vs. 0.077), a significant difference at the 10% level. Abnormal CFO is significantly lower for surviving firms, and abnormal discretionary expenses are more negative for surviving IPOs, suggesting more conservative spending behavior, consistent with Anagnostopoulou et al. (2021).

Panel C reports CEO-level characteristics. The mean CEO age is 49.97 years, and the mean tenure is 3.16 years. CEOs with MBA degrees are more common among failed IPOs (27.8%) than surviving ones (15.5%), a significant difference of -0.123 at the 1% level. Generalist CEOs are also more prevalent among failed IPOs (92.7%) compared to surviving IPOs (68.8%), with a significant difference of -0.239, which aligns with Gounopoulos and Pham (2018).

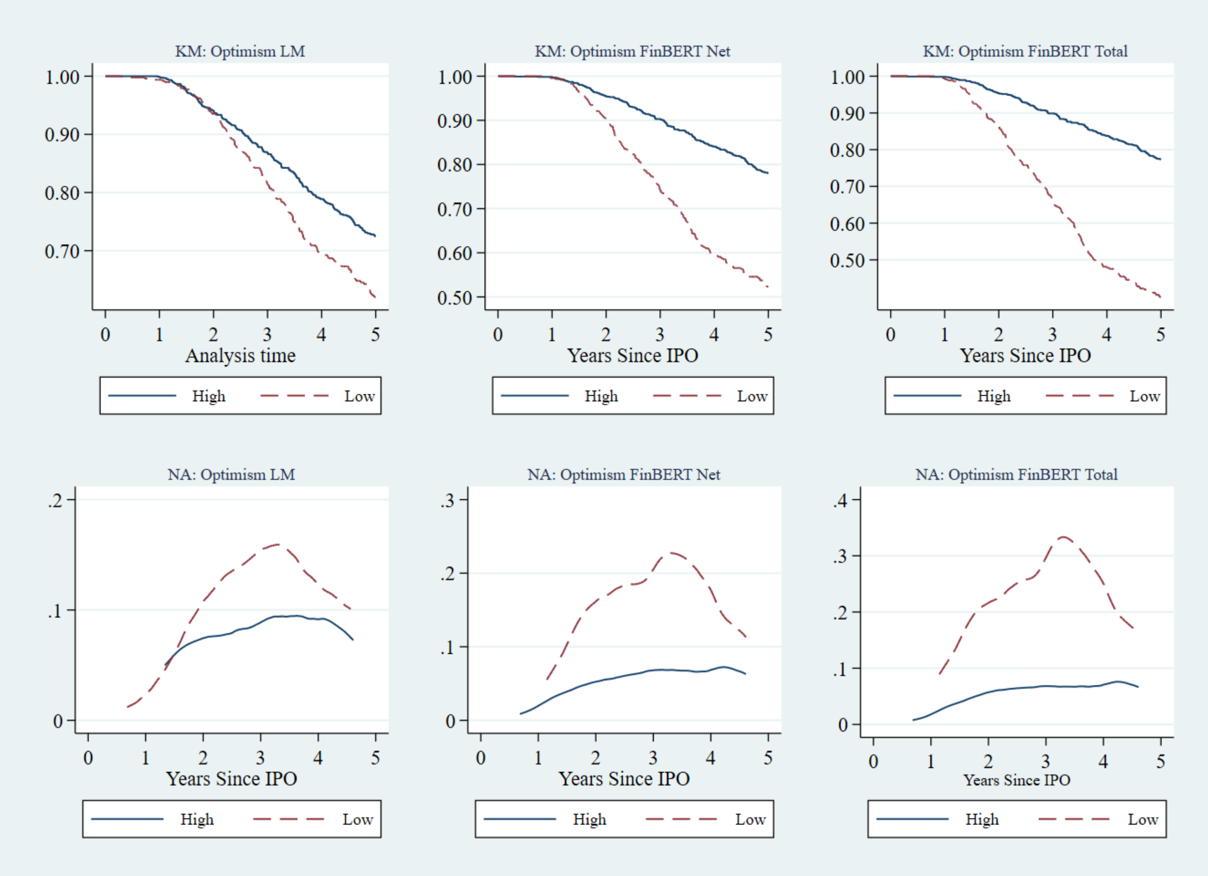
Table 2.2: Firm-Level descriptive statistics (1997-2019).
This table reports descriptive statistics for the full sample of IPOs from 1997 to 2019. *N* denotes the number of observations. Columns “Survived” and “Failed” present the mean values for survived and failed IPOs, respectively. Column “Difference” presents the difference between failed (involuntary de-listed IPO) and survived IPOs. Panel A reports net positive IPO prospectus tone variables, Panel B summarizes firm characteristics, and Panel C covers CEO characteristics. Detailed definition for all variables are available in Appendix 2.

	N	Mean	p25	p50	p75	sd	Survived	Failed	Difference
Panel A: Net Positive IPO Prospectus Tone									
Optimism FinBERT Net	3051	0.41	0.31	0.40	0.50	0.15	0.411	0.405	0.007
Optimism FinBERT Total	3051	0.45	0.40	0.45	0.50	0.11	0.454	0.447	0.007
Optimism LM	3051	0.28	0.19	0.25	0.34	0.13	0.285	0.257	0.027***
Optimism FinBERT Net MDA	3051	0.34	0.21	0.30	0.44	0.18	0.339	0.332	0.007
Optimism FinBERT Total MDA	3051	0.35	0.29	0.35	0.42	0.08	0.353	0.349	0.004
Optimism LM MDA	3051	0.36	0.29	0.35	0.42	0.12	0.362	0.345	0.016*
Panel B: Firm Characteristics									
VC backed	3051	0.54	0.00	1.00	1.00	0.50	0.550	0.443	0.107***
Underwriter reputation	3051	0.54	0.00	1.00	1.00	0.50	0.551	0.479	0.071**
Big 4	3051	0.74	0.00	1.00	1.00	0.44	0.739	0.731	0.008
Initial returns	3051	0.28	0.00	0.11	0.34	0.56	0.287	0.255	0.032
Proceeds (Millions)	3051	139.05	41.70	75.00	135.00	209.33	148.658	77.686	70.972***
Offer price ($)	3051	14.03	10.00	14.00	17.00	5.62	14.422	11.528	2.894***
Firm age (Years)	3047	16.54	5.00	9.00	17.00	22.62	17.579	9.849	7.730***
Sale (Millions)	3018	518.84	15.64	65.06	241.65	3071.02	569.305	190.419	378.886*
MTB	2956	7.07	2.14	3.67	6.70	47.32	7.323	5.436	1.887
Capital Expense	2963	2.56	1.05	2.27	3.99	2.29	2.657	1.941	0.715***
Profitability	2971	-0.07	-0.21	0.02	0.13	0.34	-0.043	-0.229	0.186***
Leverage	2967	0.31	0.00	0.04	0.42	7.70	0.263	0.641	-0.378
R&D intensity	3051	0.09	0.00	0.04	0.14	0.16	0.095	0.091	0.004
R&D expense (Millions)	2116	4.44	0.48	1.61	3.50	26.85	4.759	1.928	2.831
Advertising	3051	0.02	0.00	0.00	0.01	0.10	0.017	0.038	-0.021***
Classification Shifting	3051	0.08	0.00	0.00	0.00	0.47	0.077	0.126	-0.049*
Abnormal CFO	2589	0.03	-0.08	0.01	0.12	0.20	0.022	0.128	-0.107***
Abnormal discretionary expenses	2564	-0.08	-0.25	-0.01	0.14	0.36	-0.089	-0.021	-0.067**
Abnormal accruals	3051	0.01	-0.01	0.00	0.00	0.14	0.011	0.008	0.003
Panel C: CEO Characteristics									
CEO age (Years)	3051	49.97	46.00	49.97	54.00	7.33	50.135	48.943	1.191**
Tenure (Years)	3051	3.16	1.00	2.87	3.32	3.37	3.190	2.990	0.200
CEO duality	3051	0.35	0.00	0.00	1.00	0.48	0.365	0.269	0.097***
Gender	3051	0.97	1.00	1.00	1.00	0.18	0.964	0.971	-0.007
MBA	3051	0.17	0.00	0.00	0.00	0.38	0.155	0.278	-0.123***
PhD	3051	0.09	0.00	0.00	0.00	0.29	0.091	0.080	0.011
Generalist CEO	3051	0.72	0.00	1.00	1.00	0.45	0.688	0.927	-0.239***

2.5.1 Descriptive survival analysis

I begin by examining the differences in hazard rates and survival rates between two groups of IPO firms: those led by managers with confidence levels above the median and those led by managers with confidence levels below the median. This comparison is illustrated using four survival analysis graphs. Figure 2.1 and 2.2 present the Kaplan-Meier (KM) survival estimators and Nelson-Aalen (NA) hazard estimators, as defined by Equation 2.5 and Equation 2.4. Figure 2.1 reports the results from full S-1 fillings while Figure 2.1 reports the results from MD&A sections. The KM and NA estimators provide a descriptive summary of survival analysis, capturing the hazard dynamics at different time points, with the hazard rate depending only on time.

Figure 2.1: Descriptive survival graphs
KM means Kaplan-Meier hazard estimator and NA means Nelson-Aalen survivor estimator. The blue line (solid) represents the group with above-median net positive tone, while the red line (dashed) represents the group with below-median net positive tone. Detailed definition for all variables are available in Appendix 2. Year and industry fixed effects are applied.

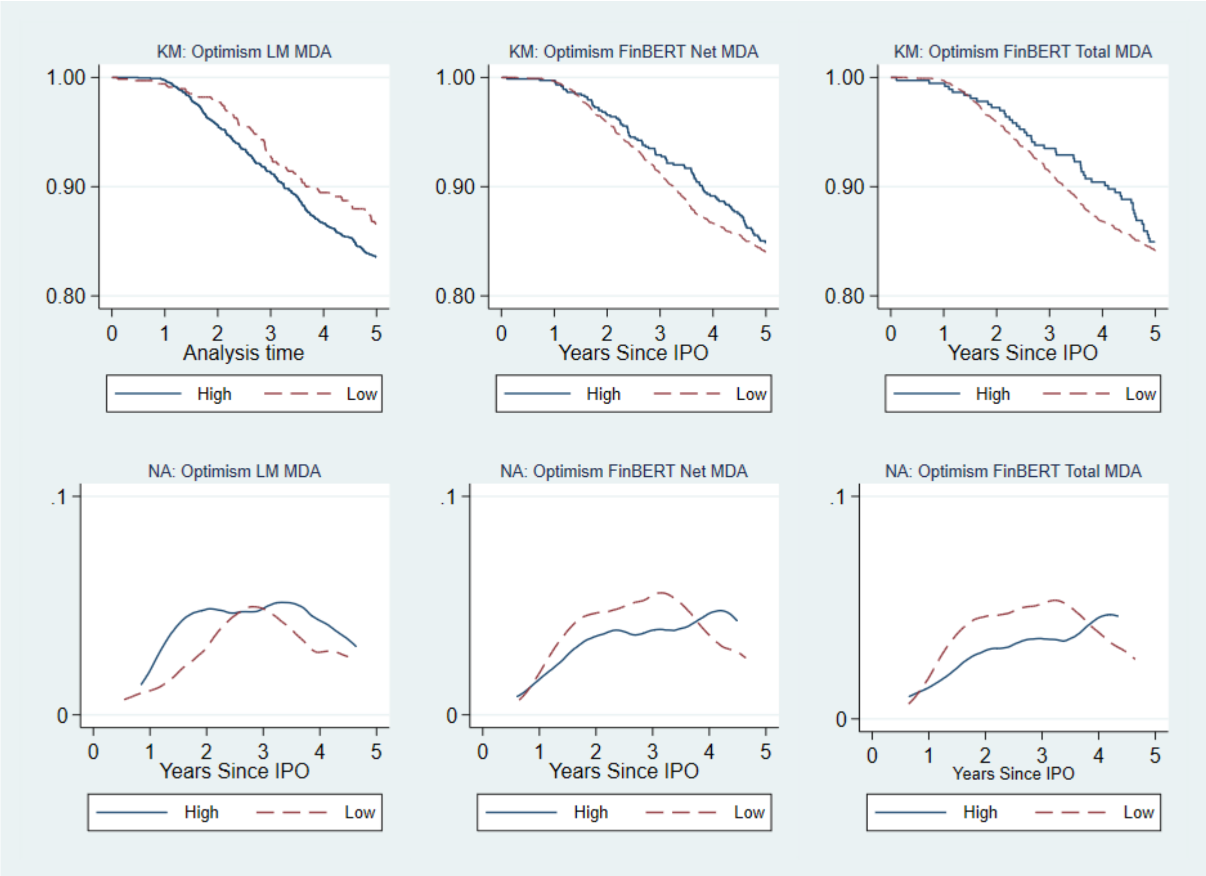


For the KM survivor estimators in Figure 2.1, the blue line represents IPO firms with above-median optimism, while the red dashed line corresponds to firms with below-median optimism. In all three panels, the survival probability is consistently higher for the high-optimism group. By the end of the five-year period, firms with more optimistic language in their prospectuses face a substantially lower probability of failure relative to firms with lower optimism. The differences are especially pronounced when optimism is measured using the FinBERT-based indices.

The NA hazard cumulative hazard estimators in the lower panels of Figure 2.1, calculated based on Equation 2.4, provide complementary evidence. Here, the red dashed line (low optimism) lies consistently above the blue line (high optimism), indicating that firms with less optimistic disclosures accumulate failure risk at a much faster rate. In contrast, firms with more optimistic tone exhibit flatter cumulative hazard functions, suggesting a persistently lower hazard over time. This pattern holds across both FinBERT- and LM-based measures.

Taken together, the KM and NA estimators demonstrate that IPOs with more optimistic disclosure tone experience higher survival rates and lower failure risk over the five years following listing. These results are consistent with the view that optimism in prospectuses serves as a credible signal of firm quality (Hanley and Hoberg 2010). Based on the KM and NA estimators, I observe that the 5-year failure rate ranges between 10% and 15%, which aligns with findings from previous studies (ibid.), aligning with prior evidence in the IPO literature (Gounopoulos and Pham 2018; Anagnostopoulou et al. 2021; Colak et al. 2021). Additional regression and mechanism analyses presented below provide further evidence on this relationship.

Figure 2.2: Descriptive survival graphs
KM means Kaplan-Meier hazard estimator and NA means Nelson-Aalen survivor estimator. The blue line (solid) represents the group with above-median net positive tone, while the red line (dashed) represents the group with below-median net positive tone. Detailed definition for all variables are available in Appendix 2. Year and industry fixed effects are applied.



For the KM survival estimators and NA cumulative hazard estimators in Figure 2.2, the results show smaller differences and lower statistical significance compared to those in Figure 2.1. The dashed line lying above the solid line in the LM subsample suggests a reverse effect, which is inconsistent with the results from FnBERT. These findings indicate that managerial optimism is not a primary driver or reliable predictor of IPO survival.

2.5.2 Main regression results of Cox proportional hazards model

Table 2.4 presents the results of the Cox proportional hazards model, evaluating the impact of net positive sentiments in IPO prospectus on IPO survival.

Table 2.4 presents the Cox proportional hazards model estimates using optimism measures derived from the full S-1 filings. Across all specifications, the coefficients for optimism are negative and highly significant, with hazard ratios well below one. In specification (1), Optimism LM is significant at the 1% level with a hazard ratio of 0.242, suggesting that IPO firms with more optimistic language in their filings face only 24.2% of the failure risk compared to firms with less optimistic tone. Similarly, in specification (5), Optimism FinBERT Net is significant at the 1% level with a hazard ratio of 0.066, indicating a pronounced reduction in failure risk. Optimism FinBERT Total in specification (9) is also negative and significant at the 1% level, with a hazard ratio of 0.021. These results remain robust when firm- and CEO-level controls are included (see specifications (2), (6), and (10)), although the magnitude of the coefficients is attenuated, as expected. These findings are consistent with Hanley and Hoberg (2010), who argue that investors perceive optimistic language from managers and underwriters—both legally liable for misstatements—as a credible signal of firm quality and future performance.

Table 2.3: Estimation of cox proportional hazards model: full S-1 reports

This table reports the estimation results of the Cox proportional hazards model for the probability of failure and time-to-failure. Optimism LM is computed by Loughran and McDonald (2016)'s financial dictionary. Optimism FinBERT Net is computed by FinBERT through Equation 2.1. Optimism FinBERT is computed by FinBERT through Equation 2.2. All regressions include industry and year fixed effects, with their coefficients omitted for brevity. Variable definitions are provided in Appendix A. Statistical significance is denoted by one, two, and three asterisks, representing the 10%, 5%, and 1% levels, respectively. Robust z-statistics, adjusted for heteroscedasticity and clustered at the industry level, are presented in parentheses below the coefficient estimates. The hazard ratio (HR) is reported for each regression. Detailed definition for all variables are available in Appendix 2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**
Optimism LM	-1.420***	0.242	-0.964***	0.381								
	(-3.34)		(-2.92)									
Optimism FinBERT Net					-2.721***	0.066	-0.743***	0.476				
					(-9.74)		(-3.89)					
Optimism FinBERT Total									-3.882***	0.021	-1.057***	0.347
									(-7.32)		(-4.18)	
Size			-0.009	0.991			-0.000	1.000			-0.002	0.998
			(-0.09)				(-0.00)				(-0.02)	
ROA			-1.336***	0.263			-1.302***	0.272			-1.286***	0.276
			(-5.84)				(-5.86)				(-5.81)	
MTB			-0.020***	0.980			-0.020***	0.980			-0.021***	0.980
			(-2.87)				(-2.89)				(-2.79)	
Leverage			0.014**	1.014			0.014**	1.014			0.014**	1.014
			(2.20)				(2.19)				(2.25)	
Tangibility			0.158	1.171			0.114	1.121			0.125	1.133

Continued on the next page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**
			(0.28)				(0.20)				(0.22)	
Advertis			-0.237	0.789			-0.204	0.815			-0.197	0.821
			(-1.02)				(-0.88)				(-0.89)	
R&D intensity			-0.556	0.574			-0.543	0.581			-0.534	0.586
			(-1.41)				(-1.37)				(-1.37)	
Big4			-0.312**	0.732			-0.317**	0.729			-0.316**	0.729
			(-2.05)				(-2.05)				(-2.04)	
Offer price			-0.893***	0.409			-0.865***	0.421			-0.882***	0.414
			(-3.98)				(-3.73)				(-3.87)	
Proceeds			-0.002	0.998			-0.002	0.998			-0.002	0.998
			(-0.45)				(-0.59)				(-0.55)	
VC			-0.301***	0.740			-0.302***	0.740			-0.294***	0.745
			(-2.84)				(-2.66)				(-2.71)	
Underwriter			-0.048	0.953			-0.059	0.943			-0.059	0.942
			(-0.54)				(-0.66)				(-0.66)	
High-tech			0.035	1.035			0.032	1.033			0.028	1.028
			(0.21)				(0.19)				(0.16)	
Crisis			-0.606***	0.545			-0.621***	0.538			-0.619***	0.538
			(-4.53)				(-4.42)				(-4.22)	
CEO tenure			-0.048	0.954			-0.046	0.955			-0.046	0.955
			(-1.38)				(-1.36)				(-1.37)	
CEO duality			-0.270***	0.763			-0.278***	0.757			-0.277**	0.758
			(-2.66)				(-2.62)				(-2.54)	

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**
Generalist CEO			1.126***	3.082			1.122***	3.070			1.118***	3.060
			(5.53)				(5.67)				(5.63)	
CEO age			-0.006	0.994			-0.006	0.994			-0.005	0.995
			(-0.65)				(-0.67)				(-0.61)	
CEO gender			-0.253	0.776			-0.280	0.756			-0.289	0.749
			(-0.84)				(-0.89)				(-0.91)	
MBA			0.582***	1.789			0.569***	1.767			0.570***	1.768
			(4.52)				(4.25)				(4.25)	
PhD			0.252**	1.287			0.227*	1.255			0.219*	1.245
			(2.44)				(1.93)				(1.83)	
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,051	3,051	2,969	2,969	3,051	3,051	2,969	2,969	3,051	3,051	2,969	2,969
χ^2	944.1	944.1	411.9	411.9	474.0	474.0	820.1	820.1	407.2	407.2	491.7	491.7

The control variables behave in line with prior IPO survival literature. For example, higher profitability (ROA) and larger audit quality (Big4) reduce failure risk, consistent with Jain and Martin Jr (2005) and Espenlaub et al. (2012). In contrast, higher leverage is associated with increased hazard, consistent with the financial fragility channel highlighted by Demers and Joos (2007). CEO characteristics further underscore heterogeneity in managerial influence: generalist CEOs significantly increase failure risk (HR above 3.0), echoing the findings of Gounopoulos and Pham (2018), whereas managers with MBAs or PhDs are associated with longer survival times, suggesting that education enhances managerial decision-making quality.

Overall, the evidence from Table 2.4 highlights the importance of disclosure tone as a determinant of IPO survival. Optimism, whether measured by LM dictionaries or FinBERT, emerges as a strong and consistent predictor of reduced failure risk. This supports **Hypothesis 1**, which posits that net positive sentiment is positively correlated with IPO survival. Furthermore, the results align with the theoretical predictions of Gervais et al. (2011) and Goel and Thakor (2008), who suggest that optimistic managers are more likely to undertake value-enhancing projects and credibly communicate favorable private information. Taken together, the results suggest that language in IPO prospectuses serves not merely as boilerplate disclosure, but as a meaningful signal consistent with the information-asymmetry perspective advanced in prior studies.

Table 2.4: Estimation of cox proportional hazards model: MD&A section
This table reports the estimation results of the Cox proportional hazards model for the probability of failure and time-to-failure. Optimism LM MDA is computed by Loughran and McDonald (2016)'s financial dictionary. Optimism FinBERT Net MDA is computed by FinBERT through Equation 2.1. Optimism FinBERT MDA is computed by FinBERT through Equation 2.2. All regressions include industry and year fixed effects, with their coefficients omitted for brevity. Variable definitions are provided in Appendix A. Statistical significance is denoted by one, two, and three asterisks, representing the 10%, 5%, and 1% levels, respectively. Robust z-statistics, adjusted for heteroscedasticity and clustered at the industry level, are presented in parentheses below the coefficient estimates. The hazard ratio (HR) is reported for each regression. Detailed definition for all variables are available in Appendix 2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**
Optimism LM MDA	-0.748*	0.473	-0.758	0.469								
	(-1.81)		(-1.60)									
Optimism FinBERT Net MDA					-1.306***	0.271	-0.021	0.979				
					(-3.67)		(-0.08)					
Optimism FinBERT Total MDA									-2.593***	0.075	-0.199	0.819
									(-3.60)		(-0.29)	
Size			-0.013	0.987			-0.000	1.000			0.002	1.002
			(-0.10)				(-0.00)				(0.02)	
Profitability			-1.161***	0.313			-1.251***	0.286			-1.249***	0.287
			(-4.30)				(-5.46)				(-5.49)	
MTB			-0.001	0.999			-0.001	0.999			-0.001	0.999
			(-0.36)				(-0.26)				(-0.26)	
Leverage			0.007*	1.007			0.007*	1.007			0.007*	1.007
			(1.81)				(1.77)				(1.81)	
Tangibility			0.060	1.061			0.025	1.025			0.027	1.027

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**
			(0.11)				(0.05)				(0.05)	
Advertising			0.196	1.216			-0.020	0.980			-0.023	0.977
			(0.43)				(-0.05)				(-0.06)	
R&D intensity			-0.954*	0.385			-0.977**	0.376			-0.976**	0.377
			(-1.94)				(-2.14)				(-2.12)	
Big 4			-0.321*	0.725			-0.333**	0.717			-0.334**	0.716
			(-1.79)				(-2.01)				(-2.03)	
Offer price			-0.903***	0.405			-0.908***	0.403			-0.907***	0.404
			(-3.66)				(-4.48)				(-4.48)	
Proceeds			-0.000	1.000			-0.001	0.999			-0.001	0.999
			(-0.62)				(-0.91)				(-0.94)	
Initial returns			-0.212***	0.809			-0.173**	0.841			-0.175**	0.839
			(-3.48)				(-2.11)				(-2.12)	
VC backed			-0.250***	0.779			-0.316***	0.729			-0.321***	0.725
			(-2.77)				(-3.74)				(-3.95)	
Underwriter reputation			-0.039	0.962			-0.086	0.918			-0.085	0.918
			(-0.41)				(-1.21)				(-1.19)	
High-tech			0.014	1.014			0.061	1.063			0.062	1.064
			(0.08)				(0.31)				(0.32)	
Crisis			-0.729	0.482			-0.637	0.529			-0.641	0.527
			(-0.77)				(-0.71)				(-0.72)	
CEO tenure			-0.054*	0.947			-0.051	0.950			-0.051	0.950
			(-1.71)				(-1.60)				(-1.61)	

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**
CEO duality			-0.298***	0.742			-0.280***	0.756			-0.280***	0.756
			(-5.19)				(-4.24)				(-4.21)	
Generalist CEO			1.198***	3.312			1.294***	3.647			1.292***	3.639
			(6.06)				(5.08)				(5.13)	
CEO age (Years)			-0.005	0.995			-0.009	0.991			-0.009	0.991
			(-0.57)				(-1.00)				(-1.00)	
CEO gender			-0.170	0.844			-0.233	0.792			-0.232	0.793
			(-0.59)				(-0.59)				(-0.58)	
MBA			0.626***	1.869			0.662***	1.939			0.661***	1.937
			(4.99)				(5.27)				(5.28)	
PhD			0.313**	1.368			0.337***	1.400			0.337***	1.401
			(2.44)				(2.99)				(2.96)	
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,051	3,051	2,893	2,893	2,861	2,861	2,708	2,708	2,861	2,861	2,708	2,708
χ^2	95.10	95.10	504.7	504.7	185.4	185.4	125.3	125.3	182.3	182.3	234.0	234.0

Table 2.4 presents the Cox proportional hazards model estimates using optimism measures derived specifically from the MD&A section of IPO prospectuses. In the baseline specifications without control variables, optimism measures are statistically significant and negatively associated with the hazard of failure. For example, in specification (1), Optimism LM MDA is significant at the 10% level with a hazard ratio of 0.473, suggesting that firms expressing greater optimism in their MD&A sections face approximately 47.3% of the failure risk compared to firms with less optimistic tone. Similarly, in specifications (5) and (9), both Optimism FinBERT Net MDA and Optimism FinBERT Total MD&A are highly significant at the 1% level, with hazard ratios of 0.271 and 0.075, respectively. Together, these findings offer preliminary support for **Hypothesis 5**, suggesting that managerial optimism—when interpreted as confidence—may play a role in enhancing post-IPO survival, at least in models without controls.

However, when firm- and CEO-level control variables are included, the significance of all three optimism measures disappears. In specifications (2), (6), and (10), the coefficients become statistically insignificant and the hazard ratios approach one, indicating no meaningful difference in survival outcomes between firms with more or less optimistic MD&A language once observable fundamentals are controlled for. These results suggest that the predictive power of MD&A optimism is largely absorbed by other firm-specific and managerial characteristics. Consequently, the evidence does not support **Hypothesis 4**, which posits a negative relationship between confidence and survival. Nor does it offer strong confirmation of **Hypothesis 5** once controls are in place. It also weakens support for **Hypothesis 5**, implying that MD&A tone alone may not reliably capture the nuanced effects of managerial confidence once broader determinants of firm outcomes are accounted for. Next, I focus more on information asymmetry view.

2.6 Additional tests for robustness and endogenous concerns

2.6.1 Robustness check

Tables 2.5 and 2.6 present robustness checks using additional control variables and alternative survival models, including the logit model and the accelerated failure time (AFT) model. These results confirm the robustness of our findings on the positive effects of optimistic tone on IPO survival. In specifications (1) and (7) of 2.5, I find that the positive effect of optimistic tone remains significant even after controlling for initial returns. The coefficients for Optimism Full and Optimism MDA are -0.982 (HR = 0.374) and -0.724 (HR = 0.485), respectively, both significant at the 1% and 10% levels. Initial returns are separated out as they are highly correlated with offer price and other financial ratios, which could otherwise confound the results. This robustness suggests that optimistic tone independently contributes to IPO survival, beyond its potential overlap with pricing and financial performance metrics. Similarly, in specifications (3) and (9) of 2.5, I further validate the positive effect of optimistic tone by including the ten best predictors identified in Colak et al. (2022)'s machine learning model. The continued significance of optimism—Optimism Full at -0.700 (HR = 0.497) and Optimism MDA at -0.627 (HR = 0.534), both significant at the 1% and 10% levels—underlines its predictive power for IPO survival, even in the presence of advanced statistical controls informed by machine learning techniques.

Moreover, in specifications (5) and (11) of 2.5, I introduce earnings management as a control variable. The results show that the positive effect of optimistic tone persists. Notably, I find that abnormal discretionary expenses contribute the most to IPO risk, although not statistically significant (HR = 1.325 and 1.337), while classification shifting (CS) is highly significant (Coef. = 0.305 and 0.300; HR = 1.356 and 1.350). These results are consistent with prior studies that highlight the detrimental impact of real earnings management on IPO survival rates. This finding aligns with the literature Alhadab et al. (2015) and Anagnostopoulou et al. (2021), which emphasizes the long-term risks associated with aggressive financial reporting practices during the IPO process. Overall, these robustness checks reinforce the importance of optimistic tone as a critical determinant of IPO survival while also shedding light on the influence of initial returns, earnings management, and machine learning-based predictors.

Table 2.5 reports Cox proportional hazards estimates with additional controls. Across specifications, all three optimism measures remain negative and economically meaningful: Optimism LM is significant at the 1% level in column (1) (Coef. $= -0.949$, HR $= 0.387$) and at the 5% level with the fuller controls in column (2) (Coef. $= -0.634$, HR $= 0.531$); Optimism FinBERT Net is significant at the 5% level in columns (5) and (7) (Coef. $= -1.013$, HR $= 0.363$ in both); and Optimism FinBERT Total is highly significant in column (9) (Coef. $= -1.230$, HR $= 0.292$) and remains significant in column (11) (Coef. $= -1.374$, HR $= 0.253$). These results are consistent with Hanley and Hoberg (2010), who argue that investors treat optimistic language from legally liable issuers and underwriters as a credible signal of firm quality; here, higher net positive tone translates into materially lower failure hazards.

The added controls connect directly to prior literature. VC reduces failure risk (e.g., columns (1), (5), and (9): HRs $= 0.773$, 0.772, and 0.778, each significant at the 1% level), in line with the certification role documented by Jain and Kini (2000) and the importance of VC reputation emphasized by Krishnan et al. (2011). MTB is negatively related to failure (HRs ≈ 0.98 across specifications), consistent with survival advantages for firms with stronger growth prospects (Demers and Joos 2007; Espenlaub et al. 2012). DLC_AT raises the hazard substantially (HRs between 2.7 and 7.9), reinforcing the financial fragility channel noted in the survival literature (Demers and Joos 2007). PI_CEQ lowers failure risk (HR ≈ 0.89), while AP_SALE increases it (HR ≈ 1.02). Offer price enters negatively in the initial models but loses significance once the broader set of controls is included.

Table 2.5: Estimation of cox proportional hazards model: additional controls

This table presents the estimation results of the Cox proportional hazards model for the probability of failure and time-to-failure. Optimism LM is computed by Loughran and McDonald (2016)'s financial dictionary. Optimism FinBERT Net is computed by FinBERT through Equation 2.1. Optimism FinBERT is computed by FinBERT through Equation 2.2. All regressions include industry and year-fixed effects, with their coefficients suppressed for clarity. Variable definitions can be found in Appendix A. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust z-statistics, adjusted for heteroscedasticity and clustered at the industry level, are reported in parentheses beneath the coefficient estimates. The hazard ratio (HR) is provided for each regression. Detailed definition for all variables are available in Appendix 2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**
Optimism LM	-0.949***	0.387	-0.634**	0.531								
	(-2.62)		(-2.44)									
Optimism FinBERT Net					-1.013**	0.363	-1.013**	0.363				
					(-2.48)		(-2.48)					
Optimism FinBERT Total									-1.230***	0.292	-1.374**	0.253
									(-6.57)		(-2.35)	
Offer price	-0.816***	0.442	-0.649	0.523	-0.782***	0.458	-0.606	0.546	-0.796***	0.451	-0.623	0.536
	(-2.85)		(-1.61)		(-2.67)		(-1.49)		(-2.74)		(-1.53)	
VC	-0.258***	0.773	-0.273	0.761	-0.259***	0.772	-0.296*	0.744	-0.251***	0.778	-0.284*	0.753
	(-3.04)		(-1.63)		(-2.99)		(-1.70)		(-2.97)		(-1.68)	
MTB	-0.020***	0.981	-0.018***	0.982	-0.020***	0.980	-0.018***	0.982	-0.020***	0.980	-0.018***	0.982
	(-3.35)		(-4.62)		(-3.36)		(-4.61)		(-3.31)		(-4.33)	
ROA_std	0.031	1.031	0.094	1.099	0.038	1.039	0.119	1.126	0.039	1.040	0.120	1.127
	(0.43)		(0.71)		(0.46)		(0.83)		(0.53)		(0.88)	
CF_std	-0.054	0.948	-0.110	0.896	-0.063	0.939	-0.136	0.873	-0.062	0.940	-0.134	0.875
	(-0.86)		(-0.89)		(-0.85)		(-1.02)		(-0.93)		(-1.05)	
rf	-0.111	0.895	-0.095	0.909	-0.094	0.910	-0.065	0.937	-0.103	0.902	-0.075	0.928

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VARIABLES	(1) Coef.	(2) HR	(3) Coef.	(4) HR	(5) Coef.	(6) HR	(7) Coef.	(8) HR	(9) Coef.	(10) HR	(11) Coef.	(12) HR
	(-0.49)		(-0.54)		(-0.41)		(-0.35)		(-0.46)		(-0.42)	
DLC_AT	0.986***	2.681	2.020*	7.535	1.088***	2.969	2.039*	7.685	1.109***	3.031	2.067*	7.903
	(2.96)		(1.66)		(3.22)		(1.69)		(3.29)		(1.70)	
PI_CEQ	-0.119**	0.888	-0.072	0.931	-0.112**	0.894	-0.065	0.937	-0.114**	0.893	-0.068	0.934
	(-2.55)		(-1.25)		(-2.44)		(-1.24)		(-2.44)		(-1.21)	
DPACT_PPENT	0.009	1.009	-0.003	0.997	0.012	1.012	0.002	1.002	0.014	1.014	0.004	1.004
	(0.11)		(-0.04)		(0.16)		(0.03)		(0.18)		(0.05)	
AP_SALE	0.010	1.010	0.020**	1.020	0.008	1.008	0.018**	1.018	0.010	1.010	0.020**	1.020
	(1.31)		(2.24)		(1.14)		(2.13)		(1.42)		(2.36)	
CS			0.302***	1.353			0.294***	1.341			0.290***	1.337
			(4.50)				(4.42)				(4.20)	
A_DISX			0.299	1.349			0.288	1.333			0.274	1.316
			(1.09)				(1.03)				(0.93)	
A_PROD			0.266*	1.305			0.250*	1.284			0.244*	1.276
			(1.96)				(1.90)				(1.83)	
A_TA			-0.328	0.721			-0.351	0.704			-0.354	0.702
			(-0.70)				(-0.78)				(-0.80)	
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,969	2,969	2,557	2,557	2,557	2,557	2,557	2,557	2,969	2,969	2,557	2,557
χ^2	267.6	267.6	88.06	88.06	9844	9844	9844	9844	57.13	57.13	89.99	89.99

I also incorporate earnings management proxies highlighted by the post-IPO performance literature. Classification shifting (CS) is positive and highly significant across columns with accounting-based controls (e.g., column (3): Coef. = 0.302, HR = 1.353), indicating higher cumulative hazard for firms engaging in such reporting tactics. Abnormal discretionary expenses (A_DISX) and abnormal production costs (A_PROD) tend to raise risk (e.g., A_PROD is significant at the 10% level), consistent with the adverse survival implications of real earnings management (Alhadab et al. 2015; Anagnostopoulou et al. 2021). These additions echo the broader predictor sets used in machine-learning approaches such as Colak et al. (2022), yet optimism retains independent predictive power.

Overall, the evidence in Table 2.5 supports **Hypothesis 1**: net positive sentiment in IPO prospectuses is positively associated with survival (i.e., lower failure hazard), whether measured by LM dictionaries or FinBERT. The persistent economic and statistical significance after adding VC certification, financing structure, profitability volatility, and earnings-management controls underscores that disclosure tone conveys information beyond standard survival determinants, consistent with the signaling view in Hanley and Hoberg (2010) and the bright-side predictions of Gervais et al. (2011) and Goel and Thakor (2008).

Table 2.6 reports robustness checks using alternative survival analysis models, namely the Accelerated Failure Time (AFT) model and the logit model, corresponding to equations 2.7 and 2.6. Panel A presents AFT results where the dependent variable is IPO survival time, while Panel B shows logit results where the dependent variable equals one if an involuntary delisting occurs within five years of the IPO and zero otherwise.

Panel A indicates that optimism consistently prolongs IPO survival time across different measures. Optimism LM in Column (1) is positive and significant at the 1% level (Coef. = 0.304), Optimism FinBERT Net in Column (2) is also positive and significant at the 1% level (Coef. = 0.513), and Optimism FinBERT Total in Column (3) is positive and significant at the 1% level (Coef. = 0.699). These results suggest that IPOs with stronger optimistic tone survive significantly longer, reinforcing **Hypothesis 1** that net positive sentiment is positively associated with IPO survival. This is consistent with Hanley and Hoberg (2010), who argue that optimistic disclosures by managers and underwriters—both legally liable for misstatements—serve as credible signals of firm quality.

Panel B further validates these findings using the logit specification. The coefficients of all optimism measures are negative and statistically significant, confirming that optimistic tone reduces the likelihood of failure. Specifically, Optimism LM in Column (1) is significant at the 5% level (Coef. = −0.716), Optimism FinBERT Net in Column (2) is highly significant at the 1% level (Coef. = −1.536), and Optimism FinBERT Total in Column (3) is also significant at the 1% level (Coef. = −1.987). The consistency across AFT and logit models underscores that optimism in prospectus language is not merely rhetorical but conveys meaningful information about survival prospects.

Table 2.6: Robustness check: alternative survival models
This table reports robustness check on different survival analysis models including AFT models and logit models. Optimism LM is computed by Loughran and McDonald (2016)'s financial dictionary. Optimism FinBERT Net is computed by FinBERT through Equation 2.1. Optimism FinBERT is computed by FinBERT through Equation 2.2. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust test statistics, adjusted for heteroscedasticity and clustered at the industry and year level, are reported in parentheses beneath the coefficient estimates. Detailed definition for all variables are available in Appendix 2.

Panel A: AFT results			
	(1)	(2)	(3)
VARIABLES	Time	Time	Time
Optimism LM	0.304***		
	(3.21)		
Optimism FinBERT Net		0.513***	
		(4.63)	
Optimism FinBERT Total			0.699***
			(3.71)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	2,557	2,557	2,557
Panel B: Logit Model results			
	(1)	(2)	(3)
VARIABLES	Failed	Failed	Failed
Optimism LM	-0.716**		
	(-2.25)		
Optimism FinBERT Net		-1.536***	
		(-5.25)	
Optimism FinBERT Total			-1.987***
			(-3.58)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	2,486	2,486	2,486
Pseudo R-squared	0.184	0.187	0.186

Overall, the robustness checks highlight the positive effects of optimistic tone in the IPO context. By reducing delisting risk and extending survival time, optimism appears to act as a credible signal of firm quality, consistent with the theoretical predictions of Hanley and Hoberg (2010), who posit that optimistic sentiments contain information about issuers. At the same time, these findings align with the broader literature on disclosure tone (Tetlock 2007; Davis et al. 2012; Davis and Tama-Sweet 2012), which shows that language captures managerial expectations about future performance.

2.6.2 Lewbel's instrumental variable and entropy balance results

Endogeneity remains a central concern in interpreting the relation between prospectus tone and IPO survival. A key alternative explanation is that optimistic tone is itself endogenous to firms' private information about future prospects. Firms with stronger fundamentals, better governance, superior growth opportunities, or more favorable demand conditions may choose more optimistic language precisely because they anticipate a higher probability of post-IPO survival. In this setting, tone may partly reflect latent firm quality rather than constitute an independent driver of future outcomes. This concern also extends to the moderating roles of underwriters and VC investors: reputable intermediaries may sort into higher-quality IPOs that are both more likely to survive and more likely to employ optimistic disclosure. Accordingly, the empirical association documented in this chapter may capture, at least in part, the information content of tone rather than a purely causal effect of tone itself.

Although tone is measured at the S-1 filing stage, before post-IPO survival outcomes are realized, this timing alone does not fully eliminate reverse-causality and omitted-variable concerns. To address these issues, I employ the internal IV approach of Lewbel (2012) and entropy balancing as complementary strategies. These methods help reduce the possibility that the main findings are driven solely by observable differences or residual heteroskedasticity-related endogeneity; however, they do not provide a fully exogenous source of variation in disclosure tone.

Entropy balancing allows me to reweight failed IPOs (the control group) such that their covariate distribution matches that of surviving IPOs (the treatment group). The algorithm iteratively adjusts weights until the means and variances of the control covariates align with those of the treated group, ensuring covariate balance across key firm-level predictors of IPO survival. This approach directly addresses concerns that the estimated optimism effect may simply capture observable differences between failed and surviving IPOs. Unlike propensity score matching, entropy balancing preserves the full sample, improves efficiency, and reduces dependence on first-stage model specification (Hainmueller 2012).

By applying both the internal IV and entropy-balancing approaches, I reduce-but do not completely eliminate-the possibility that optimistic tone is merely a by-product of expected survival. The most conservative interpretation of the evidence is therefore that prospectus optimism contains incremental information about future IPO survival beyond a broad set of observable firm characteristics and is consistent with a signaling view of disclosure. In other words, optimistic tone should be viewed primarily as an informative ex ante signal, which may partly reflect insiders' private expectations, rather than as a purely exogenous causal driver. The results from both methods, summarized in Table 2.7, support the view that optimism operates as a credible signal of firm quality.

Taken together, the entropy balancing and internal IV results provide complementary evidence that the association between prospectus optimism and IPO survival is not solely driven by observable firm differences. At the same time, these tests do not allow me to claim that tone is fully exogenous. Instead, the evidence supports a more cautious interpretation: optimistic disclosure tone contains incremental predictive content about post-IPO survival and is consistent with the view that prospectus language aggregates insiders' private information about firm quality and future viability. This interpretation accords with the signaling framework of Hanley and Hoberg (2010), under which optimistic tone conveys information about issuers' future prospects.

Accordingly, the most appropriate interpretation of the empirical design is not that it delivers a definitive causal estimate of disclosure tone on IPO survival. Rather, the analysis tests whether optimistic language in the prospectus contains incremental ex ante information about future survival prospects beyond a rich set of firm-, IPO-, and CEO-level observables. This distinction is important because, in disclosure settings, tone may simultaneously reflect both strategic reporting choices and insiders' superior private information.

Table 2.7 reports additional robustness tests addressing potential endogeneity in the relationship between prospectus optimism and IPO survival. Panel A presents Cox proportional hazard estimates using an entropy-balanced sample, while Panel B shows results from internal IV regressions following Lewbel (2012). Together, these methods mitigate concerns of omitted variables and reverse causality, strengthening the incremental predictive content of optimistic tone.

Panel A reports entropy-balanced Cox hazard estimates, where failed IPOs are reweighted to match the observable characteristics of surviving IPOs. Across all specifications, optimism remains negative and statistically significant, consistent with earlier findings. Optimism LM in Column (1) is significant at the 5% level (Coef. $= -0.896$), Optimism FinBERT Net in Column (2) is significant at the 5% level (Coef. $= -0.471$), and Optimism FinBERT Total in Column (3) is significant at the 1% level (Coef. $= -0.610$). These results indicate that, after balancing on firm-level observables, optimistic tone in IPO filings continues to predict a lower hazard of delisting, supporting **Hypothesis 1**.

Panel B displays the internal IV results, which generate instruments from heteroskedasticity in the regression residuals. The coefficients for all three optimism measures remain negative and highly significant. Optimism LM is significant at the 1% level (Coef. $= -0.073$), Optimism FinBERT Net is significant at the 1% level (Coef. $= -0.189$), and Optimism FinBERT Total is significant at the 1% level (Coef. $= -0.213$). These results demonstrate that even after addressing potential endogeneity, optimism continues to exert a strong incremental predictive power on IPO survival.

Taken together, the entropy-balancing and internal-IV results suggest that the documented relation between prospectus optimism and IPO survival is not solely driven by observable firm characteristics. At the same time, these approaches do not fully eliminate the possibility that tone reflects latent firm quality, private information, or endogenous

Table 2.7: Additional tests for endogeneity: entropy balancing and internal IV
The table reports internal IV and Cox hazard results of entropy balanced sample. Optimism LM is computed by Loughran and McDonald (2016)'s financial dictionary. Optimism FinBERT Net is computed by FinBERT through Equation 2.1. Optimism FinBERT is computed by FinBERT through Equation 2.2. Panel A reports the Cox hazard results of entropy balanced sample and panel B report internal IV results. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust test statistics, adjusted for heteroscedasticity and clustered at the industry level, are reported in parentheses beneath the coefficient estimates. Detailed definition for all variables are available in Appendix 2.

Panel A: Cox results (Balanced Sample)			
	(1)	(2)	(3)
VARIABLES	Ceof.	Ceof.	Ceof.
Optimism LM	-0.896**		
	(-2.54)		
Optimism FinBERT Net		-0.471**	
		(-2.53)	
Optimism FinBERT Total			-0.610***
			(-2.76)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	2,969	2,969	2,969
χ^2	49.35	37.62	44.26
Panel B: Internal IV			
	(1)	(2)	(3)
VARIABLES	Failed	Failed	Failed
Optimism LM	-0.073***		
	(-10.56)		
Optimism FinBERT Net		-0.189***	
		(-25.71)	
Optimism FinBERT Total			-0.213***
			(-43.03)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	2,557	2,557	2,557
R^2	0.154	0.157	0.156

disclosure choices. I therefore interpret the evidence conservatively: optimistic tone contains incremental predictive information about post-IPO survival and is consistent with a signaling view of IPO disclosure, but the analysis does not establish a fully exogenous causal effect of tone on survival.

2.7 Mechanism and further discussion

This section examines the conditions under which optimistic tone is more informative about IPO survival. Rather than interpreting the interaction results as definitive causal amplification effects, I view them as heterogeneity evidence on the credibility of disclosure tone. Specifically, the association between optimistic language and post-IPO survival is stronger when the offering is backed by venture capital investors or reputable underwriters, consistent with the idea that third-party certification enhances the information content of prospectus language.

Prior studies emphasize the certification and monitoring role of VC investors in IPOs. Jain and Kini (2000) show that VC involvement enhances IPO survival, while Krishnan et al. (2011) highlight the importance of VC reputation in reducing post-IPO risks. Consistent with these findings, our results suggest that VC backing strengthens the signaling role of optimistic language. Optimistic tone in the presence of VC involvement is more likely to be interpreted as credible, as investors perceive VC certification as validating the information conveyed in the prospectus. Hence, optimism and VC backing jointly amplify the positive impact on IPO survival.

Similarly, the quality of the underwriter moderates the role of optimistic tone. According to the bargaining power framework of Loughran and Ritter (2002), stronger issuers can induce underwriters to exert more effort even without full fee compensation. High-quality underwriters, who face legal and reputational penalties for misstatements, lend credibility to optimistic disclosures, consistent with Hanley and Hoberg (2010)'s argument that positive tone in prospectuses is viewed by investors as a credible signal of risk. Our findings align with this view: optimism has a stronger effect on IPO survival when the offering is backed by reputable underwriters, suggesting that underwriter credibility amplifies the information content of optimistic tone.

Taken together, the channel analysis highlights that both VC involvement and underwriter quality enhance the credibility and signaling power of optimistic tone. These results provide support for **Hypothesis 2** and **Hypothesis 3**, showing that optimism interacts with external certifiers—VC investors and underwriters—to further reduce IPO failure risk and improve post-IPO survival.

2.7.1 Underwriter quality and optimistic tone

Loughran and Ritter (2002) propose a theory of relative bargaining power in IPOs, suggesting that issuers with greater power can persuade underwriters to exert more effort in the pre-market stage, even if underwriting fees do not fully compensate them. High-quality underwriters, therefore, play a crucial role in certifying the information environment surrounding an IPO. Consistent with this perspective, Hanley and Hoberg (2010) find that investors interpret optimistic language in prospectuses issued under the supervision of reputable underwriters as a credible signal of firm quality, because underwriters face both reputational and legal penalties for misstatements. This literature emphasizes that underwriter reputation not only affects pricing outcomes but also shapes how disclosure tone is perceived by investors.

From the signaling perspective, underwriter quality interacts with optimistic tone to influence IPO survival. Optimistic tone in prospectuses is more likely to be discounted as “cheap talk” when underwriter quality is low, but gains credibility when backed by prestigious underwriters. In such cases, investors view optimism not merely as rhetorical embellishment, but as a signal of insiders’ superior information and commitment to the firm’s long-term performance. This mechanism implies that high-quality underwriters magnify the positive impact of optimistic tone on IPO survival by enhancing its credibility and mitigating concerns about information asymmetry.

Taken together, the theoretical and empirical evidence suggests that underwriter quality serves as an important moderator of the optimism–survival relationship. Specifically, I expect that optimistic tone in IPO prospectuses has a stronger effect on survival when accompanied by high-quality underwriters, consistent with the certification and monitoring roles highlighted in the IPO literature.

Table 2.8: Moderating effects of underwriter reputation
All regressions include industry-fixed effects, with their coefficients suppressed. Optimism LM is computed by Loughran and McDonald (2016)’s financial dictionary. Optimism FinBERT Net is computed by FinBERT through Equation 2.1. Optimism FinBERT is computed by FinBERT through Equation 2.2. Variable definitions can be found in Appendix A. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust statistics, adjusted for heteroscedasticity and clustered at the industry level, are reported in parentheses beneath the coefficient estimates. Detailed definition for all variables are available in Appendix 2.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**Coef.**	HR	**Coef.**	**HR**	**Coef.**	**HR**
Optimism LM	-0.117	0.889				
	(-0.17)					
Optimism FinBERT Net			-0.015	0.985		
			(-0.04)			
Optimism FinBERT Total					-0.303	0.739
					(-0.49)	
Underwriter reputation	0.387	1.473	0.839**	2.313	1.048*	2.852
	(1.50)		(2.51)		(1.74)	
Optimism LM*Underwriter reputation	-1.647*	0.193				
	(-1.77)					
Optimism FinBERT Net*Underwriter reputation			-2.125***	0.119		
			(-3.09)			
Optimism FinBERT Total*Underwriter reputation					-2.397*	0.091
					(-1.96)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,893	2,893	2,893	2,893	2,893	2,893
χ^2	152.0	152.0	165.4	165.4	489.9	489.9

Table 2.8 reports the moderating effect of underwriter reputation on the relationship between optimistic tone and IPO survival. I estimate Cox proportional hazard models with interaction terms between optimism measures and underwriter quality, while controlling for industry and year fixed effects.

In column (1), the interaction term *Optimism LM* $\times$ *Underwriter reputation* is negative and marginally significant (Coef. $= -1.647$, $p < 0.10$, HR $= 0.193$), indicating that optimism measured from the LM dictionary has a stronger positive effect on IPO survival when issuers are backed by high-reputation underwriters. In column (3), the interaction *Optimism FinBERT Net* $\times$ *Underwriter reputation* is highly significant at the 1% level (Coef. $= -2.125$, HR $= 0.119$), suggesting that sentence-level optimism captured by FinBERT becomes especially credible and impactful when accompanied by reputable underwriters. Similarly, in column (5), the interaction *Optimism FinBERT Total* $\times$ *Underwriter reputation* is negative and significant at the 10% level (Coef. $= -2.397$, HR $= 0.091$). Across all specifications, the interaction terms highlight that the positive role of optimism is amplified by underwriter reputation.

The direct effect of underwriter reputation is positive in columns (2)–(6), with coefficients ranging from 0.839 to 1.048, indicating that reputable underwriters independently reduce the hazard of IPO failure. More importantly, their interaction with optimism shows that underwriters not only certify IPOs through traditional monitoring channels but also enhance the information content of optimistic tone in prospectuses. These results align with the theory of relative bargaining power by Loughran and Ritter (2002), as well as with Hanley and Hoberg (2010), who argue that optimistic language under reputable underwriters is interpreted as a credible signal of firm quality due to the reputational and legal risks underwriters face.

Taken together, the findings are consistent with Hypothesis 2, but the interpretation should be cautious. Rather than concluding that underwriter quality causally amplifies the effect of optimistic tone, I interpret the results as showing that optimistic language is more strongly associated with IPO survival when it is accompanied by reputable underwriters. This pattern is consistent with a certification-based signaling view, under which underwriter reputation increases the credibility and informativeness of prospectus tone.

2.7.2 VC background and optimistic tone

Jain and Kini (2000) and Krishnan et al. (2011) highlight the critical role of VC involvement in enhancing IPO outcomes, showing that both the presence and reputation of VC investors increase IPO survival prospects. VC firms act as certifiers and monitors, reducing information asymmetry between issuers and outside investors. When IPOs are backed by reputable VCs, optimistic language in prospectuses is more likely to be interpreted as credible, since investors perceive VC certification as validating the information disclosed. This certification effect amplifies the impact of optimistic tone, as VC backing enhances the credibility of optimistic tone and strengthens its signaling value. Thus, I predict that VC involvement magnifies the positive impact of optimistic tone on IPO survival.

Table 2.9: Moderating effects of VC involvement
All regressions include industry-fixed effects, with their coefficients suppressed. Optimism LM is computed by Loughran and McDonald (2016)'s financial dictionary. Optimism FinBERT Net is computed by FinBERT through Equation 2.1. Optimism FinBERT is computed by FinBERT through Equation 2.2. Variable definitions can be found in Appendix A. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust statistics, adjusted for heteroscedasticity and clustered at the industry level, are reported in parentheses beneath the coefficient estimates. Detailed definition for all variables are available in Appendix 2.

VARIABLES	(1) Coef.	(2) HR	(3) Coef.	(4) HR	(5) Coef.	(6) HR
Optimism LM	-0.437	0.646				
	(-1.12)					
Optimism FinBERT Net			-0.689***	0.502		
			(-4.27)			
Optimism FinBERT Total					-1.190***	0.304
					(-2.63)	
VC	0.164	1.179	0.007	1.007	-0.044	0.957
	(1.08)		(0.04)		(-0.07)	
Optimism LM*VC	-1.982**	0.138				
	(-2.53)					
Optimism FinBERT Net*VC			-0.865*	0.421		
			(-1.93)			
Optimism FinBERT Total*VC					-0.634	0.530
					(-0.49)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,893	2,893	2,893	2,893	2,893	2,893
χ^2	152.0	152.0	165.4	165.4	489.9	489.9

Table 2.9 examines the moderating effect of VC involvement on the relationship between optimistic tone and IPO survival. I estimate Cox proportional hazard regressions with interaction terms between optimism measures and VC backing, controlling for year and industry fixed effects, with robust standard errors clustered at the industry level.

In column (1), the interaction term *Optimism LM* $\times$ *VC* is negative and statistically significant at the 5% level (Coef. $= -1.982$, HR $= 0.138$), indicating that VC backing strengthens the positive impact of optimism (measured using the LM dictionary) on IPO survival. In column (3), the interaction *Optimism FinBERT Net* $\times$ *VC* is also negative and marginally significant at the 10% level (Coef. $= -0.865$, HR $= 0.421$), suggesting that VC involvement amplifies the effect of optimism when sentiment is captured at the sentence level using FinBERT. By contrast, the interaction *Optimism FinBERT Total* $\times$ *VC* in column (5) is negative but statistically insignificant (Coef. $= -0.634$, HR $= 0.530$), implying that the moderating role of VC is weaker when optimism is normalized by the total number of sentences.

The direct effect of VC involvement alone is statistically insignificant across all specifications, suggesting that VC backing by itself does not directly improve IPO survival in this sample. Instead, its value lies in amplifying the credibility of optimistic tone, consistent with the certification role of VCs documented by Jain and Kini (2000) and the reputation channel emphasized by Krishnan et al. (2011). In other words, optimism in prospectuses backed by reputable VCs is more likely to be perceived as a credible signal of firm quality, thereby strengthening the optimism–survival link.

Taken together, the results are broadly consistent with Hypothesis 3, but they are best interpreted as heterogeneity in informativeness rather than clean causal amplification. Specifically, the association between optimistic tone and IPO survival is stronger among VC-backed IPOs, consistent with the view that VC certification enhances the credibility of optimistic disclosure. Thus, VC involvement appears to strengthen the signaling value of tone, even though the design does not allow a definitive causal interpretation.

2.7.3 Dot-bubble period

Ljungqvist and Wilhelm Jr (2003) and Habib and Ljungqvist (2001) document the unusual underpricing of IPOs during 1999 - 2000 dot-bubble period. Our research further finds 1999 - 2000 dot-bubble period may be the main driving factor of the positive impact of net positive tone on IPO survival. Table 2.10 provides additional tests around the dot-com bubble period by re-estimating the Cox proportional hazard models separately for 1997–2000 and the post-bubble era. I include industry and year fixed effects and cluster standard errors at the industry level.

In the bubble window (columns 1, 5, and 9), all three optimism measures strongly predict IPO survival: *Optimism LM* is negative and significant at the 1% level (Coef. $= -0.951$, HR $= 0.386$), *Optimism FinBERT Net* is negative and significant at the 1% level (Coef. $= -0.779$, HR $= 0.459$), and *Optimism FinBERT Total* exhibits the largest magnitude (Coef. $= -1.554$, HR $= 0.211$). By contrast, after 2000 (columns 2, 6, and 10 for LM/Net/Total, and columns 4, 8, and 12 in the full panel), the coefficients remain negative but lose statistical significance (e.g., LM: Coef. $= -0.818$, HR $= 0.441$; Net: Coef. $= -0.861$, HR $= 0.423$; Total: Coef. $= -0.500$, HR $= 0.607$).

These patterns limit the generality of the optimism–survival relation. I initially aimed to establish a conclusion that holds broadly over time; the evidence instead concentrates in the bubble period. Taken together, Table 2.10 supports **Hypothesis 1** primarily in the bubble subsample: optimistic tone is associated with greater IPO survival when information frictions and incentive distortions are most acute. I therefore interpret the effect as regime-dependent rather than universal. This results also explain the insignificance in FinBERT-based sentiment variables in Table 2.2.

Table 2.10: Additional tests for dot-bubble period

Optimism LM is computed by Loughran and McDonald (2016)'s financial dictionary. Optimism FinBERT Net is computed by FinBERT through Equation 2.1. Optimism FinBERT is computed by FinBERT through Equation 2.2. Total All regressions include industry-fixed effects, with their coefficients suppressed. Variable definitions can be found in Appendix A. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust statistics, adjusted for heteroscedasticity and clustered at the industry level, are reported in parentheses beneath the coefficient estimates. Detailed definition for all variables are available in Appendix 2.

	Optimism LM				Optimism FinBERT Net				Optimism FinBERT Total			
	1997-2000		after 2000		1997-2000		after 2000		1997-2000		after 2000	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**
Optimism LM	-0.951***	0.386	-0.818	0.441								
	(-2.77)		(-0.80)									
Optimism FinBERT Net					-0.779***	0.459	-0.861	0.423				
					(-2.99)		(-1.01)					
Optimism FinBERT Total									-1.554***	0.211	-0.500	0.607
									(-2.99)		(-0.70)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,256	1,256	1,637	1,637	1,256	1,256	1,637	1,637	1,256	1,256	1,637	1,637
χ^2	96356	96356	1462	1462	58638	58638	122.7	122.7	56431	56431	1294	1294

2.8 Conclusion

This chapter investigates whether optimistic language in IPO prospectuses predicts IPO survival. Using both Loughran and McDonald (2016)'s financial dictionary and FinBERT-based sentence classification, I show that more optimistic S-1 filings are associated with substantially lower post-IPO failure hazards and longer survival times. This relation remains robust after controlling for firm-, IPO-, and CEO-level characteristics, and it persists across alternative survival models, entropy balancing, and Lewbel-style internal IV estimations (Lewbel 2012). At the same time, the chapter recognizes that prospectus tone may partly reflect strategic disclosure by issuers and intermediaries who possess private information about future viability. Accordingly, the results are interpreted conservatively: optimistic tone is best understood as an ex ante disclosure signal with incremental predictive content for IPO survival rather than as a purely exogenous causal driver.

The channel analysis further shows that the positive impact of optimistic tone is amplified by VC and underwriter quality. Specifically, optimism has stronger effects on IPO survival when the IPO is backed by VC investors or reputable underwriters. These findings align with the information asymmetry hypothesis that VC backed IPOs (Jain and Kini 2000; Krishnan et al. 2011; Carter and Manaster 1990) and underwriter reputation (Hanley and Hoberg 2010; Loughran and Ritter 2002) can offer more information about the quality of IPOs. These net use of positive languages can be regarded as promising signals of IPOs and have string predictive power on IPO survival. In contrast, optimism expressed in IPOs without VC backing or with lower-quality underwriters carries weaker survival implications, suggesting that investor interpretation of language depends critically on the broader information environment.

An important limitation of this chapter is that disclosure tone is unlikely to be fully exogenous. In particular, firms with better unobserved fundamentals or more favorable private information may strategically choose more optimistic language because they already anticipate stronger post-IPO survival prospects. Although the chapter employs extensive controls, entropy balancing, and Lewbel-style internal IV estimations, these approaches cannot fully rule out reverse causality or omitted-variable bias arising from latent firm quality. For this reason, the results should be interpreted as evidence that optimistic tone is an informative ex ante signal of IPO survival, rather than definitive proof of a causal effect.

Overall, the evidence is most consistent with the information asymmetry interpretation: optimistic language in IPO filings functions as a strategic communication device that conveys favorable private assessments to the market (Loughran and McDonald 2013). Rather than concluding that tone alone mechanically causes survival, I interpret optimistic tone as a forward-looking signal that helps investors assess firm viability under conditions of substantial information asymmetry. By integrating textual analysis with IPO survival models, this chapter contributes to the growing literature on the value relevance of disclosure tone in finance and highlights the importance of language as an intangible but informative determinant of long-run IPO performance.

Chapter 3

Determinants of Organization Capital: Does CEO Matters?

3.1 Introduction

Prescott and Visscher (1980) initially theorized organizational capital as distinctive information (or knowledge) within firms. organizational capital is valuable because it facilitates the integration and mobilization of both tangible and intangible assets. The significance of organizational capital is broadly acknowledged in the field of economics, where it is recognized for its impact on corporate strategies, policies, and firm performance (Dessein and Prat 2022; Atkeson and Kehoe 2005; Eisfeldt and Papanikolaou 2013; Prescott and Visscher 1980).

While studies have examined the influence of organizational capital on various corporate behaviors and outcomes, such as M&A results, tax avoidance, and investment policies (Gao et al. 2021; Hasan et al. 2018; Carlin et al. 2012; Li et al. 2018; Leung et al. 2018; Hasan and Uddin 2022; Francis et al. 2021), limited research focuses on the determinants of organizational capital. Notably, recent theoretical models predict that CEO transitions, managerial ability, and other CEO characteristics (e.g., compensation structure) play significant roles in determining the stock of organizational capital (Dessein and Prat 2022). Dessein and Prat (ibid.) predict that talented managers prioritize long-term benefits, while managerial short-termism hinders the accumulation of organizational capital. Although Dessein and Prat (ibid.) theoretically propose CEO turnover and other CEO-related variables as determinants of organizational capital, empirical evidence remains limited.

Despite numerous studies on the CEO's impact on corporate behavior and performance (e.g., (Demerjian et al. 2012; Custódio et al. 2019; Shang 2021; Dessein and Prat 2022)) since Bertrand and Schoar (2003) demonstrated that CEO fixed effects significantly influence corporate outcomes, understanding why and how CEOs affect corporate outcomes remains essential for both academics and regulators. Huson et al. (2004) document positive corporate performance following CEO turnover; however, although CEO transitions bring shifts in management style and strategy, most studies focus on turnover determinants (e.g., Bushman et al. (2010), DeFond and Park (1999), Fiordelisi and Ricci (2014) and Jenter and Lewellen (2021)), with limited research on turnover consequences and the mechanisms behind Huson et al. (2004)'s findings. Our paper addresses key questions to fill this gap: What are the determinants of organizational capital? Why do positive outcomes follow CEO turnover? What are the consequences of CEO turnover?

CEO succession is the most consequential governance intervention boards undertake, yet its effects on a firm's organizational capital—the stock of routines, coordination technologies, and embedded knowledge—are theoretically ambiguous and empirically underexplored. organizational capital is slow-moving and central to execution, innovation, and productivity, so even modest changes around succession can have persistent real effects. Establishing whether turnover causally builds or erodes organizational capital matters for three reasons. First, it informs when boards should replace CEOs and which skills to prioritize if the objective is long-horizon capability building rather than short-run earnings management. Second, it disciplines interpretations of post-turnover selling, general, and administrative expenses (SG&A) dynamics by distinguishing investment in organizational capability from expense reshuffling. Third, it links incentive design to intangible accumulation by testing whether managerial ability, outsider origin, and relative pay amplify the organizational capital response. Pinning down these effects helps explain cross-firm heterogeneity in productivity and provides actionable guidance for succession planning and compensation policy.

Our study explores the impact of CEO turnover on organizational capital by using accumulated SG&A expense [1] as a proxy for organizational capital, treating it as the outcome variable. I also use Demerjian et al. (2012)'s managerial ability score and Gentry et al. (2021)'s CEO turnover database.

First, I highlight that CEO turnover is associated with higher post-turnover organizational capital by approximately 15% in post-turnover periods, while organizational capital levels remain stable in pre-turnover periods. Using a difference-in-differences (DiD) framework, I examine whether organizational capital is higher in post-turnover periods relative to the pre-turnover path and relative to firms not experiencing turnover. I complement the baseline two-way fixed-effects specification with staggered-adoption and doubly robust DiD estimators[2] to address concerns related to treatment-timing heterogeneity. However, I interpret these designs cautiously. While the event-study evidence is broadly supportive of the identifying assumptions, DiD estimates remain valid only under those assumptions and should therefore be viewed as informative but not mechanically definitive causal effects in every specification.

1. See: Eisfeldt and Papanikolaou (2013), who utilize SG&A expense, R&D expense, and intangible assets as proxies for organizational capital
2. See Sant'Anna and Zhao (2020), where it is argued that two-way fixed effects (TWFE) estimators may be biased when event dates vary across the treatment group. The doubly robust DiD framework provides more reliable results.

The empirical designs in this chapter identify average changes in organizational capital following CEO turnover events. Accordingly, the results speak to whether organizational capital rises on average after turnover, and whether this average response differs across successor CEO characteristics. They do not directly identify individual CEOs' intentions, strategic motives, or the precise managerial actions taken inside the firm. Throughout the chapter, I therefore avoid interpreting the estimates as direct evidence that a particular CEO deliberately undertook a specific organizational reform.

Furthermore, I examine whether the post-turnover organizational-capital response varies systematically with successor CEO characteristics. In particular, I test whether the association between CEO turnover and organizational capital is stronger when the successor CEO has higher managerial ability, stronger incentive alignment, or an outsider background. Because the data do not directly observe internal organizational changes such as hiring, training, management-system adoption, or process redesign, these analyses should be interpreted as heterogeneity tests that are consistent with theoretical mechanisms, rather than as direct evidence on the precise operational channels. Using a triple-difference (DDD) framework, I find that interaction terms between CEO ability[3] and CEO turnover are significantly positive, suggesting that capable CEOs invest more in organizational capital. Additionally, our analysis reveals that CEOs with higher compensation relative to industry peers invest significantly more in organizational capital, supporting the hypothesis that higher-paid CEOs possess greater abilities.

3. I adopt Demerjian et al. (2012)'s well-established measure of CEO ability (or managerial ability) in the management, accounting, and finance fields.

Second, I find that managerial ability has a positive effect on organizational capital. Economically significant, our results suggest that a one standard deviation increase in managerial ability leads to a 7%-8% change in the standard deviation of organizational capital. I use peer-group average value[4] of managerial ability as an instrumental variable and adopt a cutting-edge double robust machine learning (DDML) approach to mitigate endogeneity.

This paper makes the following contributions. First, it contributes to the organizational capital literature [5]. While recent empirical studies examine organizational capital's effects on corporate behavior, policies, and performance[6], fewer studies address organizational capital's determinants. Dessein and Prat (2022) highlight leadership's critical role in organizational capital accumulation, developing a model that reveals the influence of CEO characteristics and transitions on organizational capital. This paper advances organizational capital literature by empirically examining CEO transitions and variables as organizational capital determinants. I find that CEO transitions positively affect organizational capital accumulation, with managerial ability and relative compensation serving as moderating factors, refining the impact of CEO transitions on organizational capital accumulation. These findings address Dessein and Prat (ibid.)'s call for empirical studies on CEO influences on organizational capital, enhancing understanding of executive dynamics on organizational capital.

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4. I acknowledge that peer-group average IVs are sometimes limited in mitigating omitted variable bias (Gormley and Matsa 2014); therefore, I employ DDML to address endogeneity issues.
5. After Prescott and Visscher (1980) emphasized organizational capital's importance, empirical research was limited due to data challenges. Eisfeldt and Papanikolaou (2013) suggested using SG&A as an organizational capital proxy, enabling further empirical research.
6. See: Gao et al. (2021), Hasan et al. (2018), Carlin et al. (2012), Li et al. (2018), Leung et al. (2018), Hasan and Uddin (2022), Francis et al. (2021) and Eisfeldt and Papanikolaou (2013)

Second, this study contributes to CEO turnover literature. Previous studies focus on turnover determinants[7], with fewer addressing the consequences of CEO transitions[8]. Our paper enriches this literature by providing empirical evidence on how CEO transitions influence organizational capital, offering new perspectives on the strategic implications of executive changes and CEO characteristics. Third, our paper also contributes to literature on CEO ability and industry tournament incentives.

An important limitation of this chapter is that, while the data allow me to observe CEO turnover, CEO traits, compensation structures, and expenditure-based measures of organizational capital, they do not directly capture the internal organizational actions through which new CEOs may build organizational capital. In particular, I do not observe changes in hiring and training policies, the adoption of new management systems, the reorganization of internal processes, or cultural reforms. Accordingly, the chapter identifies whether organizational capital rises after CEO turnover and whether this relation is stronger for certain types of CEOs, but it does not directly establish the exact mechanism through which these effects occur. Moreover, another important limitation of the chapter is that difference-in-differences designs identify post-turnover differences under maintained assumptions rather than by themselves proving causality. In particular, the empirical interpretation depends on the plausibility of parallel counterfactual trends, the absence of confounding contemporaneous shocks, and the comparability of treated and control firms around turnover events. The chapter therefore interprets the DiD evidence as strong but still assumption-dependent evidence that CEO turnover is associated with higher subsequent organizational capital.

The remainder of the paper is organized as follows: Section 2 discusses related literature and hypothesis development. Section 3 describes the data and methodology. Section 4 shows research design. Section 5 reports empirical findings. Section 6 discusses implication, and Section 7 concludes.

7. E.g., Bushman et al. (2010), DeFond and Park (1999), Fiordelisi and Ricci (2014) and Jenter and Lewellen (2021)

8. E.g., Intintoli et al. (2017), Huson et al. (2004) and Weisbach (1995)

3.2 Literature review and hypothesis development

3.2.1 Organizational capital

organizational capital refers to firm-specific knowledge, routines, and coordination mechanisms embedded in employees and organizational processes that enable the deployment of tangible and intangible assets at scale (Prescott and Visscher 1980; Carlin et al. 2012; Dessein and Prat 2022). A growing empirical literature establishes its measurement and real effects. Using a firm-specific approach, Lev et al. (2009) construct an organization capital index and show it forecasts at least five years of abnormal operating performance and stock returns, and is positively associated with executive pay, consistent with organizational capital capturing managerial quality. In parallel, studies that capitalize SG&A expenditures—arguing that training, IT, marketing, and process design are investments in organizational knowledge—document that organizational capital improves productivity and market outcomes (Eisfeldt and Papanikolaou 2013; Leung et al. 2018; Francis et al. 2021).

organizational capital is associated with higher productivity, innovation output, and market value (Eisfeldt and Papanikolaou 2013; Francis et al. 2021; Lev et al. 2009). SG&A components that plausibly build organizational capital respond to incentive design: equity pay is linked to increases in value-creating SG&A, consistent with treating parts of SG&A as investment rather than period expense (Banker et al. 2011). At earlier firm stages, founders' organizational know-how improves financing outcomes (Hsu 2007). Governance interacts with organizational capital: the performance impact of CEO power varies with organizational capability (Chiu et al. 2022). organizational capital also appears crisis-relevant: firms with stronger organizational capital show more resilient stock performance when adaptation is valuable (Lee et al. 2025). At the same time, organizational capital can raise adjustment risk if embedded routines become mismatched to new environments (Hasan et al. 2018).

organizational capital also matters for financing frictions and long-horizon value creation. Banker et al. (2011) show that equity incentives stimulate SG&A outlays that create long-term value, reinforcing the interpretation of SG&A as investment in organizational capital rather than pure period cost. At the entrepreneurial margin, Hsu (2007) find that founders' experiential human/organizational capital materially raises venture valuation and the likelihood of obtaining high-quality investors, highlighting organizational capital's role in contracting and screening. At the top of the house, Chiu et al. (2022) report that organizational capital interacts with CEO power to shape firm performance, while cross-market evidence indicates that organizational capital improves resilience when coordination and adaptation are most valuable—e.g., stock performance during systemic crises (Lee et al. 2025). Together with evidence that organizational capital lowers borrowing costs (Danielova et al. 2023) and influences M&A and innovation (Li et al. 2018; Francis et al. 2021), these findings position organizational capital as a first-order state variable for firm strategy and valuation.

Despite these advances, I know much less about the determinants of organizational capital. Recent theory highlights leadership as a proximal driver: talented, long-term–oriented CEOs optimally invest in organizational capital, whereas short-termism depresses it (Dessein and Prat 2022). Empirically identifying which CEO attributes move organizational capital, and by how much, remains an open question that our paper addresses. Most evidence treats organizational capital as a state variable that explains outcomes. Less is known about what builds it. Theory predicts that leadership and horizons matter: high-ability, long-term–oriented CEOs invest in organizational capital; short-termism depresses it (ibid.). I bring this prediction to the data. Using expenditure-based organizational capital measures, I study whether CEO turnover changes the organizational capital path and through which CEO channels (ability, incentive structure, outsider origin) those changes arise. Our tests complement output- and practice-based literatures by providing event-time estimates around leadership changes and mapping heterogeneity to executive attributes.

3.2.2 Managerial ability

Since Bertrand and Schoar (2003) established the significance of CEO fixed effects, Dessein and Prat (2022) argue that the endogenous assignment of CEOs to firms can lead to an underestimation of the CEO's true impact on firm performance. A substantial body of literature analyzes the effect of CEOs on corporate behavior and outcomes, examining factors such as CEO ability[9] and industry tournament incentives[10] on corporate behaviors and outcomes. Concurrently, many studies investigate the determinants of CEO turnover (or transition)[11] in contexts such as external competition (DeFond and Park 1999), corporate culture (Fiordelisi and Ricci 2014), and CEO performance (Jenter and Kanaan 2015). However, fewer studies focus on the consequences of CEO turnover[12].

To focus the review on the heterogeneity most relevant to our tests, I also concentrate on managerial ability (MA). Bertrand and Schoar (2003) show that manager fixed effects explain meaningful variation in corporate policies and outcomes. Building on this, Demerjian et al. (2012) develop the MA-score—an efficiency-based construct that (i) separates the manager component from firm fundamentals and (ii) scales to large panels; follow-on work validates its content and applications (Demerjian et al. 2013). High-MA

9. See: Baik et al. (2011), Demerjian et al. (2012), Demerjian et al. (2013), Cheung et al. (2017), Doukas and Zhang (2021), Bonsall IV et al. (2017), Baik et al. (2020) and Shang (2021)
10. See: Kubick and Lockhart (2021), Kong et al. (2022), Lonare et al. (2022), Tan (2021), Nguyen and Zhao (2021), Huang et al. (2019), Islam et al. (2022) and Coles et al. (2018)
11. See: DeFond and Park (1999), Fiordelisi and Ricci (2014), Eisfeldt and Papanikolaou (2013), Murphy and Zimmerman (1993) and Jenter and Kanaan (2015)
12. Some studies on the consequences of CEO turnover include Alderson et al. (2014), Intintoli et al. (2017) and Weisbach (1995)

managers are associated with better investment efficiency, disclosure quality, and external assessments such as credit ratings, consistent with superior resource allocation and monitoring (Baik et al. 2011; Bonsall IV et al. 2017; Doukas and Zhang 2021; Baik et al. 2020; Custódio et al. 2019).

Importantly for organizational capital, MA is theoretically linked to patience and the internal accumulation of hard-to-trade assets (Dessein and Prat 2022). Empirically, proxies tied to MA correlate with higher organizational capital and stronger pay–performance sensitivity in organizational capital-creating outlays such as SG&A (Lev et al. 2009; Banker et al. 2011). This literature suggests two testable implications I bring to the data: (i) firms led by higher-ability CEOs should exhibit larger organizational capital stocks (or growth), and (ii) CEO transitions that install higher-ability leaders should raise organizational capital, with effects moderated by incentive structures that amplify long-term focus (e.g., equity-based pay, relative pay gaps). These implications organize our hypotheses and guide our identification choices below.

A large literature documents economically meaningful manager fixed effects in policies and outcomes (Bertrand and Schoar 2003). Among observable CEO traits, MA is the most directly tied to organizational capital accumulation in theory: higher-ability leaders internalize dynamic complementarities between current spending and future capability, while lower-ability or myopic leaders underinvest (Dessein and Prat 2022).

I rely on the Demerjian et al. (2012) MA-score. The procedure recovers firm-year total efficiency (DEA), then attributes residual efficiency—after controlling for fundamentals such as size, market share, complexity, and financing constraints—to managers. The score loads on manager rather than firm fixed effects and scales to large panels (Demerjian et al. 2013). Related work shows that higher MA aligns with better information quality and investment efficiency and receives favorable credit-market assessments (Baik et al.

2011; Bonsall IV et al. 2017; Doukas and Zhang 2021). Generalist experience provides an additional, portable dimension of managerial human capital relevant for reorganization (Custódio et al. 2013). Together, these measures proxy for the ability to design, communicate, and implement organizational change.

Taken together, the literature suggests that CEO characteristics and succession events are plausible determinants of organizational capital. The next subsection develops the chapter's testable hypotheses in a more formal manner.

3.2.3 Hypothesis development

Although a growing literature documents the value implications of organizational capital, much less is known about the forces that determine its accumulation. This chapter focuses on CEO-related determinants. The theoretical starting point is that organizational capital is a firm-specific stock of routines, coordination systems, managerial processes, and embedded knowledge that raises the productivity of both physical and human capital (Prescott and Visscher 1980; Eisfeldt and Papanikolaou 2013; Dessein and Prat 2022). Because organizational capital is difficult to trade in external markets and costly to build quickly, its accumulation depends heavily on internal managerial choices regarding resource allocation, process design, personnel development, and long-horizon investment. This makes the CEO a natural candidate for explaining cross-firm differences in organizational-capital accumulation.

Three broad theoretical perspectives motivate this idea. First, the resource-based view implies that organizational capital is a strategic asset that is valuable, difficult to imitate, and firm specific (Barney 1991). Second, upper echelons theory predicts that observable executive characteristics shape strategic choices and resource-allocation decisions (Hambrick 2007; Bertrand and Schoar 2003). Third, the dynamic capabilities view emphasizes that leaders play a central role in sensing opportunities, seizing them, and reconfiguring organizational routines (Teece et al. 1997; Dessein and Prat 2022). Taken together, these perspectives imply that CEO quality, incentives, and succession events should matter for the stock and growth of organizational capital.

A first implication concerns CEO ability. Human capital theory suggests that managers with superior skills, knowledge, and experience are better able to identify valuable long-term projects and to allocate resources efficiently (Becker 1964). In the context of organizational capital, higher-ability CEOs should be better at translating SG&A-type expenditures into productive organizational capabilities rather than transitory administrative costs. Dessein and Prat (2022) formalize this intuition by showing that talented managers place greater weight on future organizational capability and therefore invest more in organizational capital, whereas less capable or more myopic managers underinvest. If managerial ability improves the effectiveness and persistence of capability-building expenditures, then firms led by more able CEOs should exhibit higher organizational-capital stocks or faster accumulation.

Hypothesis 1: CEO ability/quality is positively related to the stock/growth rate of organizational capital.

A second implication concerns CEO turnover. The direction of the turnover effect is theoretically ambiguous, which motivates competing predictions. On the one hand, CEO succession can create an opportunity to reset strategy, replace underperforming routines, redesign internal processes, and reallocate resources toward long-term capability building. This logic is especially relevant when the departing CEO was poorly matched to the firm or when the board initiates succession to improve long-run performance (Huson et al. 2004; Dessein and Prat 2022). Under this view, turnover should be followed by higher organizational-capital accumulation.

Hypothesis 2: CEO turnover is positively correlated with the stock/growth rate of organizational capital.

On the other hand, organizational capital is partly embedded in firm-specific routines, relationships, and tacit knowledge. CEO turnover may therefore disrupt internal coordination, delay implementation, weaken continuity, and generate adjustment costs, especially in the short run. If succession destroys firm-specific managerial capital faster than the new CEO can rebuild it, organizational capital may decline after turnover.

Hypothesis 3: CEO turnover is negatively correlated with the stock/growth rate of organizational capital.

A third possibility is that CEO turnover has little average effect on organizational capital. Organizational capital is often slow-moving and may be constrained by existing personnel, governance structures, budgets, and organizational inertia. In that case, even substantial leadership changes may not immediately alter the organizational-capital path, particularly if boards select successors with similar strategic orientations or if internal systems are already highly institutionalized.

Hypothesis 4: CEO turnover has no effect on the stock/growth rate of organizational capital.

Beyond the average effect of turnover, theory also suggests that the identity of the successor CEO should matter. If turnover creates discretion to reshape routines and long-term capabilities, then the successor's ability should influence how strongly the firm's organizational capital responds. Higher-ability CEOs should be better able to diagnose organizational weaknesses, redesign processes, coordinate implementation, and convert post-turnover discretion into durable organizational improvements. By contrast, lower-ability successors may fail to exploit the reorganization window or may even exacerbate disruption. Thus, managerial ability should moderate the post-turnover organizational-capital response.

Hypothesis 5: CEO ability strengthens (or weakens) the positive (or negative) effect of CEO turnover on organizational capital.

CEO compensation provides a further source of heterogeneity. A CEO's compensation relative to industry peers may contain information about boards' ex ante assessment of managerial talent, the scarcity of the executive's skills, or the strength of tournament-style incentives (Carlin et al. 2012). If more highly paid CEOs are selected because they are expected to create long-term value, then higher relative pay should be associated with stronger post-turnover organizational-capital accumulation. At the same time, tournament-style compensation may also induce short-term performance pressure. The net effect is therefore an empirical question, but compensation-based heterogeneity should be informative about when turnover is most strongly associated with organizational-capital investment.

Hypothesis 6: The CEO wage gap strengthens (or weakens) the positive (or negative) effect of CEO turnover on organizational capital.

Finally, incentive alignment may shape whether newly appointed CEOs prioritize long-horizon capability building. Agency and stewardship arguments imply that stock-based pay, ownership, and other performance-related incentives can align managerial decisions with long-run firm value rather than short-run accounting outcomes (Donaldson and Davis 1991; Banker et al. 2011). Because organizational capital is an intangible asset whose returns accrue gradually, CEOs with stronger equity-based incentives should have greater motivation to undertake investments that may depress short-run earnings but enhance long-term productivity. However, some incentive components may also encourage excessive short-term risk-taking, so the sign remains empirical. Even so, theory predicts that performance-related incentives should systematically moderate the turnover–organizational-capital relation.

Hypothesis 7: CEO performance-related pay strengthens (or weakens) the positive (or negative) effect of CEO turnover on organizational capital.

Overall, the hypotheses above are organized around two questions. First, do CEO ability and CEO turnover help explain the level and evolution of organizational capital? Second, conditional on turnover, do successor CEO characteristics-including ability, relative compensation, and incentive alignment-shape the magnitude of the post-turnover organizational-capital response? These questions directly follow from recent theory (Dessein and Prat 2022) and provide the basis for the empirical tests in the next sections.

3.3 Data and methodology

I collect firm–level financials from Compustat (annual) and CEO characteristics and compensation from ExecuComp. CEO turnover dates come from Compustat; turnover reasons are validated and coded using Gentry et al. (2021). The merged panel spans fiscal years 1992–2022 and contains 36,226 firm–year observations; within this period I identify 1,666 CEO turnover events. Event–time specifications (staggered DiD and doubly robust DiD) draw on up to 1,596 unique firms (gvkeys). All regressions include firm and year fixed effects, with standard errors clustered at the firm level.

I select controls following the literature: firm size (SIZE), return on assets (ROA), market-to-book (MTB), leverage (LEV), and tangibility (TANG). To limit the influence of outliers, all continuous variables are winsorized at the 1% and 99% levels by year. Detailed variable definitions and construction choices are provided in Appendix 2.

3.3.1 Measure of CEO ability

Since managerial ability is unobservable, prior studies have used proxies such as media citations, past performance, and managerial fixed effects. However, most of these measures do not effectively distinguish the managerial effect from the firm effect (Demerjian et al. 2012). I utilize the MA-score, a recently developed measure of managerial ability[13]. The MA-score, derived from Demerjian et al. (ibid.), is based on the rationale that corporate managers, together with internal resources, serve as inputs in corporate production processes, and these jointly contribute to outputs. High managerial ability, as a valuable input, can enhance firm outcomes given a specific level of internal resources.

Demerjian et al. (ibid.) calculate a firm's relative total efficiency within its industry using a data envelopment analysis (DEA) approach. They then decompose total efficiency into components attributable to firm-specific factors and managers. This decomposition is achieved by regressing total efficiency on a set of firm-specific factors, including firm size, market share, cash availability, life cycle, operational complexity, and foreign operations. The residuals from this regression—representing the unexplained component of efficiency—are attributed to managers and regarded as the measure of managerial ability. Managers with high ability are defined as those achieving high levels of efficiency, controlling for firm-specific factors.

13. I also thank Custódio et al. (2019) for kindly sharing their general managerial ability index

Demerjian et al. (2012) validate the MA-score as a reliable proxy for managerial ability. First, the MA-score is explained largely by managerial fixed effects rather than firm fixed effects, indicating that it primarily captures managerial differences rather than firm characteristics. This suggests that the MA-score effectively separates the managerial effect from the firm effect. Second, the MA-score provides a more robust proxy for managerial ability than managerial fixed effects, as it can be applied in large-sample analyses and is not limited to firms with managerial turnover.

3.3.2 Measure of organization capital

Consistent with (Eisfeldt and Papanikolaou 2013), I measure a firm's stock of organizational capital using capitalized SG&A expenses. SG&A expenses encompass the overall non-production costs of operating a firm, including IT infrastructure, information systems, R&D, employee training, advertising, and marketing. These expenses are investments aimed at developing a firm's knowledge and business processes and enhancing the utilization of resources—thus contributing to organizational capital. I obtain firm-year accounting data from the Compustat database and compute the stock of organizational capital for firm i in year t using the perpetual inventory method, which recursively calculates the stock of organizational capital by accumulating the deflated value of SG&A expenses:

$$OC_{i,t} = (1 - \delta_{OC})OC_{i,t-1} + \frac{SGA_{i,t}}{CPI_t} \tag{3.1}$$

where $SGA_{i,t}$ represents firm i's SG&A expenses in year t; CPI_t is the consumer price index; and δ_{OC} denotes the depreciation rate of organizational capital stock, which is set to 15%, as per the U.S. Bureau of Economic Analysis (BEA) guidelines used in their 2006 R&D capital estimation (Eisfeldt and Papanikolaou 2013). The initial stock of organizational capital for firm i is determined as follows:

$$OC_{i,0} = \frac{SGA_{i,1}}{g + \delta_{OC}} \tag{3.2}$$

where g represents the average real growth rate of firm-level SG&A expenses, set at 10% in our sample (ibid.). This rate is specific to each industry (defined at the two-digit SIC level) and decade, depending on the year firm i first appears in the Compustat database (Li et al. 2018). Here, $SGA_{i,1}$ represents firm i's first-year SG&A expenses with non-missing data in Compustat. Finally, I obtain our organizational capital measure by standardizing the capitalized SG&A expenses by the firm's book value of total assets.

For our sample period from 1992 to 2022, 85% of observations have valid, non-missing SG&A expenses data. Missing values in firm i's SG&A expenses in subsequent years are treated as zero. I use several alternative methods to measure organizational capital: first, I capture organizational capital using SG&A expenses divided by CPI-adjusted total assets ($OC1$). Second, I calculate organizational capital by using the sum of SG&A expenses, advertising expenses, and R&D expenses, also divided by CPI-adjusted total assets ($OC2$). Third, I adjust $OC1$ and $OC2$ by subtracting the median of industry- and decade-specific $OC1$ and $OC2$ to generate industry-adjusted measures Adj_OC1 and Adj_OC2 for robustness checks.

3.4 Research design

To empirically test the effect of managerial ability on organizational capital, I estimate the following model:

$$OC_{i,t} = \alpha + \beta MA_{i,t} + \sum \theta_i x_{i,t} + \delta_{year} + \delta_{firm} + \varepsilon_{i,t} \tag{3.3}$$

where $OC_{i,t}$ represents the dependent variable, organizational capital; β provides an estimate of the effect of managerial ability ($MA_{i,t}$) on organizational capital; and $x_{i,t}$ represents a set of control variables. δ_{year} and δ_{firm} denote year fixed effects and firm fixed effects, respectively. $\varepsilon_{i,t}$ is the error term.

To estimate the effects of CEO turnover on organizational capital, I use the following model:

$$OC_{i,t} = \alpha + \beta TURNOVER_{i,t} + \sum \theta_i x_{i,t} + \delta_{year} + \delta_{firm} + \varepsilon_{i,t} \tag{3.4}$$

where $TURNOVER_{i,t}$ represents CEO turnover, a dummy variable that equals 1 if the fiscal year experiences a CEO turnover and 0 otherwise; $x_{i,t}$ represents a set of control variables. δ_{year} and δ_{firm} denote year fixed effects and firm fixed effects, respectively. $\varepsilon_{i,t}$ is the error term.

In the turnover analyses, the coefficients should be interpreted as average post-turnover differences in organizational capital under the maintained assumptions of the DiD framework. They do not identify the intentions or strategic decision process of any individual CEO, nor do they isolate a single operational channel through which turnover affects organizational capital.

3.5 Empirical results

3.5.1 Summary statistics

Table 3.1 provides summary statistics for key variables and CEO turnover cases in our study. Panel A presents the descriptive statistics for financial and CEO variables derived from Compustat and Execucomp databases. The main organizational capital measures, $OC1$ and $OC2$, have means of 1.32 and 1.07, respectively, with substantial variation across firms (standard deviations of 1.35 for $OC1$ and 1.18 for $OC2$). Key control variables include firm size (SIZE), with a mean of 51.83, and return on assets (ROA), with a mean of 0.05, reflecting the sample's broad range of firm characteristics. CEO-related metrics such as CEO ability (MA score) and CEO age are also summarized, highlighting the diversity in managerial experience and compensation.

Panel B categorizes CEO turnover cases by reason, illustrating the distribution across various types of CEO departures. Retirement is the leading cause of CEO turnover, accounting for 76.47% of cases, followed by dismissals due to poor performance at 14.11%. The sample consists of 1666 turnover cases and 1478 firms without turnover, enabling a comparative analysis between the treatment and control groups.

Table 3.1: Summary statistics
This table presents summary statistics for variables used in the final sample, including number of observations (N), mean, standard deviation (S.D.), 25th percentile (P25), median, and 75th percentile (P75) values. The sample period spans from 1992 to 2022. Detailed definition for all variables are available in Appendix 2.

	N	Mean	p25	p50	p75	s.d.
Panel A: Summary statistics						
OC1	36226	1.32	0.49	0.98	1.73	1.35
OC2	36226	1.07	0.37	0.76	1.40	1.18
Adj_OC1	36226	0.02	-0.62	-0.15	0.30	1.23
Adj_OC2	36226	0.04	-0.48	-0.11	0.28	1.06
SIZE	36226	51.83	39.21	49.68	62.53	16.51
ROA	36226	0.05	0.02	0.06	0.10	0.12
MTB	36226	3.58	1.47	2.34	3.91	4.36
TANG	36226	0.27	0.10	0.20	0.38	0.22
LEV	36110	0.90	0.10	0.45	0.92	1.81
CEO ability (MA score)	35968	0.00	-0.08	-0.02	0.05	0.14
CEO ability rank (MA score rank)	35968	0.54	0.30	0.50	0.80	0.30
CEO age (years)	35133	56.08	51.00	56.00	61.00	7.58
Tenure (years)	34531	8.58	3.00	6.00	11.00	7.65
Insider (Dummy)	36226	0.84	1.00	1.00	1.00	0.36
Ownership (%)	26966	0.14	0.00	0.01	0.07	0.53
Total compensation (thousands)	35969	5494.93	1389.42	3207.95	6721.33	9308.28
Cash compensation (thousands)	36037	1083.29	575.00	850.00	1200.00	1240.41
Stock compensation (thousands)	34618	2685.36	96.71	266.91	845.74	27718.64
Option compensation (thousands)	10028	2426.39	681.92	1408.74	2777.60	4995.63
Restricted stock (thousands)	19768	195.05	36.67	85.27	190.00	1336.95
Ownership: restricted stock(%)	36214	1.33	0.00	0.15	1.31	6.58
Delta (thousands)	34969	1226.12	71.89	191.05	542.93	16776.86
Option delta (thousands)	28721	311.19	33.32	97.75	269.93	2489.26
Share delta (thousands)	33760	1005.29	23.64	76.42	245.43	15907.32
Firm related wealth (thousands)	34969	114434.19	5776.58	15451.34	43557.49	1668198.19
Vega (thousands)	28716	142.87	18.01	51.93	146.27	309.16

Panel B: Summary of turnover reasons	Number of firms	Percentage (%)
	1478	100.00%
Reasons		
Illness	37	2.22%
Death	27	1.62%
Dismissed for job performance	235	14.11%
Personal issue	54	3.24%
Retirement	1274	76.47%
Other opportunity	39	2.34%
Sum	1666	100.00%

3.5.2 Univariate tests

Table 3.2 summarizes the differences in organizational capital levels between pre- and post-turnover periods. Panel A of Table 3.2 shows that post-turnover periods exhibit significantly higher organizational capital levels compared to pre-turnover periods, with a difference of -0.301 for $OC1$ and -0.232 for $OC2$, both significant at the 1% level. Panels B through E further categorize turnover cases based on the reasons for CEO departure.

Panel B presents data on involuntary CEO turnover, defined as abrupt departures due to reasons such as poor performance, illness, or personal issues. Here, the post-turnover difference is especially pronounced, with $OC1$ and $OC2$ differences of -0.524 and -0.416, respectively, both significant at the 1% level. Panel C focuses on voluntary CEO turnover, including retirements or moves to external opportunities, where the difference in organizational capital measures, while smaller, remains statistically significant (e.g., -0.182 for $OC1$ and -0.140 for $OC2$). Panel D details forced CEO turnovers, specifically due to poor performance, showing the largest increases in organizational capital, with differences of -0.588 for $OC1$ and -0.465 for $OC2$. Finally, Panel E addresses exogenous CEO departures (e.g., death or illness), where industry-adjusted organizational capital measures (Adj_OC1 and Adj_OC2) show significant differences, even though unadjusted measures do not, likely due to the smaller sample size in this category. Overall, all turnover types show higher organizational capital levels post-turnover, highlighting the potential positive impact of leadership changes on organizational capital accumulation.

Table 3.3 presents differences in CEO characteristics and compensation based on their career paths, categorizing CEOs into two sub-samples: those with a career history of increasing organizational capital ("CEOs with more organizational capital") and those with less. CEOs with more organizational capital experience tend to have higher ownership (0.132% vs. 0.111%, p<0.01) and receive greater cash compensation (1175.57 vs. 1105.22 thousand USD, p<0.01). Additionally, these CEOs exhibit significantly higher MA scores

Table 3.2: Univariate test - CEO pre-turnover vs. post-turnover
This table presents univariate tests comparing organizational capital levels in firms experiencing CEO turnover, examining the four-year periods before and after the turnover. *** p<0.01, ** p<0.05, * p<0.1. Involuntary CEO turnover is defined based on Gentry et al. (2021) dismissal codes as follows: 1 (illness), 2 (death), 3 (dismissed for job performance), and 4 (personal issue). Voluntary CEO turnover includes codes 5 (retirement) and 6 (other opportunity). Forced CEO turnover is defined by codes 3 (dismissed for job performance) and 4 (personal issue). Exogenous CEO turnover is defined by codes 1 (illness) and 2 (death). Detailed definition for all variables are available in Appendix 2

	Obs.	Non-turnover	Turnover	Difference
Panel A: All turnover				
OC1	26267	1.123	1.424	-0.301***
OC2	26267	0.920	1.152	-0.232***
Adj_OC1	26267	-0.036	0.277	-0.313***
Adj_OC2	26267	-0.011	0.241	-0.252***
Panel B: Involuntary turnover				
OC1	8235	1.317	1.842	-0.524***
OC2	8235	1.049	1.465	-0.416***
Adj_OC1	8235	0.069	0.615	-0.546***
Adj_OC2	8235	0.047	0.487	-0.440***
Panel C: Voluntary turnover				
OC1	20945	1.153	1.335	-0.182***
OC2	20945	0.950	1.090	-0.140***
Adj_OC1	20945	-0.000	0.205	-0.205***
Adj_OC2	20945	0.025	0.195	-0.170***
Panel D: Forced turnover				
OC1	7267	1.346	1.934	-0.588***
OC2	7267	1.062	1.528	-0.465***
Adj_OC1	7267	0.085	0.689	-0.604***
Adj_OC2	7267	0.050	0.533	-0.483***
Panel E: Exogenous turnover				
OC1	1091	1.110	1.224	-0.113
OC2	1091	0.934	1.048	-0.113
Adj_OC1	1091	-0.093	0.081	-0.174**
Adj_OC2	1091	-0.020	0.150	-0.171**

Table 3.3: Univariate test based on CEO career path
This table reports the univariate test for CEO characteristics based on their past work experience. "CEO with more OC" refers to CEOs for whom the number of years with increases in organizational capital exceeds the number of years with decreases over their career path, while "CEO with less OC" indicates the opposite. Detailed definition for all variables are available in Appendix 2

	N	CEO with more OC	CEO with less OC	Difference
CEO age (years)	42602	56.559	56.125	0.434***
Tenure (years)	41964	8.666	8.556	0.110
Insider (Dummy)	43733	0.857	0.858	-0.001
Ownership (%)	33046	0.132	0.111	0.021***
Total compensation (thousands)	43398	5630.703	5648.305	-17.601
Cash compensation (thousands)	43312	1175.570	1105.222	70.347***
Stock compensation (thousands)	41547	2808.327	2514.556	293.771
Delta (thousands)	41315	1306.865	970.181	336.684*
Option delta (thousands)	32234	330.837	281.424	49.414
Share delta (thousands)	40026	1069.187	779.847	289.341*
Vega (thousands)	32229	151.410	136.872	14.538***
Industry tournament incentives	34916	9.543	9.515	0.028
CEO ability (MA score)	102232	0.012	-0.007	0.019***
CEO ability rank (MA score rank)	102232	0.556	0.544	0.013***
CEO hold position in other firms	38927	0.257	0.306	-0.049***
Number of industries CEO worked	38927	1.556	1.489	0.067***
Number of firms CEO worked	38927	1.656	1.607	0.049*
Number of positions CEO held	38927	5.990	5.917	0.074*
Working experience in multi-segment firms	38927	0.854	0.851	0.003

(0.012 vs. -0.007, $p<0.01$), indicating greater managerial ability. Furthermore, CEOs with more organizational capital experience are associated with higher levels of Delta (1306.87 vs. 970.18, $p<0.10$) and Vega (151.41 vs. 136.87, $p<0.01$), which are incentive measures positively correlated with organizational capital accumulation.

Interestingly, CEO experience across multiple industries, firms, and positions is positively correlated with organizational capital accumulation, while CEOs who concurrently hold positions in other firms are less likely to focus on organizational capital development (e.g., the proportion of CEOs holding other positions is 0.257 for those with more organizational capital, compared to 0.306 for those with less, $p<0.01$). This finding underscores the link between a CEO's focus on internal firm development and organizational capital accumulation.

3.5.3 CEO ability and organization capital

This section provides empirical evidence supporting our first hypothesis, positing that CEO quality significantly impacts the stock of organizational capital. Dessein and Prat (2022) suggest that a capable CEO will prioritize long-term investments, such as organizational capital, while a less effective CEO may focus on short-term gains, potentially neglecting these strategic assets. Effective CEOs thus contribute positively to firm performance through organizational capital accumulation, whereas ineffective CEOs can have lasting adverse effects on a firm's long-term capacity.

While CEO quality is difficult to measure directly, Demerjian et al. (2013) introduce a robust proxy for managerial quality, which I adopt in our study. Table 3.4 presents the initial fixed-effects regressions between CEO ability and organizational capital. Panel A uses the MA score from Demerjian et al. (2012), while Panel B utilizes the decile rank of MA score by industry and year to test robustness. All coefficients for both MA score and MA score rank are positive and highly significant across the sixteen regressions. For example, the coefficient of MA score in model (1) for $\boldsymbol{OC}1$ is 0.751 (t-statistic = 7.28), and for $\boldsymbol{OC}2$ it is 0.565 (t-statistic = 7.62). Similarly, using MA score rank, the coefficient in model (1) for $\boldsymbol{OC}1$ is 0.360 (t-statistic = 11.75) and for $\boldsymbol{OC}2$ it is 0.290 (t-statistic = 11.54). To further validate, I use ranked versions of organizational capital measures (Rank_OC1, Rank_OC2, Rank_Adj_OC1, and Rank_Adj_OC2), and the results remain consistently positive and significant, with coefficients ranging from 0.400 to 0.632 in Panel A and from 0.213 to 0.420 in Panel B.

Table 3.5 addresses potential endogeneity by examining within-firm changes in CEO ability. This approach, similar to Baik et al. (2020), uses within-firm variation in MA score. In Panel A, the coefficient for the change in MA score in model (1) for $\boldsymbol{OC}1$ is 0.239 (t-statistic = 5.61), while in model (2) for $\boldsymbol{OC}2$ it is 0.177 (t-statistic = 6.04). Panel B reports the coefficients for changes in MA score rank, with values of 0.159 (t-statistic = 10.75) for $OC1$ and 0.119 (t-statistic = 10.82) for $OC2$. These positive and highly significant coefficients reinforce our hypothesis that CEO ability is positively associated with organizational capital accumulation.

Table 3.4: CEO ability and organizational capital

This table reports regression results of CEO ability and accumulated organizational capital. The main dependent variables are accumulated organizational capital, and the main independent variables are MA score and MA score rank. Robust t-statistics, adjusted for heteroscedasticity and clustered at the firm level, are reported in parentheses. Control variables include SIZE, ROA, MTB, TANG, LEV. The results are the same when I control CEO age, firm age, and CEO tenure. *** p<0.01, ** p<0.05, * p<0.1. Detailed definition for all variables are available in Appendix 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OC1	OC2	Adj_OC1	Adj_OC2	Rank_OC1	Rank_OC2	Rank_Adj_OC1	Rank_Adj_OC2
Panel A: MA score								
MA score	0.751***	0.565***	0.713***	0.527***	0.400***	0.339***	0.632***	0.600***
	(7.28)	(7.62)	(6.84)	(7.00)	(7.01)	(4.41)	(5.10)	(4.87)
SIZE	-0.129***	-0.100***	-0.126***	-0.098***	-0.087***	-0.087***	-0.212***	-0.205***
	(-29.38)	(-29.59)	(-28.48)	(-28.65)	(-40.13)	(-35.40)	(-46.22)	(-44.99)
ROA	-0.959***	-0.650***	-0.948***	-0.643***	-0.104***	0.098**	-0.252***	0.024
	(-12.26)	(-10.38)	(-12.21)	(-10.21)	(-2.95)	(2.28)	(-3.49)	(0.34)
MTB	0.009***	0.005**	0.010***	0.006**	0.048***	0.044***	0.108***	0.102***
	(3.10)	(2.14)	(3.42)	(2.54)	(29.90)	(23.05)	(28.53)	(27.66)
TANG	0.344**	0.243**	0.433***	0.300**	0.455***	0.390***	1.314***	1.110***
	(2.30)	(1.99)	(2.96)	(2.49)	(5.09)	(3.91)	(6.64)	(5.77)
LEV	0.012***	0.011***	0.011**	0.010**	-0.070***	-0.064***	-0.160***	-0.152***
	(2.70)	(2.81)	(2.42)	(2.48)	(-17.56)	(-14.04)	(-18.44)	(-18.10)
Observations	88,757	88,757	88,757	88,757	88,757	88,757	88,757	88,757
Adj.R^2	0.689	0.708	0.638	0.657	0.871	0.860	0.706	0.718
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panle B: MA score rank								
MA score rank	0.360***	0.290***	0.346***	0.278***	0.213***	0.210***	0.420***	0.406***
	(11.75)	(11.54)	(11.19)	(10.92)	(9.71)	(7.95)	(8.42)	(8.23)
Observations	88,757	88,757	88,757	88,757	88,757	88,757	88,757	88,757
Adj.R^2	0.689	0.709	0.638	0.657	0.871	0.860	0.707	0.719
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.5: Change in CEO ability and organization capital

This table reports regression results of change in CEO ability and accumulated organizational capital. The main dependent variables are accumulated organizational capital, and the main independent variables are change in MA score and change in MA score rank. Robust t-statistics, adjusted for heteroscedasticity and clustered at the firm level, are reported in parentheses. Control variables include SIZE, ROA, MTB, TANG, LEV. The results are the same when I control CEO age, firm age, and CEO tenure. *** p<0.01, ** p<0.05, * p<0.1. Detailed definition for all variables are available in Appendix 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OC1	OC2	Adj_OC1	Adj_OC2	Rank_OC1	Rank_OC2	Rank_Adj_OC1	Rank_Adj_OC2
Panel A: Change in MA score								
MA score	0.239***	0.177***	0.246***	0.179***	0.156***	0.112***	0.311***	0.295***
	(5.61)	(6.04)	(5.72)	(6.01)	(6.67)	(3.62)	(5.48)	(5.60)
Observations	78,032	78,032	78,032	78,032	78,032	78,032	78,032	78,032
Adj.R^2	0.720	0.736	0.674	0.690	0.874	0.863	0.728	0.739
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panle B: Change in MA score rank								
MA score rank	0.159***	0.119***	0.158***	0.118***	0.119***	0.098***	0.262***	0.242***
	(10.75)	(10.82)	(10.67)	(10.64)	(13.99)	(10.05)	(12.47)	(11.90)
Observations	78,032	78,032	78,032	78,032	78,032	78,032	78,032	78,032
Adj.R^2	0.705	0.723	0.656	0.674	0.876	0.864	0.716	0.727
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

To address concerns of selection bias and omitted variable issues, I employ the doubly robust machine learning (DDML) framework developed by Chernozhukov et al. (2017) and Knaus (2022), as well as an instrumental variable (IV) approach.

To further assess the robustness of the relation between CEO ability and organizational capital, I employ both an instrumental-variable approach and a double debiased machine learning (DDML) framework. Following Demerjian et al. (2020) and Doukas and Zhang (2021), I use industry-average MA scores and MA score ranks as instruments to generate alternative variation in CEO ability. These specifications provide a useful complementary perspective, although the exclusion restriction underlying the IV design is not directly testable and therefore does not by itself establish causal validity.

Following Demerjian et al. (2020) and Doukas and Zhang (2021), I use industry-average MA scores and MA score ranks as instruments to create exogenous variation. In the first-stage regression. In the first-stage regression, Panel A of Table 3.6 shows a strong positive correlation between the instrumental variable and the MA score. In the second-stage regressions, the coefficients on MA score and MA score rank remain positive and statistically significant. These findings are consistent with the baseline evidence that firms led by more able CEOs tend to exhibit higher organizational capital, while stopping short of claiming definitive causality.

Panel B of Table 3.6 reports DDML results using random forest, gradient boosting, and Lasso learners. Across learners, the estimated coefficients remain positive and statistically significant. I interpret these results as evidence that the documented relation is robust to more flexible functional forms and richer controls. However, DDML improves robustness and reduces model dependence; it does not, by itself, prove a causal relationship.

Table 3.6: CEO ability and organizational capital: IV and DDML analysis
Panel A presents instrumental variable (IV) model results examining the relationship between CEO ability and accumulated organizational capital. Robust t-statistics, adjusted for heteroscedasticity and clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Panel B shows Double Debiased Machine Learning (DDML) results within the IV framework, utilizing three learners: random forest, gradient boosting (GradBoost), and Lasso. Control variables include SIZE, ROA, MTB, TANG, LEV. The results are the same when I control CEO age, firm age, and CEO tenure. Detailed definition for all variables are available in Appendix 2

	(1) MA score	(2) OC1	(3) MA score	(4) OC2	(5) MA score rank	(6) OC1	(7) MA score rank	(8) OC2
Panel A: IV results								
IV_avg_score	0.820***		0.820***					
	(27.57)		(27.57)					
MA score		0.595***		0.429***				
		(3.62)		(3.03)				
IV_avg_rank					0.835***		0.835***	
					(18.51)		(18.51)	
MA score rank						1.407***		1.018***
						(3.61)		(3.10)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	88,757	88,757	88,757	88,757	88,757	88,757	88,757	88,757
F-stat	13.08		9.142		12.81		9.410	
Adj.R^2		0.198		0.183		0.197		0.181

Panle B: Double-debiased machine learning	(1) OC1	(2) OC2
Learners		
MA: Random Forest	5.516***	4.1546***
MA: Grand Boost	5.1886***	3.9896***
MA: Lasso	5.2806***	4.1636***
MA rank: Random Forest	2.6466***	2.0726***
MA rank: Grand Boost	2.5566***	1.9666***
MA rank: Lasso	2.6686***	2.1066***

3.5.4 CEO turnover and organization capital

This section examines whether organizational capital is systematically higher after CEO turnover relative to the pre-turnover path and relative to firms not experiencing turnover. The empirical evidence is broadly consistent with the view that CEO succession is associated with subsequent organizational-capital accumulation, but the interpretation of the difference-in-differences estimates remains conditional on the identifying assumptions of each design. Dessein and Prat (2022) theoretically predicts that the stock of organizational capital is influenced by endogenous CEO transitions and CEO-specific variables. However, they do not specify which CEO characteristics affect the direction of change in organizational capital following CEO turnover. According to Dessein and Prat (ibid.), CEO quality is one of the most critical characteristics that influence the stock of organizational capital. They hypothesize that the stock of organizational capital will increase if the successor CEO is effective, and decrease if the successor CEO is less competent.

Our analysis reveals a positive effect of CEO turnover on organizational capital across all turnover types, with stronger impacts in the involuntary and forced turnover subsamples. In Table 3.2, Panel B shows that involuntary turnover results in a significant increase in organizational capital, with a difference of -0.524 for $OC1$ and -0.416 for $OC2$, both significant at the 1% level. Forced turnover, as shown in Panel D, exhibits even larger increases in organizational capital, with differences of -0.588 for $OC1$ and -0.465 for $OC2$, also significant at the 1% level. In contrast, voluntary turnover (Panel C) has a smaller, though still significant, positive impact on organizational capital, with differences of -0.182 for $OC1$ and -0.140 for $OC2$.

To estimate the treatment effects of CEO turnover, I employ three methods: a TWFE model, a staggered difference-in-differences model, and a doubly robust (or heterogeneous) difference-in-differences model. Across all three models, our estimates consistently indicate that CEO turnover significantly increases the stock of organizational capital, with particularly robust results for involuntary and forced turnover. This pattern is consistent with the view that newly appointed CEOs, especially after performance-related turnover, are associated with greater post-turnover investment in organizational capital. The results affirm our hypothesis that effective CEO transitions contribute positively to organizational capital, enhancing the firm's long-term capacity for sustained performance.

3.5.4.1 TWFE estimation

Tables 3.7 and 3.8 present the TWFE estimations of the treatment effects of CEO turnover on organizational capital. Table 3.7 details the overall impact of CEO turnover, while Table 3.8 explores the effects of specific types of turnover. Specifically, Panel A in Table 3.8 addresses the impact of involuntary turnover, Panel B discusses voluntary CEO turnover, and Panel C examines forced CEO turnover. The independent variable 'post' represents the four-year period following CEO turnover.

The coefficients on *Post* are positive and statistically significant across the specifications, indicating that organizational capital is higher in the post-turnover period relative to the comparison period within the TWFE design. These estimates are consistent with Dessein and Prat (2022)'s theory that CEO transitions may affect the stock of organizational capital, although the TWFE coefficients should be interpreted in light of the standard assumptions and known limitations of two-way fixed-effects estimators under staggered treatment timing. In Table 3.7, the baseline results indicate that CEO turnover is associated with higher post-turnover organizational capital significantly across all measures, with coefficients of 0.091 for $OC1$ (t-statistic = 5.55) and 0.070 for $OC2$ (t-statistic = 5.39), both significant at the 1% level. Adjusted organizational capital measures also show positive effects, with coefficients of 0.078 for Adj_OC1 (t-statistic = 4.59) and 0.059 for Adj_OC2 (t-statistic = 4.38).

Table 3.8 further investigates the effects by turnover type. Panel A shows that involuntary turnover has a strong positive impact on organizational capital, with coefficients of 0.152 for $OC1$ (t-statistic = 3.33) and 0.135 for $OC2$ (t-statistic = 3.88), both significant at the 1% level. Adjusted measures also show strong positive effects, with Adj_OC1 and Adj_OC2 having coefficients of 0.144 (t-statistic = 3.07) and 0.128 (t-statistic = 3.60), respectively. Panel B examines voluntary turnover, showing smaller but significant impacts, with a coefficient of 0.051 for $OC1$ (t-statistic = 2.82) and 0.040 for $OC2$ (t-statistic = 2.77). Panel C reports forced turnover effects, where the coefficients are particularly high, such as 0.179 for $OC1$ (t-statistic = 3.50) and 0.162 for $OC2$ (t-statistic = 4.15), indicating that forced turnover results in the largest organizational capital increases.

Table 3.7: Baseline result - CEO turnover and organization capital
TWFE results of CEO turnover and accumulated organization capital. Robust t-statistics, adjusted for heteroscedasticity and clustered at the firm level, are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Post is dummy variable equals 1 for 4 year post-turnover period and 0 otherwise. The results are the same when I control CEO age, firm age, and CEO tenure. Control variables include SIZE, ROA, MTB, TANG, LEV. Detailed definition for all variables are available in Appendix 2

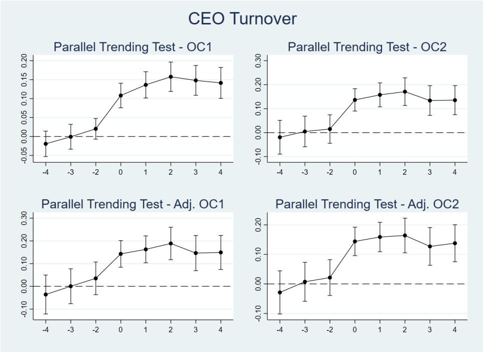
	(1) OC1	(2) OC2	(3) Adj_OC1	(4) Adj_OC2	(5) Rank_OC1	(6) Rank_OC2	(7) Rank_Adj_OC1	(8) Rank_Adj_OC2
Post (TURNOVER)	0.091***	0.070***	0.078***	0.059***	0.103***	0.099***	0.201***	0.184***
	(5.55)	(5.39)	(4.59)	(4.38)	(6.23)	(5.36)	(4.92)	(4.49)
SIZE	-0.119***	-0.092***	-0.115***	-0.089***	-0.093***	-0.094***	-0.235***	-0.226***
	(-12.96)	(-13.11)	(-12.16)	(-12.29)	(-23.56)	(-20.51)	(-25.61)	(-24.82)
ROA	-0.779***	-0.408***	-0.708***	-0.349***	-0.324***	-0.030	-0.960***	-0.561**
	(-5.57)	(-3.80)	(-5.22)	(-3.29)	(-3.66)	(-0.22)	(-4.87)	(-2.50)
MTB	0.007*	0.003	0.007*	0.003	0.000	-0.001	0.006	0.008
	(1.77)	(1.06)	(1.89)	(1.17)	(0.04)	(-0.28)	(0.73)	(1.06)
TANG	0.686***	0.621***	0.762***	0.654***	1.175***	1.029***	2.446***	2.218***
	(3.94)	(4.20)	(4.39)	(4.43)	(6.78)	(5.56)	(6.45)	(6.15)
LEV	-0.001	0.003	-0.001	0.004	0.009	0.016*	0.010	0.020
	(-0.18)	(0.55)	(-0.15)	(0.64)	(1.28)	(1.80)	(0.69)	(1.38)
Observations	26,178	26,178	26,178	26,178	26,178	26,178	26,178	26,178
Adj.R^2	0.799	0.823	0.743	0.768	0.898	0.889	0.755	0.766
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.8: Baseline result - CEO turnover and organization capital
TWFE results of CEO turnover and accumulated organization capital. Robust t-statistics, adjusted for heteroscedasticity and clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Post is dummy variable equals 1 for 4 year post-turnover period and 0 otherwise. The results are the same when I control CEO age, firm age, and CEO tenure. Detailed definition for all variables are available in Appendix 2

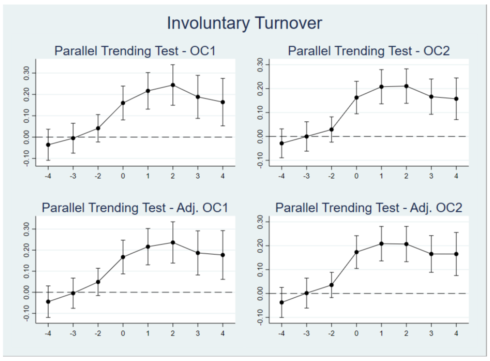
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OC1	OC2	Adj_OC1	Adj_OC2	Rank_OC1	Rank_OC2	Rank_Adj_OC1	Rank_Adj_OC2
Panel A: CEO involuntary turnover								
Post (TURNOVER)	0.152***	0.135***	0.144***	0.128***	0.132***	0.111***	0.366***	0.386***
	(3.33)	(3.88)	(3.07)	(3.60)	(4.03)	(2.99)	(4.65)	(4.95)
Observations	12,681	12,681	12,681	12,681	12,681	12,681	12,681	12,681
R^2	0.817	0.846	0.771	0.801	0.928	0.921	0.806	0.818
Adj.R^2	0.790	0.823	0.737	0.772	0.918	0.909	0.778	0.791
Panel B: CEO voluntary turnover								
Post (TURNOVER)	0.051***	0.040***	0.042**	0.032**	0.052***	0.055***	0.109**	0.084*
	(2.82)	(2.77)	(2.25)	(2.15)	(2.90)	(2.70)	(2.46)	(1.89)
Observations	22,302	22,302	22,302	22,302	22,302	22,302	22,302	22,302
R^2	0.835	0.861	0.787	0.813	0.914	0.905	0.795	0.801
Adj.R^2	0.815	0.844	0.761	0.791	0.904	0.893	0.771	0.777
Panel C: forced CEO turnover								
Post (TURNOVER)	0.179***	0.162***	0.163***	0.149***	0.134***	0.122***	0.377***	0.369***
	(3.50)	(4.15)	(3.09)	(3.72)	(3.83)	(3.08)	(4.38)	(4.34)
Observations	11,909	11,909	11,909	11,909	11,909	11,909	11,909	11,909
R^2	0.817	0.847	0.771	0.803	0.929	0.921	0.807	0.818
Adj.R^2	0.790	0.824	0.737	0.774	0.918	0.909	0.778	0.790
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Figure 3.1: Parallel trend plots.

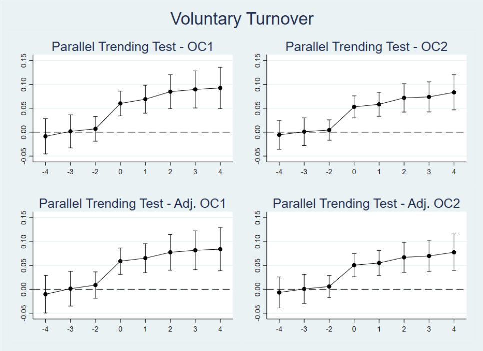
(a) CEO turnover



(b) Involuntary turnover



(c) Voluntary turnover



(d) Forced turnover

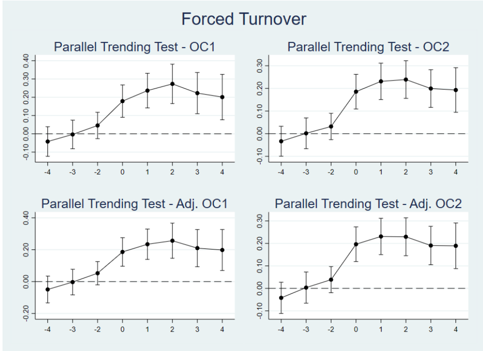


Figure 3.1 reports event-time plots associated with the TWFE specifications. The pre-turnover coefficients are generally small and mostly statistically insignificant, which is reassuring for the identifying assumptions. At the same time, these plots do not by themselves prove parallel trends, and they should be interpreted as supportive rather than definitive evidence.

3.5.4.2 Event study

Next, I employ a staggered DiD framework to trace the event-time pattern around CEO turnover. The results show that post-turnover coefficients are generally positive, whereas the pre-turnover coefficients are mostly small and statistically insignificant. This pattern is supportive of the identifying assumptions and reduces concern about strong differential pre-trends, although it does not completely rule out all sources of bias. The findings remain robust when using Sant'Anna and Zhao (2020)'s improved doubly robust DiD estimator based on inverse probability tilting and weighted least squares.

Table 3.9: Staggered DID: CEO turnover and organizational capital
This table reports staggered DID results where pre and post are dummy variables. E.g., Pre 4 equals 1 if the distance between this year and turnover year is 4 years, 0 otherwise. Robust t-statistics, adjusted for heteroscedasticity and clustered at the firm level, are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Detailed definition for all variables are available in Appendix 2

	(1) OC1	(2) OC2	(3) Adj_OC1	(4) Adj_OC2	(5) Rank_OC1	(6) Rank_OC2	(7) Rank_Adj_OC1	(8) Rank_Adj_OC2
Pre4	-0.021	-0.011	-0.028	-0.018	0.004	0.004	-0.002	-0.002
	(-1.32)	(-0.83)	(-1.60)	(-1.29)	(0.22)	(0.22)	(-0.03)	(-0.03)
Pre3	-0.002	0.006	0.001	0.006	-0.008	-0.008	0.009	0.009
	(-0.09)	(0.43)	(0.05)	(0.42)	(-0.35)	(-0.35)	(0.15)	(0.15)
Pre2	0.024	0.026*	0.028	0.026	0.028	0.028	0.060	0.060
	(1.34)	(1.66)	(1.48)	(1.59)	(1.19)	(1.19)	(1.00)	(1.00)
Pre1	0.020	0.022	0.038*	0.033*	0.039	0.039	0.093	0.093
	(1.05)	(1.30)	(1.82)	(1.83)	(1.61)	(1.61)	(1.48)	(1.48)
TURNOVER	0.051**	0.048***	0.068***	0.061***	0.056**	0.056**	0.225***	0.225***
	(2.42)	(2.60)	(3.03)	(3.18)	(2.19)	(2.19)	(3.47)	(3.47)
Post1	0.082***	0.074***	0.087***	0.076***	0.090***	0.090***	0.271***	0.271***
	(3.91)	(3.93)	(3.94)	(3.98)	(3.74)	(3.74)	(4.33)	(4.33)
Post2	0.081***	0.071***	0.079***	0.072***	0.079***	0.079***	0.182***	0.182***
	(3.72)	(3.77)	(3.52)	(3.72)	(3.32)	(3.32)	(2.91)	(2.91)
Post3	0.071***	0.064***	0.063***	0.056***	0.079***	0.079***	0.148**	0.148**
	(3.68)	(3.76)	(3.14)	(3.25)	(3.50)	(3.50)	(2.53)	(2.53)
Post4	0.066***	0.057***	0.060***	0.050***	0.068***	0.068***	0.122**	0.122**
	(3.99)	(4.01)	(3.50)	(3.39)	(3.35)	(3.35)	(2.23)	(2.23)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-trend test pass	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,110	36,110	36,110	36,110	36,110	36,110	36,110	36,110
Number of gvkey	1,596	1,596	1,596	1,596	1,596	1,596	1,596	1,596
Adj.R^2	0.247	0.239	0.216	0.215	0.436	0.436	0.149	0.149

Tables 3.9 and 3.10 present the event study results of the effects of CEO turnover on the stock of organizational capital. The dummy variables Pre1, Pre2, Pre3, and Pre4 represent the years leading up to CEO turnover, indicating one, two, three, and four years before the turnover, respectively. The variables Post1, Post2, Post3, and Post4 capture the years following CEO turnover, representing one to four years after the event. Table 3.9 summarizes the overall impact of CEO turnover, while Table 3.10 explores the effects of specific turnover types. Specifically, Panel A in Table 3.10 covers involuntary turnover, Panel B focuses on voluntary turnover, and Panel C examines forced turnover.

Table 3.10: Staggered DID: other types of CEO turnover and organizational capital
This table reports staggered DID results where pre and post are dummy variables. E.g., Pre 4 equals 1 if the distance between this year and turnover year is 4 years, 0 otherwise. Robust t-statistics, adjusted for heteroscedasticity and clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Detailed definition for all variables are available in Appendix 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OC1	OC2	Adj_OC1	Adj_OC2	Rank_OC1	Rank_OC2	Rank_Adj_OC1	Rank_Adj_OC2
Panel A: Involuntary turnover								
Pre4	-0.023	-0.009	-0.041	-0.026	-0.001	-0.001	-0.152*	-0.152*
	(-0.70)	(-0.32)	(-1.17)	(-0.89)	(-0.04)	(-0.04)	(-1.65)	(-1.65)
Pre3	-0.015	0.003	-0.012	0.003	-0.026	-0.026	-0.094	-0.094
	(-0.39)	(0.09)	(-0.31)	(0.09)	(-0.64)	(-0.64)	(-0.90)	(-0.90)
Pre2	0.038	0.044	0.056	0.056	0.030	0.030	-0.007	-0.007
	(0.87)	(1.14)	(1.26)	(1.42)	(0.77)	(0.77)	(-0.07)	(-0.07)
Pre1	0.046	0.057	0.086	0.086*	0.041	0.041	0.052	0.052
	(0.86)	(1.26)	(1.60)	(1.84)	(0.98)	(0.98)	(0.48)	(0.48)
Turnover	0.084	0.087*	0.110*	0.113**	0.077*	0.077*	0.213*	0.213*
	(1.41)	(1.73)	(1.82)	(2.16)	(1.71)	(1.71)	(1.84)	(1.84)
Post1	0.129**	0.126**	0.136**	0.129**	0.117**	0.117**	0.319***	0.319***
	(2.27)	(2.52)	(2.42)	(2.57)	(2.56)	(2.56)	(2.71)	(2.71)
Post2	0.167***	0.148***	0.172***	0.151***	0.090*	0.090*	0.272**	0.272**
	(3.06)	(3.16)	(3.16)	(3.20)	(1.88)	(1.88)	(2.24)	(2.24)
Post3	0.133***	0.111***	0.140***	0.114***	0.126***	0.126***	0.313***	0.313***

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Table 3.10 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OC1	OC2	Adj_OC1	Adj_OC2	Rank_OC1	Rank_OC2	Rank_Adj_OC1	Rank_Adj_OC2
	(2.90)	(2.87)	(3.05)	(2.92)	(2.68)	(2.68)	(2.59)	(2.59)
Post4	0.104***	0.086***	0.123***	0.096***	0.103**	0.103**	0.308***	0.308***
	(2.71)	(2.75)	(3.22)	(3.03)	(2.29)	(2.29)	(2.71)	(2.71)
Observations	12,469	12,469	12,469	12,469	12,469	12,469	12,469	12,469
Number of gvkey	566	566	566	566	566	566	566	566
Adj.R^2	0.260	0.247	0.230	0.228	0.469	0.469	0.146	0.146
Panel B: Voluntary turnover								
Pre4	-0.028*	-0.020	-0.028	-0.022	0.001	0.001	0.051	0.051
	(-1.67)	(-1.41)	(-1.48)	(-1.41)	(0.03)	(0.03)	(0.87)	(0.87)
Pre3	-0.002	0.001	0.002	0.002	-0.003	-0.003	0.043	0.043
	(-0.09)	(0.06)	(0.08)	(0.10)	(-0.12)	(-0.12)	(0.64)	(0.64)
Pre2	0.015	0.012	0.013	0.008	0.027	0.027	0.083	0.083
	(0.74)	(0.77)	(0.61)	(0.47)	(1.01)	(1.01)	(1.22)	(1.22)
Pre1	0.006	0.003	0.014	0.007	0.039	0.039	0.100	0.100
	(0.28)	(0.17)	(0.62)	(0.36)	(1.42)	(1.42)	(1.44)	(1.44)
Turnover	0.030	0.024	0.041*	0.031*	0.045	0.045	0.215***	0.215***
	(1.47)	(1.43)	(1.83)	(1.72)	(1.59)	(1.59)	(3.10)	(3.10)
Post1	0.054***	0.044***	0.056**	0.045**	0.070***	0.070***	0.228***	0.228***

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Table 3.10 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OC1	OC2	Adj_OC1	Adj_OC2	Rank_OC1	Rank_OC2	Rank_Adj_OC1	Rank_Adj_OC2
	(2.69)	(2.62)	(2.54)	(2.53)	(2.71)	(2.71)	(3.42)	(3.42)
Post2	0.039**	0.034**	0.035*	0.033*	0.064**	0.064**	0.128*	0.128*
	(1.99)	(2.05)	(1.66)	(1.90)	(2.49)	(2.49)	(1.94)	(1.94)
Post3	0.041**	0.039**	0.029	0.029*	0.056**	0.056**	0.080	0.080
	(2.19)	(2.46)	(1.43)	(1.71)	(2.41)	(2.41)	(1.31)	(1.31)
Post4	0.048***	0.043***	0.037**	0.032**	0.052**	0.052**	0.062	0.062
	(2.85)	(3.08)	(2.01)	(2.13)	(2.43)	(2.43)	(1.06)	(1.06)
Observations	25,719	25,719	25,719	25,719	25,719	25,719	25,719	25,719
Number of gvkey	1,153	1,153	1,153	1,153	1,153	1,153	1,153	1,153
Adj.R^2	0.249	0.232	0.217	0.208	0.438	0.438	0.145	0.145
Panel C: Forced turnover								
Pre4	-0.027	-0.010	-0.039	-0.025	0.023	0.023	-0.075	-0.075
	(-0.74)	(-0.34)	(-0.99)	(-0.78)	(0.60)	(0.60)	(-0.71)	(-0.71)
Pre3	-0.011	0.008	-0.005	0.010	-0.003	-0.003	-0.019	-0.019
	(-0.25)	(0.23)	(-0.11)	(0.27)	(-0.07)	(-0.07)	(-0.16)	(-0.16)
Pre2	0.041	0.046	0.065	0.063	0.044	0.044	0.054	0.054
	(0.84)	(1.10)	(1.29)	(1.43)	(0.99)	(0.99)	(0.45)	(0.45)
Pre1	0.053	0.065	0.097	0.098*	0.047	0.047	0.127	0.127

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Table 3.10 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OC1	OC2	Adj_OC1	Adj_OC2	Rank_OC1	Rank_OC2	Rank_Adj_OC1	Rank_Adj_OC2
	(0.86)	(1.27)	(1.58)	(1.86)	(1.01)	(1.01)	(1.00)	(1.00)
Turnover	0.096	0.098*	0.124*	0.127**	0.081	0.081	0.268**	0.268**
	(1.37)	(1.67)	(1.74)	(2.06)	(1.57)	(1.57)	(2.00)	(2.00)
Post1	0.147**	0.141**	0.158**	0.146**	0.139***	0.139***	0.365***	0.365***
	(2.24)	(2.46)	(2.40)	(2.51)	(2.60)	(2.60)	(2.70)	(2.70)
Post2	0.189***	0.165***	0.195***	0.169***	0.090	0.090	0.363***	0.363***
	(2.98)	(3.02)	(3.04)	(3.03)	(1.59)	(1.59)	(2.67)	(2.67)
Post3	0.148***	0.120***	0.151***	0.119***	0.117**	0.117**	0.344**	0.344**
	(2.83)	(2.69)	(2.84)	(2.62)	(2.14)	(2.14)	(2.53)	(2.53)
Post4	0.109**	0.084**	0.119***	0.086**	0.088*	0.088*	0.292**	0.292**
	(2.45)	(2.32)	(2.65)	(2.30)	(1.65)	(1.65)	(2.24)	(2.24)
Observations	10,991	10,991	10,991	10,991	10,991	10,991	10,991	10,991
Number of gvkey	502	502	502	502	502	502	502	502
Adj.R^2	0.266	0.251	0.237	0.232	0.462	0.462	0.151	0.151
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

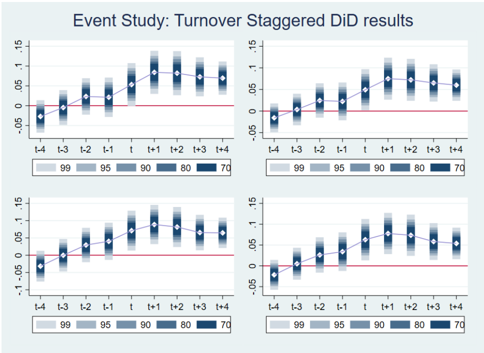
In Tables 3.9 and 3.10, the coefficients for *Pre4* through *Pre1* are generally small and mostly statistically insignificant. This pattern is consistent with the absence of strong pre-turnover differences, though it should be interpreted as suggestive rather than conclusive evidence on parallel trends. In contrast, the coefficients for Post1 through Post4 are statistically significant and positive. For example, in Table 3.9, the coefficient for Post1 in model (1) for $OC1$ is 0.082 (t-statistic = 3.91) and for $OC2$ is 0.074 (t-statistic = 3.93), both significant at the 1% level. This positive effect persists over time, with Post4 showing coefficients of 0.066 (t-statistic = 3.99) for $OC1$ and 0.057 (t-statistic = 4.01) for $OC2$.

Table 3.10 further explores these effects by turnover type. Panel A shows that for involuntary turnover, the Post1 coefficient for $OC1$ is 0.129 (t-statistic = 2.27) and 0.126 (t-statistic = 2.52) for $OC2$. The effects continue positively in subsequent years, with Post4 showing 0.104 (t-statistic = 2.71) for $OC1$ and 0.086 (t-statistic = 2.75) for $OC2$. Panel B, focusing on voluntary turnover, also reveals significant positive post-turnover effects, although smaller, with Post1 for $OC1$ at 0.054 (t-statistic = 2.69). Forced turnovers in Panel C exhibit the highest post-turnover coefficients, with Post1 showing 0.147 (t-statistic = 2.24) for $OC1$ and 0.141 (t-statistic = 2.46) for $OC2$, indicating a robust increase in organizational capital following forced turnover.

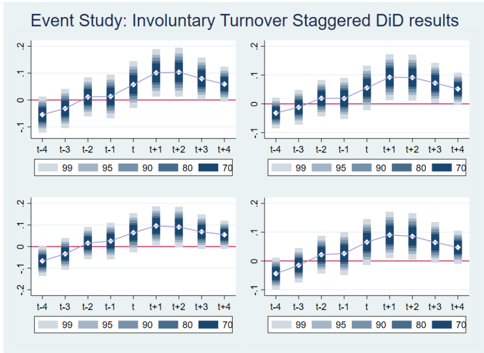
The results align with our TWFE findings, demonstrating significant positive treatment effects post-turnover. Figure 3.2 displays event study plots for the staggered DiD results from Tables 3.9 and 3.10, illustrating a consistent positive trend in the stock of organizational capital post-turnover across all turnover types.

Figure 3.2: Event study plots - staggered DiD results.

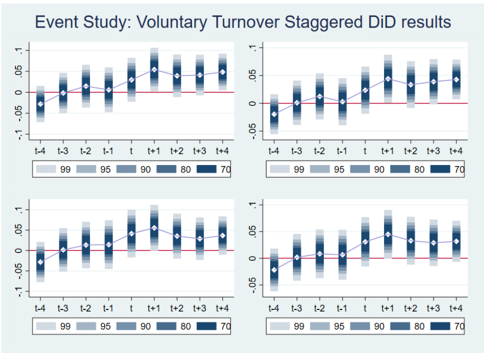
(a) CEO turnover



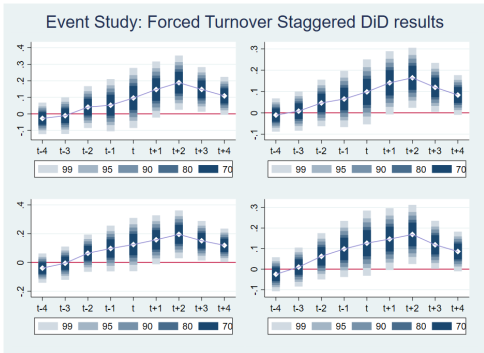
(b) Involuntary turnover



(c) Voluntary turnover



(d) Forced turnover



3.5.4.3 Callaway and Sant'Anna's (2020) doubly robust estimation

Finally, I report doubly robust DiD estimates to address concerns related to staggered timing and treatment-effect heterogeneity. These estimators improve upon conventional TWFE designs under weaker assumptions, but they do not remove the need for careful interpretation. In particular, they still rely on assumptions about the evolution of untreated potential outcomes and the adequacy of the comparison group. [14] Table 3.11 presents the doubly robust DiD estimation results, indicating a positive and statistically significant post-turnover average treatment effect on organizational capital.

14. Recent studies suggest that staggered DiD estimates may be biased in such contexts. The improved doubly robust DiD estimator, based on inverse probability tilting and weighted least squares, offers a promising solution (Sant'Anna and Zhao 2020).

Table 3.11: Doubly robust DiD estimators
This table reports the doubly robust DiD estimators. Robust t-statistics, adjusted for heteroscedasticity and clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Detailed definition for all variables are available in Appendix 2

	(1) OC1	(2) OC2	(3) Adj. OC1	(4) Adj. OC2
Panel A: CEO turnover				
Pre_avg	-0.00234	0.000642	0.00144	0.00412
	(-0.23)	(0.08)	(0.14)	(0.49)
Post_avg	0.0781***	0.0584***	0.0798***	0.0615***
	(3.57)	(3.29)	(3.55)	(3.37)
Observations	36,110	36,110	36,110	36,110
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Panel B: Involuntary CEO turnover				
Pre_avg	0.0203	0.0178*	0.0224*	0.0181
	(1.88)	(2.07)	(1.97)	(1.94)
Post_avg	0.278***	0.232***	0.264***	0.219***
	(6.58)	(6.57)	(6.17)	(6.06)
Observations	12,469	12,469	12,469	12,469
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Panel C: Voluntray CEO turnover				
Pre_avg	-0.00387	-0.00403	-0.000921	-0.00158
	(-0.43)	(-0.57)	(-0.10)	(-0.21)
Post_avg	0.0431*	0.0350	0.0379	0.0324
	(1.99)	(1.96)	(1.69)	(1.74)
Observations	25,719	25,719	25,719	25,719
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Panel D: Forced CEO turnover				
Pre_avg	0.0214	0.0180*	0.0254*	0.0200*
	(1.89)	(1.98)	(2.13)	(2.03)
Post_avg	0.330***	0.275***	0.312***	0.260***
	(6.97)	(6.96)	(6.50)	(6.48)
Observations	10,991	10,991	10,991	10,991
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel A of Table 3.11 shows positive and statistically significant post-turnover average treatment effects for the full turnover sample, which is consistent with the baseline findings. For involuntary and forced turnover, the estimated post effects are even larger. However, the corresponding pre-period averages in some subsamples are marginally significant, suggesting that the causal interpretation should be more cautious in these cases. I therefore interpret the doubly robust DiD results as strengthening the evidence that CEO turnover is associated with higher post-turnover organizational capital, while recognizing that they do not eliminate all identification concerns.

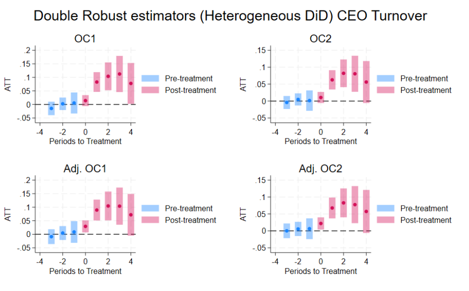
Examining specific turnover types, Panel B reports the effect of involuntary CEO turnover. The post-turnover average treatment effect is notably higher, with a value of 0.278 (t-statistic = 6.58) for OC1 and 0.232 (t-statistic = 6.57) for OC2, showing a pronounced impact on organizational capital. Panel D reveals a similar trend for forced turnover, where the post-turnover average treatment effect reaches 0.330 (t-statistic = 6.97) for OC1 and 0.275 (t-statistic = 6.96) for OC2, again highly significant.

In contrast, Panel C shows that the effect of voluntary turnover is weaker, with a post average treatment effect of 0.0431 (t-statistic = 1.99) for OC1, significant at the 10% level, but other measures remain insignificant, suggesting a less clear impact on organizational capital in cases of voluntary CEO turnover.

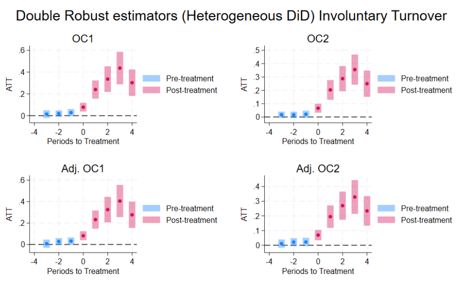
Regarding pre-turnover effects, the Pre_avg coefficients for involuntary and forced turnovers in Panels B and D show marginally significant pre-event trends, with values such as 0.0203 (t-statistic = 1.88) in Panel B for OC1 and 0.0214 (t-statistic = 1.89) in Panel D, indicating slight upward trends before turnover events. However, the overall turnover in panel A and voluntary turnover results in Panel C show no significant pre-turnover effect, with coefficients close to zero.

Figure 3.3: Event study plots - Doubly robust (Heterogeneous) DID estimators.

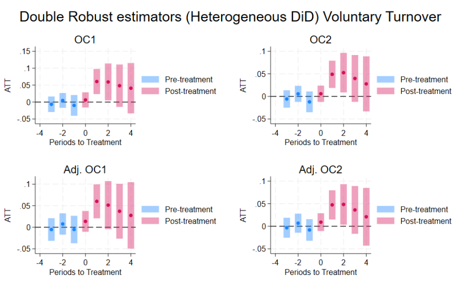
(a) CEO turnover



(b) Involuntary turnover



(c) Voluntary turnover



(d) Forced turnover

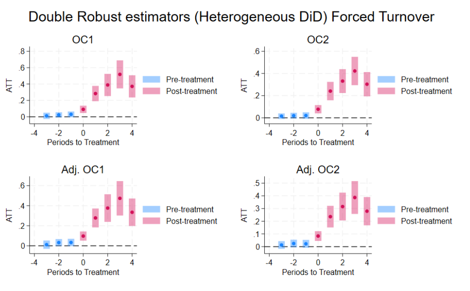


Figure 3.3 illustrates the event study plots for Table 3.11, highlighting that the pre-event period coefficients are close to zero and statistically insignificant, while the post-event period coefficients remain significantly above zero. The plots in Figure 3.3 visually reinforce the broader empirical pattern that post-turnover coefficients are generally above zero. They are consistent with the view that CEO turnover-particularly involuntary and forced turnover-is associated with higher subsequent organizational capital, while still leaving the interpretation conditional on the validity of the DiD assumptions.

3.6 Heterogeneity in the post-turnover organizational capital response

This section examines whether the post-turnover association with organizational capital is stronger for certain types of successor CEOs. Specifically, I study heterogeneity along three dimensions: (i) CEO ability and background, (ii) compensation incentives-both relative compensation and performance-based incentives, and (iii) CEO origin (insider versus outsider). These tests are motivated by theories predicting that some CEOs are more likely than others to invest in long-horizon organizational capabilities after taking office.

Importantly, these analyses do not directly observe the internal organizational actions through which such changes may occur. The data do not contain direct measures of hiring and training reforms, the adoption of management systems, or the redesign of internal processes. Therefore, the results in this section should be interpreted as indirect evidence consistent with particular mechanisms, rather than as definitive demonstrations of the mechanisms themselves. Moreover, the interaction estimates in this section capture average differences in the post-turnover organizational-capital response across types of successor CEOs. They should not be interpreted as evidence that individual CEOs consciously chose a particular strategy or deliberately reallocated resources in a specific way. Rather, the results indicate that the average organizational-capital response following turnover differs systematically with observable CEO characteristics.

3.6.1 CEO ability and CEO turnover

Table 3.12 presents the results from the interaction terms between CEO turnover and CEO ability, as well as CEO turnover and outsider CEOs. Columns (1) to (4) report the regression outcomes for the interaction between post-turnover and CEO ability, while columns (5) to (8) focus on the interaction between post-turnover and outsider CEOs.

In columns (1) to (4), the coefficients of the interaction terms between post-turnover and CEO ability are highly significant and positive across all specifications. For instance, the coefficient in column (1) is 0.516 (t = 4.52), and in column (3), it is 0.493 (t = 4.09). These positive interaction effects indicate that the post-turnover increase in organizational capital is more pronounced when the successor CEO has higher managerial ability. This pattern is consistent with Dessein and Prat (2022)'s prediction that capable CEOs place greater weight on long-term capability building and are more likely to invest in organizational capital after taking office. This suggests that CEOs with higher managerial ability are more inclined to make substantial investments in organizational capital, aligning with our initial findings and this pattern is consistent with theories (ibid.) predicting that higher-ability CEOs are associated with greater long-horizon capability building.

This pattern is consistent with theories predicting that higher-ability CEOs are associated with greater long-horizon capability building.

Columns (5) to (8) examine the interaction term between post-turnover and outsider CEOs. The results show that the interaction is positive and statistically significant when using OC1 and Adj. OC1 as dependent variables (column (5): 0.137, t = 2.87; column (7): 0.121, t = 2.41). The positive interaction terms for outsider CEOs suggest that the average post-turnover increase in organizational capital is larger when the successor is hired from outside the firm. This pattern is consistent with the view that outsider succession is associated with greater organizational change, but the estimates do not directly identify whether outsider CEOs intentionally implemented specific reforms. However, the interaction terms in columns (6) and (8) (OC2 and Adj. OC2 as dependent variables) are not statistically significant, suggesting that the effect of outsider CEOs on organizational capital may vary depending on the measures of organizational capital.

Overall, the results suggest that the positive post-turnover association with organizational capital is concentrated among firms led by higher-ability CEOs and, to a lesser extent, outsider CEOs. These findings are consistent with the view that some successor CEOs are more likely than others to undertake long-horizon organizational investments after turnover. At the same time, because the chapter does not directly observe the underlying organizational actions, I interpret these estimates as heterogeneity evidence on when CEO turnover is most strongly associated with organizational capital accumulation, rather than as direct proof that ability or outsider status operates through a specific organizational reform channel.

Table 3.12: Channel Analysis: CEO turnover and CEO ability
This table reports the interaction term results of TWFE model between CEO turnover and CEO ability. Robust t-statistics, adjusted for heteroscedasticity and clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Detailed definition for all variables are available in Appendix 2

	(1) OC1	(2) OC2	(3) Adj_OC1	(4) Adj_OC2	(5) OC1	(6) OC2	(7) Adj_OC1	(8) Adj_OC2
Post	0.108***	0.083***	0.093***	0.070***	0.088***	0.072***	0.076***	0.063***
	(7.33)	(6.69)	(6.03)	(5.44)	(5.23)	(5.07)	(4.36)	(4.33)
Outsiders					-0.123***	-0.064*	-0.119***	-0.053
					(-2.90)	(-1.83)	(-2.68)	(-1.46)
MA score	-0.110	-0.024	-0.069	-0.026				
	(-0.93)	(-0.23)	(-0.58)	(-0.25)				
Post*MA score	0.516***	0.331***	0.493***	0.330***				
	(4.52)	(3.51)	(4.09)	(3.28)				
Post*Outsiders					0.137***	0.062	0.121**	0.043
					(2.87)	(1.54)	(2.41)	(1.03)
Observations	19,479	19,479	19,479	19,479	19,637	19,637	19,637	19,637
Adj.R^2	0.826	0.837	0.775	0.787	0.823	0.836	0.772	0.785
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

3.6.2 Expensive CEO and CEO turnover

Table 3.13 presents the interaction term results from the TWFE model, examining the relationship between CEO turnover and CEO industry tournament incentives. Here, "Indgap1" represents the industry tournament incentives, while "Indgap2" refers to the industry-adjusted incentives, accounting for high and low sales companies.

The coefficients for the interaction term "Post*Indgap1" are consistently positive and statistically significant across the first four columns: 0.026 (t = 4.51) in Column (1), 0.016 (t = 3.17) in Column (2), 0.024 (t = 3.64) in Column (3), and 0.015 (t = 2.55) in Column (4). Similarly, for "Post*Indgap2," positive and significant coefficients appear in Columns (5) through (8), with values of 0.026 (t = 4.81) in Column (5), 0.016 (t = 3.45) in Column (6), 0.024 (t = 3.84) in Column (7), and 0.015 (t = 2.71) in Column (8). These findings suggest that following CEO turnover, CEOs with higher tournament incentives tend to make greater investments, as indicated by the positive interaction coefficients.

Additionally, the coefficients for "Indgap1" and "Indgap2" alone are significant and negative across various specifications. For instance, "Indgap2" shows a significant effect in Columns (1) through (4), with a coefficient of -0.027 (t = -4.87) in Column (1) and -0.018 (t = -3.66) in Column (2). These negative coefficients imply that, independently, higher industry tournament incentives are associated with reduced organizational capital investment. However, the positive interaction terms indicate that this trend reverses in the post-turnover period, particularly for expensive CEOs incentivized by tournament structures.

The findings in Table 3.13 suggest that the post-turnover increase in organizational capital is stronger when successor CEOs face steeper industry-relative compensation incentives. These patterns are consistent with the idea that relative pay reflects either stronger talent selection or stronger incentives to invest in long-horizon organizational assets after turnover. The positive and significant interaction terms for "Post*Indgap1" and "Post*Indgap2" reveal that expensive CEOs, as indicated by higher industry tournament incentives, are indeed more inclined to invest in organizational capital following turnover. This behavior aligns with Dessein and Prat's (2022) theoretical model, which suggests that CEOs motivated by long-term incentives are associated with the accumulation of intangible assets, such as organizational capital. The negative coefficients for "Indgap1" and "Indgap2" alone suggest that, in general, high tournament incentives are associated with reduced organizational capital investment. However, the results indicate that the average post-turnover increase in organizational capital is stronger among firms led by CEOs with steeper industry-relative compensation. This pattern is consistent with stronger long-horizon incentives or talent-related selection, but it should not be interpreted as direct evidence that individual CEOs consciously shifted their focus toward organizational capital. These results, therefore, provide empirical support for Dessein and Prat's (2022) predictions, reinforcing the idea that leadership transitions amplify the effects of CEO incentives on organizational capital investment, particularly when the CEO is classified as expensive. This evidence is consistent with incentive-alignment theories, but it does not reveal the subjective intentions of individual CEOs.

Taken together, the results in Table 3.13 indicate that the post-turnover organizational-capital response is stronger among firms led by CEOs with higher industry-relative compensation. This evidence is consistent with theoretical arguments that compensation structures may proxy for managerial quality, selection, or long-horizon incentives. However, these results do not directly show how such CEOs build organizational capital in practice. I therefore interpret the interaction terms as indirect evidence that the turnover–organizational-capital relation is stronger in settings with higher-powered CEO incentive structures, rather than as direct proof of the exact mechanism.

Table 3.13: Channel Analysis: CEO turnover and expensive CEO

This table reports the interaction term results of TWFE model between CEO turnover and CEO industry tournament incentives. Robust t-statistics, adjusted for heteroscedasticity and clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Detailed definition for all variables are available in Appendix 2

	(1) OC1	(2) OC2	(3) Adj_OC1	(4) Adj_OC2	(5) OC1	(6) OC2	(7) Adj_OC1	(8) Adj_OC2
Post	-0.135**	-0.070	-0.133**	-0.075	-0.131***	-0.070	-0.127**	-0.071
	(-2.53)	(-1.48)	(-2.14)	(-1.32)	(-2.67)	(-1.60)	(-2.21)	(-1.38)
Indgap1					-0.020***	-0.013***	-0.015***	-0.009*
					(-4.28)	(-3.06)	(-2.80)	(-1.77)
Indgap2	-0.027***	-0.018***	-0.020***	-0.012**				
	(-4.87)	(-3.66)	(-3.27)	(-2.18)				
Post*Indgap1	0.026***	0.016***	0.024***	0.015**				
	(4.51)	(3.17)	(3.64)	(2.55)				
Post*Indgap2					0.026***	0.016***	0.024***	0.015***
					(4.81)	(3.45)	(3.84)	(2.71)
Observations	19,131	19,131	19,131	19,131	19,028	19,028	19,028	19,028
Adj.R^2	0.824	0.837	0.773	0.787	0.824	0.837	0.774	0.787
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

3.6.3 CEO performance incentives and CEO turnover

Table 3.14 reports the interaction term results of CEO turnover and CEO ownership incentives. The coefficients for the interaction term “Post*Stocks” are consistently positive and statistically significant across the first four columns: 0.026 (t = 2.92) in Column (1), 0.023 (t = 2.81) in Column (2), 0.029 (t = 3.10) in Column (3), and 0.024 (t = 2.91) in Column (4). The positive interaction terms suggest that the post-turnover increase in organizational capital is stronger when successor CEOs have greater stock-based incentives or ownership stakes.

Additionally, the interaction terms between “Post” and “Ownership” are positive and statistically significant in Columns (5) through (8): 0.339 (t = 1.73) in Column (5), 0.323 (t = 2.01) in Column (6), 0.393 (t = 1.97) in Column (7), and 0.360 (t = 2.20) in Column (8). These findings suggest that CEOs with higher ownership stakes are more likely to increase investments in organizational capital after a turnover event.

The findings in Table 3.14 are consistent with the idea that incentive alignment matters for post-turnover organizational-capital accumulation. Specifically, the positive interaction terms for *Post*Stocks* and *Post*Ownership* suggest that CEOs with stronger equity-based incentives are more likely to be associated with higher organizational capital after taking office.

Taken together, these results indicate that the positive association between CEO turnover and organizational capital is stronger when successor CEOs have greater stock compensation and ownership incentives. This pattern is consistent with long-horizon incentive alignment. At the same time, the analysis does not directly observe the internal changes through which these incentives operate. Accordingly, I interpret these results as indirect evidence that incentive alignment is associated with stronger post-turnover organizational-capital accumulation, rather than as direct evidence on the specific underlying mechanism.

Table 3.14: Channel Analysis: CEO turnover and ownership

This table reports the interaction term results of TWFE model between CEO turnover and CEO ownership. Robust t-statistics, adjusted for heteroscedasticity and clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Detailed definition for all variables are available in Appendix 2

	(1) OC1	(2) OC2	(3) Adj_OC1	(4) Adj_OC2	(5) OC1	(6) OC2	(7) Adj_OC1	(8) Adj_OC2
Post	-0.044	-0.052	-0.071	-0.071	0.103***	0.067***	0.086***	0.054***
	(-0.83)	(-1.10)	(-1.30)	(-1.47)	(4.65)	(3.61)	(3.71)	(2.76)
Stocks	-0.024**	-0.022***	-0.027***	-0.024***				
	(-2.52)	(-2.65)	(-2.79)	(-2.89)				
Ownership					0.006	-0.028	-0.042	-0.078
					(0.07)	(-0.35)	(-0.47)	(-0.94)
Post*Stocks	0.026***	0.023***	0.029***	0.024***				
	(2.92)	(2.81)	(3.10)	(2.91)				
Post*Ownership					0.339*	0.323**	0.393**	0.360**
					(1.73)	(2.01)	(1.97)	(2.20)
Observations	18,539	18,539	18,539	18,539	12,809	12,809	12,809	12,809
Adj.R^2	0.826	0.839	0.775	0.789	0.838	0.843	0.797	0.801
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

3.7 Implications

This study has implications for both academic research and corporate governance practice. The evidence suggests that CEO turnover is often followed by meaningful changes in organizational capital, especially when the successor CEO has stronger measured ability or longer-horizon incentives. These patterns do not establish definitive causality, but they indicate that leadership transitions are closely related to changes in intangible capability accumulation and therefore deserve attention from boards, investors, and researchers. Primarily, our findings suggest that CEO turnover is often followed by higher organizational-capital accumulation, especially when the successor CEO appears to have stronger ability or longer-horizon incentives. This reinforces the notion that leadership changes are often followed by meaningful shifts in organizational capital, suggesting that CEO succession can coincide with important changes in intangible capability accumulation, which are crucial for long-term corporate performance.

From a managerial perspective, this research underscores the role of executive characteristics, particularly CEO ability and compensation structures, in shaping organizational outcomes. Companies could consider these insights when structuring CEO incentive programs, as higher compensation levels are associated with increased investments in organizational capital, suggesting that rewarding long-term performance can align executive actions with sustained corporate value creation. Moreover, the results indicate that both internal and external stakeholders, such as boards of directors and investors, should closely monitor CEO transitions, especially in cases of forced or performance-related turnover, as these scenarios tend to yield more substantial positive shifts in organizational capital.

For policy makers and regulatory bodies, these findings emphasize the need to incorporate executive quality and turnover dynamics into broader corporate governance frameworks. Given that CEO changes can influence intangible assets that impact firm value, policies that encourage transparency in executive transitions and succession planning may aid in promoting sustainable corporate growth and investor confidence.

Lastly, this study fills a critical gap in the organizational capital literature by providing empirical support for the theoretical models linking CEO characteristics and organizational capital. Future research could build on these insights by exploring the nuanced effects of various compensation structures and examining how different types of organizational capital respond to leadership changes across diverse industry contexts.

3.8 Conclusion

This paper investigates the determinants of organizational capital, with particular emphasis on CEO-related factors. Using multiple empirical frameworks, I find that CEO ability and CEO turnover are robustly associated with higher organizational capital accumulation. In the main specifications, CEO turnover is followed by an approximately 15% increase in organizational capital, with especially pronounced patterns in involuntary and forced turnover settings. involuntary and forced turnover settings.

Further analysis highlights important heterogeneity in the post-turnover organizational-capital response. In particular, the positive association between CEO turnover and organizational capital is stronger when successor CEOs have higher measured ability, steeper industry-relative compensation, and stronger equity-based incentives. The post-turnover increase in organizational capital is substantially larger, on average, when successor CEOs have higher measured ability. This finding supports theoretical predictions emphasizing managerial talent as central to long-term strategic investments. Additionally, the average post-turnover organizational-capital response is stronger when successor CEOs have higher industry-relative compensation incentives. Moreover, firms with successor CEOs holding greater stock awards and ownership stakes exhibit larger post-turnover increases in organizational capital on average.

My study contributes empirical evidence to the literature on organizational capital determinants by integrating management turnover events and CEO characteristics into a unified analytical framework. By employing multiple methodological approaches, including fixed-effects regressions, difference-in-differences models, and doubly robust machine learning techniques, I address potential endogeneity and omitted variable biases. Taken together, the findings provide consistent empirical support for recent theoretical insights linking CEO transitions and managerial quality with organizational capital accumulation.

This paper also offers valuable practical implications for corporate governance and managerial incentive design. Companies and boards of directors are advised to strategically manage CEO transitions by placing particular emphasis on recruiting high-quality successors with robust incentive structures. Given the significant impact of CEO ability and compensation on organizational capital, these factors should be carefully considered in CEO selection processes and succession planning to ensure sustained corporate growth.

An important limitation of this chapter is that the evidence on mechanisms is indirect. Although the results show that the post-turnover increase in organizational capital is stronger for higher-ability CEOs, outsider CEOs, and CEOs with stronger incentives, the chapter does not directly observe the internal organizational actions through which such changes occur. In particular, I do not observe changes in hiring and training practices, the adoption of new management systems, the redesign of internal processes, or cultural and structural reforms. Therefore, the interaction results should be interpreted as heterogeneity evidence consistent with theoretical channels, rather than as definitive proof of specific mechanisms. Moreover, another important limitation of the chapter is that the difference-in-differences estimates are assumption-dependent and should not be overinterpreted. Although the event-study evidence is broadly reassuring and the staggered and doubly robust DiD specifications strengthen the empirical case, these approaches do not by themselves prove causality in a mechanical sense. In particular, the interpretation still depends on the plausibility of parallel counterfactual trends and the absence of other contemporaneous shocks around turnover events. Accordingly, I interpret the DiD results as strong evidence consistent with a causal effect of CEO turnover on organizational capital, rather than as definitive proof in every subsample and specification.

A final limitation is that the empirical approaches used in this chapter strengthen reliability and robustness more than they establish strict causal validity. The difference-in-differences, instrumental-variable, and machine-learning-based analyses all depend on assumptions that cannot be fully verified in the data. As a result, the chapter does not claim to prove a causal relationship between CEO turnover, CEO ability, and organizational capital. Instead, I interpret the evidence more conservatively as showing robust, theory-consistent, and economically meaningful associations that remain stable across a wide range of empirical specifications.

My study contributes empirical evidence to the literature on organizational-capital determinants by integrating CEO turnover events and CEO characteristics into a unified analytical framework. By employing multiple empirical approaches, including firm fixed-effects regressions, staggered difference-in-differences models, and doubly robust estimators, the chapter documents a robust positive association between CEO turnover and subsequent organizational-capital accumulation, especially in involuntary and forced turnover settings.

Overall, the evidence suggests that CEO turnover is associated with greater organizational-capital accumulation and that this association is stronger when successor CEOs appear better equipped or better incentivized to undertake long-horizon investments. These findings enrich our understanding of how leadership transitions relate to intangible capability building, while also clarifying that the precise organizational mechanisms remain a topic for future direct investigation.

Chapter 4

Managerial Overconfidence and Pay-for-Luck

4.1 Introduction

"It is not compensation that is in the interest of shareholders in any way" (Andreani et al. 2025)

Executive compensation remains a central topic in corporate finance, particularly concerning whether change in CEO pay is aligned with firm performance or reflects managerial influence over the pay-setting process. Traditional agency theory posits that compensation contracts are designed to align executive incentives with shareholder interests (Holmström 1979). However, the rent-extraction view suggests that powerful CEOs can influence their own pay structures, extracting undue compensation beyond their firm-specific contributions (Bertrand and Mullainathan 2001). A key manifestation of this is the phenomenon of pay-for-luck, where CEOs receive compensation increases due to favorable external market conditions rather than their own skill.

Empirical studies document substantial evidence of pay-for-luck in executive compensation. Bertrand and Mullainathan (2001) find that CEOs in the oil and gas industry receive higher pay when oil prices rise, even though they exert little control over commodity markets. Similarly, Garvey and Milbourn (2006) show that CEO compensation structures reward executives for industry-wide booms but do not penalize them symmetrically for downturns. More recently, Andreani et al. (2025) exploit the U.S. Tax Cuts and Jobs Act (TCJA) of 2017 as an exogenous event and find that weakly monitored CEOs secured significant pay raises following tax windfalls but were not penalized for corresponding tax losses. These findings challenge the notion that executive compensation contracts are purely incentive-driven and raise concerns that pay-for-luck may reflect inefficient rent-seeking behavior.

Despite extensive research on pay-for-luck, relatively little is known about the individual-level determinants that shape its magnitude. Specifically, why do some CEOs receive greater pay-for-luck than others? One potential explanation lies in CEO overconfidence, a behavioral trait that affects risk-taking, corporate decision-making, and executive compensation (Malmendier and Tate 2005a, 2008; Humphery-Jenner et al. 2016). Overconfident CEOs tend to attribute good firm outcomes to their own ability while blaming negative outcomes on external factors—a cognitive bias known as self-attribution bias (Kim 2013; Billett and Qian 2008). This bias may lead them to demand higher compensation increases when performance is boosted by luck while resisting pay cuts when market conditions deteriorate.

This paper examines whether CEO overconfidence amplifies the pay-for-luck phenomenon in executive compensation. We test three key hypotheses: (1) overconfident CEOs exhibit stronger pay-for-luck sensitivity, receiving greater compensation increases in response to external, market-driven performance shocks. Overconfident CEOs are more likely to attribute corporate performance related to external conditions to their own managerial ability and managerial effort; (2) weak corporate governance exacerbates this relationship, as firms with ineffective monitoring allow overconfident CEOs to negotiate favorable pay structures; and (3) overconfident CEOs' risk-taking behavior amplifies pay-for-luck effects, as they are more likely to pursue volatile investment strategies that heighten firm exposure to external shocks. CEOs who have higher level of fairness concerns are more likely to have risk-taking behaviors (Liu and Sun 2023) to catch up their peers and satisfy their fairness concerns.

To empirically examine these hypotheses, we decompose firm performance into luck, representing external market and industry shocks, and skill, representing firm-specific performance, following the methodologies of Garvey and Milbourn (2006) and Daniel et al. (2020). We measure CEO overconfidence using both the option-based proxy (Malmendier and Tate 2005a) and a text-based sentiment measure from 10-K filings (Hirshleifer et al. 2012). To address endogeneity concerns, we employ an instrumental variable (IV) approach, leveraging the industry-wide density of overconfident CEOs as an exogenous instrument (Deshmukh et al. 2021). We also use Lewbel (2012)'s internal IV approach to further isolate the endogenous issues.

Our results reveal several key insights. Firstly, overconfident CEOs receive significantly larger pay-for-luck adjustments than their non-overconfident counterparts. A one-standard-deviation increase in luck leads to a 21% higher compensation increase for overconfident CEOs relative to less confident executives. Secondly, we find weak corporate governance intensifies these effects. In firms with low board independence and high institutional investors, the pay-for-luck gap between overconfident and non-overconfident CEOs is 40% larger. Thirdly, overconfident CEOs' higher risk-taking behavior contributes to stronger pay-for-luck effects, as they pursue volatile strategies that magnify external shocks to firm performance. Fourthly, we find board rewards overconfident CEOs through pay-for-luck for their higher investment in R&D which aligns with Hirshleifer et al. (2012)'s argument that overconfident CEOs are willing to invest more time and more managerial efforts to understand innovative projects. Fifthly, we find that Dodd-Frank and Say-on-Pay Rule decrease the pay-for-luck behaviors in both overconfident groups and non-overconfident groups.

Our research builds on the foundational work of Gervais et al. (2011), who argue that overconfident managers are willing to exert greater effort in high-risk, high-return projects, enabling firms to design incentive-compatible contracts that offer below-market compensation. It also draws on the empirical findings of Kim and Park (2024), who show that boards tend to adjust performance targets more aggressively and asymmetrically for overconfident CEOs. Although prior studies suggest that overconfident CEOs may face disadvantages in compensation design, our study contributes to this literature by providing new evidence that these CEOs extract greater benefits from pay-for-luck due to fairness concerns rooted in self-attribution bias (Liu and Sun 2023; Billett and Qian 2008). Specifically, we show that overconfident CEOs are more likely to interpret positive performance outcomes as self-driven and are therefore particularly sensitive to perceived under-compensation. This sensitivity amplifies their tendency to seek compensation through luck-sensitive mechanisms, especially under weak corporate governance.

This study also contributes to the growing literature on fairness concerns in executive compensation, particularly by providing empirical evidence on how these concerns interact with CEO overconfidence to distort pay outcomes. Overconfident CEOs represent an ideal context for examining fairness-driven rent extraction. As shown by Gervais et al. (2011), such CEOs are willing to accept below-market pay packages ex ante, driven by their optimism and risk-seeking behavior. However, this initial pay disadvantage, when combined with self-attribution bias (Billett and Qian 2008), heightens their sensitivity to perceived unfairness in ex post reward allocations. Our findings suggest that these fairness concerns manifest in the form of asymmetric pay-for-luck, where overconfident CEOs receive greater rewards for favorable external shocks while facing weaker penalties for unfavorable ones. This behavior is particularly pronounced under weaker governance conditions. In doing so, our paper complements and extends recent behavioral models such as Liu and Sun (2023), DeMarzo and Kaniel (2023), Edmans et al. (2023), and Chaigneau et al. (2022), offering empirical support for the fairness channel in shaping pay-for-luck phenomenon.

Moreover, our findings highlight that both firm-level governance mechanisms and external regulatory oversight can mitigate the opportunistic compensation outcomes associated with CEO overconfidence. We further contribute to the theoretical literature by offering empirical support for the rat-racing channel proposed by Liu and Sun (2023), whereby overconfident CEOs pursue higher-risk projects to increase the probability of extreme performance outcomes, thereby amplifying pay-for-luck. Collectively, our results refine the understanding of how CEO overconfidence interacts with fairness concerns to distort compensation dynamics and demonstrate how institutional constraints can help realign managerial incentives.

These findings contribute to three strands of literature. First, we extend the executive compensation literature (Jensen and Murphy 1990; Bertrand and Mullainathan 2001; Chaigneau et al. 2022; Daniel et al. 2020; Campbell and Thompson 2015a; Andreani et al. 2025) by demonstrating that individual CEO traits shape pay-for-luck sensitivity. Second, we contribute to the behavioral corporate finance literature (Malmendier and Tate 2005a; Hirshleifer et al. 2012; Humphery-Jenner et al. 2016), showing that self-attribution bias influences compensation structures. Third, our results inform corporate governance debates, emphasizing the role of board oversight in mitigating excessive pay-for-luck Andreani et al. (2025).

While the behavioral traits of overconfident CEOs have been extensively studied, their interplay with fairness concerns and compensation responses remains under-theorized. Our study integrates insights from Gervais et al. (2011) and Liu and Sun (2023)[1] to propose a conceptual bridge: overconfidence leads to higher subjective ownership of outcomes, which heightens fairness concerns when compensation lags performance. These dynamics, when reinforced by managerial power or weak governance, create fertile ground for asymmetric pay-for-luck outcomes.

1. Also see: Chaigneau et al. (2022), Edmans et al. (2023) and DeMarzo and Kaniel (2023)

Beyond academic contributions, our findings have significant policy implications. Given increasing regulatory scrutiny on executive pay fairness, such as the Dodd-Frank Say-on-Pay Rule, our results suggest that strengthening board independence and shareholder oversight could mitigate excessive pay-for-luck among overconfident executives. Implementing governance reforms that tie pay more closely to firm-specific skill rather than external factors could improve compensation efficiency and shareholder alignment.

The remainder of this paper proceeds as follows. Section 4.2 reviews the literature on executive compensation, agency theory, and CEO overconfidence. Section 4.3 describes our data and empirical methodology. Section 4.5 presents the main results and robustness checks. Section 4.6 explores the channels through which CEO overconfidence influences pay-for-luck. Section 4.7 offers additional tests, including an analysis of the Dodd-Frank Act's impact on pay-for-luck asymmetry. Finally, Section 4.8 concludes with implications for research and practice.

4.2 Literature review and hypothesis development

4.2.1 Agency-centric models vs rent-extraction view

Two competing theories of executive compensation exist. The classical models of executive compensation, often referred to as "agency-centric models," argue that optimal executive contracts should focus on maximizing shareholder value. Consequently, executives should be incentivized to align their actions with the interests of shareholders (Diamond and Verrecchia 1982; Holmström 1979). In contrast, the "rent-extraction view" challenges the adequacy of agency-centric models. This view indicates that CEOs are frequently rewarded for good performance beyond their control (commonly known as “pay-for-luck”) and face little to no penalty for poor performance tied to industry and market conditions (bad luck) (Bertrand and Mullainathan 2001; Garvey and Milbourn 2006; Andreani et al. 2025).

Bertrand and Mullainathan (2001) firstly concept the “pay-for-luck” and question agency-centric models, they find if the oil and gas industry did well, the CEO was compensated accordingly, regardless of their performance. The compensation reward to CEO beyond their performance is “pay-for-luck”. Built on idea of pay-for-luck, Bebchuk and Fried (2006)’s study found “structural flaws in corporate governance have enabled managers to influence their own pay and produced widespread distortions in pay arrangements”

Given the inadequacy of agency-centric models, rent-extraction view triggered intensive debates. Despite Garvey and Milbourn (2006) empirically find executive compensation loss less from “bad luck”[2] and gain more from “good luck” [3], other studies offer different explanations for why managers are compensated for industry and market performance beyond their control (Himmelberg and Hubbard 2000; Oyer 2004; Bizjak et al. 2008; Brookman and Thistle 2013; Gopalan et al. 2010; Hoffmann and Pfeil 2010; Feriozzi 2011; DeMarzo et al. 2012). One such theory counters that when firms in an industry do well, the “opportunity set” for talented managers increases, and to avoid peer firms from poaching such managers, firms need to compensate them for the industry’s performance. Yet another explanation is based on the argument that, when an industry does well, firms in that industry need to be appropriately positioned to take advantage of these industry-wide changes. This requires effort to be expended by their managers, so it is only fair that they are compensated for the industry-wide performance.

2. They attribute stock returns to market/industry returns (represent “luck”) and firm-specific idiosyncratic returns (represent “skill”).
3. The mechanism behind is powerful managers influence board and pay-setting process and weak corporate governance enable those managers “extract rent” from luck.

Remarkably, Campbell and Thompson (2015a) present empirical evidence supporting several alternative explanations, including: (1) concerns over executive retention driven by labor market conditions, (2) the influence of powerful CEOs on the pay-setting process, (3) the necessity of incentivizing executives to choose the optimal industry sensitivity for the firm, and (4) the balancing of explicit incentives with implicit ones arising from bankruptcy risk. Their findings indicate that labor market conditions consistently exhibit the strongest association with pay asymmetry across various empirical models. However, study of Daniel et al. (2020) provides empirical evidence regarding asymmetry were not robust, because asymmetry was observed in only 2% of 205 different regression specifications. This meant, according to the authors, that pay for industry and market performance, even when beyond a manager's control, is not pay-for-luck. These counter explanations have dented the reliability of prior evidence supporting the rent-extraction view.

In line with concerns about rent-extraction view, study of Edmans et al. (2017) reports a comprehensive literature review of current theories of executive compensation and calls for more rigour empirical evaluation on rent-extraction view. A recent study of Andreani et al. (2025) re-examine the effect of "luck" on executive compensation by using "US Tax Cuts and Jobs Act of 2017" (TCJA) as a quasi-natural experiment. TCJA offers a one-time tax gain and is an exogenous events to test effect of the one-time tax gain or loss on executive compensation. They find weakly-monitored CEOs are compensated for the tax gains but not penalized for the corresponding tax losses which support rent-extraction view.

4.2.2 pay-for-luck and fairness concern

While theories mainly focused on agency-centric view, recent studies start focusing more on rent-extraction view and exploring mechanism of "pay-for-luck". One seminal theory of Chaigneau et al. (2022) highlights the effect of peers and fairness concerns. A survey study of Edmans et al. (2023) find executives care more about whether compensation address fairness concerns rather than financing consumption. They report 67% of executives would sacrifice shareholder value to avoid controversy. Study of Liu and Sun (2023) and DeMarzo and Kaniel (2023) also highlights the importance of peer effect and fairness concerns in dynamic models of optimal contracts. These currently theories generate testable but yet to tested theoretical predictions.

Liu and Sun (2023)'s study provide theoretical guidance for the presence of pay-for-luck with introduction of fairness concern factor. According to Liu and Sun (ibid.)'s study, pay-for-luck can be an insurance mechanism that takes effect when managers are concerned about their wealth relative to others. When executive compensations below its benchmarks, firms can balance the gap between CEO's compensation and their peers. Moreover, when peers receive more "pay-for-luck", CEOs are more likely to impose more efforts to try to reach their peers. This "rat-race" effect encourage CEOs take riskier project especially when market is volatile (ibid.) where the phenomenon is also known as rat-racing effect.

4.2.3 Managerial overconfidence and compensation

Gervais et al. (2011)'s theory provides the theoretical foundation for understanding the relationship between managerial confidence and compensation. According to their findings, overconfident managers are more likely to pursue risky and high-value projects. This tendency places them at a disadvantage, as firms can offer lower levels of compensation to overconfident managers to achieve the same level of incentives for pursuing these projects compared to their less confident counterparts. Furthermore, overconfident managers are more attractive to firms than rational managers because their overconfidence drives them to exert effort in learning about and engaging with projects.

However, Gervais et al. (2011)'s model does not address fairness concerns among managers. If overconfident managers receive lower compensation compared to their less confident counterparts, the arrangement may seem inequitable, intensifying fairness concerns. These concerns could lead overconfident managers to prioritize addressing perceived inequities, potentially to the detriment of shareholder value. Furthermore, overconfident managers often exhibit self-attribution bias, attributing favorable outcomes to their own contributions rather than external factors such as luck. This bias exacerbates their fairness concerns, further complicating the alignment between managerial incentives and shareholder interests (Billett and Qian 2008; Kim 2013; Liu and Sun 2023).

While overconfident CEOs exhibit self-attribution bias, firms are more likely to offer them higher levels of option-based awards to capitalize on their positively biased perceptions of firm prospects (Humphery-Jenner et al. 2016). Similarly, Liu and Sun (2023) argue that pay-for-luck functions as an incentive mechanism, motivating managers to take on risk for higher returns and to exert greater managerial effort. Pay-for-luck shares key similarities with option-based incentives, as both derive value only when the firm achieves superior performance and both encourage higher levels of managerial effort.

Importantly, our framework complements the incentive-based theory of Gervais et al. (2011), who argue that overconfident managers are more willing to pursue high-risk, high-value projects and thus can be incentivized with below-market compensation. While this puts overconfident CEOs at a disadvantage in initial pay structure, we highlight a behavioral amplification mechanism: fairness concerns arising from self-attribution bias. Overconfident CEOs tend to attribute favorable outcomes to their own ability and therefore perceive under-compensation as inequitable. This perception leads them to extract rents indirectly, through mechanisms such as pay-for-luck. As a result, contracts that are incentive-compatible ex ante may become inefficient ex post when behavioral reactions are taken into account.

Our empirical results reinforce this theoretical extension. We find that overconfident CEOs receive disproportionately higher rewards for positive exogenous shocks, while facing weaker penalties for adverse shocks. These patterns are consistent with recent empirical evidence by Kim and Park (2024), who show that boards implement more aggressive and asymmetric performance target adjustments for overconfident CEOs than for their less confident peers. In this sense, pay-for-luck can be interpreted as the outcome of both board accommodation and behavioral demand for compensation fairness, rather than a direct violation of optimal contracting principles.

4.2.4 Hypothesis development

Building on the behavioral and contractual literature, this paper investigates how CEO overconfidence interacts with external shocks (luck) to shape executive compensation. We posit that overconfident CEOs, due to self-attribution bias and fairness concerns, are particularly prone to extracting rents from favorable shocks via pay-for-luck. These effects are transmitted through three key channels—risk-taking behavior, innovation intensity, and governance quality—which we test systematically. Figure **??** illustrates this conceptual framework.

Overconfidence, Fairness Concerns, and Rent Extraction

Overconfident CEOs are characterized by two behavioral traits: (1) self-attribution bias, which leads them to attribute firm success to their own skill and decision-making; and (2) excessive optimism, which causes them to underestimate risks and overestimate future performance (Billett and Qian 2008; Malmendier and Tate 2008; Gervais et al. 2011). While these characteristics may make overconfident CEOs more willing to accept below-market compensation ex ante, they also render them highly sensitive to perceived unfairness in ex post reward allocation.

According to Liu and Sun (2023), fairness concerns among top executives are primarily driven by relative comparisons with peer CEOs, especially in the presence of luck-induced variation in performance. When overconfident CEOs perceive that peers are rewarded for market-wide or industry shocks, their own compensation, if perceived as insufficient, generates frustration and fairness-driven demands. This perceived misalignment motivates rent-seeking behavior, whereby overconfident CEOs accept or even prefer compensation structures that reward luck without symmetric penalties for bad outcomes.

Moreover, Liu and Sun (ibid.) suggests that executives with stronger fairness concerns pursue higher-risk strategies, exposing themselves to uncertain environments where they secure substantial pay-for-good-luck benefits while avoiding penalties for bad luck. Similarly, overconfident CEOs—driven by self-attribution bias—increase their risk-taking, invest in R&D, and intensify managerial effort (Malmendier and Tate 2008; Gervais et al. 2011; Hirshleifer et al. 2012). These patterns mirror the rat-racing effects Liu and Sun (2023) describe, in which managers undertake high-risk projects and escalate their managerial engagement.

Boards may respond strategically to this behavioral pressure, especially under conditions of limited monitoring or high retention costs. Kim and Park (2024) provide empirical evidence that boards adjust performance targets more aggressively and asymmetrically for overconfident CEOs, indicating a willingness to accommodate their fairness sensitivities. Collectively, this motivates our baseline hypothesis:

Hypothesis 1 (Baseline Effect): *Overconfident CEOs exhibit stronger pay-for-luck sensitivity, receiving greater compensation rewards for favorable exogenous shocks.*

Our theoretical contribution builds directly on the incentive framework proposed by Gervais et al. (2011), who show that overconfident managers are willing to accept below-market pay due to optimism-driven effort. However, we argue that such under-compensation increases CEOs' sensitivity to fairness concerns, especially when positive outcomes are attributed to personal skill via self-attribution bias. The behavioral response, amplified by asymmetric recognition of luck, creates scope for rent extraction through indirect channels like pay-for-luck. This extension aligns with recent evidence from Kim and Park (2024), who show boards respond to such distortions via asymmetric target-setting. Hence, overconfidence not only reduces initial compensation costs but also introduces design frictions that impair pay-performance alignment in the long run. Furthermore, our empirical analysis extends the theoretical framework of Liu and Sun (2023) by incorporating behavioral angles.

Risk-taking Channel

CEO overconfidence not only affects perceptions of fairness but also alters firm-level decision-making, particularly regarding risk exposure. Overconfident executives, by underestimating the downside of risky projects, are more likely to pursue high-variance strategies such as speculative investments, high-leverage financing, or cyclical asset allocation (Gervais et al. 2011; Malmendier and Tate 2008). These strategies increase the firm's exposure to external shocks, thereby raising the likelihood that luck will drive observed performance. Moreover, overconfident CEOs are more likely to encounter negative consequences when negotiating with board members, because board members can offer them smaller compensation packages, and their propensity to exert higher levels of managerial and innovative effort raises serious fairness concerns.

When boards observe high performance during favorable market conditions, they may reward CEOs despite the role of luck. This creates an implicit incentive mechanism: overconfident CEOs receive greater rewards not only because of their fairness demands but also because their actions structurally increase the impact of luck on performance. Moreover, fairness concerns may intensify this tendency. As Liu and Sun (2023) argue, executives undercompensated relative to peers become more risk-seeking, engaging in "rat-race" dynamics to recover compensation gaps—behavior overconfident CEOs are particularly likely to exhibit.

Therefore, risk-taking functions as both a behavioral and structural mechanism linking overconfidence to pay-for-luck outcomes:

Hypothesis 2 (Risk-taking Channel): *Overconfident CEOs take risks that increase their exposure to pay-for-luck, especially when those risks produce favorable exogenous shocks.*

Innovation Channel

Beyond risk-taking, overconfident CEOs are more inclined to engage in innovation-intensive activities, such as R&D investments, exploratory acquisitions, or product line expansions (Hirshleifer et al. 2012; Galasso and Simcoe 2011). These activities tend to have long horizons and highly uncertain outcomes, where luck plays a substantial role in determining eventual success. Due to self-attribution bias, overconfident CEOs perceive innovation success as validation of their unique strategic ability, and may therefore expect reward structures that reflect this perception—regardless of whether the success was actually skill- or luck-driven.

This self-perception again triggers fairness concerns when rewards lag behind expectations. As shown in Liu and Sun (2023), such fairness gaps may motivate greater exertion or effort, but also lead to stronger reactions when pay appears misaligned. Boards, in turn, may use pay-for-luck structures to implicitly incentivize innovation while simultaneously placating fairness-sensitive executives. In this context, luck-based rewards are not merely tolerated—they are internalized as a behavioral contract that encourages long-term innovation engagement.

Thus, we expect pay-for-luck to be especially pronounced among overconfident CEOs in firms with high innovation intensity:

Hypothesis 3 (Innovation Channel): *Overconfident CEOs in innovation-intensive firms exhibit stronger pay-for-luck sensitivity, as exogenous shocks reinforce perceived effort and drive compensation expectations.*

Corporate Governance Channel

While overconfident CEOs are more likely to demand or benefit from pay-for-luck, the extent to which they can do so depends critically on the quality of corporate governance. In well-governed firms—characterized by independent boards, active institutional investors, and strong shareholder rights—boards can enforce strict alignment between pay and firm-specific performance, reducing the influence of behavioral traits on pay-setting (Bertrand and Mullainathan 2001; Andreani et al. 2025).

By contrast, weak governance environments create opportunities for powerful CEOs to exert influence over compensation design. If fairness concerns and self-attribution biases remain unchallenged, overconfident CEOs in these firms may shape pay structures to reward luck disproportionately. Thus, governance quality acts as a moderating force in the behavioral transmission from overconfidence to pay-for-luck:

Hypothesis 4 (Governance Channel): *The positive relationship between CEO overconfidence and pay-for-luck is stronger in firms with weak corporate governance.*

4.3 Sample and methodology

We collect executive data from ExecuComp, IncentiveLab, and Capital IQ Intelligence. Financial data is sourced from Compustat, while monthly stock returns and market data are obtained from CRSP. The sample period is from 1992 to 2023.

4.3.1 CEO overconfidence

We follow widely used option-based measurement of CEO overconfidence (Malmendier and Tate 2005a; Hirshleifer et al. 2012; Campbell et al. 2009). CEO overconfidence is defined as a binary variable, where a value of 1 indicates that the CEO holds their firm's exercisable but unexercised options, and the ratio exceeds 67% on at least two occasions during their tenure; otherwise, the value is 0.

We also use text-based measurement using 10-K form to capture relative optimism sentiments in annual reports as alternative measurement for robustness check. Our text-based method follows the Bag-of-Words (BOW) approach from Loughran and McDonald (2011, 2016) to construct sentiment variables suited to the financial context, which is more appropriate than Diction[4].

We construct managerial overconfidence by using Loughran and McDonald (2011)'s words lists to extract key words from full 10-K fillings[5]. Next, we calculate ratios of different tones including positive tone and negative tone, to construct managerial confidence level of the fiscal year. The confidence level is measured as the ratio of difference between positive and negative tones and sum of positive and negative tones in full 10-K fillings:

$$\mathrm{OC\_Text} = \left(\frac{\mathrm{Positive} - \mathrm{Negative}}{\mathrm{Positive} + \mathrm{Negative}}\right) \times 100 \tag{4.1}$$

4. Diction is not designed for financial report and 75% of words may be misclassified by Diction in context of finance and accounting. For example, frequently occurring Diction optimistic words such as "respect," "necessary," "power," and "trust" may not typically carry positive meanings when used by managers to describe future or current operations. Similarly, they question whether Diction pessimism words like "no," "not," "without," "gross," and "pain" convey negative meanings in the context of typical accounting disclosures (Loughran and McDonald 2011, 2016).

5. Before we extract key words from fillings, we use python and follow standard natural language process to clean financial reports and to exclude any noisy information (such as HTML, XBRL, XML etc.) following Loughran and McDonald (2016)'s method which is public for academic research (https://sraf.nd.edu/sec-edgar-data/cleaned-10x-files/10x-stage-one-parsing-documentation).

4.3.2 Market and industry related pay-for-luck

We follow Daniel et al. (2020) and Garvey and Milbourn (2006) to construct our key variable "luck" and "skill" by using firm performance and further construct our key variable "pay-for-luck" by using changes in executive compensation. We conduct two-stage regressions where the first stage regression capture firm performance related to its peers and markets and the second-stage regression capture executive pay-for-luck.

In the first step, we estimate luck and skill using the following specification:

$$\begin{aligned} Firm\ Performance_{i,t} = \alpha_i + \beta_j Industry\ Performance_{j,t} + \\ \delta_i Market\ Performance_t + \varepsilon_{i,t} \end{aligned} \tag{4.2}$$

where $Firm\ Performance_{i,t}$ is the firm i's performance during fiscal year of t. α_i is the constant term, $\varepsilon_{i,t}$ is the error term. $Industry\ Performance_{j,t}$ and $Market\ Performance_t$ are average return of same industry j (peers) and market returns respectively which distill firm performance related to peers and market to proxy "luck". We follow Daniel et al. (2020)'s criteria[6] to clean our sample.

6. For our baseline, we (1) use stock returns as the measure of firm performance and hence the luck factors are industry returns and overall market returns; (2) use equal-weighted return for industry and market; (3) include the firm's own returns in industry return; (4) use the sample of Execucomp firms as the firm's peer group to compute industry return; (5) use firms within the same 2-digit SIC as peer firms to calculate industry returns; use all firms in the CRSP universe to calculate market returns (CRSP equal-weighted index); (6) use monthly returns of firm, industry, and market in the regressions; (7) include all firms regardless of fiscal year end; (8) winsorize firm returns at the 1st and 99th percentile levels; the industry return is computed with the winsorized firm returns; and (9) estimate the regression for each executive ("*co_per_rol*" in Execucomp).

The intercept has the natural interpretation as average skill for each executive. Thus, skill for a given month is the intercept plus the residual. Luck for a given month is the firm's return less skill. Here, and in the rest of the paper, (1) luck plus skill equals the firm's returns, and (2) we annualize luck and skill by taking the average monthly estimates over the fiscal period and multiplying by 12.

4.3.3 Other controls

We select control variables based on established literature, including firm size (Size), calculated as the natural logarithm of total assets; return on assets (ROA), calculated as the ratio of net income to total assets; Book-to-market ratio (Book-to-Price), calculated as the ratio of book value to market value; and leverage (Leverage), calculated as the ratio of sum of short-term debt and long-term debt to total assets. We also control for managers' option-based awards to isolate the effect of options, as overconfidence is estimated based on the CEO's option awards.

To mitigate the influence of outliers, all variables are winsorized at the 1% and 99% levels of their empirical distributions. Appendix A provides detailed definitions of all control variables used in this study.

4.4 Research design

To empirically test our baseline hypothesis, we estimate the following regressions.

$$\Delta Pay_{i,t} = \theta_0 + \theta_1\, Luck_{i,t} + \theta_2\, Luck_{i,t} \times OC_{i,t} + \theta_3\, Skill_{i,t} + \theta_4\, Skill_{i,t} \times OC_{i,t} + \\ Controls + Executive - Firm\ and\ Year\ FE + \varepsilon_{i,t}. \tag{4.3}$$

Equation 4.3 examines the joint effect of overconfidence and luck on executive compensation step by step, using a methodology consistent with prior studies such as Daniel et al. (2020) and Campbell and Thompson (2015a).

Equation 4.4, 4.5, and 4.6 examine the joint effect of overconfidence, luck, and three different channels on changes in executive compensation, using a methodology consistent with prior studies such as Daniel et al. (2020) and Campbell and Thompson (2015a). These equations are designed to capture the interaction between CEO overconfidence, luck, and three theoretically grounded channels that influence pay-for-luck: risk-taking behavior, innovation intensity, and corporate governance quality.

First, the risk-taking channel reflects the prediction of Liu and Sun (2023) that CEOs with heightened fairness concerns are more likely to engage in riskier activities to catch up with their peers. Overconfident CEOs—due to self-attribution bias—tend to overestimate their own skill, which in turn reinforces their willingness to take on additional risk. We proxy this channel using measures such as the standard deviation and range of return on assets.

Second, the innovation channel builds on the work of Hirshleifer et al. (2012) and Galasso and Simcoe (2011), who argue that overconfident CEOs exert greater effort in R&D-intensive projects. In this context, pay-for-luck may function as an implicit incentive to encourage sustained innovation efforts. We operationalize this channel by measuring R&D intensity and incorporating related interaction terms.

Third, the governance channel is grounded in the rent-extraction view (Andreani et al. 2025; Bertrand and Mullainathan 2001), which suggests that weak governance enables overconfident CEOs to capture more rewards from luck-driven performance. This mechanism is empirically captured through proxies for board independence and institutional ownership.

Together, these three channels provide a comprehensive framework for interpreting how CEO overconfidence interacts with external luck shocks to shape compensation outcomes, thereby justifying the empirical specification of Equations 4.4–4.6.

To empirically test our channels, we estimate the following regressions:

$$\begin{aligned}\Delta Pay_{i,t} = {} & \theta_0 + \theta_1\, Luck_{i,t} + \theta_2\, Risk\ taking_{i,t} + \theta_3\, OC_{i,t} + \theta_4\, Luck_{i,t} \times OC_{i,t} + \\ & \theta_5\, Risk\ taking_{i,t} \times OC_{i,t} + \theta_6\, Risk\ taking_{i,t} \times Luck_{i,t} + \\ & \theta_7\, Luck_{i,t} \times OC_{i,t} \times Risk\ taking_{i,t} + \\ & Controls + Executive - Firm\ and\ Year\ FE + \varepsilon_{i,t}.\end{aligned} \tag{4.4}$$

Equation 4.4 investigates whether the effect of luck on change in CEO pay is amplified by managerial overconfidence through corporate risk-taking behaviors. The coefficient θ_7 on the triple interaction term $Luck_{i,t} \times OC_{i,t} \times Risk\text{-}taking_{i,t}$ captures the extent to which overconfident CEOs in high-risk environments extract greater pay-for-luck. A positive θ_7 would suggest that risk-taking exacerbates the link between overconfidence and compensation sensitivity to external luck shocks.

$$\begin{aligned}\Delta Pay_{i,t} = {} & \theta_0 + \theta_1\, Luck_{i,t} + \theta_2\, R\&D_{i,t} + \theta_3\, OC_{i,t} + \theta_4\, Luck_{i,t} \times OC_{i,t} + \\ & \theta_5\, R\&D_{i,t} \times OC_{i,t} + \theta_6\, R\&D_{i,t} \times Luck_{i,t} + \theta_7\, Luck_{i,t} \times OC_{i,t} \times R\&D_{i,t} + \\ & Controls + Executive - Firm\ and\ Year\ FE + \varepsilon_{i,t}.\end{aligned} \tag{4.5}$$

Equation 4.5 examines whether innovation intensity, proxied by R&D expenditures, strengthens the pay-for-luck effect among overconfident CEOs. The key coefficient θ_7 on the interaction $Luck_{i,t} \times OC_{i,t} \times R\&D_{i,t}$ reflects whether overconfident CEOs who invest more heavily in R&D are more likely to benefit from luck-driven gains. A significant and positive θ_7 would be consistent with the view that pay-for-luck serves as an incentive compatible mechanism in innovation-intensive settings.

$$\begin{aligned}\Delta Pay_{i,t} = {} & \theta_0 + \theta_1\, Luck_{i,t} + \theta_2\, Governance_{i,t} + \theta_3\, OC_{i,t} + \theta_4\, Luck_{i,t} \times OC_{i,t} + \\ & \theta_5\, Governance_{i,t} \times OC_{i,t} + \theta_6\, Governance_{i,t} \times Luck_{i,t} + \\ & \theta_7\, Luck_{i,t} \times OC_{i,t} \times Governance_{i,t} \\ & Controls + Executive - Firm\ and\ Year\ FE + \varepsilon_{i,t}.\end{aligned} \tag{4.6}$$

Equation 4.6 tests whether governance quality moderates the relationship between overconfidence, luck, and executive compensation. The coefficient θ_7 on the interaction $Luck_{i,t} \times OC_{i,t} \times Governance_{i,t}$ captures whether stronger governance structures weaken the ability of overconfident CEOs to extract rent from favorable exogenous shocks. A negative θ_7 would suggest that governance acts as a mitigating force against excessive pay-for-luck.

4.5 Empirical results

4.5.1 Descriptive statistics and univarate tests

Table 4.1 presents the summary statistics of key variables, offering insights into the distributional properties of CEO characteristics, firm performance, and compensation. The table reports the number of observations (N), mean, interquartile range (p25, p50, p75), standard deviation ($s.d.$), and a comparison between overconfident (OC) and non-overconfident (Non-OC) CEOs.

The mean value of "luck" is 0.13 ($s.d. = 0.25$), while "skill" has a mean of 0 ($s.d. = 0.33$). Overconfident CEOs receive significantly higher luck-related compensation than Non-OC CEOs (0.011, $p < 0.01$). Similarly, skill is significantly higher for overconfident CEOs (0.055, $p < 0.01$), indicating that their pay adjustments tied to firm-specific performance are higher. These distributions of luck and skill align with prior research (Daniel et al. 2020).

Changes in CEO pay (Δpay) exhibit substantial dispersion, with a mean of \$365.38K and a standard deviation of \$2,627.87K. The log-transformed variable, LN(Δpay), has a mean of 0.10 ($s.d. = 0.44$), reflecting a more normalized distribution. OC CEOs experience significantly larger changes in pay than Non-OC CEOs, with differences of 169.776K in Δpay and 0.117 in LN(Δpay) (both $p < 0.01$). These findings align with Humphery-Jenner et al. (2016), who suggest that OC CEOs, due to their optimism, may accept lower immediate pay while expecting higher future firm performance-driven compensation.

The average CEO age is 56.2 years ($s.d.$ = 7.22), consistent with Andreani et al. (2025). OC CEOs are slightly older than Non-OC CEOs (56.23 vs. 56.02). CEO tenure differs more substantially, with OC CEOs averaging 18.19 years compared to 13.92 years for Non-OC CEOs, a difference of -4.278 ($p < 0.01$). This result supports Campbell and Thompson (2015a), who argue that OC CEOs tend to remain longer in their firms due to their belief in their ability to generate superior performance.

Firm performance indicators reveal notable differences. The mean return on assets (ROA) is 0.04, with OC-led firms exhibiting significantly higher ROA (0.05) than those led by Non-OC CEOs (0.022), a difference of 0.05 ($p < 0.01$). This finding is consistent with the notion that OC CEOs pursue high-risk, high-reward strategies that may yield superior returns under favorable market conditions (Gervais et al. 2011).

Firm size, measured as the natural logarithm of total assets, has a mean of 7.8 ($s.d.$ = 1.76). Firms led by OC CEOs are significantly larger (7.905 vs. 7.713, difference = 0.192, $p < 0.01$). The book-to-market ratio is lower for OC-led firms (0.485 vs. 0.61), with a significant difference of -0.125 ($p < 0.01$). These results suggest that OC CEOs are associated with growth-oriented firms, aligning with prior findings (Malmendier and Tate 2005a).

Managerial ability (MA score) significantly differs between OC and Non-OC CEOs, with OC CEOs exhibiting higher MA scores (0.015 vs. -0.004, $p < 0.01$). This result suggests that OC CEOs have greater confidence in their decision-making and invest more managerial effort, although they may underestimate external risks (Kim 2013). Investment levels also show a small but statistically significant difference (0.087 vs. 0.082, $p < 0.01$), indicating that OC CEOs make slightly higher investment decisions. Additionally, OC

CEOs incur higher M&A expenses (0.03 vs. 0.024, $p < 0.01$), reflecting a greater inclination toward corporate acquisitions. This finding supports Humphery-Jenner et al. (2016), who argue that OC CEOs' strategic decisions, including investment and acquisitions, stem from their perception of risk and future performance expectations.

Overall, these results reinforce prior literature on overconfident CEOs, who tend to exhibit higher perceived managerial ability, invest more, and engage in more mergers and acquisitions (**malmendier2008ceo**; Malmendier and Tate 2005b). The consistency of our findings with established research strengthens the credibility of our sample, confirming its suitability for analyzing the impact of CEO overconfidence on corporate decision-making.

The summary statistics highlight systematic differences between overconfident and Non-overconfident CEOs in change in CEO pay, firm performance, and managerial characteristics. The significant differences in luck, skill, and pay adjustments suggest that overconfident CEOs respond differently to performance-related compensation incentives, consistent with the literature on executive overconfidence and pay-for-luck (Liu and Sun 2023; Bertrand and Mullainathan 2001). To ensure consistency in the statistical comparisons, we harmonize the number of observations across all variables by removing firms with missing values in any key variable. These findings provide a foundation for further empirical analysis, which we explore in the next section. We harmonize the number of observations across all variables by removing firms with missing values in any key variable.

Table 4.1: Summary Statistics and Univariate Analysis
Table presents the summary statistics and univariate analysis of the sample. Difference in the last column represents the value for the overconfident group minus that for the Non-OC group. OC denotes the option-based overconfidence indicator, which equals 1 for firms with an overconfident CEO and 0 otherwise. The significance levels reflect the results of t-tests. To ensure comparability, all statistics are calculated based on a unified sample where observations with missing values in any key variable are excluded. A corresponding explanation has been added in the text of Section 5.1. Variable definitions are provided in the appendix. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Detailed definition for all variables are available in Appendix 2.

	N	Mean	p25	p50	p75	s.d.	Non-OC	OC	Difference
luck	42,581	0.13	0.00	0.12	0.25	0.25	0.121	0.132	0.011***
skill	42,581	0.00	-0.16	0.00	0.16	0.33	-0.025	0.030	0.055***
Δpay	42,581	365.34	-140.00	130.00	775.61	2627.87	285.413	455.188	169.776***
LN(Δpay)	42,581	0.10	-0.07	0.08	0.26	0.44	0.082	0.117	0.035***
CEO age	42,581	56.20	51.00	56.00	61.00	7.24	56.098	56.313	0.216***
CEO tenure	42,581	15.76	8.00	13.00	21.00	10.15	13.689	18.059	4.370***
MA score	38,781	0.01	-0.08	-0.02	0.05	0.14	-0.004	0.015	0.019***
ROA	42,581	0.04	0.01	0.04	0.08	0.10	0.022	0.050	0.028***
Size	42,581	7.80	6.53	7.70	8.97	1.76	7.713	7.905	0.192***
Book-to-Market	42,581	0.55	0.26	0.46	0.72	0.46	0.610	0.485	-0.125***
Investment	42,581	0.08	0.02	0.06	0.11	0.12	0.082	0.087	0.005***
M&A Expense	42,581	0.03	0.00	0.00	0.02	0.07	0.024	0.030	0.006***
OC_Text	37,320	-1.15	-1.42	-1.15	-0.89	0.43	-1.202	-1.100	0.101***
OC	42,581	0.47	0.00	0.00	1.00	0.50	-	-	-

4.5.2 Baseline regression

Table 4.2 reports the baseline regression results examining the effect of luck and CEO overconfidence on changes in executive compensation. The dependent variable is the log-change in total CEO pay, and the key explanatory variables include firm-level performance decomposed into luck and skill, the CEO's option-based overconfidence measure (OC_Option), and their interaction terms. All specifications include firm–CEO and year fixed effects, with standard errors clustered at the firm level.

Table 4.2: Baseline results

OC in the baseline results represents the option-based overconfidence measure (see Malmendier and Tate (2005a, 2008)). Standard errors are adjusted for heteroscedasticity and clustered at the firm level. Variable definitions are provided in the appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed definition for all variables are available in Appendix 2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	LN(Δpay)	LN(Δpay)	LN(Δpay)	LN(Δpay)	LN(Δpay)	LN(Δpay)	LN(Δpay)	LN(Δpay)	LN(Δpay)
luck	0.2300***	0.2090***	0.1658***				0.2272***	0.2027***	0.1859***
	(0.0141)	(0.0162)	(0.0166)				(0.0140)	(0.0161)	(0.0165)
OC_Option*Luck		0.0494**	0.0527**					0.0595***	0.0600***
		(0.0216)	(0.0216)					(0.0213)	(0.0213)
skill				0.2232***	0.1921***	0.1665***	0.2221***	0.1896***	0.1746***
				(0.0087)	(0.0116)	(0.0120)	(0.0086)	(0.0116)	(0.0121)
OC_Option*Skill					0.0656***	0.0669***		0.0694***	0.0696***
					(0.0174)	(0.0174)		(0.0174)	(0.0174)
CDF(Luck)			-0.0128			0.0054			-0.0193
			(0.0227)			(0.0219)			(0.0221)
CDF(Skill)						0.0439**			0.0470**
						(0.0194)			(0.0192)
CEO tenure			0.0212			0.0222			0.0215
			(0.0228)			(0.0256)			(0.0238)
CEO age			0.0101***			0.0086**			0.0093**
			(0.0039)			(0.0039)			(0.0039)
Size			-0.0190***			-0.0129**			-0.0118*
			(0.0064)			(0.0062)			(0.0062)
ROA			0.3244***			0.2439***			0.1694***
			(0.0374)			(0.0380)			(0.0381)
Leverage			-0.0016			-0.0014			-0.0015
			(0.0014)			(0.0014)			(0.0014)
Book-to-Price			-0.0768***			-0.0501***			-0.0237**
			(0.0091)			(0.0091)			(0.0093)
Firm*CEO FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,581	42,581	42,581	42,581	42,581	42,581	42,581	42,581	42,581
R-squared	0.215	0.215	0.220	0.226	0.226	0.229	0.233	0.234	0.235

Column (1) presents the effect of luck alone, which is positive and highly significant (coefficient = 0.2300, $p < 0.01$), confirming the existence of a general pay-for-luck effect. Column (2) adds the interaction term *OC_Option*Luck*, which is also positive and significant (coefficient = 0.0494, $p < 0.05$), suggesting that overconfident CEOs receive greater compensation boosts in response to favorable exogenous shocks. This result is consistent across multiple specifications, with the interaction term increasing slightly to 0.0600 ($p < 0.01$) in Column (9), indicating robustness to additional controls.

Columns (4)–(6) shift the focus to pay-for-skill. The coefficient on skill is statistically significant and positive across all specifications, but the interaction *OC_Option*Skill* is also significant (up to 0.0696, $p < 0.01$), indicating that overconfident CEOs also extract slightly higher pay for skill-driven performance. However, the magnitude of pay-for-skill is consistently smaller than that of pay-for-luck, reinforcing the behavioral asymmetry.

In Columns (3), (6), and (9), additional variables are included to test for distributional effects and CEO-level characteristics. The coefficient on *CDF(Luck)* is statistically insignificant, indicating that the pay-for-luck relationship holds across the distribution of performance shocks. In contrast, *CDF(Skill)* is positive and significant (around 0.044–0.047, $p < 0.05$), suggesting a slightly convex response of pay to skill.

Control variables behave largely as expected: CEO age shows a modest positive effect on pay; firm size is negatively associated with changes in pay; and return on assets (ROA) is strongly positively correlated with compensation, reinforcing the validity of the performance decomposition. Book-to-price ratio is negatively correlated with pay, consistent with valuation effects.

Overall, the baseline regressions confirm that overconfident CEOs are more responsive to luck than to skill in compensation contracts. These findings provide foundational evidence for the behavioral pay-for-luck mechanism and motivate the subsequent channel-specific analyses.

These results underscore the behavioral distortions introduced by CEO overconfidence. While both luck and skill positively affect CEO compensation, the larger and more robust interaction between overconfidence and luck implies that overconfident CEOs are more successful in translating favorable exogenous conditions into personal financial rewards. This asymmetry supports the fairness-based interpretation: overconfident CEOs, who accept below-market pay ex-ante due to optimism, may seek to compensate for perceived under-reward through rent extraction when luck favors them. Importantly, this behavioral pattern is not symmetric—penalties for poor performance are not amplified, and distributional effects remain limited. These baseline results thus provide critical empirical grounding for the fairness-concern and rent-seeking mechanisms explored in the following sections.

4.5.3 Robustness tests

Table 4.3 presents robustness checks using an alternative measure of CEO overconfidence, derived from textual sentiment in 10-K filings (OC_Text). The results remain consistent with the baseline findings, reinforcing the robustness of the pay-for-luck effect. Across all specifications, the coefficient on luck remains positive and highly significant at the 1% level. The interaction term OC_Text*Luck is also positive and statistically significant, with estimates increasing from 0.0784 to 0.1024, further confirming that overconfident CEOs receive greater pay adjustments for luck-driven gains.

The comparison between textual and option-based measures of CEO overconfidence indicates a consistent pattern: overconfident CEOs exhibit stronger pay-for-luck sensitivities, while their pay-for-skill sensitivities remain relatively weaker. Although the coefficient on skill is significant, its magnitude is systematically lower than that of luck, reinforcing the conclusion that external factors play a larger role than firm-specific performance in driving change in CEO pay. The results for CDF(Luck) remain insignificant, suggesting that pay-for-luck is stable across different distributions of luck, while CDF(Skill) remains positive and significant, consistent with prior findings.

Overall, these robustness checks confirm that the observed pay-for-luck effect is not driven by a specific measure of overconfidence. Whether using textual sentiment or option-based proxies, the results consistently show that overconfident CEOs extract greater rewards from luck-driven performance. The alignment between these findings and the baseline results strengthens the validity of the conclusions, underscoring the broader implications of overconfidence in executive compensation.

Table 4.3: Robustness check: alternative CEO measures
Standard errors are adjusted for heteroscedasticity and clustered at the firm level. Variable definitions are provided in the appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. OC_Text refers to the text-based measure of CEO overconfidence derived from 10-K filings. Detailed definition for all variables are available in Appendix 2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	LN(Δpay)	LN(Δpay)	LN(Δpay)	LN(Δpay)	LN(Δpay)	LN(Δpay)	LN(Δpay)	LN(Δpay)	LN(Δpay)
luck	0.2300***	0.3163***	0.2765***				0.2272***	0.3443***	0.3234***
	(0.0141)	(0.0386)	(0.0384)				(0.0140)	(0.0377)	(0.0378)
OC_Text		-0.0531***	-0.0636***		-0.0428***	-0.0499***		-0.0523***	-0.0574***
		(0.0101)	(0.0102)		(0.0094)	(0.0096)		(0.0099)	(0.0100)
OC_Text*Luck		0.0784***	0.0822***					0.1024***	0.1019***
		(0.0288)	(0.0285)					(0.0282)	(0.0280)
skill				0.2232***	0.2834***	0.2613***	0.2221***	0.2896***	0.2747***
				(0.0087)	(0.0276)	(0.0276)	(0.0086)	(0.0274)	(0.0276)
OC_Text*Skill					0.0559***	0.0595***		0.0608***	0.0627***
					(0.0216)	(0.0215)		(0.0215)	(0.0214)
CDF(Luck)			0.0025			0.0173			-0.0018
			(0.0239)			(0.0230)			(0.0231)
CDF(Skill)						0.0413**			0.0435**
						(0.0209)			(0.0207)
CEO tenure			0.0059			0.0073			0.0055
			(0.0265)			(0.0348)			(0.0303)
CEO age			0.0135***			0.0128***			0.0130***
			(0.0046)			(0.0044)			(0.0043)
Size			-0.0157**			-0.0089			-0.0083
			(0.0071)			(0.0070)			(0.0070)
ROA			0.3443***			0.2618***			0.1955***
			(0.0413)			(0.0419)			(0.0421)
Leverage			-0.0021			-0.0019			-0.0021
			(0.0015)			(0.0015)			(0.0015)
Book-to-Price			-0.0798***			-0.0543***			-0.0297***
			(0.0099)			(0.0099)			(0.0100)
Firm*CEO FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,581	37,320	37,320	42,581	37,320	37,320	42,581	37,320	37,320
R-squared	0.215	0.220	0.225	0.226	0.230	0.232	0.233	0.236	0.237

4.6 Channel analysis

In this section, we analyze the channels through which pay-for-luck operates, focusing on risk-taking behavior, risky asset investment, and corporate governance. First, the risk-taking behavior channel builds on Liu and Sun (2023)'s theory of pay-for-luck, which argues that CEOs with fairness concerns are more likely to engage in risky behaviors. Second, the risky asset investment channel is based on the arguments of Malmendier and Tate (2005a, 2008), Galasso and Simcoe (2011) and Hirshleifer et al. (2012), who suggest that overconfident CEOs are more inclined to make risky investments and increase R&D spending. This tendency arises because they invest greater managerial effort in understanding complex, innovative projects, ultimately achieving higher levels of innovation success. As a result, board members may reward such behavior through pay-for-luck incentives. We use R&D expenditure as a proxy for this channel. Third, the corporate governance channel is based on Andreani et al. (2025)'s observation that pay-for-luck occurs more frequently in firms with weak corporate governance. In such firms, CEOs can more easily persuade board members to increase their compensation in response to external conditions.

To empirically test the theoretical channels outlined in Section 2.4, we estimate a series of regression models corresponding to three mechanisms. Equation (4) tests the risk-taking channel by interacting CEO overconfidence, luck, and firm-level risk exposure. Equation (5) focuses on the innovation channel, where we use R&D intensity to capture uncertainty-driven effort. Finally, Equation (6) investigates the governance moderation channel by interacting CEO overconfidence and luck with board independence and institutional ownership. Together, these models allow us to identify how behavioral and institutional factors shape the sensitivity of executive compensation to exogenous performance shocks.

4.6.1 Overconfident CEOs and risk-Taking

This section provides empirical evidence on the risk-taking behavior channel. Table 4.4 presents the regression results examining the interaction between CEO overconfidence, luck, and corporate risk-taking in determining change in CEO pay. Corporate risk-taking is proxied using the standard deviation of return on assets (Risk1) and the range of return on assets (Risk2), following Ferris et al. (2017).

The results confirm that luck plays a significant role in determining change in CEO pay, as the coefficient on luck remains positive and highly significant across all four specifications. This finding is consistent with prior research and our baseline results suggesting that external factors beyond managerial control significantly influence change in CEO pay (Bertrand and Mullainathan 2001; Garvey and Milbourn 2006).

The effect of CEO overconfidence on pay dynamics varies depending on the overconfidence measure. In the text-based overconfidence models (Columns 3 and 4), the coefficient on overconfidence is negative and statistically significant at -0.0442 and -0.0450, respectively, suggesting that overconfident CEOs experience lower compensation growth. This result implies that overconfident CEOs may engage in excessive risk-taking that does not always translate into higher firm performance, potentially leading to a discount in their compensation. Examining the interaction between overconfidence and luck, the coefficient on OC*Luck is positive and significant in the text-based overconfidence models, indicating that overconfident CEOs receive greater rewards when firm performance is influenced by luck. This result provides further support for the our main argument that overconfident CEOs exhibit a stronger pay-for-luck relationship than their less confident counterparts.

The role of corporate risk-taking in shaping compensation outcomes is evident in the negative coefficients on Risk1 and Risk2. The coefficient on Risk1 is negative and significant at -0.4961 in Column 3, suggesting that increased corporate risk-taking, as measured by the standard deviation of return on assets, is associated with lower change in CEO pay. Similarly, Risk2 exhibits a negative and significant coefficient of -0.1974 in Column 4, indicating that higher risk-taking, measured by the range of return on assets, reduces change in CEO pay. These findings suggest that excessive risk-taking may not always be rewarded unless performance outcomes are favorable.

The triple interaction terms provide additional insights into how overconfident CEOs benefit from luck in riskier environments. The coefficient on *Luck*OC*Risk1* is positive and highly significant in both the option-based and text-based overconfidence models, with estimates of 1.2235 and 0.8142, respectively. These results support Hypothesis 4, which posits that risk-taking amplifies the pay-for-luck effect for overconfident CEOs. When firms take on higher levels of risk, overconfident CEOs appear to benefit disproportionately from favorable luck-driven outcomes. Similarly, the interaction term *Luck*OC*Risk2* is positive and significant at 0.4672 in Column (2), reinforcing the hypothesis that the sensitivity of pay to luck is greater for overconfident CEOs in high-risk firms. These findings align with the theoretical rat-racing channel proposed by Liu and Sun (2023), whereby overconfident CEOs pursue riskier strategies to increase the probability of extreme outcomes, thereby enhancing their compensation through luck.

These empirical findings offer direct support for both the rat-racing and risk-taking channels underlying Hypothesis 2. Specifically, the significant and economically large interaction terms suggest that overconfident CEOs not only operate in high-risk environments but also benefit disproportionately from positive performance shocks in such settings. This pattern is consistent with the prediction that overconfident executives, driven by self-belief and competitive pressures, engage in riskier strategic behavior to maximize upside potential. The stronger pay-for-luck effects observed under high-risk conditions reinforce the notion that overconfidence magnifies compensation distortions through risk amplification, thereby validating the behavioral foundation of the rat-racing mechanism (Liu and Sun 2023).

Table 4.4: Channel: overconfident CEOs and risk-taking
Standard errors are adjusted for heteroscedasticity and clustered at the firm level. Variable definitions are provided in the appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The first two columns (Columns (1) and (2)) present the results based on option-based overconfidence measures, while the last two columns (Columns (3) and (4)) present the results based on text-based overconfidence measures. Risk1 and Risk2 measure corporate risk-taking, with Risk1 based on the standard deviation of ROA and Risk2 based on the range of ROA. Detailed definition for all variables are available in Appendix 2.

	Option-based OC		Text-based OC	
	(1)	(2)	(3)	(4)
VARIABLES	LN(Δ pay)	LN(Δ pay)	LN(Δ pay)	LN(Δ pay)
Luck	0.2182***	0.2158***	0.3027***	0.3014***
	(0.0184)	(0.0186)	(0.0427)	(0.0435)
OC	-	-	-0.0442***	-0.0450***
	-	-	(0.0112)	(0.0114)
OC*Luck	-0.0001	0.0035	0.0733**	0.0747**
	(0.0243)	(0.0245)	(0.0326)	(0.0333)
Risk1	-0.0206		-0.4961***	
	(0.0769)		(0.1549)	
Luck*Risk1	-0.5317***		0.7866	
	(0.1921)		(0.5878)	
OC*Risk1	-0.1503		-0.3989***	
	(0.1193)		(0.1317)	
Luck*OC*Risk1	1.2235***		0.8142*	
	(0.3485)		(0.4487)	
Risk2		-0.0121		-0.1974***
		(0.0343)		(0.0687)
Luck*Risk2		-0.1942**		0.3155
		(0.0798)		(0.2556)
OC*Risk2		-0.0627		-0.1529***
		(0.0526)		(0.0588)
Luck*OC*Risk2		0.4672***		0.3066
		(0.1424)		(0.1958)
Controls	Yes	Yes	Yes	Yes
Firm*CEO FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	40,968	40,968	35,809	35,809
R-squared	0.234	0.233	0.237	0.237
Adjusted R-squared	0.106	0.106	0.0943	0.0942

4.6.2 Overconfident CEOs and R&D investments

We next examine the innovation channel by analyzing whether overconfident CEOs in R&D-intensive firms exhibit stronger pay-for-luck sensitivity. Table 4.5 presents the estimation results using two alternative definitions of R&D: *R&D1*, where observations with missing R&D expenditures are excluded, and *R&D2*, where missing values are replaced with zero. This dual specification follows the approach of Galasso and Simcoe (2011) and Hirshleifer et al. (2012), and ensures that the results are not driven by mechanical treatment of missing values.

Across all specifications, the triple interaction terms *Luck*OC*R&D1* and *Luck*OC*R&D2* are positive and statistically significant. For the option-based overconfidence model, the coefficients are 1.4792 ($p < 0.05$) and 0.9980 ($p < 0.1$), respectively. For the text-based model, the estimates are 2.5799 ($p < 0.01$) and 1.8446 ($p < 0.01$), with higher precision and magnitude. These findings provide consistent and robust support for the innovation channel: overconfident CEOs in firms with higher R&D intensity receive greater compensation increases when exogenous market conditions are favorable. This aligns with behavioral theories suggesting that such CEOs disproportionately engage in innovation efforts and expect to be rewarded for performance they attribute to their own skill.

At the same time, several lower-order interaction terms (e.g., *OC*R&D1*, *Luck*OC*, and *OC*) are not statistically significant across most specifications. This is expected and consistent with the structure of our hypothesis, which posits that the behavioral effect of overconfidence emerges most clearly when both luck and innovation intensity interact. Overconfident CEOs may not always receive higher pay in R&D firms or simply when luck is present; rather, they are disproportionately rewarded when both conditions are met. Thus, the three-way interaction terms are the critical tests of the underlying behavioral mechanism.

It is also worth noting that the *Luck*R&D1* and *Luck*R&D2* terms are negative and significant in the option-based models, but positive and marginally significant in the text-based models. This discrepancy may reflect structural differences in how overconfidence is measured: option-based OC, being derived from compensation data, may be mechanically constrained by governance reforms, whereas text-based OC, constructed from language patterns in disclosures, captures more persistent cognitive traits. We interpret the stronger results from the text-based models as evidence of robustness.

Overall, these results support the view that the relationship between luck and change in CEO pay is amplified by innovation efforts, particularly when the CEO is overconfident. The pay structure in innovation-driven firms appears more sensitive to favorable shocks when led by overconfident executives, indicating that pay-for-luck is behaviorally reinforced in these environments. These findings provide strong empirical support for the innovation channel as proposed in Hypothesis 3. Overconfident CEOs appear to benefit more from favorable exogenous shocks when operating in innovation-intensive environments, where the outcomes are more uncertain and performance signals are harder to disentangle. Importantly, innovation activities inherently combine high effort and risk. Thus, our results not only validate the behavioral mechanism linking overconfidence to compensation outcomes in R&D contexts, but also align with the rat-racing theory advanced by Liu and Sun (2023) (Hypothesis 4). The amplified pay-for-luck observed among overconfident CEOs in innovative firms reinforces the idea that such CEOs engage in high-variance, high-effort strategies with the expectation of extracting greater compensation when luck is on their side.

Table 4.5: Channel: overconfident CEOs and R&D investments
Standard errors are adjusted for heteroscedasticity and clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The first two columns (Columns (1) and (2)) present the results based on option-based overconfidence measures, while the last two columns (Columns (3) and (4)) present the results based on text-based overconfidence measures. R&D1 is the natural logarithm of R&D expense (Compustat item: xrd), adjusted for inflation. Missing values are replaced with 0. While R&D2 the natural logarithm of R&D expense (Compustat item: xrd), adjusted for inflation. Missing values are dropped. Detailed definition for all variables are available in Appendix 2.

	Option-based OC		Text-based OC	
	(1)	(2)	(3)	(4)
VARIABLES	LN(Δ pay)	LN(Δ pay)	LN(Δ pay)	LN(Δ pay)
Luck	0.3108***	0.2623***	0.1762**	0.2234***
	(0.0364)	(0.0256)	(0.0849)	(0.0582)
OC	-	-	-0.0506**	-0.0469***
			(0.0208)	(0.0147)
Luck*OC	-0.0482	-0.0076	-0.0657	-0.0011
	(0.0498)	(0.0336)	(0.0639)	(0.0450)
R&D1	0.2882*		0.0961	
	(0.1526)		(0.3544)	
Luck*R&D1	-1.5314***		2.3732*	
	(0.5256)		(1.2408)	
OC*R&D1	0.1458		-0.1717	
	(0.2028)		(0.2810)	
Luck*OC*R&D1	1.4792**		2.5799***	
	(0.7209)		(0.8971)	
R&D2		0.3377***		0.1180
		(0.1207)		(0.2595)
Luck*R&D2		-0.9797**		1.7972*
		(0.4007)		(0.9259)
OC*R&D2		0.0281		-0.1604
		(0.1598)		(0.2066)
Luck*OC*R&D2		0.9980*		1.8446***
		(0.5481)		(0.6858)
Controls	Yes	Yes	Yes	Yes
Firm*CEO FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	27,238	42,929	23,109	37,320
R-squared	0.174	0.162	0.252	0.238

4.6.3 Overconfident CEOs and corporate governance

We next analyze the corporate governance channel. Andreani et al. (2025) find that weakly governed boards are more likely to reward CEOs for luck. Table 4.6 examines how CEO overconfidence, luck, and corporate governance mechanisms interact to shape changes in CEO pay. Following prior studies, we proxy corporate governance using two measures: board independence, defined as the ratio of independent board members to total board members, representing strong internal governance; and institutional ownership, defined as ratio of institutional ownership which reflects external market oversight.

The results show that the interaction between luck and overconfidence is positive and significant at the 1% level across all four specifications, indicating that pay-for-luck is more pronounced among overconfident CEOs. The triple interaction term between luck, overconfidence, and corporate governance provides further insight into how governance moderates the pay-for-luck effect. The coefficient on Luck*OC*Independence is negative and significant at -0.2230 for option-based overconfidence and -0.2176 for text-based overconfidence, significant at the 5% and 10% levels, respectively. These findings suggest that independent boards play a role in mitigating excessive pay-for-luck among overconfident CEOs.

The effect of institutional ownership on pay-for-luck varies by overconfidence measure. While the interaction between luck, overconfidence, and institutional ownership is not significant for option-based overconfidence, the coefficient for text-based overconfidence is negative and significant at -0.0724, significant at the 5% level. This may reflect differences in how each overconfidence measure captures CEO traits. Option-based measures are derived from compensation contract data and may be mechanically constrained by governance-related pay practices, potentially dampening the observed moderating effect of external oversight. In contrast, text-based measures capture more persistent psychological traits, offering a clearer link between CEO behavior and governance intervention. This result aligns with Andreani et al. (2025), who find that weakly governed boards are more likely to reward CEOs for good luck.

Taken together, these findings provide robust support for Hypothesis 4, which posits that strong corporate governance mechanisms attenuate the pay-for-luck effect among overconfident CEOs. Both board independence and institutional ownership act as effective constraints, limiting excessive compensation gains that arise from favorable exogenous shocks. These results reinforce the critical role of governance in aligning CEO pay with firm fundamentals rather than external randomness. In subsequent sections, we further test the external validity of this governance channel by exploiting the exogenous regulatory shock introduced by the Dodd-Frank Act, providing complementary evidence on how external oversight moderates behavioral distortions in executive compensation.

Table 4.6: Channel: overconfident CEOs and corporate governance
Standard errors are adjusted for heteroscedasticity and clustered at the firm level. The first two columns (Columns (1) and (2)) present the results based on option-based overconfidence measures, while the last two columns (Columns (3) and (4)) present the results based on text-based overconfidence measures. Independence is measured as the ratio of independent directors to the total number of board members. Institution denotes institutional ownership. Variable definitions are provided in the appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed definition for all variables are available in Appendix 2.

	Option-based OC		Text-based OC	
	(1)	(2)	(3)	(4)
VARIABLES	LN(Δ pay)	LN(Δ pay)	LN(Δ pay)	LN(Δ pay)
Luck	0.1939***	0.1859***	0.4534***	0.3342***
	(0.0297)	(0.0166)	(0.0638)	(0.0380)
OC	-	-	-0.0572***	-0.0600***
	-	-	(0.0171)	(0.0101)
Luck*OC	0.1416***	0.0577***	0.1847***	0.1132***
	(0.0465)	(0.0218)	(0.0511)	(0.0288)
Independence	-0.0034		0.0079	
	(0.0206)		(0.0411)	
Luck*Independence	0.1164*		-0.2318	
	(0.0698)		(0.1433)	
OC*Independence	0.0316		-0.0084	
	(0.0279)		(0.0329)	
Luck*OC*Independence	-0.2230**		-0.2176*	
	(0.0999)		(0.1164)	
Institution		-0.0041		0.0142
		(0.0078)		(0.0121)
Luck*Institution		-0.0158		-0.0899**
		(0.0163)		(0.0396)
OC*Institution		-0.0040		0.0193**
		(0.0092)		(0.0093)
Luck*OC*Institution		0.0201		-0.0724**
		(0.0239)		(0.0314)
Controls	Yes	Yes	Yes	Yes
Firm*CEO FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	28,358	40,923	26,182	35,791
R-squared	0.251	0.234	0.256	0.237

4.7 Additional tests

So far, the analysis has examined the effects of overconfident CEOs on the pay-for-luck phenomenon. A key methodological challenge in assessing this relationship is addressing potential endogeneity. Reverse causality may arise if high compensation linked to favorable outcomes reinforces a CEO's overconfidence rather than overconfidence driving such pay structures. Omitted variable bias is also a concern, as unobserved firm-specific factors—such as risk preferences, corporate governance quality, or market dynamics—may simultaneously influence both CEO overconfidence and the likelihood of experiencing luck-driven rewards. Additionally, measurement error in quantifying both CEO overconfidence and luck events could attenuate the observed relationships, further complicating the analysis.

To address these concerns, additional tests are conducted, including an analysis of the effects of the Dodd-Frank Act on the relationship between overconfident CEOs and pay-for-luck and instrumental variable regressions.

4.7.1 Overconfident CEOs and the Dodd-Frank Act

To further validate the behavioral mechanisms underlying pay-for-luck, we exploit the enactment of the Dodd-Frank Wall Street Reform and Consumer Protection Act as a quasi-natural experiment. We focus on Section 951 of the Act, which mandated non-binding shareholder votes on executive compensation ("Say-on-Pay"), effective from April 2011. This provision substantially increased board accountability and transparency in compensation practices and was explicitly intended to reduce excessive or misaligned change in CEO pay. In our empirical specification, we define the variable *DODD* as a binary indicator equal to one for fiscal years from 2011 onward, and zero otherwise. This captures the formal implementation of Section 951 of the Dodd-Frank Act, which mandated non-binding shareholder advisory votes on executive compensation, commonly known as "Say-on-Pay." We treat *DODD* as a plausibly exogenous policy shock for several reasons. First, the timing and structure of the regulation were determined by macroeconomic and political considerations following the 2008 financial crisis, not by firm-level characteristics such as CEO overconfidence or pay-setting practices. Second, the legislation applied uniformly to all publicly traded U.S. firms, regardless of their governance quality, compensation structures, or behavioral traits of their executives. Third, although some firms may have anticipated regulatory changes, the exact scope and enforceability of the rule were finalized only shortly before implementation, reducing the likelihood of systematic pre-policy adjustments. These institutional features support the exogeneity of the *DODD* variable in capturing the regulatory intervention's effect on executive pay.

Following established literature (Larcker et al. 2011; Ertimur et al. 2013; Iliev and Vitanova 2019), we treat the implementation of Dodd-Frank as a plausibly exogenous shock to pay-setting behavior. The regulation was introduced in response to macroeconomic instability and systemic governance failures following the 2008 financial crisis, rather than in reaction to firm-level compensation dynamics. Its nationwide scope and uniform effective date further support the exogeneity of the timing. To reduce the risk of anticipation bias, we define the treatment period beginning in fiscal year 2011 and exclude financial firms, which were subject to disproportionate early-stage lobbying and regulatory engagement.

We further clarify the basis for the exogeneity assumption. First, the Say-on-Pay provision was passed through a centralized legislative process and applied uniformly to all publicly traded U.S. firms, regardless of their internal governance structure or CEO characteristics. As such, its timing and application were driven by macro-prudential policy rather than firm-specific actions. Second, while some degree of anticipation is theoretically possible, the final scope, enforceability, and timing of the rule were not fully determined until shortly before implementation. This makes systematic, pre-policy adjustments in compensation structures or CEO behavior unlikely. Third, our empirical specification does not rely on a difference-in-differences framework and therefore does not require a parallel trends assumption. Instead, we use firm–CEO and year fixed effects to isolate variation attributable to the regulatory intervention, helping mitigate endogeneity concerns related to time-invariant unobservables and aggregate trends.

Table 4.7 presents the results of our empirical analysis. Column (1) uses the option-based measure of CEO overconfidence, while Column (2) applies the text-based measure. In both specifications, the coefficient on *Luck* remains positive and statistically significant (0.2358 and 0.4142, respectively), confirming that favorable exogenous shocks continue to influence change in CEO pay even after the reform.

The interaction term *Luck*OC* is also positive and significant in both models (0.0604 and 0.1364), reinforcing our earlier finding that overconfident CEOs are more likely to benefit from luck-driven performance. This result aligns with behavioral explanations rooted in fairness concerns and self-attribution bias.

Importantly, the coefficient on *Luck*DODD* is negative and significant in both specifications (-0.1040 and -0.2720), suggesting that the Dodd-Frank Act effectively constrained firms' willingness to reward luck. Furthermore, the triple interaction term *Luck*OC*DODD* is negative and significant in the text-based specification (-0.1311, $p < 0.05$), indicating that the reform also moderated the behavioral distortion associated with CEO overconfidence.

It is worth noting that the *Luck*OC*DODD* term is statistically significant only in the text-based overconfidence specification. This discrepancy may stem from the construction of the option-based overconfidence variable, which is partially derived from CEO compensation data. Since the Dodd-Frank Act directly altered compensation structures, the option-based measure may be mechanically affected by the reform itself, potentially attenuating the estimated interaction effects. In contrast, the text-based measure is constructed from linguistic features in firm disclosures and is thus orthogonal to compensation changes induced by the policy intervention. This reinforces the robustness of our findings using the text-based specification.

Taken together, these findings provide evidence that regulatory reforms aimed at enhancing transparency and shareholder oversight can meaningfully attenuate behavioral distortions in executive compensation. In particular, the Dodd-Frank Act appears to have reduced the capacity of overconfident CEOs to extract rents from favorable shocks, thereby improving the alignment between pay and firm-specific performance.

Table 4.7: Channel: overconfident CEOs and Dodd-Frank Act
Standard errors are adjusted for heteroscedasticity and clustered at the firm level. The Columns (1) presents the results based on option-based overconfidence measures, while the Columns (2) presents the results based on text-based overconfidence measures. Variable definitions are provided in the appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. DODD is a post-2011 indicator equal to 1 for years after the implementation of the Dodd-Frank Act's Section 951 ("Say on Pay") provision. Detailed definition for all variables are available in Appendix 2.

	Option-based OC	Text-based OC
	(1)	(2)
VARIABLES	LN(Δ pay)	LN(Δ pay)
Luck	0.2358***	0.4142***
	(0.0240)	(0.0468)
OC	-	-0.0672***
		(0.0119)
Luck*OC	0.0604*	0.1364***
	(0.0312)	(0.0381)
Luck*DODD	-0.1040***	-0.2720***
	(0.0316)	(0.0782)
OC*DODD	-0.0140	0.0333**
	(0.0142)	(0.0157)
Luck*OC*DODD	-0.0329	-0.1311**
	(0.0415)	(0.0599)
Controls	Yes	Yes
Firm*CEO FE	Yes	Yes
Year FE	Yes	Yes
Observations	42,581	37,320
R-squared	0.235	0.238

4.7.2 Instrumental variable approach

To further mitigate concerns regarding endogeneity in the relationship between CEO overconfidence and pay-for-luck, our research implements both external and internal instrumental variable (IV) strategies. The results are reported in Table 4.8.

Following Deshmukh et al. (2021), our research constructs an external instrument based on industry-level behavioral characteristics. Specifically, I instrument the interaction term *OC*Luck* (or *OC_Text*Luck*) using *Luck*Incidence*, where *Incidence* denotes the proportion of overconfident CEOs (based on the Holder67 measure) within each Fama-French 48 industry-year. This specification captures plausibly exogenous variation in CEO overconfidence that is driven by the behavioral composition of managerial peers in the same industry and time period.

The underlying identification logic rests on two assumptions. First, behavioral traits such as overconfidence often cluster within industries, as CEOs tend to face similar strategic environments and social comparison pressures. Peer effects, industry norms, and selection mechanisms contribute to convergence in managerial traits, making it more likely for CEOs in the same sector to share common behavioral dispositions. Second, while the industry-level prevalence of overconfidence may shape a firm's behavioral environment, it is unlikely to exert a direct effect on any individual CEO's compensation response to luck. That is, *Luck*Incidence* influences *OC*Luck* through the channel of CEO overconfidence but is not itself correlated with firm-specific shocks to pay-for-luck.

By leveraging cross-sectional and temporal variation in industry-level overconfidence, this instrument isolates exogenous shifts in the likelihood that a given CEO is overconfident, thereby enhancing causal identification and mitigating concerns about endogeneity due to reverse causality or omitted firm-level factors.

To complement this strategy, our research also applies the heteroskedasticity-based internal IV approach developed by Lewbel (2012), which constructs instruments from higher-order moments of the data. This method provides an alternative identification strategy when suitable external instruments are scarce and strengthens robustness against unobserved heterogeneity.

Panel A of Table 4.8 presents the results using the external instrument. The first-stage regressions confirm the relevance of *Luck*Incidence*, with coefficients of 0.9778 ($p < 0.01$) for the option-based model and 1.8571 ($p < 0.01$) for the text-based model, both significant at the 1% level. The corresponding first-stage F-statistics are 85.30 and 1708.83, exceeding the conventional weak-instrument threshold of 10.

In the second stage, the instrumented interaction terms remain statistically significant. The coefficient on *OC_Option*Luck* is 0.2688 ($p < 0.1$), while the coefficient on *OC_Text*Luck* is 0.1480 ($p < 0.01$), indicating that CEO overconfidence continues to amplify the pay-for-luck effect when instrumented with exogenous variation. Both the Kleibergen–Paap LM statistic and the Anderson–Rubin Wald statistic are significant, indicating that the study's instrument is both strongly relevant and exogenous. Moreover, the Kleibergen–Paap rk Wald F statistic exceeds the Stock–Yogo (10 %) critical value, confirming that the study's identification remains robust under heteroskedasticity and firm-level clustering.

In addition to the external instrument, we implement the internal IV strategy developed by Lewbel (ibid.), which constructs instruments directly from the model's own data by leveraging the inherent structure of heteroskedasticity. This approach is particularly well suited to empirical corporate finance settings, where traditional external instruments are often unavailable or potentially invalid. The Lewbel method offers a data-driven identification strategy that is both theoretically grounded and empirically validated in a wide range of structural applications. By allowing for causal inference without relying on external exclusion restrictions, it serves as a powerful complement to our external IV strategy. The use of both methods in tandem strengthens the overall identification strategy and enhances the credibility and robustness of our findings.

Panel B reports the results using the internal IV approach. For the option-based overconfidence measure, the coefficient on *OC_Option*Luck* is 0.0541 ($p < 0.05$), significant at the 5% level. The corresponding first-stage F-statistic is 211.25, and the Kleibergen-Paap LM statistic is 945.243 ($p < 0.01$), both strongly rejecting the null of under-identification. The Kleibergen-Paap rk Wald F statistic is 350.177 which is larger than 10% Stock-Yogo weak ID test critical values validating our results, and the Anderson-Rubin Wald test yields 260.03, significant at the 1% level, confirming inference robustness even under weak-instrument conditions.

For the text-based overconfidence measure, the coefficient on *OC_Text*Luck* is 0.0609, significant at the 10% level. The first-stage F-statistic is 193.16 ($p < 0.01$) , the Kleibergen-Paap LM statistic is 288.990 ($p < 0.01$), and the Kleibergen-Paap rk Wald F statistic is 211.253. The Anderson-Rubin Wald test yields 181.70, also significant at the 1% level.

These results support a causal interpretation: overconfident CEOs amplify the sensitivity of pay to favorable exogenous shocks. The consistency of identification across multiple tests strengthens confidence in the internal IV strategy. Although both specifications yield statistically significant effects, the larger point estimate and tighter standard errors in the text-based model suggest that this measure may be less prone to attenuation bias, potentially due to its construction being independent of compensation outcomes.

Together, these findings reinforce the behavioral mechanism through which CEO overconfidence interacts with luck to distort pay outcomes in a statistically and economically meaningful way. These findings are also consistent with our earlier evidence from the corporate governance channel. In both specifications, stronger governance constraints, whether imposed externally through regulation (Dodd-Frank) or internally through firm-level governance structures, reduce the ability of overconfident CEOs to extract rents from luck-driven performance. The convergence of these results reinforces the interpretation that governance mechanisms play a disciplining role in curbing behavioral distortions in compensation design. The consistency across regulatory and structural governance measures strengthens the credibility of the governance channel as a core mechanism in shaping the pay-for-luck relationship.

Table 4.8: Endogenous concerns: IV results
Standard errors are adjusted for heteroscedasticity and clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed definition for all variables are available in Appendix 2.

Panel A: instrumental variable				
	Option-based OC		Text-based OC	
	(1)	(2)	(3)	(4)
	First	Second	First	Second
VARIABLES	OC*Luck	LN(Δ pay)	OC_Text*Luck	LN(Δ pay)
Luck*Incidence	0.9778***		1.8571***	
	(0.1459)		(0.2573)	
OC_Option*Luck		0.2688*		
		(0.1380)		
OC_Text*Luck				0.1480***
				(0.0365)
Controls	Yes	Yes	Yes	Yes
Firm*CEO FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	42,929	42,929	37,754	37,754
First-stage F-stat	85.30***	-	1708.83***	-
Kleibergen-Paap LM-stat (Under-identification test)		43.469***		61.253***
Kleibergen-Paap rk Wald F statistic		43.806		48.210
Stock-Yogo weak ID test critical values 10% (Weak identification test)		16.36		16.36
Anderson-Rubin Wald test (Weak-instrument-robust inference)		3.88**		2.85*

Panel B: Lewbel (2012)'s internal instrumental variable		
	Option-based OC	Text-based OC
	(1)	(2)
OC_Option*Luck	0.0541**	
	(0.0253)	
OC_Text*Luck		0.0609*
		(0.0334)
Controls	Yes	Yes
Firm*CEO FE	Yes	Yes
Year FE	Yes	Yes
Observations	43,131	38,003
First-stage F-stat	211.25***	193.16***
Kleibergen-Paap LM-stat (Under-identification test)	945.243***	288.990***
Kleibergen-Paap rk Wald F statistic	350.177	211.253
Stock-Yogo weak ID test critical values 10% (Weak identification test)	16.36	16.36
Anderson-Rubin Wald test (Weak-instrument-robust inference)	260.03***	181.70***

4.7.3 Overconfident CEOs and asymmetry in pay-for-Luck

To further understand the behavioral dynamics of CEO compensation, this section investigates whether overconfident CEOs exhibit asymmetric responses to exogenous performance shocks—commonly referred to as "pay-for-luck." We employ both option-based and text-based measures of overconfidence to examine whether firms disproportionately reward overconfident CEOs for favorable external outcomes while shielding them from adverse ones.

Table 4.9: Overconfident CEOs and asymmetry pay-for-luck
Standard errors are adjusted for heteroscedasticity and clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The Columns (2) to (4) present the results based on option-based overconfidence measures, while the Columns (5) to (7) presents the results based on text-based overconfidence measures. Detailed definition for all variables are available in Appendix 2.

		Option-based OC			Text-based OC		
			Sub-sample regressions			Sub-sample regressions	
	Baseline	Overall	Bad luck	Good luck	Overall	Bad luck	Good luck
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Luck	0.2318***	0.2348***	0.0197	0.2505***	0.3188***	0.5410***	0.3141***
	(0.0203)	(0.0266)	(0.0680)	(0.0298)	(0.0580)	(0.1355)	(0.0615)
Luck*OC_Option		-0.0073	0.2875***	-0.0241			
		(0.0338)	(0.0903)	(0.0366)			
Bad Luck	0.0007	-0.0028			0.0342		
	(0.0083)	(0.0105)			(0.0217)		
Bad Luck*Luck	-0.0593	-0.1496***			0.1533		
	(0.0445)	(0.0540)			(0.1172)		
Bad Luck*OC_Option		0.0143					
		(0.0152)					
Bad Luck*Luck*OC_Option		0.2608***					
		(0.0814)					
OC_Text					-0.0544***	0.0153	-0.0577***
					(0.0133)	(0.0308)	(0.0149)
Luck*OC_Text					0.0836*	0.3016***	0.0730
					(0.0440)	(0.1000)	(0.0469)
Bad Luck*OC_Text					0.0233		
					(0.0177)		
Bad Luck*Luck*OC_Text					0.1487*		
					(0.0841)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm*CEO FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,581	42,581	8,035	31,457	37,320	6,840	27,622
R-squared	0.234	0.234	0.400	0.257	0.237	0.406	0.259

Following the methodological framework of Campbell and Thompson (2015b) and Daniel et al. (2020), we decompose performance shocks into good and bad luck components and interact them with CEO overconfidence indicators. The regression specifications include firm*CEO and year fixed effects to control for time-invariant heterogeneity and macroeconomic fluctuations. Standard errors are clustered at the firm level to address serial correlation and heteroskedasticity.

Column (1) of Table 4.9 presents the baseline specification and shows that the coefficient on *Luck* is 0.2318 and significant at the 1% level (p = 0.000), indicating that CEOs are systematically rewarded for performance driven by external factors. Column (2) incorporates the interaction between option-based overconfidence and luck. Although the interaction term *OC*Luck* is negative and not statistically significant (coefficient = -0.0634), further decomposition reveals a notable asymmetry.

In Column (3), which isolates the bad luck subsample, the coefficient on the interaction term *OC*Luck* is 0.2875 and significant at the 1% level. This finding suggests that overconfident CEOs are insulated from the disciplinary impact of poor external performance. In contrast, under good luck conditions (Column 4), the interaction term is negative (coefficient = -0.0482) and not statistically significant, indicating that overconfidence does not amplify compensation gains from favorable shocks. The triple interaction term *Bad Luck*Luck*OC* in Column (2) has a coefficient of 0.2608 and is significant at the 1% level, confirming that the asymmetry is concentrated in the lower tail of the performance distribution.

Columns (5) through (7) replicate this analysis using the text-based overconfidence measure. The coefficient on *Luck* remains positive and highly significant across specifications. In the bad luck subsample (Column 6), the coefficient is 0.5410 and significant at the 1% level, suggesting that firms continue to reward performance regardless of its source. Notably, the interaction term *Luck*OC_Text* in the bad luck condition (Column 6) has a coefficient of 0.3016 and is significant at the 1% level, again implying reduced penalties for poor performance when the CEO is perceived as overconfident. The triple interaction term *Bad Luck*Luck*OC_Text* in Column (5) yields a coefficient of 0.1487 and is marginally significant at the 10% level, reinforcing the asymmetry narrative.

Importantly, Column (5) also shows that the interaction term *Luck*OC_Text* is positive and statistically significant, indicating that overconfident CEOs not only avoid penalties during unfavorable conditions but also receive greater compensation for favorable exogenous shocks. This result highlights that the observed pay-for-luck effect is not solely driven by asymmetry in punishment avoidance; it also reflects amplified rewards when good luck occurs. Together, these findings confirm that the compensation advantage of overconfident CEOs stems from both enhanced gains in positive scenarios and muted penalties in negative ones.

These results provide strong empirical support for the hypothesis that overconfident CEOs benefit from asymmetric pay-for-luck dynamics. While overconfidence does not appear to amplify rewards under good luck, it significantly reduces exposure to downside risk, particularly in bad luck scenarios. This asymmetry persists across both behavioral measures of overconfidence, though it is more pronounced with option-based proxies. The findings underscore a potential misalignment in CEO incentive structures, where behavioral biases distort the intended function of performance-based compensation. By embedding asymmetry into pay schemes, firms may inadvertently encourage excessive risk-taking while weakening accountability mechanisms.

4.8 Conclusion

This study examines the extent to which CEOs are rewarded for luck, external factors beyond their control, and assesses whether such compensation structures align with optimal corporate governance. Our findings indicate that change in CEO pay often reflects exogenous industry and macroeconomic shocks, suggesting that existing incentive structures may not fully align managerial rewards with firm-specific performance. This pattern is particularly pronounced in firms with weaker governance mechanisms, implying that board oversight plays a critical role in mitigating rent extraction.

While some theories suggest that rewarding CEOs for luck can maintain incentive compatibility in settings with high managerial risk aversion, our results do not consistently support this argument. Instead, they highlight potential inefficiencies in pay structures that could distort executive decision-making.

Our results resonate with recent empirical findings by Kim and Park (2024), who document that boards adjust performance targets more aggressively and asymmetrically for overconfident CEOs. This practice, while potentially mitigating fairness concerns, may unintentionally accommodate rent-seeking behavior. Together with our findings, this suggests that overconfidence does not merely shape effort levels ex ante, but also affects ex post compensation negotiation dynamics through fairness-driven mechanisms. Accordingly, pay-for-luck is not purely a governance failure, but may reflect the board's implicit response to perceived motivational or retention risks posed by overconfident executives.

Our research contributes to the broader literature on executive compensation by refining our understanding of how luck influences pay. Unlike prior studies that focus solely on pay-performance sensitivity, we provide empirical evidence on the governance conditions that amplify or mitigate pay-for-luck effects.

From a theoretical perspective, our findings challenge the assumption that all performance-contingent pay mechanisms enhance firm value. If CEOs are systematically rewarded for luck, this weakens the fundamental justification for performance-based compensation and raises concerns about agency costs. Future theoretical models should account for governance heterogeneity when predicting the efficiency of pay-for-luck structures.

From a practical standpoint, our results suggest that firms and policymakers should reevaluate executive pay schemes to ensure they distinguish between skill-based and luck-driven performance. Stronger governance interventions—such as tighter board oversight and improved performance metrics—may be necessary to curb excessive pay-for-luck effects.

While our study provides robust evidence on the determinants of pay-for-luck, several limitations remain. First, our dataset primarily covers large publicly traded firms, and future research could explore whether similar patterns hold in private firms or emerging markets. Second, while we control for various governance characteristics, unobserved firm-specific factors may still influence pay structures. Finally, further research could investigate whether investors internalize these distortions by adjusting stock valuations accordingly.

Overall, our study highlights the importance of distinguishing between justifiable and distortive elements of CEO compensation, emphasizing the role of governance in ensuring fair and efficient pay practices.

Chapter 5

Conclusion

The thesis includes three empirical chapters. The first empirical chapter analyzes the predictive power of IPO prospectuses on IPO survival, with a particular focus on optimistic tone. The second chapter examines the determinants of organizational capital. The third empirical chapter investigates the effects of overconfident CEOs on pay-for-luck.

The first empirical paper finds that optimistic tone positively predicts IPO survival after controlling for the best predictors from Colak et al. (2022). The results suggest that information in IPO prospectuses can signal future IPO survival rates, contributing an important predictor of long-run IPO performance. Furthermore, the analysis shows that underwriter quality and VC backing strengthen this relationship, amplifying the positive effect of optimistic tone on IPO survival.

This research provides empirical evidence of the predictive power of language in IPO prospectuses. Practitioners can incorporate sentiment information from IPO filings when valuing IPO firms. Moreover, the research contributes to the academic literature on both IPO survival and managerial tone.

The second empirical chapter examines the determinants of organizational capital, with a particular focus on how CEO turnover interacts with CEO-specific characteristics. Using a large panel of firm-level data and various DID frameworks, the analysis reveals that CEO turnover positively affects organizational capital investment, but the magnitude and significance of this effect depend on the characteristics of the incoming CEO.

Specifically, the findings show that CEOs with higher managerial ability significantly amplify the positive effect of turnover on OC, suggesting that capable leadership plays a crucial role in driving long-term intangible investment. Similarly, CEOs with strong financial incentives—such as high tournament-based compensation and equity holdings—are more likely to undertake OC-enhancing actions after a turnover event. The effect is also more pronounced for outsider CEOs, who often bring strategic renewal and structural changes. These results support the idea that leadership transitions provide an opportunity for firms to reset their strategic focus, particularly when the new CEO is well-incentivized or possesses high ability.

This research contributes to the literature on organizational capital by highlighting the conditional nature of leadership effects on OC. It also bridges corporate governance and intangible investment by identifying the types of CEOs more likely to support long-term value creation following turnover. The findings offer practical implications for boards managing succession planning and incentive design, emphasizing the importance of matching CEO profiles with firm innovation objectives.

The third empirical chapter investigates how CEO overconfidence affects the sensitivity of executive compensation to exogenous performance shocks, commonly known as pay-for-luck. I find that overconfident CEOs receive significantly higher compensation increases in response to favorable market or industry-wide shocks, even when those outcomes are unrelated to firm-specific skill. This effect is amplified under weak corporate governance and in firms with high R&D intensity, consistent with theories of behavioral rent extraction and fairness concerns.

Using both option-based and text-based measures of CEO overconfidence, the analysis shows that overconfident CEOs are more likely to attribute external success to their own ability (self-attribution bias), thereby demanding higher rewards when luck is favorable while avoiding penalties when performance deteriorates. I identify three transmission channels—risk-taking, innovation intensity, and governance quality—that moderate the pay-for-luck effect. Risk-taking and innovation amplify the relationship, while strong governance attenuates it.

To address endogeneity, I implement both external and internal instrumental variable strategies, including industry-level overconfidence incidence and heteroskedasticity-based identification. The results remain robust, reinforcing a causal interpretation.

Finally, I find that the Dodd-Frank Act and Say-on-Pay provision significantly reduce pay-for-luck behavior, particularly among overconfident CEOs, highlighting the importance of regulatory oversight in constraining behavioral distortions in compensation. Collectively, this chapter contributes to the literature on executive compensation by integrating behavioral finance, governance mechanisms, and regulatory interventions to explain asymmetric and suboptimal pay outcomes.

Taken together, the three empirical chapters offer a cohesive perspective on how qualitative disclosures, managerial traits, and governance mechanisms jointly shape firm performance and strategic outcomes. By integrating insights from textual analysis, behavioral finance, and corporate governance, the thesis contributes to a growing literature that moves beyond traditional quantitative indicators to understand firm behavior. The findings have important implications for investors, boards, and regulators seeking to evaluate firm prospects, design effective incentive schemes, and foster innovation in increasingly intangible-driven capital markets.

Appendices

A Additional Tests

APPENDIX A: Estimation of cox proportional hazards model: Diction's measurements

This table reports the estimation results of the Cox proportional hazards model for the probability of failure and time-to-failure. All regressions include industry and year fixed effects, with their coefficients omitted for brevity. Variable definitions are provided in Appendix A. Statistical significance is denoted by one, two, and three asterisks, representing the 10%, 5%, and 1% levels, respectively. Robust z-statistics, adjusted for heteroscedasticity and clustered at the industry level, are presented in parentheses below the coefficient estimates. The hazard ratio (HR) is reported for each regression.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**
Optimism	-1.539*	0.215						
	(-1.65)							
Certainty			0.721	2.056				
			(0.64)					
Optimism MDA					-1.569*	0.208		
					(-1.69)			
Certainty MDA							-0.491	0.612
							(-0.47)	
Size	-0.023	0.977	-0.024	0.977	-0.008	0.992	-0.015	0.985

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VARIABLES	(1) Coef.	(2) HR	(3) Coef.	(4) HR	(5) Coef.	(6) HR	(7) Coef.	(8) HR
	(-0.22)		(-0.22)		(-0.08)		(-0.15)	
ROA	-1.147***	0.317	-1.158***	0.314	-1.183***	0.306	-1.174***	0.309
	(-5.15)		(-5.16)		(-5.60)		(-5.54)	
MTB	-0.019**	0.981	-0.019**	0.981	-0.019**	0.981	-0.019**	0.981
	(-2.40)		(-2.40)		(-2.55)		(-2.56)	
Leverage	0.014**	1.014	0.014**	1.014	0.012*	1.012	0.013**	1.013
	(2.07)		(2.08)		(1.74)		(1.99)	
Tangibility	0.060	1.062	0.076	1.079	0.141	1.152	0.091	1.095
	(0.11)		(0.14)		(0.26)		(0.17)	
Advertising	-0.003	0.997	-0.020	0.980	-0.110	0.896	-0.067	0.935
	(-0.01)		(-0.10)		(-0.63)		(-0.37)	
Big4	-0.308**	0.735	-0.320**	0.726	-0.344**	0.709	-0.340**	0.712
	(-2.09)		(-2.20)		(-2.47)		(-2.53)	
High-tech	-0.001	0.999	-0.004	0.996	-0.010	0.990	-0.006	0.994

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**
	(-0.01)		(-0.02)		(-0.06)		(-0.04)	
Crisis	-0.660***	0.517	-0.638***	0.528	-0.625***	0.535	-0.648***	0.523
	(-4.95)		(-4.95)		(-4.60)		(-4.83)	
Offer price	-0.866***	0.421	-0.878***	0.415	-0.896***	0.408	-0.889***	0.411
	(-3.48)		(-3.73)		(-3.84)		(-3.88)	
Proceeds	-0.002	0.998	-0.002	0.998	-0.004	0.996	-0.003	0.997
	(-0.58)		(-0.51)		(-0.88)		(-0.85)	
Underpricing	-0.148**	0.862	-0.145***	0.865	-0.149***	0.862	-0.138**	0.871
	(-2.46)		(-2.58)		(-2.71)		(-2.49)	
VC	-0.278**	0.757	-0.269**	0.764	-0.301***	0.740	-0.285***	0.752
	(-2.54)		(-2.48)		(-3.08)		(-2.75)	
Underwriter	-0.026	0.975	-0.027	0.974	-0.007	0.993	-0.015	0.985
	(-0.29)		(-0.30)		(-0.07)		(-0.15)	
CEO tenure	-0.053	0.949	-0.049	0.953	-0.049	0.953	-0.049	0.952

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**
	(-1.48)		(-1.35)		(-1.31)		(-1.38)	
CEO duality	-0.252**	0.777	-0.260**	0.771	-0.276***	0.759	-0.274***	0.760
	(-2.37)		(-2.38)		(-2.88)		(-2.86)	
Generalist CEO	1.171***	3.227	1.174***	3.235	1.156***	3.178	1.165***	3.205
	(5.84)		(5.94)		(5.87)		(5.88)	
CEO age	-0.007	0.993	-0.007	0.993	-0.007	0.993	-0.008	0.992
	(-0.76)		(-0.77)		(-0.80)		(-0.85)	
CEO gender	-0.313	0.731	-0.339	0.713	-0.344	0.709	-0.347	0.707
	(-0.90)		(-0.97)		(-1.02)		(-1.03)	
MBA	0.597***	1.817	0.601***	1.823	0.611***	1.843	0.610***	1.840
	(5.01)		(5.18)		(5.34)		(5.37)	
PhD	0.190	1.209	0.192	1.211	0.190	1.209	0.200	1.221
	(0.95)		(0.98)		(0.96)		(1.07)	

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**	**Coef.**	**HR**
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,881	2,881	2,881	2,881	2,881	2,881	2,881	2,881
χ^2	312.8	312.8	87.90	87.90	12675	12675	562.1	562.1

B Definition

APPENDIX B.1: Chapter 1 Variable Definitions

Variable	**Definition**	**Source**
Dependent Variable		
Survived	Dummy variable equal to 1 if the IPO survived within 5 years, and 0 otherwise. Survived firms are those that are still actively trading (delisting code between 100 - 199).	CRSP Events
Voluntary	Dummy variable equal to 1 if the IPO fails within 5 years, and 0 otherwise. Failed firms are those that are delisted for positive reasons (delisting code between 200-299 (Mergers), 300-399 (Exchanges)).	CRSP Events
Involuntary	Dummy variable equal to 1 if the IPO fails within 5 years, and 0 otherwise. Failed firms are those that are delisted for negative reasons (delisting code between 400-499 (Liquidations), 500-599 (Dropped)).	CRSP Events
Key Independent Variable		
Optimism ML	Net positive tone of full IPO prospectus computed from equation 2.3 based on Loughran and McDonald (2016)'s financial dictionary	EDGAR

Variable	Definition	Source
Optimism FinBERT Net	Net positive tone of full IPO prospectus computed from equation 2.1 based on FinBERT	EDGAR
Optimism FinBERT Total	Net positive tone of full IPO prospectus computed from equation 2.2 based on FinBERT	EDGAR
Optimism ML MDA	Net positive tone of MD&A section of IPO prospectus computed from equation 2.3 based on Loughran and McDonald (2016)'s financial dictionary	EDGAR
Optimism FinBERT Net MDA	Net positive tone of MD&A section of IPO prospectus computed from equation 2.1 based on FinBERT	EDGAR
Optimism FinBERT Total MDA	Net positive tone of MD&A section of IPO prospectus computed from equation 2.2 based on FinBERT	EDGAR
CEO Variables		
CEO age	Logarithm of CEO age	Execucomp, BoardEx, Hand-collected from S-1 fillings
Tenure	Logarithm of CEO tenure	Execucomp, BoardEx, Hand-collected from S-1 fillings

Variable	Definition	Source
CEO duality	Dummy variable equal to 1 if the CEO is also the chairman, and 0 otherwise.	Execucomp, BoardEx, Hand-collect
Gender	Dummy variable equal to 1 if the CEO is male, and 0 otherwise.	Execucomp, BoardEx, Hand-collect
MBA	Dummy variable equal to 1 if the CEO holds an MBA degree, and 0 otherwise.	Execucomp, BoardEx, Hand-collect
PhD	Dummy variable equal to 1 if the CEO holds a PhD degree, and 0 otherwise.	Execucomp, BoardEx, Hand-collect
Generalist CEO	Dummy variable that equals one if the CEO is a generalist, and zero otherwise. The CEO is classified as a generalist if his or her generalist skills index is equal or above the sample median. Generalist skills index is the first factor of applying principal component analysis to five proxies of general managerial skills: Number of roles, Number of firms, Number of industries, CEO experience dummy, and Conglomerate experience dummy.	BoardEx
IPO Characteristic		
IPO age	Logarithm of IPO age	Jay Ritter's database

Variable	Definition	Source
VC backed	Dummy variable equal to 1 if the IPO is VC-backed, and 0 otherwise.	Jay Ritter's database
Underwriter reputation	Dummy variable equal to 1 if the IPO is underwritten by a prestigious underwriter, and 0 otherwise.	Jay Ritter's database
Big 4	Dummy variable equal to 1 if the IPO is audited by Big 4 audit firms, and 0 otherwise.	Eikon
Initial returns	The first-day return after the IPO	Eikon
Offer price	Logarithm of offer price adjusted by inflation	Eikon
Proceeds	Logarithm of proceeds adjusted by inflation	Eikon
Firm Characteristic		
CS	Classification shifting calculated by McVay (2006)'s method.	Compustat
A_TA	Abnormal levels of total accruals, calculated as the difference between actual and normal levels of accruals. The normal levels of accruals are measured using the modified cross-sectional Jones model Dechow (1995).	Compustat

Variable	Definition	Source
A_DISX	Abnormal levels of discretionary expenses multiplied by negative one, where abnormal levels of discretionary expenses are calculated as the difference between actual and normal levels of discretionary expenses following Roychowdhury (2006).	Compustat
A_PROD	Abnormal levels of production costs, calculated as the difference between actual and normal levels of production costs following Roychowdhury (ibid.).	Compustat
Market-to-Book (MTB)	Ratio of market value to book value	Compustat
Leverage	Ratio of sum of long-term and short-term debt to total assets	Compustat
R&D intensity	Ratio of R&D expense to total assets	Compustat
R&D level	Logarithm of R&D expense adjusted by inflation	Compustat
Advertising intensity	Ratio of advertising expense to total assets	Compustat
Capital expenditure	Logarithm of capital expenditure adjusted by inflation	Compustat
Profitability	Logarithm of EBITDA	Compustat
Tangibility	Ratio of tangible assets to total assets	Compustat
Additional Controls		
ROA_std	One of 10 best predictors in Colak et al. (2022)'s model, quarterly ROA volatility.	Compustat

Variable	Definition	Source
CF_std	One of 10 best predictors in Colak et al. (2022)'s model, quarterly cashflow volatility.	Compustat
DLC_AT	One of 10 best predictors in Colak et al. (ibid.)'s model. Ratio of total current liabilities to total assets	Compustat
PI_CEQ	One of 10 best predictors in Colak et al. (ibid.)'s model. Ratio of pretax income to common equity	Compustat
DPACT_PPENT	One of 10 best predictors in Colak et al. (ibid.)'s model. Ratio of accumulated depreciation, depletion and amortization to total property, plant and equipment	Compustat
AP_SALE	One of 10 best predictors in Colak et al. (ibid.)'s model. Ratio of account payable to total sales	Compustat
PPENT_AT	One of 10 best predictors in Colak et al. (ibid.)'s model. Ratio of accumulated depreciation, depletion and amortization to total sales	Compustat

APPENDIX B.2: Chapter 2 Variable Definitions

Variable	Definition
Dependent Variables	
OC1	Organizational capital scaled by total assets, defined as $OC_{i,t} = (1-\delta_{OC})OC_{i,t-1} + \frac{SGA_{i,t}}{CPI_t}$ with an initial condition $OC_{i,0} = \frac{SGA_{i,1}}{g+\delta_{OC}}$
Adj. OC1	Organizational capital scaled by total assets and adjusted for industry
OC2	Organizational capital scaled by total assets, with organizational capital proxied by the sum of SG&A expenses, advertising expenses, and R&D expenses
Adj. OC2	Organizational capital scaled by total assets and adjusted for industry, with organizational capital proxied by the sum of SG&A expenses, advertising expenses, and R&D expenses
Key Independent Variables	
CEO Ability	Managerial ability score following Demerjian et al. (2012)
Turnover	Indicator variable from Gentry et al. (2021)'s CEO turnover database, set to 1 if the firm experiences CEO turnover
Involuntary Turnover	Defined as CEO turnover with dismissal codes in Gentry et al. (ibid.) equal to 1 (illness), 2 (death), 3 (dismissed for job performance), or 4 (personal issue)
Voluntary Turnover	Defined as CEO turnover with dismissal codes in Gentry et al. (ibid.) equal to 5 (retirement) or 6 (other opportunity)
Forced Turnover	Defined as CEO turnover with dismissal codes in Gentry et al. (ibid.) equal to 3 (dismissed for job performance) or 4 (personal issue)

Variable	Definition
Exogenous Turnover	Defined as CEO turnover with dismissal codes in Gentry et al. (2021) equal to 1 (illness) or 2 (death)
Firm Variables	
SIZE	Firm size, measured as the logarithm of total assets (Compustat item: at)
ROA	Return on assets, calculated as the ratio of EBITDA (Compustat item: ebitda) to total assets (Compustat item: at)
MTB	Market-to-book ratio, defined as the ratio of market value of equity (Compustat item: mkvalt) to book value of equity (Compustat item: bkvlps)
TANG	Asset tangibility, calculated as the ratio of tangible assets (Compustat item: ppent) to total assets (Compustat item: at)
LEV	Leverage, defined as the ratio of liabilities (Compustat item: dltt + dlc) to equity (Compustat item: seq)
CEO Variables	
CEO Age	Logarithm of CEO's age
Tenure	Logarithm of (1 + CEO tenure)
Outsiders	Indicator variable for CEO origin, classified as internal if the CEO joined the company at least two years before becoming CEO; otherwise classified as external
Ownership	Ratio of CEO stock awards to equity

Variable	Definition
Total Compensation	Logarithm of total annual compensation for the firm's CEO in a given fiscal year, based on data from ExecuComp (item *total_sec*), S&P Capital IQ (item ctype23), or ISS (item totalComp); where missing, calculated as the sum of salary, bonus, non-equity incentive plans, stock awards, option awards, long-term incentives, and other compensation collected from these databases
Fixed Compensation	Fixed portion of the CEO's compensation, measured as the log of salary
Discretionary Compensation	Variable portion of the CEO's compensation, calculated as the logarithm of total compensation minus salary, following Ellahie et al. (2017)
Stocks	Logarithm of CEO's stock awards
Cash	Logarithm of CEO's cash awards
Option	Logarithm of CEO's option awards
GAI	General ability index from Custódio et al. (2019)
Indgap1	Industry tournament incentives, calculated as the difference between a CEO's total compensation and the highest compensation within the same industry, based on the FF-30 industry classification.
Indgap2	Industry tournament incentives, defined as the difference between a CEO's total compensation and the highest compensation within the same industry, identified by SIC 2-digit code and further grouped by higher or lower sales categories (Coles et al. 2018).
Delta	Sensitivity of CEO's wealth (stock and stock options) to changes in the company's stock price
Vega	Sensitivity of CEO's wealth (stock and stock options) to changes in the company's stock price volatility

Variable	Definition
Option Delta	Sensitivity of CEO's stock options to changes in the company's stock price
Share Delta	Sensitivity of CEO's stock awards to changes in the company's stock price
Firm-Related Wealth	Sum of the value of CEO's stocks, options, and long-term incentives, including both vested and unvested amounts

APPENDIX B.3: Chapter 3 Variable Definitions

Variable	Definition
Luck Variables	
Luck	Industry and market-related performance, estimated using Equation 4.2.
Skill	Firm-specific performance unrelated to industry and market effects, estimated using Equation 4.2.
Bad Luck	Dummy variable equal to 1 if luck is negative, and 0 otherwise.
Bad Skill	Dummy variable equal to 1 if skill is negative, and 0 otherwise.
CDF(Luck)	Cumulative distribution function of variance of luck.
CDF(Skill)	Cumulative distribution function of variance of skill.
Firm Variables	
Size	Natural logarithm of total assets (Compustat item: at).
ROA	Return on assets, calculated as EBITDA (Compustat item: ebitda) divided by total assets (Compustat item: at).
Book-to-Price	Ratio of book value of equity (Compustat item: bkvlps) to market value of equity (Compustat item: mkvalt).
Leverage	Ratio of total liabilities (Compustat item: dltt + dlc) to equity (Compustat item: seq).
Return	Average weekly stock return, based on CRSP data.
Volatility	Standard deviation of weekly stock returns, based on CRSP data.
HighTech	Dummy variable equal to 1 for firms in high-technology industries (e.g., computer hardware, communications equipment, electronics, software), identified using SIC codes, and 0 otherwise.

Variable	Definition
R&D1	Natural logarithm of R&D expense (Compustat item: xrd), adjusted for inflation. Missing values are replaced with 0.
R&D2	Natural logarithm of R&D expense (Compustat item: xrd), adjusted for inflation. Missing values are dropped.
Investment	Natural logarithm of capital expenditures (Compustat item: capx), adjusted for inflation.
M&A Expense	Natural logarithm of merges&acquisitions expenditures (Compustat item: aqa), adjusted for inflation.
Risk1	Risk1 proxies for corporate risk-taking in investment decisions and operations based on the standard deviation of ROA (Ferris et al. 2017; Antoniou et al. 2024).
Risk2	Risk2 proxies for corporate risk-taking in investment decisions and operations based on the the range of ROA (Ferris et al. 2017; Antoniou et al. 2024).
CEO Variables	
CEO Age	Natural logarithm of CEO age.
CEO Tenure	Natural logarithm of (1 + CEO tenure).
ΔPay	Changes in total annual compensation for the CEO, derived from ExecuComp, S&P Capital IQ, or ISS databases.
$LN(\Delta Pay)$	Natural logarithm of changes in total annual compensation for the CEO, derived from ExecuComp, S&P Capital IQ, or ISS databases.
OC_Option	Dummy variable equal to 1 if the CEO holds exercisable but unexercised options exceeding 67% on at least two occasions during tenure.
OC_Text	Text-based measurement of CEO overconfidence, details can be found in Equation 4.1.

Variable	Definition
Incidence	Industry-level density of overconfident CEOs in a given year.
CEO Ability (MA Score)	Managerial ability score, following Demerjian et al. (2012).
Institution	Ratio of institutional ownership collected from Thomson 13f fillings.
Independence	Ratio of independent board members.

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