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Study into Stock Market Tail Risk and Information Asymmetry

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Abstract

The first study, using firm-level climate change exposure data, demonstrates that firms with higher exposure to climate change face an increased likelihood of stock price crashes. These risks arise from managerial incentives to withhold bad news due to concerns about market devaluation associated with high exposure. However, during periods of heightened public attention, the difficulty of concealing bad news increases, thereby mitigating this effect. This chapter further examines the causal impact of Donald Trump's unexpected election victory on firms' exposure to climate regulation and the associated crash risk. A difference-in-differences (DiD) model is estimated around the 2016 U.S. presidential election. The results show that after Trump assumed office in 2017, firms previously subject to climate regulation experienced a disproportionate decline in crash risk compared with firms not affected by such rules. The findings also indicate that firms exposed to climate regulation were more likely to withhold negative information from investors before the election shock.

The second study investigates the effect of risk-taking incentives, measured by debt-based compensation for both CEOs and CFOs, on firm-level intangible intensity using three empirical approaches. Theoretically, intangible intensity is closely related to information asymmetry; hence, it is hypothesized that debt-based compensation discourages managers from

accumulating intangible assets. Using U.S. data from 2006 to 2022, panel regression results indicate that higher levels of debt-based compensation for both CEOs and CFOs significantly reduce intangible intensity. Across multiple estimation methods, the results indicate that CEO incentives have a stronger influence than those of CFOs.

The third study explores the positive relationship between economic policy uncertainty (EPU) and country-level stock market tail risk. The effect of EPU on financial market tail risk is significant across all countries, especially for emerging markets. As a major source of global policy uncertainty, pandemic-related concerns—measured by the weighted frequency of epidemic-related discussions—and trade policy uncertainty are further examined. The regression results confirm that higher levels of these uncertainties are associated with greater market tail risk.

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Contents

Abstract **i**

Acknowledgements **iii**

List of Tables **viii**

List of Figures **ix**

Abbreviations **1**

Chapter 1 Introduction **1**

1.1 Research Background and Motivations 2

1.2 Aim and Research Questions 17

1.3 Potential Contribution 22

1.4 Thesis Structure 24

Chapter 2 Literature Review **25**

2.1 Green Finance 26

2.2 Stock Price Crash Risk 29

2.3 Intangible Assets 32

2.4 Inside Debt 35

2.5 Economic Policy Uncertainty 38

2.6 Tail Risk 43

Chapter 3 Study One – Climate Change Exposure and Stock Price Crash risk **47**

3.1 Introduction 48

3.2 Literature Review 55

3.3 Data Source and Summary Statistics 62

3.4 Empirical Analysis 73

3.5 The Test of Bad News Hoarding 82
3.6 Climate Change Exposure, Price Crash Risk, and Public Attention to Climate Change 86
3.7 The Causal Effect of President Trump Election 89
3.8 Conclusion 94
3.9 Tables 97
3.10 Figures 118

Chapter 4 Study two – CEO Versus CFO: Debt-based Compensation and Intangible Assets 119

4.1 Introduction 120
4.2 Related Literature and Hypothesis 128
4.3 Data, Variables, and Methodology 139
4.4 Empirical Analysis 156
4.5 Conclusions 173
4.6 Tables 176

Chapter 5 Study Three – Economic Policy Uncertainty and Cross-Country Tail Risk 195

5.1 Introduction 196
5.2 Literature Review 208
5.3 Data, Variables, and Methodology 219
5.4 Empirical Analysis 231
5.5 Conclusions 244
5.6 Tables 246

Chapter 6 Conclusions 260

6.1 Overview 261
6.2 Main Findings 261
6.3 Contributions 265
6.4 Limitations and Recommendations for Future Studies 269

6.5 Summary 272

Bibliography **275**

List of Tables

3.1 Summary Statistics 97

3.2 Correlation (Columns 1–6) 98

3.3 Correlation (Columns 7–18) 99

3.4 Correlation (Columns 19–26) 100

3.5 Results for Climate Change Exposure 101

3.6 Results for Climate Change Risk Measurements 102

3.7 Summary Results for Different Types of Exposure 103

3.8 Summary Results for Different Types of Risk Exposure . . . 105

3.9 Estimates of Stock Price Crash Due to Breaks in Earnings String Caused by Climate Change Exposure 107

3.10 High Attention Effect. 108

3.11 Definition of Variables 110

3.12 Top Ten Sectors 112

3.13 The Causal Effect of Exposure to Climate Regulation on the Risk of Stock Price Crash 113

3.14 Parallel Trend Tests: Pre-Event Trends in Crash Risk 115

3.15 Placebo Tests: Causal Effect of Exposure to Climate Regulation on Stock Price Crash Risk Based on Pseudo-Samples . 116

3.16 Placebo Test: The Causal Effect of Exposure to Climate Regulation on the Risk of Stock Price Crash during Obama's Second Term 117

4.1 Summary Statistics 176

4.2 Definition of Variables 177
4.3 Baseline Regression Results 179
4.4 Stage II Results of Instrumental Variable Methods for CEO and CFO Inside Debt on Intangible Intensity 182
4.5 Results of Changes in Variables for CEO and CFO Inside Debt on Intangible Intensity 185
4.6 Robustness of CEO and CFO Inside Debt to Intangible Intensity 186
4.7 Stage II Instrumental Variable Methods for Robustness Tests 188
4.8 Robustness Test: Results of Changes in Variables for CEO and CFO Inside Debt on Intangible Intensity 190
4.9 Robustness of CEO and CFO Inside Debt to Bid-Ask Spread 192

5.1 Summary Statistics 246
5.2 Definition of Variables 247
5.3 Baseline Relationship Between the *BBD* Index and Tail Risk 248
5.4 2SLS Results of the *BBD* Index and Tail Risk 250
5.5 Robustness Test Using Indicator for One Month Prior to U.S. Election 252
5.6 Robustness Test Using Indicator for Three Months Prior to U.S. Election 254
5.7 Robustness Test Using Indicator for Six Month Prior to U.S. Election 256
5.8 Robustness Test Using the Index of Discussion on Epidemics and World Trade Policy Uncertainty 258

List of Figures

3.1 Placebo Test: Density Estimates of the Impact of Exposure to Climate Regulation on Crash Risk 118

Chapter 1

Introduction

1.1 Research Background and Motivations

The significance of left-tail risk in financial assets, as well as the factors that shape its impact on financial decision-making, has been extensively documented in academic research. Since the seminal work of Fama (1965), this topic has continued to receive considerable scholarly attention. Over the decades, studies have examined both how investors respond to extreme market events and the underlying drivers of such events. Modern financial theory now treats tail risks as an essential market characteristics. Because tail risks embody investors' fears, they require higher expected returns as compensation. This fundamental risk–return trade-off establishes a predictive link between asset prices and left-tail risk, a relationship supported by a wide range of empirical evidence. For instance, Kelly and Jiang (2014) shows that tail risk is positively associated with aggregate market returns, even though left-tail risk itself varies over time. Similarly, Bollerslev and Todorov (2011b) demonstrates that the variance risk premium, defined as the difference between realized variance and risk-neutral expected variance, can predict market returns. Building on Bansal and Shaliastovich (2011), they decompose the variance risk premium into two parts: normal-sized price fluctuations and jump tail risk. Their findings suggest that most of the predictive power stems from compensation for bearing jump tail risk.

The literature also addresses practical puzzles by assuming that investors account for the possibility of rare extreme events. Some studies suggest that the main source of uncertainty in financial markets is rarely occurring extreme events, known as "Black Swan events". The catastrophic consequences of the 2007–2008 global financial crisis exemplify investors' sensitivity to such events. Similarly, the Coronavirus Disease 2019 (COVID-19) outbreak has caused substantial uncertainty in global financial markets.

The increasing frequency of extreme events highlights the importance of understanding left-tail risk, the central focus of this thesis.

Stock price crash risk represents a critical manifestation of left-tail risk in equity markets and carries significant implications for portfolio theory and asset pricing. Kim and Zhang (2014) emphasizes the importance of tail risk, showing that it affects option-based asset pricing by influencing investor confidence through the disclosure or concealment of bad news. Furthermore, negative skewness in stock return distributions indicates that downside risk occurs more frequently than extreme positive returns, highlighting the need for effective risk management. Harvey and Siddique (2000) suggests that conditional skewness has strong implications for asset pricing, as it is negatively related to expected returns and momentum. This relationship implies that investors demand higher returns when conditional skewness is considered. In addition, exogenous shocks, particularly regulatory changes, can trigger sudden stock market crashes (Huang and Liu, 2021), making it essential for investors to understand the mechanisms and characteristics of price crashes for better investment decisions and asset pricing.

Given the economic and asset-pricing importance of left-tail exposures documented above, Chapter 3 focuses on a prominent manifestation in equity markets, namely stock price crash risk, and examines its firm-level determinants. Most research on the determinants of stock price crash risk follows the framework of Jin and Myers (2006), which identifies information asymmetry between corporate managers and external investors as the primary source. The model shows that managers, motivated to protect their interests, may withhold negative information over time. This opacity allows insiders to conceal bad news while reducing perceived volatility for investors, but when accumulated negative information reaches a tipping point, it is

released to the market and often triggers substantial price declines. This "bad news hoarding" mechanism demonstrates how information asymmetry can harm investors and generate left-tail risk in financial markets. Empirical studies based on this framework identify several managerial incentives affecting crash risk, including Chief Executive Officer (CEO) age (Andreou et al., 2017), stock liquidity (Chang et al., 2017), financial report readability (Kim and Zhang, 2014), insider trading (Jinshuai et al., 2014), and managerial equity compensation (Kim et al., 2011a).

Beyond firm-specific managerial incentives, broader environmental challenges also play a role in shaping downside risk. Climate change represents an important source of such risk. The catastrophic consequences of global warming have prompted governments to introduce regulations controlling carbon emissions, such as carbon taxes, emission targets, and emission limits. While green investments can mitigate investment risk and channel funds toward sustainable industries (Taghizadeh-Hesary and Yoshino, 2019; Eyraud et al., 2013; Wang and Zhi, 2016), climate-related regulations impose heterogeneous shocks across firms. For instance, carbon-intensive firms face higher costs related to taxes and corporate governance, making investments in these firms inherently riskier. Sautner et al. (2020) demonstrates that such firms are naturally more exposed to climate change based on firm-level climate exposure measures. Consequently, firm-level climate change exposure is expected to be positively associated with stock price crash risk.

These climate-related risks are further shaped by the political environment. For example, President Trump's opposition to climate-related policies and reversal of environmental regulations created a political environment favoring firms with high fossil fuel dependence, thereby potentially influencing their stock price crash risk. Prior studies explore related mechanisms: En-

gle et al. (2020) implements a schedule to form portfolios hedging against climate risk using high-dimensional newspaper coverage data, and Ilhan et al. (2021) proposes that carbon regulation risks can be priced in the options market, allowing downside risk protection.

While climate-related regulations constitute a key source of uncertainty by imposing heterogeneous costs across firms, they should also be understood as part of the broader category of policy-related risks that interact with political and economic shocks. In this regard, frequent and severe political and economic extreme events, such as the 2007–2008 global financial crisis, the COVID-19 pandemic, and regional conflicts, further amplify the role of regulatory interventions in shaping stock price crash risk. Regulatory changes that follow these events further raise uncertainty in the business and economic environment, which can impact financial markets and contribute to stock price crash risk. Empirical studies indicate that Economic Policy Uncertainty (EPU) captures such effects. Specifically, Ilhan et al. (2021) emphasizes that environmental policy uncertainty should also be considered, as these risks can be priced in the option market.

Building on these insights, the role of climate-related regulation deserves particular attention. Such regulations can increase costs in taxes and corporate governance for carbon-intensive firms and heighten the risk of investing in those firms. Based on the firm-level climate change exposure measurement proposed by Sautner et al. (2020), such firms are naturally highly exposed to climate change; consequently, firm-level climate exposure is expected to be positively related to stock price crash risk. Meanwhile, President Trump's stance against climate-related policy and the reversal of environmentally friendly regulations means his electoral success might be profitable for firms that use large amounts of traditional fuel—an effect that would be revealed through the aforementioned relationship with crash

risk. Motivated by these findings, Chapter 3 investigates how firm-level climate exposure interacts with external political shocks to influence left-tail risk in the stock market.

To complement the external perspective of Chapter 3, Chapter 4 explores the internal firm-level mechanisms through which information asymmetry manifests in left-tail risk, focusing on managerial incentives and intangible assets. Information asymmetry lies at the core of the stock price crash risk mechanism. When managers possess private information and withhold negative news, the eventual release of accumulated bad news can trigger sharp downward price corrections. This mechanism not only explains why crash risk is a manifestation of managerial opportunism but also highlights the broader role of information asymmetry in shaping corporate risk profiles. Beyond stock market outcomes, information asymmetry amplifies accounting and corporate finance risks, transmitting managerial decisions into asset market volatility.

Moreover, extreme corporate events such as bankruptcy and credit shocks also reflect the consequences of information asymmetry in financial markets. Derrien et al. (2016) shows that greater information asymmetry raises the cost of debt and increases the incidence of credit events, while Steiger (2010) documents that credit risk and implied volatility strongly predict stock returns, particularly for distressed firms. Beyond firm-level effects, bankruptcy risk can also spill over to industry peers through shared creditors or counterparty exposures, amplifying the propagation of bad news across firms. Finally, Chenari et al. (2025) emphasizes that debt maturity structure affects both bankruptcy risk and crash risk, since short-term debt strengthens managerial incentives to conceal information. Together, these findings highlight that bankruptcy and credit risks are not only financial distress signals but also key channels through which information

asymmetry translates into left-tail outcomes.

Therefore, exploring how managerial incentives, asset structure, and financial distress contribute to information asymmetry and left-tail risk offers a more integrated understanding of the determinants of extreme events. This forms the motivation of Chapter 4, which investigates the role of intangible assets, managerial incentives, and corporate financial risks in shaping firms' exposure to tail risk.

Building on the central role of information asymmetry in shaping extreme events, this study further examines intangible intensity as a key firm-level characteristic that may amplify left-tail risk. The growing prominence of intangible assets among U.S. firms underscores their significance in driving competitiveness and innovation. Investment in intangible assets fosters technological innovation and enhances a firm's reputation, boosting distinctiveness and competitive advantage. As a larger portion of firm assets becomes intangible, concerns over information asymmetry between managers and investors naturally increase.

According to Wu and Lai (2020), intangible assets are associated with information asymmetry due to two main factors: measurement errors arising from the lack of standardized valuation and managerial incentives to overprice assets such as patents and goodwill to improve acquisition value. Unlike tangible assets, intangibles such as R&D, software, brand equity, or proprietary data are difficult to observe and value objectively. Their benefits often materialize over a long horizon, and the absence of standardized accounting treatment allows managers substantial discretion in capitalization and reporting. Consequently, investors face greater uncertainty in assessing firm value and performance, while managers possess private information that is not fully captured in financial statements. This structural

opacity makes firms with high intangible intensity inherently more prone to information asymmetry.

Beyond their causal relationship with stock price crash risk, intangible assets also link directly to several types of accounting and corporate finance risks. Hansen et al. (2005) suggests that intangible capital should be considered a risk premium beyond the market-to-book ratio, finding that intangible-intensive firms exhibit lower average returns and higher earnings volatility compared to tangible-intensive firms. Elkemali (2024) further highlights that investors require compensation for exposure to intangible-intensive firms.

Due to their inherent opacity and non-physical nature, intangible assets complicate credit evaluation, increasing information asymmetry and potentially heightening systemic financial risk. Traditional credit assessment models struggle with these assets, and banks face significant information asymmetry due to accounting's inability to adequately capture intangibles such as R&D, human capital, and brand value. This opacity can lead to credit mispricing, where lenders undervalue resilient firms or overfinance fragile ones. Moreover, intangibles are often unsuitable as collateral due to illiquidity and difficulty in separation during default, increasing the likelihood that financial distress translates into extreme stock price movements.

These challenges are further amplified by regulatory and accounting frameworks, which shape how financial institutions assess and respond to the risks posed by intangibles. Regulatory frameworks like Basel II exacerbate these challenges by diverting resources from developing robust assessment methodologies (Guimón, 2005). Differences in impairment approaches under various accounting standards further complicate bankruptcy prediction, while R&D investments are often associated with financial con-

straints, increasing risk exposure for firms with high intangible intensity (Li, 2011). Overstatement of intangible values, for example through goodwill, can trigger severe earnings shocks and disproportionate price declines, while accounting standards like International Financial Reporting Standards (IFRS) may systematically underestimate bankruptcy risk relative to more conservative frameworks. Intangibles thus act as "latent vectors of fragility," amplifying information asymmetry and translating accounting ambiguity into systemic risk, ultimately affecting both credit and equity markets and contributing to left-tail extreme events.

High levels of intangible assets are also associated with increased agency costs. Outside investors typically lack detailed knowledge of managerial decisions, particularly in technology-driven firms, which allows managers significant discretion (Martins et al., 2010). The uncertain recognition of intangibles in financial statements complicates valuation, making private information acquisition profitable and necessitating greater analyst coverage (Barth et al., 2001b). Consequently, firms with substantial intangible assets exhibit pronounced information asymmetry and agency costs. The connection between intangibles and extreme risk has been empirically documented (Jia, 2018; Wu and Lai, 2020), motivating the research in Chapter 4.

The relationship between managerial incentives and firm outcomes is closely shaped by information asymmetry between managers and investors. Empirical evidence suggests that compensation structures influence how managers make decisions under asymmetric information. For example, Kim et al. (2011a) finds that equity-based compensation for Chief Financial Officers (CFOs) significantly affects managerial behavior, whereas similar incentives for CEOs show no measurable effect, indicating that the design of incentives can alter risk-taking and reporting practices. Similarly, He

(2015) examines the role of CEO inside debt holdings, which create long-term stakes in the firm and align managerial actions with the interests of creditors. Managers with inside debt are more likely to act conservatively and prioritize financial stability, thereby reducing agency conflicts and improving the reliability of corporate reporting. Building on these insights, the second study of this thesis investigates how managerial incentives, particularly inside debt holdings, interact with information asymmetry to shape firm-level outcomes.

Chapter 4 further investigates how a firm's holding of intangible assets is influenced by top managers' risk-taking incentives. The study addresses gaps in understanding the determinants of intangible asset levels from a managerial perspective. Managers with compensation tied to debt, so-called inside debt, are motivated by the firm's overall value rather than equity alone (Jensen and Meckling, 1976). This incentive structure mitigates agency costs, discourages unnecessary risk-taking, encourages ethical behavior, reduces bankruptcy risk, and promotes transparent corporate reporting. Intuitively, the presence of inside debt holdings among managers is expected to be negatively related to a firm's intangible intensity, providing a direct link between managerial incentives, information asymmetry, and the firm's asset composition.

Having examined how information asymmetry and firm characteristics drive crash risk at the micro level, Chapter 5 turns to the macro perspective, investigating how country-level political and economic uncertainty contributes to aggregate stock market tail risk. Another essential source of extreme events comes from political and economic uncertainty. Increasingly frequent global shocks, such as unexpected policy or regulatory changes, strongly influence corporate stock market performance, as examined in previous chapters. Because these shocks rarely remain confined within national

borders, their spillover effects on international financial markets raise important questions about systemic vulnerabilities. Chapter 5 therefore extends the analysis to the cross-country level, investigating how external shocks transmit across markets and amplify tail risk in the global financial system.

External shocks, including the contagious impact of COVID-19 or surprising election outcomes, can deliver abrupt and powerful disruptions that affect not only local stock markets but also the global financial system. COVID-19, the third major coronavirus outbreak in less than two decades, evolved into the most severe global pandemic, resulting in millions of cases and fatalities worldwide and inflicting substantial damage on the global economy. The pandemic and the widespread shutdowns across countries undermined tourism, trade, and transport industries, and even generated food shortages (Albulescu, 2020), thereby inevitably harming financial markets, increasing volatility, and eroding investors' confidence. Historical parallels reinforce this point: Barro et al. (2020) documents similar effects of the 1918–20 Great Influenza Pandemic, which depressed stock returns and heightened volatility. Collectively, these episodes reveal that major external events induce heightened uncertainty in both policymaking and the macroeconomic environment. Similar impacts have been documented from other sources, including natural disasters (Kowalewski and Śpiewanowski, 2020), news events (Li, 2018), environmental policies (Guo et al., 2020), and even sports outcomes (Buhagiar et al., 2018).

As one of the most influential external factors, Economic Policy Uncertainty (EPU) plays a central role in shaping stock market volatility. EPU captures the fear and ambiguity generated by unstable policy environments, and empirical evidence consistently shows its strong effect on financial markets (Zhu et al., 2019; Antonakakis et al., 2019; Chen and Chiang, 2020). Li

(2020), for instance, reveals the causal impact of domestic EPU on China's market volatility, as well as the spillover effect from U.S. policy uncertainty shocks. Moreover, national elections are closely tied to policy consistency and regulatory outcomes, directly influencing investor confidence. For example, President Trump's reversal of environmentally friendly policies after his electoral victory negatively affected firms dependent on traditional chemical fuels, particularly in industrial and transport sectors. These examples illustrate that political and policy-driven uncertainty can function as a trigger for broad market disruptions and constitute an important driver of financial instability.

Against this backdrop, it is crucial to clarify why this chapter emphasizes systematic tail risk rather than firm-level crash risk, in contrast to other chapters of this study. Contemporary financial research increasingly recognizes two distinct dimensions of extreme downside risk exposure: systematic tail risk and firm-level stock price crash risk. Although both phenomena manifest as severe negative returns, their origins, transmission mechanisms, and implications for financial stability differ fundamentally.

Systematic tail risk originates from macroeconomic shocks with the potential to disrupt the entire financial system. Such shocks include global recessions, geopolitical crises, or liquidity spirals that simultaneously affect broad asset classes. During the 2008 financial crisis, for example, correlated institutional failures created feedback loops in which forced asset liquidations depressed asset prices, which in turn triggered additional rounds of deleveraging across the banking sector. These dynamics reflect the fat tails observed in market return distributions and indicate non-diversifiable systemic risks. By contrast, firm-level crash risk arises from firm-specific vulnerabilities, especially from hiding bad news, leading to return patterns with frequent small gains and occasional sharp declines. Unlike systematic

shocks, these episodes are largely confined to the affected firm or sector.

Three key differences highlight the distinct economic nature of systematic tail risk and stock price crash risk. First, scope and contagion. Systematic tail risk affects the entire market because assets are correlated and institutions are interconnected. For example, during the COVID-19 market collapse in March 2020, what began as localized selloffs quickly turned into an 18-trillion-dollar global equity decline as liquidity dried up across asset classes. By definition, systematic tail risk is closely linked to systemic crises. In a broad market crash, all stocks lose value, but those with higher tail betas suffer more. During the 2008–09 financial crisis, high-tail-beta stocks lost about two to three times as much as low-tail-beta stocks. In contrast, stock price crash risk is mostly a firm-level phenomenon. Macroeconomic shocks, such as high inflation, sanctions, or other adverse trends, can increase the likelihood of firm-specific crashes, however, measures of crash risk (like NCSKEW or DUVOL) mainly reflect residual, firm-specific variation, even during market downturns.

Second, diversifiability. Systematic tail risk cannot be easily reduced through diversification, because it is embedded in market-wide exposures. Firm-specific risks, including stock price crashes, tend to decrease when investors hold diversified portfolios, since the risks are idiosyncratic.

Third, measurement. Systematic tail risk is typically measured using extreme value techniques, tail beta calculations, or macroeconomic left-tail quantile regressions, such as GDP growth tail quantiles. Stock price crash risk, on the other hand, is measured with firm-level indicators, such as negative skewness of returns or the probability of earnings restatements. Systematic tail risk is influenced by country-level economic conditions, because broad shocks, such as GDP declines, financial crises, or policy uncertainty,

affect the whole market and increase the likelihood and severity of extreme losses. Stock price crash risk is influenced by these shocks only indirectly, to the extent that they change the environment in which firm-specific bad news is released or concealed.

The prioritization of systematic tail risk in this chapter is not merely an academic choice but one aligned with the research objective of studying cross-country financial fragility under uncertainty. Firm-level crash risk primarily erodes shareholder value within individual corporations, and while costly, such events are often mitigated through portfolio diversification and corporate governance reforms. By contrast, systematic tail risk carries unparalleled societal costs: macro-tail events ignite self-reinforcing liquidity spirals, leading to margin calls, forced liquidations, collapsing asset prices, and further rounds of distress. This mechanism was evident not only in 2007–09 but also in subsequent crises, including the 2020 pandemic. Asset pricing evidence further underscores its significance: Bartram et al. (2021) documents that a 1% increase in macroeconomic tail risk, measured by consumption growth tail probabilities, raises expected equity returns by approximately 2.3%, highlighting that investors receive a substantial equity premium specifically for exposure to systemic catastrophes, which is not present in the pricing of firm-specific crash risk.

Methodologically, this choice follows the approach of Kelly and Jiang (2014). Their aggregate downside risk measure is specifically designed to capture a common market-wide tail factor by combining information from all listed firms. Using this framework at the country level maintains consistency with its original purpose. In contrast, applying it at the firm level would diverge from the model's assumptions. It would also fail to isolate the systemic component that is most relevant for macroeconomic shocks, such as EPU.

Moreover, systemic shocks impose broader structural consequences that firm-level collapses cannot replicate. The U.S.–China tariff escalation in 2025, for instance, initially disrupted individual supply chains but rapidly spread into market-wide distress through correlated panic selling and institutional deleveraging. Within days, liquidity dried up across equities, bonds, and even safe-haven assets like gold, erasing trillions in market capitalization. Such episodes illustrate how macroeconomic or geopolitical uncertainty transforms into systemic fragility, undermining not just firms but the integrity of the global financial architecture. Equally important, the cross-country design of this chapter further motivates the use of aggregate tail risk: while firm-level crash risk reflects firm-specific characteristics, its distribution is inevitably influenced by country-specific factors such economic growth, industry structure, and inflation situation; aggregate tail measures provide a consistent and comparable metric across markets, enabling coherent international analyses.

Therefore, this chapter adopts systematic tail risk as the focal variable because it better captures the undiversifiable, market-wide consequences of political and economic uncertainty. While firm-level crash risk remains important in corporate governance and microfinance studies, it is systematic tail risk that most directly reflects the destabilizing impact of pandemics, elections, or policy shocks on international financial markets. This choice ensures consistency with the overarching research question of this chapter: to understand how global uncertainty translates into systemic market dislocations and amplifies financial instability at the macroeconomic level.

The empirical result of this thesis is organized into three chapters, each addressing tail risks from a different perspective, but all contributing to a unified research agenda on the determinants and implications of extreme downside risk in financial markets.

Chapter 3 investigates the role of external shocks, focusing on climate-change exposure and its impact on firm-level stock price crash risk. Building on the bad news hoarding framework, this chapter examines whether firms more exposed to climate-related risks are more likely to crash, whether the effect varies with the intensity and dimension of exposure, and whether climate-related regulations exert a causal influence on downside risk. The analysis is situated within the growing literature on climate finance and corporate disclosure, providing novel evidence on how environmental factors propagate into financial fragility.

Chapter 4 turns inward to the firm's internal structure, examining how managerial incentives and information asymmetry interact to shape financial fragility.A central focus is the role of intangible assets, whose opacity and valuation difficulty heighten information asymmetry between managers and investors. This asymmetry not only encourages selective disclosure of adverse information but also increases credit and corporate finance vulnerabilities, ultimately transmitting risk to equity markets and amplifying the likelihood of extreme downside events. The chapter explores whether incentives for conservative managerial behavior, particularly those associated with inside debt, mitigate these risks by discouraging opportunistic reporting and excessive intangible accumulation. By linking managerial-compensation structures to firms' tail-risk exposure via intangibles, the chapter highlights the micro-level governance and accounting mechanisms through which information asymmetry transforms into systemic vulnerability. In doing so, it complements the external perspective of Chapter 3 by showing how endogenous firm characteristics and internal governance arrangements also drive crash risk.

Chapter 5 broadens the lens to the macroeconomic environment, analyzing how country-level Economic Policy Uncertainty (EPU) affects systemic

tail risks in equity markets. By linking policy-induced uncertainty with the distribution of aggregate market returns, this chapter shows that tail risks are not only driven by firm-level exposures or internal governance structures but also by macroeconomic policy dynamics that amplify downside vulnerabilities.

Taken together, the three chapters provide a comprehensive and multi-layered analysis of financial tail risks. Chapter 3 emphasizes the role of external shocks (climate change), Chapter 4 demonstrates how information asymmetry and managerial incentives generate vulnerabilities within firms, and Chapter 5 investigates macro-level policy uncertainty. By integrating these perspectives, the dissertation contributes to a deeper understanding of how tail risks emerge, interact, and propagate across different levels of the financial system. This integrated framework not only advances academic debates in asset pricing, corporate governance, and financial economics, but also offers practical insights for policymakers and market participants seeking to mitigate the adverse consequences of extreme downside risk.

1.2 Aim and Research Questions

Financial markets are inherently exposed to extreme downside risks, commonly referred to as left-tail risks, which capture the probability of severe negative returns. These risks are particularly consequential because they not only affect individual investors' portfolios but can also propagate through the financial system, potentially leading to broader economic instability. Over the past decades, episodes of market crashes, corporate scandals, and global crises have highlighted the importance of understanding the determinants of left-tail risk. However, despite substantial academic

attention, several critical gaps remain.

First, while a rich literature examines firm-level determinants of stock price crash risk, the role of emerging environmental factors, such as climate change exposure, remains underexplored. Climate-related risks have become increasingly salient due to regulatory shifts, investor attention, and physical risks associated with global warming. Understanding how these risks translate into extreme downside movements in stock prices is therefore essential, yet empirical evidence remains limited.

Second, firm-level studies often emphasize observable financial metrics but frequently overlook the interaction between managerial incentives, corporate governance, and intangible assets in shaping risk outcomes. Information asymmetry and bad news hoarding, for example, are theorized to amplify crash risk, yet few studies systematically link these internal corporate mechanisms with firm characteristics over time, especially considering the evolving structure of executive compensation.

Third, at the macro level, uncertainty, whether stemming from economic policy, trade disputes, or global shocks, has been shown to affect market-wide tail risk. However, the underlying drivers of systematic tail risk itself remain relatively underexplored. Much of the existing literature analyzes firm-specific or cross-country risks in isolation, leaving limited understanding of what triggers extreme market-wide events.

Addressing these gaps is crucial for both academic understanding and practical risk management. By linking firm-level exposures, managerial behavior, and macroeconomic uncertainty to left-tail risk, this thesis aims to provide a more comprehensive understanding of the factors driving extreme downside events in financial markets. This integrated perspective allows for a richer investigation of the interplay between microeconomic and macroe-

conomic determinants of tail risk, highlighting channels that are relevant for policymakers, regulators, and investors alike.

The aim of this thesis is to thoroughly investigate several factors that may cause left-tail risk in financial markets at different levels. Across the chapters, equity market risks are analyzed separately at the firm level and the cross-country level. At the firm level, the thesis focuses on stock price crash risk, as it strongly reflects the distributional characteristics of stock prices and the degree of tail risk. Typically, investors expect higher returns for higher skewness (Harvey and Siddique, 2000), implying that stock price crash risk is an important factor in asset pricing. Against the backdrop of growing concerns about global warming and climate change, Chapter 3 investigates how exposure to climate change affects stock market risk at the firm level, with stock price crash risk as the primary research focus.

A panel dataset comprising measures of stock price crash risk, firm-level climate change exposure, and a set of control variables for all firms listed on U.S. stock exchanges during the period 2006–2020 is employed for the empirical analysis. The panel regression results indicate a significant positive relationship between firms' climate change exposure and stock price crash risk. Moreover, using data from the same period, the theory of bad news hoarding is also validated in this context. By further applying a difference-in-differences (DiD) model, the causal effect of the external shock caused by Trump's election is demonstrated. Specifically, for firms exposed to climate-change-related regulations, the election of President Trump was beneficial for stock market performance.

The mechanism underlying stock price crash risk is closely related to the bad news hoarding theory, as developed by Jin and Myers (2006). Beyond crash risk itself, information asymmetry is a central driver of various corpo-

rate vulnerabilities, influencing accounting quality, financial reporting, and broader firm-level risk exposures. Building on this perspective, Chapter 4 investigates how internal corporate factors shape the level of information asymmetry. In particular, the chapter focuses on firms' holdings of intangible assets, which are inherently opaque and have been linked not only to stock price crash risk (Wu and Lai, 2020) but also to broader financial and corporate risks. It further examines how managerial incentives to avoid misconduct, such as compensation structures tied to inside debt, affect the accumulation of intangibles and, consequently, the firm's exposure to tail risk.

The sample for this chapter covers all firms listed on U.S. stock exchanges from 2006 to 2022, as the SEC's expansion of executive compensation disclosure requirements in 2006 provides the starting point for the analysis. Using ExecuComp data to construct measures of inside debt and combining these with firm characteristics, the analysis documents a negative relationship between CEO and CFO inside debt and firms' intangible asset intensity. To further address endogeneity concerns and ensure the validity of the results over a longer term, instrumental variable methods and first-difference regressions are employed. To provide robustness against outliers while offering a fuller picture of the results, quantile regression methods are also applied. Additionally, bid-ask spread is used as an alternative measure in robustness tests to account for potential market microstructure effects. The empirical evidence confirms the robustness of the conclusion that managerial incentives help promote ethical decision-making, with CEOs playing a particularly important role in this process.

At the cross-country level, the aggregate tail risk measure introduced by Kelly and Jiang (2014) is applied to capture the left-tail features of stock markets across countries. Motivated primarily by the outbreak of COVID-

19 and its catastrophic impact on the global economy, Chapter 5 investigates whether and how Economic Policy Uncertainty (EPU) increases financial market risk at the cross-country level. Tail risk measures are constructed using data from all publicly listed firms in each country's equity market, following Kelly and Jiang (2014). Using these tail risk measures, the EPU measurement denoted as *BBD* index to capture EPU, and a set of control variables for country-level economic conditions, panel regression methods are employed to test the positive relationship between EPU and country-level tail risk. To ensure robustness, the U.S. presidential election, which is arguably the most influential political event globally, is included as an indicator in the regression. Political polarization is used as an instrumental variable to further validate the causal interpretation of the results, and the findings remain consistent. Beyond EPU, this chapter also investigates other uncertainty measures, such as World Trade Uncertainty and global concerns about pandemics, in light of the catastrophic consequences of the unprecedented COVID-19 event.

The research questions of this thesis can be summarized as follows:

1) Is firm-level stock price crash risk influenced by exposure to climate change?

2) How does the degree and type of climate change exposure affect stock price crash risk?

3) Does this effect follow the theoretical framework of bad news hoarding?

4) Is there a causal effect of climate-change-related regulation on stock price crash risk?

5) Do managerial incentives for conservative behavior affect firms' intangible asset holdings?

6) Between CEOs and CFOs, which plays a more important role in this relationship?

7) Does country-level Economic Policy Uncertainty influence equity market tail risks at the cross-country level?

1.3 Potential Contribution

This thesis offers several significant contributions to the literature on left-tail risks in financial markets, particularly focusing on firm-level dynamics and cross-country analyses.

At the firm level, this thesis explores the relationship between climate change exposure and stock price crash risk. Building upon the "bad news hoarding" theory, it empirically demonstrates that firms with greater exposure to climate-related risks tend to withhold negative information, leading to an increased likelihood of stock price crashes. This finding aligns with recent studies indicating that firms' climate risk exposure negatively impacts stock liquidity and may contribute to higher crash risk.

Furthermore, this research extends the understanding of climate-related risks by introducing a novel metric for firm-level climate risk exposure, addressing the challenge of capturing idiosyncratic climate impacts. The analysis reveals that firms highly exposed to climate change experience more severe stock price crashes, highlighting the importance of incorporating environmental factors into asset pricing models.

The second part of this thesis delves into the role of managerial incentives

in shaping firms' intangible asset holdings and their implications for stock price crash risk. By examining the relationship between CEO and CFO inside debt holdings and the intensity of intangible assets, the study finds a negative association, suggesting that managerial incentives to mitigate risk-taking behaviors influence the accumulation of intangible assets.

This finding contributes to the literature by providing empirical evidence on how executive compensation structures can impact corporate decision-making regarding intangible assets. It also offers insights into the mechanisms through which managerial incentives can influence firm-level risk profiles, particularly in the context of information asymmetry and the potential for stock price crashes, financial misreporting, and other corporate vulnerabilities.

At the cross-country level, this thesis investigates the impact of Economic Policy Uncertainty (EPU) on aggregate tail risk in equity markets. Utilizing the tail risk measurement framework proposed by Kelly and Jiang (2014), the study demonstrates that higher levels of EPU are associated with increased left-tail risk in national stock markets. This finding underscores the importance of macroeconomic policy stability in maintaining financial market resilience.

Additionally, the research examines the effects of specific political events, such as the U.S. presidential election, on market uncertainty, providing further evidence of how political factors can influence global financial markets. The analysis also explores the implications of global concerns, such as the COVID-19 pandemic, on cross-country tail risk, highlighting the interconnectedness of global events and financial stability.

1.4 Thesis Structure

The thesis is organized into six chapters. Chapter 1 introduces the overall framework of the study, outlining the research background and motivation, the aims and objectives, the research questions, the expected contributions, and the structure of the thesis. Chapter 2 provides a comprehensive review of the literature relevant to the research themes.

Chapter 3 presents the first empirical study, which examines the link between firm-level climate change exposure and stock price crash risk. The second empirical analysis, focusing on the role of CEO versus CFO debt-based compensation in shaping the reporting of intangible assets, is discussed in Chapter 4. Chapter 5 investigates the association between economic policy uncertainty (EPU) and systemic tail risk at the cross-country level. Finally, Chapter 6 concludes the thesis by summarizing the key findings and highlighting their theoretical and practical implications.

Chapter 2

Literature Review

2.1 Green Finance

Climate change is widely regarded as one of the most serious challenges facing global society. The damage it causes can affect every individual on the planet by altering the Earth's living environment. Consequently, growing concern about climate change inevitably influences the economy and financial markets. Empirical studies, including Burke et al. (2015), Dell et al. (2012), and Hsiang (2010), provide evidence that macroeconomic activity is substantially depressed by global warming. Governments' increasing focus on combating climate change introduces significant risks for corporate management, as related regulations can alter the business environment differently across firms, generating heterogeneous uncertainty. Fossil fuels, for instance, have been widely used over past decades and remain crucial to industrial production in almost every sector, while large-scale greenhouse gas emissions are a primary contributor to global warming. Heightened concern over this issue can significantly affect future economic and financial activity, particularly for carbon-intensive firms, which may experience reduced investor confidence.

The uncertainty induced by climate change on the macroeconomy arises through multiple channels. One strand of research examines how rare climate disasters affect economic activity. Weitzman (2014) investigates how low-probability yet potentially catastrophic climate events increase the social cost of carbon emissions. Barro (2015) explores the trade-off between the probability of rare disasters and optimal environmental investment, while Bansal et al. (2017) demonstrates that climate shocks can have persistent impacts on welfare and consumption dynamics, both in the present and in the future. At the firm level, climate-related regulations can have heterogeneous effects. For carbon-intensive firms, regulatory interventions

may increase operational costs or restrict access to external financing from institutions such as banks, which seek to comply with climate-related regulatory standards (Litterman, 2021).

The financial sector plays a central role in shaping the economic consequences of climate change. It not only intermediates capital allocation for environmentally sustainable projects but also serves as a transmission channel for climate-related regulation (Wang and Zhi, 2016). Green finance, for instance, can guide investment flows toward sustainable businesses, reallocate capital in an environmentally responsible manner, and mitigate financial risks associated with climate change (Eyraud et al., 2013; Taghizadeh-Hesary and Yoshino, 2019). Furthermore, climate risk is typically classified into two categories: physical risk, arising directly from climate impacts (e.g., production losses due to rising sea levels), and transition risk, reflecting the challenges of adapting business models and corporate practices to low-carbon requirements (Giglio et al., 2020).

Different types of climate risks affect financial assets heterogeneously, and this heterogeneity has important implications for asset pricing. A growing body of empirical research seeks to quantify how climate-related risks are incorporated into financial markets. For example, Ilhan et al. (2021) examines tail risks associated with carbon emissions in options markets and find differential effects depending on firms' carbon intensity. Engle et al. (2020) develops a climate news index based on textual analysis of high-dimensional newspaper data, which has been employed by Huynh and Xia (2021) to demonstrate that bonds with higher climate-news betas tend to yield lower subsequent returns. From a theoretical perspective, Lemoine (2021) adopts an asset-pricing framework to show that climate-related uncertainty affects future consumption through precautionary savings motives, damage scaling with consumption, and the covariance between future consumption and

current emission reductions. Collectively, these studies highlight that climate risk is increasingly priced across different asset classes.

The impact of climate change on financial markets is also evident at the industry level. Hong et al. (2019) documents that droughts reduce profitability and stock returns for firms in the food sector, while Giglio et al. (2021) and McKenzie and Levendis (2010) provide evidence that climate risk is priced in real estate markets. Taken together, these findings suggest that heterogeneous exposure to climate risk serves as a determinant of asset returns and tail risks in equity markets, thereby underscoring the importance of examining firm-level climate exposure as a potential driver of stock price crash risk.

A central challenge in climate finance is measuring firms' exposure to climate change. Sautner et al. (2020) develops a firm-level climate change exposure metric using machine learning combined with text analysis of 10-K financial reports. This measure has been shown to effectively price climate-related risk in equity markets, and Sautner et al. (2023) further applies this metric to estimate equity premia based on firm-level climate exposure. Similarly, Li et al. (2020a) constructs a corporate climate risk exposure index using earnings call transcripts. These methodological advances provide a foundation for studying how firm-level climate exposure may contribute to financial tail risk, particularly stock price crash risk.

Linking these firm-level measures with theories of information asymmetry and "bad news hoarding" (Hong et al., 2019; Giglio et al., 2021) offers a framework for understanding how climate exposure can translate into idiosyncratic tail risk in the stock market. Firms with higher exposure to climate-related risks may face more severe negative shocks in equity returns, highlighting the importance of integrating environmental factors

into asset pricing and risk management models.

2.2 Stock Price Crash Risk

Stock price crash risk is a critical feature of stock return distributions, reflecting the left-tail risk of equity returns. It carries important implications for asset pricing across various financial instruments, including stocks and options. For instance, Kim and Zhang (2014) links crash risk to option pricing theory by connecting financial reporting opacity with the volatility smirk, a key anomaly in option pricing models. Similarly, Harvey and Siddique (2000) finds that conditional skewness contributes to explaining the cross-sectional variation in expected asset returns, highlighting the relevance of left-tail risk for asset pricing.

The theoretical foundation for most empirical studies on stock price crashes is provided by Jin and Myers (2006), who argue that information asymmetry is the primary driver of crashes. Managers may withhold negative information to protect their benefits and employment, and when accumulated bad news reaches a tipping point, its sudden disclosure can trigger dramatic declines in stock prices (Kothari et al., 2009; Jin and Myers, 2006). Transparency and accounting conservatism play a key role in mitigating such risks. Firms that maintain transparent financial reporting are less likely to conceal negative information, and empirical evidence supports this relationship. For example, Hutton et al. (2009) finds that opaque firms are more susceptible to crashes, while Kim and Zhang (2014) shows that accounting conservatism reduces crash risk. Furthermore, Zhu (2016) documents a positive association between high accruals and stock price crashes, suggesting that aggressive income management, which is often linked to

managerial benefits, contributes to bad news hoarding.

Internal factors within firms can influence the likelihood of stock price crashes through policies and reporting practices. Financial conservatism (Kim and Zhang, 2016) and the adoption of International Financial Reporting Standards (IFRS) (DeFond et al., 2015) enhance the credibility of financial information, especially in environments with poor information quality. The quality and readability of financial disclosures are also crucial: He (2015) and Kim et al. (2019) demonstrate that higher reporting quality and more readable 10-K filings are associated with lower crash risk, indicating that transparency mitigates the propensity to hoard negative information. Other internal corporate behaviors, such as tax avoidance (Kim et al., 2011b) and corporate social responsibility practices (Kim et al., 2014), further shape managerial incentives and affect crash likelihood.

Managerial characteristics represent another key dimension influencing crash risk. CEO traits, such as age, overconfidence, and power, have been found to affect the likelihood of crashes. For example, younger CEOs are more willing to take risks to enhance personal benefits, whereas older CEOs prioritize firm stability (Andreou et al., 2017). CEO overconfidence (Kim et al., 2016) and high levels of managerial power (Al Mamun et al., 2020; Harper et al., 2020) are positively associated with crash risk. Other personal factors, such as marital status, may also influence risk-taking behavior (Kim et al., 2022). Similar patterns have been observed for CFOs, where overconfidence and equity-based incentives can drive riskier corporate decisions, potentially exacerbating crash risk (Qiao et al., 2022; Kim et al., 2011a).

External factors, including governance structures, monitoring, and market conditions, further contribute to the dynamics of stock price crashes. Insti-

tutional investor oversight generally reduces crash risk, as does ownership by public pension funds (Callen and Fang, 2013). Auditors providing tax-related services can also help mitigate crashes, supporting the notion that effective external supervision reduces information asymmetry (Habib and Hasan, 2016). Conversely, certain governance arrangements, such as directors appointed by local governments, may intensify crash risk by prioritizing state interests over shareholder value, reinforcing agency problems (Lee and Wang, 2017). Chen et al. (2001) suggests that unusually high trading volumes may indicate bad news hoarding, while Chang et al. (2017) finds that high market liquidity can increase crash risk because managers anticipate investor reactions to negative information. Callen and Fang (2015b) shows that higher short-term interest rates can amplify crashes as investors exploit price declines through short-selling strategies.

Overall, the literature demonstrates that stock price crash risk arises from a complex interplay of internal and external factors, such as managerial incentives, corporate policies, governance structures, and market dynamics, but remains largely focused on traditional determinants. Existing studies predominantly examine how these mechanisms operate through channels of information asymmetry and limited risk diversification, thereby shaping crash risk in asset pricing. However, relatively little attention has been paid to emerging systemic shocks, particularly those associated with climate change and sustainability-related regulatory interventions. Given the increasing salience of environmental and policy uncertainties in financial markets, investigating the influence of firm-level climate change exposure represents a critical and timely extension of the existing literature.

2.3 Intangible Assets

Intangible assets are conceptualized as a class of economic resources that generate value for firms despite lacking physical substance. The growing importance of intangible assets has been widely recognized in the literature, as traditional accounting and financial reporting models often fail to capture the value created by innovation, skills, knowledge, and creativity (Blair and Wallman, 2003; Bond et al., 2000). Blair and Wallman (2003) defines intangible assets as non-tradable resources that can be applied in production and are expected to generate future economic benefits. With the rapid development of technological innovations, including advances in computing and artificial intelligence, intangible assets have become increasingly central to firms' competitiveness and differentiation (Lev, 2000), prompting a growing body of research focused on their measurement, valuation, and management.

Accurately classifying and defining intangible assets remains a challenging task. Ideally, classifications should enhance the utility of intangible asset measurement, yet the objectives of such classification are often ambiguous (Khalidi, 2013; Abeysekera, 2016; Nobes, 2018). This conceptual ambiguity contributes to ongoing debates regarding the measurement of intangible assets. Basu and Waymire (2008) emphasizes the cumulative, synergistic, and frequently inseparable nature of intangible assets from tangible assets, arguing that they are inherently geared toward creating future value. In contrast, others regard many intangible expenditures as current expenses rather than capital investments, particularly when the assets, such as brands, are unique and difficult to value (Lonergan, 2009). Such differences in interpretation and reporting create significant challenges for investors attempting to assess the real value of a firm's intangible resources.

To better understand the practical implications of these conceptual challenges, empirical studies have examined how intangible assets are reported and perceived in the market. These studies further explore whether intangible assets are value-relevant and reliable. Dahmash et al. (2009) finds that while intangible assets are indeed value-relevant, their reporting reliability varies. For instance, goodwill is often reported conservatively, whereas identifiable intangible assets tend to be reported more aggressively. This asymmetry exacerbates information problems and contributes to financial constraints. Investments in intangible assets are generally more sensitive to financing limitations compared with tangible assets (Masayuki et al., 2012), as they are difficult to pledge as collateral (Fedderke et al., 2007). Consequently, many firms treat expenditures on intangible assets as current-period expenses rather than capital investments (Yallwe and Buscemi, 2014), reflecting a lack of standardized accounting guidelines. This inconsistency in recognition, measurement, and reporting amplifies agency costs and creates potential for adverse selection and moral hazard, which can undermine the effective contribution of intangible assets to corporate value.

The literature also highlights the impact of intangible asset disclosure on market perceptions. Kallapur and Kwan (2004) finds that stock prices respond positively to announcements of brand capitalization, with the magnitude of the response increasing with the reliability of the reported information. Similarly, Lev (2000) underscores the difficulty for investors to fully comprehend knowledge- and skill-based resources, which increases agency costs and information asymmetry. Experimental evidence by Luft and Shields (2001) shows that firms' decisions to capitalize rather than expense intangible expenditures affect the accuracy and consistency of future profit forecasts, further emphasizing the importance of disclosure quality.

Conversely, Skinner (2008) argues that current accounting standards fail to recognize knowledge-based intangibles, which may lead to a growing divergence between book values and market values. Nevertheless, this gap does not necessarily impede firms' ability to raise capital, as the stock market may assign value to such intangible resources (Fama and French, 2004), highlighting the role of intangible assets from an asset-pricing perspective.

Importantly, the treatment and reporting of intangible assets are closely linked to corporate governance and managerial decision-making. The incentives and discretion of top executives, particularly CEOs and CFOs, can influence both the accumulation and disclosure of intangible assets, as well as broader financial policies. For example, managerial risk preferences, equity-based compensation, and internal debt holdings may shape how firms invest in, capitalize, and report intangible resources. Understanding these dynamics is critical because they affect not only the efficiency of resource allocation within the firm but also the transparency and informativeness of financial reporting, which ultimately influences stock market behavior and firm valuation. Therefore, exploring the interaction between managerial incentives and intangible assets provides a natural extension of the literature on corporate finance, accounting conservatism, and information asymmetry, and lays the groundwork for subsequent analyses of how executive behavior affects firm-level risks, including stock price crash risk.

Building on this perspective, recent studies emphasize the downside risks associated with intangible assets in relation to bankruptcy and credit distress. Because they cannot be easily liquidated or pledged, intangibles often amplify financing constraints and information asymmetry. Goodwill accounting, with impairment-only testing, creates additional volatility by generating sudden downward shocks that heighten creditors' concerns (Amoros et al., 2023). Empirical work further shows that while advertising

and R&D may enhance long-term earnings potential, they can complicate liquidation and creditor negotiations, thus undermining recovery prospects in bankruptcy. Jones (2011) finds that failing firms capitalize intangible assets more aggressively than non-failing firms, that such capitalization is strongly associated with earnings management, and that voluntary capitalization of intangibles has significant predictive power for firm failure. Horsch et al. (2021) shows that patent invalidation leads to an exogenous reduction in firms' intangible capital, which in turn reduces leverage by approximately 14%, with the effect being stronger for smaller or less creditworthy firms. This evidence suggests that firms that rely heavily on intangible assets for financing are more exposed to shocks affecting leverage and short-term debt management, thereby facing higher bankruptcy risk. Overall, fluctuations in intangible assets not only affect financing capacity but also influence financial stability through changes in capital structure. Jindal and McAlister (2015) finds that although these assets improve bankruptcy prediction models, their protective role is conditional, and Jindal (2020) stresses that they operate as a double-edged sword: expected cash flows may rise, but distress costs and survival risks often increase when markets turn adverse. Overall, intangible intensity tends to heighten operational and financial fragility, making firms more exposed to bankruptcy and credit risk when external conditions deteriorate.

2.4 Inside Debt

Equity-based compensation is widely recognized as a source of agency problems between managers and shareholders, as documented extensively in the literature (Coles et al., 2006; Low, 2009). Specifically, when managers are compensated primarily through equity, such as stock or options, they may

prioritize the interests of shareholders over those of debt holders, generating potential conflicts between the two. This issue was first formalized by Jensen and Meckling (1976), who proposed that firms should design an optimal compensation structure that balances equity- and debt-based incentives to mitigate such conflicts. In particular, this framework highlights the role of "inside debt" compensation, which is unsecured and unfunded but aligned with corporate performance, as it encourages managers to reduce debt costs and adopt less risky strategies to lower the probability of financial distress.

Subsequent studies have explored the optimal structure of equity- and debt-based compensation in more detail. Edmans and Liu (2011) emphasizes that inside debt exposes managers to the same default risk faced by external debt holders, thereby aligning managerial wealth with the liquidation value of the firm under default scenarios. Similarly, Agrawal and Mandelker (1987) and Barnea et al. (1980) argue that a carefully structured combination of debt- and equity-based compensation has been argued to mitigate managerial incentives to favor either shareholders or debt holders, suggesting that the optimal compensation structure should reflect the firm's capital structure. By doing so, firms can reduce agency costs and promote decision-making that is more consistent with the overall interests of the firm.

Empirical evidence supports the idea that inside debt encourages more conservative managerial behavior. For example, Wei and Yermack (2011) finds that CEOs with high levels of inside debt tend to hold firms with relatively high debt value but lower equity value, and this is associated with more prudent financial policies. Cassell et al. (2012) further demonstrates that empirical evidence indicates that CEO inside debt holdings are negatively associated with the volatility of future stock returns, R&D expenditures,

and financial leverage, while positively associated with firm diversification and asset liquidity. Additional studies report that CEO inside debt is linked to lower cost of debt (Anantharaman et al., 2014; Chava and Purnanandam, 2010; Wang et al., 2010), higher abnormal bond returns and long-term operating performance during M&A transactions (Phan, 2014), fewer restrictive covenants on private loans (Anantharaman et al., 2014), higher firm cash holdings (Liu et al., 2014), and reduced default risk with better management outcomes during financial crises (Bennett et al., 2015; Chen et al., 2010). Collectively, these findings illustrate that inside debt not only constrains managerial risk-taking but also aligns managerial incentives with both shareholder and debtholder interests.

The theoretical rationale behind the effectiveness of inside debt is closely related to its role in mitigating agency problems. Debt-based compensation exposes managers to the risk of firm underperformance and bankruptcy (Edmans and Liu, 2011), thereby discouraging unethical or overly aggressive behavior (Noe, 2009; Nachman and Noe, 1995). In this context, managers thereby assume dual roles as both agents and stewards of corporate resources. The asymmetry of information, whereby executives possess privileged knowledge about corporate assets, can create opportunities for self-serving behaviors, such as tunneling. By tying compensation to the firm's default and liquidation outcomes, inside debt reduces these agency costs, encouraging managers to safeguard corporate assets and make prudent financial decisions.

Importantly, inside debt differs from fixed compensation schemes such as salaries and bonuses, which exhibit lower sensitivity to the firm's liquidation value. As Edmans and Liu (2011) points out, inside debt provides positive payoffs proportional to the liquidation value in bankruptcy, ensuring that managers share the risk exposure of external debtholders. In

contrast, traditional bonuses may offer zero payoff under default conditions and, in some scenarios, may inadvertently induce executives to engage in excessive risk-taking in order to avoid bankruptcy. This alignment effect is particularly relevant in ensuring that managerial decisions are not only oriented toward short-term performance but also toward preserving firm value under adverse conditions.

Taken together, the extant literature demonstrates a robust association between managerial inside debt holdings and more conservative corporate behavior, with significant implications for corporate finance and risk governance. Executives with greater exposure to inside debt tend to implement less aggressive financial policies, mitigate firm default risk, and exhibit heightened accountability in decision-making processes. These empirical insights provide a critical foundation for examining how executive compensation structures shape firm-level risk-taking, inform capital structure decisions, and influence the strategic management of both financial and operational resources.

2.5 Economic Policy Uncertainty

Political and economic uncertainty can generally be defined as the occurrence of unpredictable changes or announcements of regulations that affect fiscal, monetary, or other public policies, which in turn influence financial markets, economic ecosystems, and corporate management (Abel, 1983). Over the past few decades, globalization has interconnected economies more closely than at any previous point in human history, contributing to the augmentation of global productivity and economic development. At the same time, this interconnectedness increases the potential for the spillover

of unexpected events, demonstrate that abrupt shocks can engender substantial and pervasive consequences across countries. Historical instances such as the 9/11 terrorist attacks, the Arab Spring, the surprising victory of President Trump in the 2016 U.S. presidential election, Brexit, and the COVID-19 pandemic illustrate how sudden shocks can produce severe and widespread consequences on global economic and financial systems (Baker et al., 2016). Given the central role of major economies such as the United States in global trade and finance, political disputes and policy uncertainty have become critical areas of concern, especially during periods of contested elections or unexpected policy shifts. These developments underscore the necessity of understanding economic policy uncertainty (EPU), particularly considering the lessons learned from past crises, such as the 2008 global financial downturn, where abrupt changes in fiscal, financial, taxation, and monetary regulations contributed to systemic economic losses (Al-Thaqeb and Algharabali, 2019).

Economic policy uncertainty has been shown to have significant effects on macroeconomic variables. Elevated EPU can suppress GDP growth (Balcilar et al., 2016), reduce corporate investment (Bernanke, 1983), and slow overall economic development (Bloom, 2009). Household investment, as a key component of domestic consumption and a reflection of market confidence, is especially responsive to variations in economic policy uncertainty. Under conditions of elevated uncertainty, households tend to defer consumption and investment decisions because assets appear less attractive, personal incomes are uncertain, and corporate profitability may decline (Bloom, 2009; Pastor and Veronesi, 2012). These effects are markedly pronounced during economic recessions (Giglio et al., 2016) and can have long-term consequences for capital formation (Barrero et al., 2017). Uncertainty in the economic environment also influences employment decisions,

as firms tend to limit hiring or reduce labor expenditures in anticipation of potential shocks (Bloom, 2014), thereby indirectly affecting household consumption and economic growth.

The recognition of these significant macroeconomic effects has motivated efforts to quantify economic policy uncertainty more accurately. A widely employed indicator is the Chicago Board Options Exchange's implied volatility index (VIX), which captures equity market uncertainty at the firm level. However, the VIX is limited to equity market fluctuations and fails to fully capture broader dimensions of economic and policy risk. Other approaches have explored uncertainty through news-based indices, investor sentiment, firm-level conference calls, election outcomes, and macroeconomic indicators (Da et al., 2015; Hassan et al., 2019; Scotti, 2016; Julio and Yook, 2012; Jurado et al., 2015). Although informative, these methodologies frequently exhibit limited generalizability, require extensive data collection, and are difficult to replicate (Al-Thaqeb and Algharabali, 2019). To address these limitations, Baker et al. (2016) develops the EPU measurement denoted as the *BBD* index for the United States, which integrates information from news coverage, policy announcements, market behavior, and economic indicators into a single, comprehensive metric. The *BBD* index correlates strongly with other indicators of uncertainty, such as the VIX, and provides a robust tool for analyzing both historical and contemporary periods of heightened uncertainty. Extending this framework, Davis (2016) constructs global EPU indices for sixteen major economies, enabling cross-country comparisons of political and policy risk exposure.

Economic policy uncertainty has profound implications for corporate finance through both internal and external channels. Internally, elevated economic policy uncertainty engenders greater managerial prudence, leading executives to reduce risk-taking and adopt more conservative opera-

tional strategies (Bloom, 2009). Externally, uncertainty can increase the cost of capital by restricting access to credit and increasing financial constraints, thereby raising the probability of corporate default. Empirical studies provide consistent evidence for these channels. For example, Çolak et al. (2017) finds that gubernatorial elections in the United States substantially depress IPO activity in the two years preceding elections, accompanied by declining stock prices, whereas post-election periods witness a subsequent recovery in activity. Similarly, Nguyen and Phan (2017) documents that EPU negatively affects M&A activity, lowers bid premiums, and encourages firms to complete acquisitions with stock rather than cash, extending the time required for transaction completion. Bonaime et al. (2018) confirms these findings, showing that fiscal, monetary, and financial regulations have the strongest depressive effect on M&A activity, whereas policies in healthcare, national security, and trade exert minimal influence. In response, firms undertake vertical or cross-border mergers to mitigate risk exposure to diversify risk and protect stockholder value under heightened uncertainty.

Corporate investment is highly sensitive to political uncertainty. Empirical evidence shows that exogenous shocks from political events, particularly closely contested U.S. presidential elections, can significantly suppress investment activity, with estimates suggesting a 5% reduction during election years (Jens, 2017; Julio and Yook, 2012). This pattern is further illustrated by the 2007–2008 financial crisis, during which both capital expenditures and borrowing declined sharply, highlighting the pronounced sensitivity of corporate investment to policy-induced uncertainty (Kahle and Stulz, 2013; Gulen and Ion, 2016). Interestingly, while policy uncertainty (EPU) tends to dampen short-term investment, it can paradoxically encourage long-term R&D expenditure, as firms seek to sustain profitability in uncertain

environments (Stein and Stone, 2013).

The effect of EPU is not uniform across all firms. Those that are more financially constrained, operate in less competitive industries, or undertake more irreversible investments experience more pronounced negative impacts. In addition to decreased external financing availability, firms also engage in precautionary cash hoarding to mitigate the risk associated with high uncertainty (Kahle and Stulz, 2013; Riddick and Whited, 2009; Im et al., 2017). This behavior reflects risk-averse incentives engendered by heightened policy uncertainty, further depressing short-term investment despite potential long-term benefits.

Finally, economic policy uncertainty can be conceptualized as a systematic risk factor priced within financial markets. According to Pastor and Veronesi (2012), unexpected policy changes tend to depress stock prices, and the magnitude of this effect increases with higher uncertainty levels. This framework positions EPU as a systematic risk factor that is priced into equity and credit markets. Subsequent research has validated this perspective, showing that policy uncertainty affects stock option pricing (Pástor and Veronesi, 2013), firm-level stock volatility (Aye et al., 2018), and credit spreads (Gilchrist et al., 2014). Emerging market economies exhibit heightened sensitivity to economic policy uncertainty, with stronger effects observed on investment and private consumption compared to developed economies (Carrière-Swallow and Céspedes, 2013). Additionally, policy shocks can influence the correlation between asset classes, including stock-bond correlations (Li et al., 2015; Fang et al., 2017) and the variance of gold futures (Fang et al., 2018), further underscoring the pervasive impact of policy-induced uncertainty on financial decision-making and market outcomes.

2.6 Tail Risk

Infrequent extreme events, often referred to as "black swan" events, significantly affect economic activity and investment behavior. Portfolio managers have long been concerned with left-tail risk since Fama (1963) and Mandelbrot (1963) identify the heavy-tailed nature of unconditional return distributions, which can be described using power-law distributions. Building on this foundation, subsequent research has emphasized the time-varying nature of tail risk (Quintos et al., 2001; Galbraith and Zernov, 2004). This observation aligns with the empirical fact that extreme events are rare and inherently difficult to predict. Together, their rarity and unpredictability make tail risks particularly critical for both risk management and asset pricing considerations.

Tail risks are recognized as essential factors in asset pricing models, and their relevance to investors is well-documented. For example, Straetmans and Chaudhry (2015) investigates tail risk at both the individual bank level and the systemic level in the U.S. and the eurozone, revealing higher levels of both individual and systemic tail risk in U.S. markets. Similarly, Gilli and Këllezi (2006) applies extreme value theory to six major stock market indices—Hang Seng, Dow Jones, Euro Stoxx 50, FTSE 100, Nikkei 225, Swiss Market Index, and S&P 500—using metrics such as Value-at-Risk (VaR), Expected Shortfall, and return levels, with associated confidence intervals. Their results consistently show that the left tails of all indices are fatter than the right tails, highlighting the prominence of extreme negative returns.

Empirical evidence also indicates that equity returns exhibit increased correlation during periods of heightened market volatility (Van Oordt and Zhou, 2016). For instance, King and Wadhwani (1990) analyzes the 1987

stock market crash and attributed it to information transmission across markets, whereby rational investors inferred market-wide risk. Longin and Solnik (1995) further examines monthly excess returns and found a positive relationship between correlation and volatility, suggesting that tail risk dynamics influence inter-market co-movements. In the same vein, Karolyi and Stulz (1996) documents that international correlations, such as between U.S. and Japanese markets, are affected by broad market index uncertainty. Subsequent studies (Longin and Solnik, 2001; Ang and Bekaert, 2002) show that these correlation effects are amplified during bear markets but not during bull markets, emphasizing the asymmetric nature of tail risk. Collectively, these findings underscore the predictive power of tail risk for stock market returns and its dynamic evolution over time.

The relevance of tail risk extends directly to asset pricing. Arzac and Bawa (1977) proposes a model in which investors maximize utility under VaR constraints. Bollerslev and Todorov (2011b) analyzes the interplay between variance risk premiums and quality premiums, while Chapman et al. (2018) demonstrates that the tail risk index developed by Kelly and Jiang (2014) captures a significant component of cross-sectional return discount rates. Additional empirical work (Bali et al., 2009; Chollete and Lu, 2011; Huang et al., 2012) validates the intertemporal relationship between tail risk measures and market excess returns. Other studies explore higher-order moments, showing that conditional skewness (Harvey and Siddique, 2000) and kurtosis (Dittmar, 2002) meaningfully contribute to explaining cross-sectional stock returns. Moreover, Bakshi et al. (2003) links variations in risk-neutral skewness and kurtosis to option pricing dynamics.

Macro-financial implications of rare disasters are also well-documented. Gourio (2012) incorporates a time-varying rare disaster probability into a closed economy business cycle model, demonstrating that such disas-

ters reduce output, investment, stock prices, and risk-free interest rates via both capital accumulation and productivity channels. Extending this framework, Gourio (2012) examines firms' capital structure decisions and shows that although debt financing provides tax shields in normal times, it also increases firms' exposure to bankruptcy risk during rare disasters, thereby raising the cost of capital and widening credit spreads. The importance of tail risk for financial institutions is further underscored by Muir (2017), who finds that asset price declines during crises, wars, meanwhile recessions are especially pronounced in financial crises, highlighting the systemic relevance of extreme events for investors.

One of the most notable contributions of tail risk research is its ability to address long-standing asset pricing puzzles. The equity premium puzzle (Mehra and Prescott, 1985) highlights the unexpectedly high return on stocks relative to government bills, which standard consumption-based risk models cannot explain. Similarly, the equity volatility puzzle, which is defined as the discrepancy between observed stock return volatility and the volatility of underlying cash flows, challenges traditional models such as the consumption CAPM. Research indicates that incorporating low-probability economic disasters into asset pricing frameworks helps reconcile these anomalies. For example, Rietz (1988) extends the Lucas-Mehra model by including a rare, depression-like third state, successfully accounting for high equity risk premia and low risk-free rates.

The volatility puzzle is also linked to predictive relationships involving the price-dividend ratio (Fama and French, 1989; Cochrane, 1992; Keim and Stambaugh, 1986). Excess returns are determined by realized and expected future cash flows, including dividends, and discount rates. The classical consumption CAPM assumes stock return volatility should match consumption volatility; however, empirical evidence contradicts this, par-

ticularly during financial crises and recessions, where consumption volatility remains relatively stable while stock return volatility rises dramatically. Barro (2006) proposes a solution by introducing stochastic, persistent variation in the probability of rare economic disasters, thereby relaxing the i.i.d. assumption of shocks to productivity growth and aligning model predictions with observed high equity premiums, low risk-free rates, and volatile stock returns.

Modeling time-varying rare disaster probabilities naturally raises challenges in measurement. Several methods have been developed to quantify left-tail risk and its implications for financial markets. Arzac and Bawa (1977) employs VaR-constrained utility maximization, while Bali and Cakici (2004) links VaR and firm characteristics to expected stock returns, validating the positive association between VaR and monthly market returns. Bollerslev and Todorov (2011b) introduces an Investor Fear Index connecting tail risk to equity premia. More recently, Dierkes et al. (2024) systematically evaluates sixteen tail risk measures grouped into four categories: option-implied measures (Andersen et al., 2020; Bollerslev and Todorov, 2011b, 2014; Bollerslev et al., 2015; Gormsen and Jensen, 2022; Gao et al., 2018), stock-return-based measures (Kelly and Jiang, 2014; Christoffersen et al., 2012; Maheu et al., 2013), option-return-based measures (Lu and Murray, 2019; Cremers et al., 2015), and macroeconomic data-based measures (Adrian et al., 2019). Their results indicate that certain measures, particularly those proposed by Bollerslev and Todorov (2011a) and Kelly and Jiang (2014), demonstrate significant predictive ability for future tail events, tail volatility, and market returns over both short and long horizons.

Chapter 3

Study One – Climate Change Exposure and Stock Price Crash risk

3.1 Introduction

The increasing attention to climate change and its potential risks and costs to the financial market has sparked a surge in research in this area, raising concerns among both firms and investors. In a speech at Lloyd's of London, Mark Carney, the former Governor of the Bank of England, emphasized that extreme weather events could have devastating and destabilizing effects on financial markets (Carney, 2015). These effects include higher costs arising from extreme weather events, depreciation of fossil fuel assets, and lawsuits against companies implicated in climate change. Polluting firms are also exposed to risks such as environmental protests, reputational damage, and government fines. Carney warned that the costs of climate change, which the current generation has little incentive to address, will ultimately be borne by future generations. He urged governments to do more to encourage firms to confront this issue and disclose their current and future carbon emissions.

Motivated by these concerns, recent scholarship increasingly investigates the extent to which climate risks are priced in asset markets. Recent studies highlight the importance of incorporating climate risks into investment decisions. For instance, Bansal et al. (2016) treats climate risk as a long-run risk factor in asset pricing models, suggesting that it is worth hedging through financial instruments. Other works, such as Bolton and Kacperczyk (2021) and Hsu et al. (2020), examine the cross-section of carbon risk and the environmental pollution premium in stock markets, showing that these issues are highly relevant for investors. Research on the pricing of environmental risk further reveals that climate risk often exerts an influence on security markets, particularly equities, but is sometimes mispriced (Hong et al., 2019; Daniel et al., 2016; Kumar et al., 2019).

At the firm level, the realized effects of climate change are already visible in corporate performance. The influence of climate risk on asset pricing partly reflects its realized effects on corporate performance. A related strand of the literature focuses on the firm-level effects of extreme weather events. Addoum et al. (2021) shows that corporate earnings are adversely affected by extreme temperatures. Similarly, Pankratz et al. (2019) documents that firm revenues and operating income decline with increased exposure to high temperatures, while Kruttli et al. (2021) analyzes how stock and options markets react to extreme weather events. Collectively, these studies demonstrate the critical importance of pricing climate risk in equity markets, as this has direct implications for investors' decision-making.

There is also evidence linking corporate environmental practices and investor behavior. For example, Hoepner et al. (2018) connects environmental policies with downside and overall portfolio risks, finding that stronger environmental policies reduce such risks. They also show that investors are attentive to firms' attitudes toward climate issues, with Environmental, Social, and Governance (ESG) disclosure serving as a credible signal that helps mitigate downside risk.

Precisely because environmental issues exert significant impacts on the economy and investment, governments have strong incentives to intervene. Such interventions, however, often take the form of climate policies and regulations, which themselves generate further repercussions for financial markets. This is especially true for firms that are highly exposed to climate rules. Hsu et al. (2022) develops a general equilibrium model in which firms' cash flows are a function of environmental policy changes. Their results suggest that stricter regulation reduces emissions but also lowers firm profitability. The adverse financial impact, reflected in stock price declines, is most pronounced among high-emission firms that are more vulnerable to

regulatory shifts, compared to low-emission firms. Similarly, Seltzer et al. (2022) emphasizes regulation as a primary channel through which environmental risks are embedded in security prices, given its immediate relevance for market participants (Krueger et al., 2020). Devaluation of firms heavily exposed to climate regulation can also hurt financial institutions and pension funds that hold such investments, potentially undermining consumer confidence and destabilizing the global economy, leading to a decline in living standards. Such extreme financial outcomes may translate into tail risk in equity returns, motivating the examination of stock price crash risk.

However, quantifying firm-level exposure to climate change remains empirically challenging, yet it is a crucial step for analyzing its financial consequences. Assessing such exposure is complicated by uncertainties regarding climate developments, evolving policy responses, and firm heterogeneity (Sautner et al., 2020). To address these challenges, Sautner et al. (2020) proposes a novel approach employing textual analysis and machine learning on earnings call transcripts. This method captures climate exposure more effectively than traditional ESG reports or 10-K filings, as analysts often raise targeted questions even when managers avoid explicit climate-related disclosures.

Extreme firm-level outcomes from climate exposure, such as sudden earnings shocks, regulatory penalties, or managerial bad news hoarding, can propagate to stock prices, creating asymmetric downside risk. Firms with high climate vulnerability may experience abrupt declines in equity value when negative information is revealed or when anticipated regulatory costs materialize. Moreover, investors increasingly demand compensation for climate-related exposure (Bolton and Kacperczyk, 2021; Krueger et al., 2020), indicating that such extreme outcomes are both likely and financially material. These considerations underscore the relevance of stock

price crash risk as a measurable reflection of firms' exposure to climate-driven extreme events and motivates the study of this chapter.

To capture this risk, three widely used metrics are employed: negative skewness ($NCSKEW$), down-to-up volatility ($DUVOL$), and the yearly gap between stock crashes and stock jumps ($COUNT$). Consistent with the "bad news hoarding" theory, the accumulation of undisclosed negative information has been shown to be a significant driver of stock price crashes (Ball, 2009; Kothari et al., 2006). Accordingly, the relationship between firm-level climate exposure and stock price crash risk is examined, integrating both the financial consequences of extreme climate events and managerial information behavior.

Recent studies further support this perspective by showing that investors explicitly price climate-related tail risks. Both investors and scholars increasingly emphasize the need for compensation for climate-related exposures (Bolton and Kacperczyk, 2021; Krueger et al., 2020). Evidence also indicates that investors pay attention to firms' environmental practices (Hoepner et al., 2018; Murata and Hamori, 2021). Consistent with this, Ilhan et al. (2021) documents that the cost of protecting against option market tail risk is higher for carbon-intensive firms. Collectively, these studies provide strong motivation for the present analysis, suggesting that climate change exposure creates incentives for managers to hoard bad news, thereby raising the likelihood of stock price crashes.

The empirical setting for this study is the U.S. stock market. The United States provides a particularly relevant environment for analyzing the link between climate change exposure and stock price crash risk. A key reason is the political and regulatory landscape. The 2016 presidential election marked a sharp turning point in U.S. climate policy. The Trump adminis-

tration reversed environmental regulations and initiated withdrawal from the Paris Agreement, producing a discontinuity in corporate expectations regarding climate-related policies (Wagner et al., 2018). This policy reversal is not only a domestic event but also one of the most globally salient political shocks to climate governance. As the world's largest economy and one of the largest emitters of greenhouse gases, U.S. policy signals under the Trump administration shaped global discourse on climate regulation and influenced the credibility of international agreements. However, the immediate and most direct effects were concentrated in the U.S. market, where firms faced sudden changes in regulatory oversight, disclosure requirements, and enforcement intensity. Other countries experienced these shocks only indirectly through spillover channels, such as shifts in global climate negotiations or trade policies. Prior work shows that this political shock had heterogeneous financial consequences: firms with high climate vulnerability experienced negative valuation effects, whereas carbon-intensive firms were temporarily rewarded by anticipated deregulation (Chatjuthamard et al., 2024). Thus, the U.S. provides not only a unique quasi-natural experiment for studying the market consequences of climate-related policy shifts but also the most direct and immediate setting in which to capture the financial impact of such globally significant political events.

Beyond regulation, the U.S. offers unparalleled data infrastructure that enables a rigorous examination of climate change exposure and stock price crash risk. CRSP and Compustat provide comprehensive and high-quality stock return and accounting data, allowing researchers to construct well-established crash risk measures. The Federal Election Commission (FEC) further supplies detailed records of corporate political donations, which have been extensively used to capture managerial political orientation, an important determinant of crash risk that has been documented in prior

U.S.-based studies (Chen et al., 2022). Similarly, cultural variables such as religiosity and local social norms have been shown to significantly affect firms' disclosure practices, risk-taking behavior, and ultimately crash risk (Callen and Fang, 2015a). These measures are uniquely available and reliable in the U.S., but largely absent in international markets. Importantly, because the U.S. stock market is among the most efficient and liquid in the world, consistent with the Efficient Market Hypothesis, these political, cultural, and textual factors are more likely to be rapidly incorporated into market prices. Indeed, empirical research has already demonstrated the effectiveness of these channels in explaining variation in stock price crash risk within the U.S. context. To ensure comparability with the extant literature and to fully account for external influences, this study therefore relies on the U.S. market, which offers both the most comprehensive data infrastructure and the highest level of empirical tractability for examining climate-related crash risk.

This chapter hypothesizes that firms with greater exposure to climate change are more susceptible to stock price crashes. The sample includes U.S. firms listed between 2006 and 2020, and companies with higher climate exposure are more likely to trigger stock price crashes, particularly those facing intense regulatory scrutiny. The underlying mechanism is the uncertainty surrounding regulation, which incentivizes managers to conceal negative news. In this context, Myers et al. (2007) argues that firms often extend positive earning strings by hoarding bad news, and crashes occur when accumulated negative information is released all at once.

In addition to regulatory uncertainty, the role of public attention is also examined. Choi et al. (2020) shows that abnormally high temperatures increase public awareness of climate change, and in financial markets, during periods of heightened attention, carbon-intensive firms underperform

relative to low-carbon firms. This suggests that public scrutiny imposes pressure and oversight on managers, making it harder to conceal adverse information. Building on this idea, the chapter tests whether stock price crashes linked to climate exposure diminish during periods of high public attention, using Google search volume to construct dummy variables for high-attention periods.

Finally, the chapter examines the effect of President Trump's unexpected election victory and his subsequent environmental policies. A difference-in-differences (DiD) estimation with all control variables included is designed to compare high- and low-exposure firms, and results confirm that firms highly exposed to climate regulation benefited disproportionately from Trump's deregulatory stance. Together, these analyses highlight how climate exposure, regulatory uncertainty, public attention, and political shocks jointly influence stock price crash risk.

This chapter makes several contributions. First, it adds to the literature on green finance. Prior work highlights that climate-related uncertainty affects corporate performance and policy-making, thereby influencing financial markets (Ilhan et al., 2021; Ryan, 2012; Seltzer et al., 2022). Scholars have also developed methods to price and hedge climate risks (Engle et al., 2020; Avramov et al., 2021; Bansal et al., 2016; Barnett et al., 2020). This chapter extends these studies by directly linking climate risk exposure with stock market performance.

Second, it contributes to the literature on stock price crash risk. The theoretical foundation was laid by Jin and Myers (2006), who argue that managers' hoarding of firm-specific bad news can lead to stock price crashes when the information is suddenly released. Building on this, subsequent research identifies various channels through which crash risk operates. For

instance, Hutton et al. (2009) links opaque financial reporting to crash risk, while Kim et al. (2011a) highlights the role of executive equity incentives. Later studies show that managerial characteristics also influence crash risk, such as age (Andreou et al., 2017) or strategic orientation (Jia, 2018). Market competition has also been shown to play a role (Li and Zhan, 2019). This chapter complements the literature by introducing climate change exposure as a new motivation for bad news hoarding. Firms heavily exposed to climate risks face higher potential costs and devaluation in capital markets, which heightens managerial incentives to conceal adverse information.

The remainder of this chapter proceeds as follows. Section 3.2 develops the hypothesis and situates the study within the existing literature. Section 3.3 describes variable construction, research design, and methodologies. Section 3.4 presents the empirical results. Section 3.5 explores the bad news hoarding channel. Section 3.6 investigates how public attention interacts with climate exposure to influence the likelihood of stock price crashes. Section 3.7 investigates the effect of Trump's election on highly exposed firms. Finally, Section 3.8 concludes this chapter.

3.2 Literature Review

3.2.1 Stock Price Crash Risk and Bad News Hoarding Theory

A growing body of research has developed widely accepted measures to proxy the risk of infrequent stock price crashes. Chen et al. (2001) introduces two influential measures: the negative coefficient of skewness

($NCSKEW$) and down-to-up volatility ($DUVOL$), both of which capture firm-level crash risk. Building on these measures, Jin and Myers (2006) links the concept of stock price crash risk to the bad news hoarding theory. This theory explains that managers, motivated by self-interest, have a tendency to withhold negative information from investors. However, such concealment cannot persist indefinitely. Over time, as the accumulation of negative news or poor performance reaches a tipping point, managers are forced to release the information all at once. This sudden disclosure leads to a sharp drop in stock prices, i.e., a crash.

According to this theoretical framework, stock price crashes can arise from conflicts of interest between managers and investors. For example, Bleck and Liu (2007) argues that managers sometimes continue projects with poor prospects in order to protect their private benefits, even at the expense of shareholder value. Similarly, Benmelech et al. (2010) provides evidence that managers conceal bad news to preserve the growth potential of their future stock options. Further, Andreou et al. (2017) demonstrates that younger CEOs have a greater propensity to withhold or delay the disclosure of adverse operational outcomes. Because their current and future wealth is more sensitive to corporate performance, they face stronger incentives to accumulate hidden losses, thereby increasing the likelihood of severe stock price crashes. In addition, Kim et al. (2019) shows that information opacity also matters: firms with more readable 10-K reports, indicating lower information opacity, tend to have lower crash risk, whereas lengthy and complex reports are associated with higher crash risk due to concealed bad news.

The occurrence of stock price crashes can be understood within the framework of asymmetric information. Recent studies extend the mechanism of crash risk along several dimensions. As summarized by Habib et al.

(2018), these include financial reporting and corporate disclosures (Hutton et al., 2009; Chen et al., 2017), managerial incentives and characteristics (Kim et al., 2011b; He, 2015), capital market transactions (Callen and Fang, 2015b), corporate governance mechanisms (Andreou et al., 2016; Yuan et al., 2016), and informal institutional factors such as social norms or religion (Cao et al., 2016; Callen and Fang, 2015a). Collectively, this literature highlights that stock price crash risk is deeply rooted in both information asymmetry and managerial incentives.

3.2.2 Green Finance and Firm level climate exposure

This study examines the hypothesis that stock price crash risk at the firm-year level is systematically related to a firm's exposure to climate change, where exposure is measured using textual analysis of conference call transcripts. The central idea is that climate change represents a non-traditional but increasingly salient risk factor, one that investors are concerned about and actively respond to in their portfolio decisions.

A number of prior studies have provided supporting evidence. For example, Choi et al. (2020) investigates public attention to climate change using Google search volume. They find that attention increases in response to unusual climate events, such as abnormal spikes in temperature. During such periods, retail investors tend to sell the stocks of carbon-intensive firms, thereby generating climate-related risks for these companies. Similarly, Ilhan et al. (2021) demonstrates that climate policy uncertainty amplifies tail risks in the option market, particularly for carbon-intensive firms. Hoepner et al. (2018) shows that shareholder engagement on environmental ESG issues reduces downside risks, while Murata and Hamori (2021) corroborates this finding with alternative methodologies, emphasizing that

ESG-related engagement lowers crash risk. Together, these studies suggest that investors are highly attentive to climate-related risks, and that such risks manifest in financial markets through multiple channels.

Among these channels, policy and regulation are paramount. Climate policies and regulations designed to mitigate climate change may induce sharp downward adjustments in asset prices, especially for firms with high carbon exposure. Anticipating this, institutional investors, such as pension funds, may reduce holdings in these firms to avoid potential losses. This can erode consumer confidence and destabilize broader markets. At the firm level, the heightened possibility of compliance costs, litigation expenses, and reputational damage creates incentives for managers to conceal these costs from investors. Indeed, litigation risks are substantial: according to Setzer and Higham (2021), as of May 2021, there were 1,841 climate-related lawsuits worldwide, of which 1,387 were filed in the U.S. While most targeted governments, a growing number were directed at corporations, highlighting their vulnerability. Ilhan et al. (2021) models how governments choose between strong versus weak climate policies, and show that option-implied downside protection costs rise with climate policy uncertainty. Carbon-intensive firms, in particular, bear higher costs of hedging tail risk, implying their greater vulnerability to regulatory shocks. These costs can strain firms' financial conditions, increasing bankruptcy risk, and further motivating managers to hoard bad news to avoid immediate market penalties.

Beyond litigation and regulation, climate change concerns are also priced in other financial instruments. For instance, Huynh and Xia (2021) shows that corporate bonds of firms more exposed to climate news earn lower excess returns, consistent with investors treating such bonds as hedges against climate risk. Similarly, Seltzer et al. (2022) demonstrates that firms with higher carbon footprints face lower ratings and wider yield spreads in bond

markets, especially in jurisdictions with stricter environmental regulation. Furthermore, climate change affects firms' internal financial strategies: Heo (2021) documents that, following the Paris Agreement, firms more vulnerable to climate risks increased cash holdings as a buffer against uncertainty, particularly in climate-sensitive industries.

Institutional investors, given their long-term horizons, are particularly attentive to firms' climate-related disclosures. Drawing on Kothari et al. (2009), which highlights management's tendency to withhold bad news, disclosure quality has become a critical ethical and strategic issue. Studies on ESG disclosures emphasize that they shape investor perceptions. For example, Starks et al. (2017) finds that investors with longer horizons prefer firms with stronger ESG performance, implicitly associating weaker ESG disclosure with higher climate exposure. Similarly, Krueger et al. (2020) reveals that institutional investors actively demand climate-related disclosures and allocate capital accordingly, particularly when firms disclose through Carbon Disclosure Project (CDP)-based channels. This evidence suggests that disclosure quality not only influences investor preferences but also interacts with managerial incentives to hoard bad news.

Empirical studies directly connect ESG disclosure to crash risk. Murata and Hamori (2021) shows that ESG disclosure significantly lowers crash risk, though the predictive effect varies by region: it is significant in Europe and Japan but weaker in the U.S. In a related study, Hoepner et al. (2018) confirms that ESG engagement, particularly on environmental issues, reduces downside risk. From an ethical perspective, ESG disclosure signals managerial commitment to transparency and to addressing climate-related risks, reducing the incentives for concealment.

Quantifying firm-level exposure to climate change remains a major chal-

lenge, and it is unclear whether ESG-related information can serve as a reliable proxy. The difficulty arises from uncertainty about the evolution of climate change, heterogeneous firm-level impacts, and the lack of established academic solutions. To address this, Sautner et al. (2020) develops a textual analysis and machine learning approach to construct firm-level measures of climate change exposure. Building on this framework, the present study links such exposure to the risk of stock price crashes. The underlying hypothesis is that conference calls provide a key channel through which investors access financial and managerial information, and managers may recognize that climate-related discussions in these calls influence investor reactions. Consequently, they may have incentives to withhold negative news, which increases crash risk.

Earnings calls are particularly suitable as a data source for this purpose. First, they are the primary medium for investors and analysts to understand management perspectives and business activities, making them a natural focus for evaluating firm risk. Second, compared with ESG reports, earnings calls are less susceptible to greenwashing, as analysts can pose direct questions and management responses are recorded. This interactive nature also captures analysts' concerns, which further reduces managerial discretion over disclosure. While ESG reports or carbon emission data can be shaped by corporate intent, earnings calls provide a more transparent and less manipulable record. Overall, Sautner et al. (2020) offers a method to quantify firm-level climate exposure more accurately, providing a foundation for assessing its implications for stock price crash risk.

To sum up, the evidence supports the hypothesis that higher climate exposure increases managerial stress, thereby amplifying incentives to hoard bad news. Such concealment, in turn, raises the likelihood of stock price

crashes.

Hypothesis 1 *Firms with higher exposure to climate change would suffer a higher extent of stock price crash risk.*

The central hypothesis of this chapter is that firm-level exposure to climate change increases stock price crash risk through the channel of bad news hoarding. As argued by Myers et al. (2007), long consecutive strings of earnings growth may often reflect the concealment of negative information. When such concealment collapses, the break in the earnings string coincides with a crash. Following Andreou et al. (2017), this study introduces an $CRASH_BREAK_STRING$ variable, a dummy equal to one when a crash occurs simultaneously with an earnings string break, to identify whether climate change exposure increases the probability of such events:

Hypothesis 2 *The firm level climate change exposure would significantly positively affect the possibility of occurrence of stock price crash induced by the break of the increasing earning string.*

If this assumption is empirically confirmed, it would provide evidence that climate change exposure induces stock price crashes via the channel of bad news hoarding.

In addition, public attention to climate change can moderate this relationship. For instance, Choi et al. (2020) shows that public attention spikes during abnormal weather, leading investors to sell carbon-intensive stocks. Ilhan et al. (2021) further argues that rising public attention amplifies policy uncertainty, thereby raising the costs of concealment. As the costs of hoarding bad news increase, managers face greater difficulty in sustaining

concealment, weakening the link between exposure and crash risk. Thus, the next hypothesis is:

Hypothesis 3 *The extent of stock price crash risk caused by climate change exposure would drop in times when public attention to climate change is higher.*

Finally, the political environment provides an external shock to test causality. The unexpected election of President Trump in 2016 represented a major reversal of U.S. climate policy. Within six months of taking office, Trump announced U.S. withdrawal from the Paris Agreement, and over his tenure rolled back nearly 100 climate-related rules, such as relaxing methane regulations, freezing fuel efficiency standards, and dismantling the Clean Power Plan (Schwartz, 2019). These policy shifts disproportionately benefited carbon-intensive firms while reducing regulatory pressures. This context motivates the final hypothesis:

Hypothesis 4 *Since the climate policy reversal by President Trump after his election affected US firms differently based on their exposure to climate change regulation, those are most exposed to regulation risk would benefit the most.*

3.3 Data Source and Summary Statistics

3.3.1 Climate Change Exposure Measurement

To measure firm-level climate change exposure, this study employs the dataset provided by Sautner et al. (2020). The database covers firms from

several countries between 2006 and 2020, which defines the sample period and aligns with the availability of data on top managers' characteristics. The exposure measures are constructed through text-analysis of earnings call transcripts at the quarter-firm level, and then aggregated to the year-firm level by averaging the four quarterly measures. For computational convenience, the exposure variables are scaled by one thousand.

The empirical setting of this study is the U.S. stock market, which provides both a theoretically compelling and empirically tractable environment for analyzing the link between climate change exposure and stock price crash risk. A central justification lies in the efficient market hypothesis (EMH): in one of the world's most liquid and efficient markets, stock prices incorporate information rapidly, allowing extreme outcomes such as crashes to be more cleanly attributed to fundamental shocks, such as managerial bad-news hoarding or abrupt policy shifts, rather than market frictions or data deficiencies. This theoretical clarity renders the U.S. market particularly suitable for identifying the mechanisms of crash risk.

An additional advantage of the U.S. setting is the availability of a salient and exogenous policy shock. The 2016 presidential election marked a sharp reversal in U.S. climate policy under the Trump administration, characterized by deregulation and withdrawal from the Paris Agreement (Wagner et al., 2018). This political reversal created a discontinuity in corporate expectations regarding climate-related regulation and provides a quasi-natural experiment well suited for a difference-in-differences framework. Importantly, while this event was globally salient, the most immediate and direct effects were concentrated in the U.S. market, where firms faced sudden changes in regulatory oversight, disclosure requirements, and enforcement intensity. International markets experienced these shocks only indirectly through spillover channels such as shifts in climate negotiations

or trade policies. Prior studies confirm that this policy shock generated heterogeneous valuation effects, with climate-vulnerable firms experiencing negative consequences, whereas carbon-intensive firms were temporarily rewarded by anticipated deregulation (Chatjuthamard et al., 2024).

A further consideration is comparability with existing literature. Although a number of studies have extended their analyses to international settings, many of the most influential works examining the interaction of politics, culture, and firm outcomes still rely on U.S. data due to its unique availability of granular information. For example, recent studies utilize natural disasters (*DISASTER*, following Zhao et al., 2024), religiosity (*RELIGION*, following Callen and Fang, 2015a), and managerial political orientation (*POI*, following Chen et al., 2022) to capture how political and cultural contexts shape corporate behavior and financial risk. These variables have been shown to significantly affect the risk of stock price crash. However, comparable measures are largely absent or incomplete outside the U.S., making it challenging to replicate such identification strategies in other markets. By situating the analysis in the U.S., this study not only leverages the rich institutional and data infrastructure but also ensures methodological alignment with this stream of literature. In this way, the findings can be directly compared with existing studies and contribute to the broader debate on how political and cultural forces shape financial risks.

The construction of the exposure measures relies on a machine learning–based approach to text analysis. Specifically, the algorithm begins with a small set of seed bigrams that are unambiguously related to climate change topics. It then uses this initial list to identify additional bigrams that appear in earnings call transcripts and are likely associated with climate change. This iterative learning process enables the construction of a comprehensive set of climate-related bigrams derived from the actual lan-

guage used in conference calls. A key advantage of this method is that it allows the model to "learn" meaningful expressions from the text, overcoming the limitations of manual approaches, which are often inefficient in identifying relevant terms. Importantly, the algorithm requires only a small number of initial bigrams as input, yet it can expand this set systematically to capture new and contextually relevant terms.

The baseline measure of climate change exposure, denoted as CC_EXPO, is defined as the proportion of words in conference call transcripts that belong to the climate-related bigram list. Formally,

$$CC_EXPO_{j,t} = \frac{1}{B_{j,t}} \sum_{b}^{B_{j,t}} (\mathbf{1}|b \in C)\,, \tag{3.1}$$

where $b = 0, 1, \ldots, B_{j,t}$ are the bigrams contained in the conference call transcripts of firm j in fiscal year t, C is the set of climate change bigrams, and $\mathbf{1}[\bullet]$ is the indicator function.

For further analysis, Sautner et al. (2020) decomposes climate change exposure into three subcategories: regulatory-, physical-, and opportunity-based exposure. The first category captures regulatory interventions, the second reflects physical risks such as damage from climate events, and the third refers to opportunities arising from climate change, including terms like "renewable energy" or "solar energy." These components are informative for this study, as they allow for testing of heterogeneous mechanisms that may generate stock market risks depending on the specific type of exposure investors perceive as most relevant. The three variables are denoted as RG_CC_EXPO, PH_CC_EXPO, and OP_CC_EXPO, constructed from the respective word lists C^{REG}, C^{PHY}, and C^{OPP}. However, it should be noted that the tone of these exposures may vary: references can reflect

either positive or negative expectations, which makes it difficult to evaluate the sign of their impact on the stock market solely based on exposure levels.

To address this issue, Sautner et al. (2020) also introduces several alternative measures. Among them, the risk exposure measure, denoted as CC_RISK, is central to this research. It specifically captures references to climate change that occur in sentences also containing words such as "risk" or "uncertainty," thereby directly reflecting investors' perception of risk, which will be further examined as robustness test. Formally,

$$CC_RISK_{j,t} = \frac{1}{B_{j,t}} \sum_{b}^{B_{j,t}} \left(\mathbf{1}[|b \in C] \times \mathbf{1}[b, r \in S] \right), \tag{3.2}$$

where S represents a sentence containing bigrams $b = 0, 1, \ldots, B_{j,t}$, while r contains the words "risk" or "uncertainty."

Similarly, three sets of variables are constructed using words lists C^{REG}, C^{PHY} and C^{OPP} mentioned before, denoted as RG_CC_RISK, PH_CC_RISK and OP_CC_RISK.

The measure of exposure to climate change from the database have been retrieved, made publicly available by Sautner et al. (2020).[1] The authors noted that within their sample of conference call transcripts, the most prevalent regulation bigrams indicate regulatory and governmental actions linked to climate change mitigation and the reduction of carbon emissions.

[1] https://osf.io/4xuvz/ (retrieved on 9th February 2022)

3.3.2 Measures of Stock Price Crash Risk

Three measures of firm-specific stock price crash risk, proposed by Chen et al. (2001); Kim et al. (2011a,b) and Wu and Lai (2020), are employed in the analysis. All the measures are based on firm-specific weekly returns, denoted $W_{j,w}$ for firm j and week w, and are estimated as the natural logarithm of one plus the residuals (i.e., $W_{j,w} = \ln(1 + \hat{\varepsilon}_{j,w})$) computed from the following expanded market model:

$$r_{j,w} = \alpha_j + \beta_{1,j} r_{m,w-2} + \beta_{2,j} r_{m,w-1} + \beta_{3,j} r_{m,w} + \beta_{4,j} r_{m,w+1} + \beta_{5,j} r_{m,w+2} + \varepsilon_{j,w} \tag{3.3}$$

where $r_{j,w}$ is the return on firm j in week w and $r_{m,w}$ is the return on the CRSP value-weighted market index in the same week. The lead and the lag terms of the market returns to account for the effects of non-synchronous trading (Dimson, 1979; Hutton et al., 2009) is also included. The data on individual stock prices and the market index is downloaded from CRSP.

The first crash risk measure, $COUNT_{j,t}$, is calculated as the difference between the number of stock price crashes and the number of jumps, experienced by firm j and observed within fiscal year t. A crash (jump) occurs when $W_{j,w}$ falls below (above) 3.09 standard deviations from the average weekly return measured over fiscal year t.

The second measure is the negative coefficient of skewness of $W_{j,w}$ over fiscal year t, defined as follows:

$$NCSKEW_{j,t} = \frac{-\left[n\,(n-1)^{\frac{3}{2}} \sum W_{j,w}^3\right]}{(n-1)\,(n-2)\left(\sum W_{j,w}^2\right)^{\frac{3}{2}}}, \tag{3.4}$$

where n stands for the number of weekly return observations during fiscal year t. The $NCSKEW$ measure normalises the negative value of the third

moment of $W_{j,w}$, using the standard deviation of $W_{j,w}$ raised to the third power. The use of minus sign in the calculation of *NCSKEW* allows for a natural interpretation of the variable where a large positive value of *NCSKEW* corresponds to a high crash risk value.

The third measure is the down-to-up volatility, denoted $DUVOL$, and is calculated as follows:

$$DUVOL_{j,t} = \ln \left[\frac{(n_u - 1) \sum_{\text{Down}} W_{j,w}^2}{(n_d - 1) \sum_{\text{Up}} W_{j,w}^2} \right], \tag{3.5}$$

where n_u and n_d denote, respectively, the number of up and down weeks within fiscal year t. The firm specific weekly returns $W_{j,w}$ is separated above and below the annual mean firm-specific return and regard each week as an "up" and "down" week, respectively. Finally, the natural logarithm of the ratio of the standard deviation of the "down" weeks to the standard deviation of the "up" weeks is calculated.

3.3.3 Other Control Variables

The set of control variables includes a range of firm-, CEO-, and environment-level characteristics that have been shown to influence stock price crash risk. Financial data for constructing these variables are primarily drawn from Compustat and CRSP. Following Chen et al. (2001) and Hutton et al. (2009), several firm-level controls are employed. Firm size (*SIZE*) is measured as the natural logarithm of market value, where market value is defined as the product of shares outstanding and the closing stock price at fiscal year-end. The market-to-book ratio (*MARKET_TO_BOOK*) is calculated as the ratio of market value to book value of equity, where book value is the sum of stockholders' equity, deferred taxes, and investment

tax credits (if available), minus the book value of preferred stock, following Daniel and Titman (2006). Research and development intensity ($R\&D$) is measured as R&D expenditure scaled by total assets, while leverage ($LEVERAGE$) is defined as the ratio of total long-term debt to total assets. Profitability is captured by return on assets (ROA), defined as earnings before interest and taxes divided by total assets. Firm-specific returns (RET) are calculated as the average of weekly stock returns for each firm during the fiscal year, and changes in trading activity ($DTURN$) are measured as the difference between the average monthly stock turnover in the current fiscal year and that in the previous fiscal year, where monthly turnover is defined as monthly trading volume divided by shares outstanding. Yearly firm-specific volatility (VOL) is measured as the annual standard deviation of daily stock returns. Distributional characteristics of stock returns are also controlled for: skewness ($SKEWNESS$) and kurtosis ($KURTOSIS$) are measured from weekly firm-specific returns within the fiscal year. Finally, following Dechow et al. (1995), accounting opacity is controlled for using discretionary accruals ($ACCM$), defined as the three-year moving sum of the absolute value of discretionary accruals estimated via the modified Jones model.

Beyond firm fundamentals, CEO characteristics are also controlled for, given evidence that managerial attributes significantly affect crash risk. Andreou et al. (2017) documents that younger or longer-tenured CEOs tend to behave more aggressively, which may increase bad news hoarding and crash risk. To capture these effects, data from ExecuComp are used to construct several variables: the logarithm of CEO age (LN_CEO_AGE), salary (LN_CEO_SAL), and tenure (LN_CEO_TENURE). CEO overconfidence ($CEO_OVERCONFIDENCE$) is also included, following Kim et al. (2016). This variable is constructed by first calculating the realizable value

per option (the total realizable value of exercisable options divided by the number of exercisable options), estimating the average exercise price (fiscal year-end stock price minus realizable value per option), and then defining moneyness as the realizable value per option divided by the estimated average exercise price. Then a CEO is defined as overconfident if the CEO holds options at least twice during the sample period that are more than 100% in the money. In addition, CEO power (*CEO_POWER*), defined as a dummy for CEOs who simultaneously serve as both board chair and president (Al Mamun et al., 2020), is controlled for, as greater power may facilitate managerial discretion. Several CEO turnover indicators are also included: a dummy for change of CEO in the fiscal year (*CHANGE*), a retirement dummy (*RETIRE*), and an indicator for whether the CEO serves as board chair (*CHAIR*).

Finally, the analysis incorporates additional external and institutional factors that may affect crash risk. Natural disasters (*DISASTER*) are measured using EM-DAT data, following Zhao et al. (2024), and capture the annual frequency of disasters in the state of the firm's headquarters. The rationale is that disaster shocks can generate heightened financial stress and elevate crash risk. Cultural effects are captured by religiosity (*RELIGION*), following Callen and Fang (2015a), defined as the proportion of religious adherents to total population in the firm's headquarters county. Prior research suggests that higher religiosity is associated with stronger ethical norms and lower crash risk. Finally, managerial political orientation (*POI*) is constructed following Chen et al. (2022), using Federal Election Commission data on political contributions. The variable is built in three steps: first, a manager's cycle-specific political orientation (*POCYCLE*) is calculated for each two-year election cycle as (Republican Contributions – Democratic Contributions) / (Total Contributions), yielding values be-

tween –1 (strong Democrat) and +1 (strong Republican). Second, these scores are averaged across all available cycles to obtain a personal political orientation (PO), with PO set to zero if no contributions exist. Third, the firm-level *POI* is computed as the average PO of the five highest-paid managers. This measure captures the conservatism of managerial political preferences and is expected to be negatively related to stock price crash risk.

3.3.4 Summary and Statistics

The research sample covers firm-year observations of climate change exposure and climate risk exposure, together with a broad set of control variables derived from financial data in CRSP, Compustat, ExecuComp, EM-DAT, FEC, and the U.S. County Religiosity Data website. The sample period spans 2006–2020, providing 14 years of data. In total, the baseline dataset includes 42,576 firm-year observations for the main variables, providing sufficient statistical power for empirical analysis. Summary statistics for the key variables are reported in Table 3.1.

Over the sample period, the average values of the three dependent variables are –0.057 for $NCSKEW$, –0.052 for $DUVOL$, and –0.109 for $COUNT$, with corresponding standard deviations of 1.189, 0.843, and 0.748. The measure of climate change exposure, $CC_EXPO \times 1000$, has a mean of 0.716 and a standard deviation of 1.475, suggesting substantial heterogeneity across firms and years. By contrast, the climate risk exposure measure has an average close to zero and relatively limited variation, indicating that only a small fraction of firms explicitly reference climate-related risks in their disclosures.

The set of control variables is comprehensive, covering firm characteristics, managerial attributes, and external environmental factors that may jointly influence climate exposure and crash risk. Firm-level characteristics include firm size (*SIZE*, the natural logarithm of market value), financial leverage (*LEVERAGE*, ratio of long-term debt to total assets), market-to-book ratio (*MARKET_TO_BOOK*), profitability (*ROA*), R&D intensity (*R&D*), accruals (*ACCM*), average firm-specific returns (*RET*), stock return volatility (*VOL*), turnover (*DTURN*), and higher-order moments of returns including skewness (*SKEWNESS*) and kurtosis (*KURTOSIS*).

Managerial and governance characteristics include CEO age (*LN_CEO_AGE*), CEO salary (*LN_CEO_SALARY*), CEO tenure (*LN_CEO_TENURE*), CEO overconfidence (*CEO_OVERCONFIDENCE*), CEO power concentration (*CEO_POWER*), CEO turnover (*CHANGE*), CEO retirement (*RETIRE*), and whether the CEO serves as board chair (*CHAIR*). Firm-level political orientation is captured by *POI*, while external environmental and social factors include county-level religiosity (*RELIGION*) and the annual frequency of natural disasters in the firm's headquarters state (*DISASTER*).

These variables jointly account for cross-sectional heterogeneity in both firm operations and managerial behavior, helping isolate the incremental effect of climate exposure on stock price crash risk.

Table 3.2, 3.3 and 3.4 reports the correlation matrix for all variables. The three dependent variables are highly correlated with one another, consistent with prior crash risk studies. For example, the correlation between *DUVOL* and *NCSKEW* is 0.929, while *COUNT* correlates 0.728 with *NCSKEW* and 0.617 with *DUVOL*. In contrast, the climate change exposure and risk exposure measures exhibit only weak correlations with the dependent

variables. For instance, the correlation between *CC_EXPO* and *NCSKEW* is 0.012, suggesting that they capture distinct information not explained by firm fundamentals. These low correlations highlight the importance of multivariate regression analysis to properly identify the role of climate-related exposures in explaining stock price crash risk.

3.4 Empirical Analysis

3.4.1 Benchmark Model and Results

In this section, the relation between climate change exposure and stock price crash risk will be tested using a panel regression method. The dependent variables slated for testing encompass the stock price crash risk metrics previously outlined, which include negative skewness ($NCSKEW$), down-up volatility ($DUVOL$), and the count of crashes ($COUNT$). Various control variables and climate change exposure will be included in the equation at a firm-year level. Moreover, the stock price crash risk measurements are one-period previous to independent variables to alleviate endogeneity problems following all previous research, and the regression process follows:

$$Crash_{i,t+1} = \alpha + \beta CC_EXPO_{i,t} + \gamma X_{i,t} + \theta_i + \phi_t + \tau + \epsilon_{i,t} \tag{3.6}$$

$$Crash_{i,t+1} = \alpha + \beta CC_RISK_{i,t} + \gamma X_{i,t} + \theta_i + \phi_t + \tau + \epsilon_{i,t} \tag{3.7}$$

Where for firm i in year t, $Crash_{i,t+1}$ represents various crash risk measures including $NCSKEW$, $DUVOL$, and $COUNT$; $CC_EXPO_{i,t}$ is the overall

climate change exposure, and $CC_RISK_{i,t}$ is the climate-related risk exposure. $X_{i,t}$ denotes a comprehensive set of control variables, including firm characteristics (such as *SIZE*, *LEVERAGE*, *MARKET_TO_BOOK*, *ROA*, *R&D*, *ACCM*, *RET*, *VOL*, *DTURN*, *SKEWNESS*, and *KURTOSIS*), managerial and governance attributes (including *LN_CEO_AGE*, *LN_CEO_SALARY*, *LN_CEO_TENURE*, *CEO_OVERCONFIDENCE*, *CEO_POWER*, *CHANGE*, *RETIRE*, and *CHAIR*), as well as external environment factors (*RELIGION*, *DISASTER*, and *POI*). θ_i, ϕ_t, and τ represent firm-, year-, and industry-fixed effects, respectively. Firm-level fixed effects control for unobserved heterogeneity within firms, while year- and industry-fixed effects capture period-specific and industry-specific shocks, such as those related to regulatory changes following major climate agreements.

For the regression results, the primary interest lies in the coefficients of climate change exposure (*CC_EXPO*) and climate change risk exposure (*CC_RISK*) in Eq. (3.6) and Eq. (3.7), respectively. The hypothesis posits that greater discussion of climate change during earnings calls increases the likelihood of managers hoarding bad news, especially in the context of risks, thereby raising the probability of a stock price crash. Consequently, the coefficients on crash risk measures (*NCSKEW*, *DUVOL*, and *COUNT*) are expected to be positive.

On the other hand, the assessment of climate change risk exposure is formulated using sets of bigrams containing the terms "risk" or "uncertainty." This approach is presumed to have a stronger correlation with the risks associated with stock price crashes. Therefore, this alternative metric is incorporated into the benchmark regression analysis as a robustness test. As mentioned in Table 3.1, only a few firms are exposed to climate change risk, which implies a higher extent of risk exposure, something significant enough to be emphasized by senior firm managers and analysts. This leads

to a similar expectation that this risk exposure would also be significantly and positively related to stock price crash risk measures. Additionally, tests based on this alternative are conducted to assess the robustness of the hypothesis.

The panel regression is applied with fixed effects at the year and industry levels. By including these fixed effects, the estimation process can capture heterogeneity across different industry sectors, as well as minor yearly changes over the sample period. Meanwhile, the standard errors of the regression are clustered at the firm level.

Table 3.5 reports the estimation results. Columns (1)–(3) present univariate regressions including only fixed effects (firm, year, state, and industry), while columns (4)–(6) incorporate the full set of control variables. In the multivariate specifications, *CC_EXPO* is positively and significantly associated with *NCSKEW* (coef. $= 0.019$, $t = 2.228$) and is marginally significant for *DUVOL* (coef. $= 0.012$, $t = 1.754$), while the coefficient for *COUNT* is positive but statistically insignificant (coef. $= 0.012$, $t = 1.196$). A one-standard-deviation increase in *CC_EXPO* corresponds to approximately a 1.9% rise in the standard deviation of *NCSKEW* and a 1.2% rise in that of *DUVOL*. Although the magnitudes are modest, the consistency of signs across crash proxies suggests that climate change exposure has a systematic positive link with downside crash risk.

Table 3.6 reports results for the alternative measure, *CC_RISK*, constructed from bigrams containing "risk" or "uncertainty." In the univariate regressions, *CC_RISK* is strongly and positively associated with *NCSKEW* (coef. $= 0.903$, $t = 3.908$), *DUVOL* (coef. $= 0.819$, $t = 4.289$), and *COUNT* (coef. $= 0.336$, $t = 1.966$). However, once the full set of controls is included, the coefficients attenuate substantially: the effect on *NCSKEW* becomes eco-

nomically small and statistically insignificant (coef. = 0.172, t = 0.397), while the association with *DUVOL* remains positive and marginally significant (coef. = 0.539, t = 1.725). For *COUNT*, the coefficient turns negative and insignificant (coef. = –0.274, t = –0.562). These results suggest that much of the explanatory power of *CC_RISK* overlaps with firm- and market-level control variables, but the residual effect on *DUVOL* indicates that climate risk–related language still carries incremental information about downside volatility risk.

The regression results show that measures of return performance are the most consistent predictors of crash risk. *RET* is significantly negative across all specifications, indicating that firms with stronger past returns face lower crash risk. Likewise, *SKEWNESS* is highly significantly negative (e.g., coef. = -1.090, t = -51.729 for *NCSKEW* under *CC_RISK*), suggesting that favorable return asymmetry strongly reduces crash likelihood. In contrast, *KURTOSIS* is positive and significant in all models, consistent with extreme return distributions increasing crash risk. Earnings management, proxied by *ACCM*, is positively associated with the *COUNT* measure, further supporting the notion that accrual manipulation elevates crash susceptibility. Other firm- and CEO-level controls (e.g., *SIZE*, *ROA*, *MARKET_TO_BOOK*) are generally insignificant, with only weak evidence for *LEVERAGE* and marginal effects for certain governance variables. Overall, the results underscore that return asymmetry, past returns, return extremes, and earnings management are the most robust determinants of crash risk.

Overall, the results from both measures support the hypothesis that climate change discourse can act as a meaningful signal of elevated crash risk at the firm level. The effects are stronger and more robust for the broader *CC_EXPO* measure, whereas *CC_RISK* captures a narrower but more

risk-salient dimension whose explanatory power is more sensitive to the inclusion of controls. These findings are consistent with the view that institutional investors monitor climate-related disclosures closely (Krueger et al., 2020) and that managerial communications during earnings calls can serve as a credible, forward-looking indicator of potential downside risk (Sautner et al., 2020).

The empirical results of the baseline model support the hypothesis of this chapter: climate change exposure, as measured by Sautner et al. (2020), significantly increases the likelihood of stock price crash risk at the firm-year level. This finding can be explained from several perspectives, consistent with prior research, including the growing importance of climate change for institutional investors (Krueger et al., 2020). Investors are concerned about the risks posed by climate change and respond to firms' business conditions and managerial behavior accordingly. Earnings call transcripts, which provide information disclosed by senior managers and questions raised by analysts, represent a particularly valuable source of insight for investors. Accordingly, climate change exposure derived from such transcripts can serve as a proxy for the extent to which firms are subject to climate-related risks, independent of voluntary disclosure effects (Murata and Hamori, 2021; Hoepner et al., 2018). This conclusion also suggests an incentive for managers to withhold bad news, which may ultimately lead to stock price crashes once the accumulated negative information reaches a tipping point, which is a mechanism that will be further examined in Section 3.5.

3.4.2 Exposure with Different Content

Next, distinct exposure measurement components are tested. Sautner et al. (2020) constructs three types of exposures utilizing a similar algorithm, but with different components of bigram lists. The original bigram lists are divided into three parts, which indicate regulatory impact, physical impact, and opportunity impact brought by climate risk, respectively, so that each calculated exposure could be used as the risk exposure for various risks faced by firms. Following previous research, including Ilhan et al. (2021), policy uncertainties and their effects on firms are considered the source of risks to be valued arising from climate change. This part hypothesizes that regulatory-based climate change exposure would significantly affect the measurements. The equation for these tests follows:

$$\begin{aligned} Crash_{i,t+1} =& \alpha + \beta_1 RG_CC_EXPO_{i,t} + \beta_2 PH_CC_EXPO_{i,t} \\ &+ \beta_3 OP_CC_EXPO_{i,t} + \gamma X_{i,t} \\ &+ \theta_i + \phi_t + \tau + \epsilon_{i,t} \end{aligned} \tag{3.8}$$

$$\begin{aligned} Crash_{i,t+1} =& \alpha + \beta_1 RG_CC_RISK_{i,t} + \beta_2 PH_CC_RISK_{i,t} \\ &+ \beta_3 OP_CC_RISK_{i,t} + \gamma X_{i,t} \\ &+ \theta_i + \phi_t + \tau + \epsilon_{i,t} \end{aligned} \tag{3.9}$$

Where RG_CC_EXPO, PH_CC_EXPO and OP_CC_EXPO represents regulatory- ,physical- and opportunity-based climate change exposure, RG_CC_RISK, PH_CC_RISK and OP_CC_RISK represents regulatory- ,physical- and opportunity-based climate change risk exposure separately.

The research interest lies in the coefficients for the three categories of cli-

mate change exposure, β_1, β_2, and β_3, to verify whether distinct bigram lists and contents would affect the results. Regulatory-based exposure can be explained as the exposure to regulatory topics. Physical-based exposure proxies for physical damage–related topics, while opportunity-based exposure measures topics related to contents including renewable energy, which are commonly regarded as bringing opportunities along with conversations concerning climate change. For the second equation, the bigram lists for the three risk-based exposure measurements all involve words including "risk" or "uncertainty," so the tone is unambiguously negative and related to the risks that firms would have to embrace. It is rational to posit a positive impact of this exposure on stock market performance, thereby suggesting positive coefficients for all three measurements, particularly for regulatory-based climate change exposure and risk exposure, due to the fact that the risk of climate change is widely regarded as being applied through policy and regulatory channels.

The empirical results in Table 3.7 are largely consistent with the hypothesis. Columns (1)–(3) report the regression coefficients for three distinct measures of stock price crash risk: the negative conditional skewness of firm-specific weekly returns ($NCSKEW$), the down-to-up volatility measure ($DUVOL$), and the frequency of extreme negative returns ($COUNT$). Among the three categories of climate change exposure, namely regulatory-based, physical-based, and opportunity-based, the results show that the regulatory-based exposure variable (RG_CC_EXPO) stands out as the most consistent and economically meaningful predictor. Specifically, RG_CC_EXPO is positively associated with both $NCSKEW$ (coefficient = 0.778, $t = 1.831$) and $DUVOL$ (coefficient = 0.155, $t = 1.897$), both significant at the 10% level. Economically, these coefficients imply that a one–standard deviation increase in regulatory-based exposure corresponds

to approximately 0.12% and 0.17% increases in *NCSKEW* and *DUVOL*, respectively. These magnitudes, though seemingly small, are meaningful in the context of crash risk measures, which are designed to capture rare but severe downside events.

The positive relationship between *RG_CC_EXPO* and crash risk measures is consistent with the theoretical argument. Heightened uncertainty in climate change policy, resulting from new taxation schemes, stricter industry licensing requirements, and higher compliance costs for environmental protection, can affect managerial decision-making. Specifically, under such uncertainty, managers, particularly CEOs, may have greater incentives to withhold adverse information from the market in order to delay the recognition of potential negative impacts on firm value. This withholding behavior can lead to an accumulation of bad news, which, when eventually released, may trigger sudden and severe drops in stock prices. This mechanism is consistent with prior empirical studies linking policy uncertainty to managerial disclosure behavior and stock price crash risk.

In contrast, the results for the physical-based exposure variable (*PH_CC_EXPO*) and the opportunity-based exposure variable (*OP_CC_EXPO*) are generally weak and inconsistent. *PH_CC_EXPO* is negatively and significantly associated with *DUVOL* (coefficient = –0.424, t = –2.134), suggesting that higher attention to physical climate risks may, in some contexts, reduce short-term volatility asymmetry. However, this effect does not carry over to *NCSKEW* or *COUNT*, where the coefficients are statistically insignificant. One plausible interpretation is that physical damages, often caused by extreme weather events, are localized, transitory, and already accounted for in other firm-level risk controls or fixed effects, thereby diminishing their statistical detectability in a panel regression framework.

For *OP_CC_EXPO*, the coefficients are close to zero and insignificant across all crash risk measures, with the exception of a small positive but insignificant association with *DUVOL*. This lack of significance could be attributed to the nature of the opportunity-based keyword list, which often includes terms related to clean energy and renewable technologies. These discussions may capture long-term growth potential or market optimism rather than downside risk exposure, thereby diluting any direct link to short-term crash risk. In addition, such opportunities might be perceived as hedging instruments against broader environmental risks, further weakening their statistical relationship with measures of extreme negative returns.

Turning to Table 3.8, which reports the effects of climate change risk variables (*RG_CC_RISK*, *PH_CC_RISK*, and *OP_CC_RISK*), *RG_CC_RISK* consistently exhibits a positive impact on multiple dimensions of stock price crash risk. Specifically, *RG_CC_RISK* is positive and significant at the 10% level for *NCSKEW* (coefficient = 2.789, t = 1.669) and at the 5% level for *DUVOL* (coefficient = 3.016, t = 1.997), indicating that greater regulatory-related climate risk is associated with higher crash risk. While its coefficient for *COUNT* is positive but not statistically significant, the overall pattern supports the notion that regulatory-based climate risk contributes to the likelihood of extreme negative stock returns. Similarly, *PH_CC_RISK* shows positive and significant effects for *DUVOL* and *COUNT*, though its predictive power appears more pronounced for certain dimensions of crash risk, while *OP_CC_RISK* does not exhibit statistically significant effects for any of the crash risk measures.

The weaker and less consistent results for the risk-based variables could stem from the narrower scope of the keyword lists used in their construction. By explicitly including "risk" and "uncertainty," these measures may

capture only direct references to downside concerns, omitting broader contextual discussions where risks are implicitly embedded in policy or compliance discussions, particularly in regulatory contexts. For example, many regulatory-related conversations that affect firm behavior may not explicitly mention "risk" or "uncertainty" but still carry significant implications for future downside events. This narrower focus may lead to measurement error and attenuated coefficients in the regression results.

Overall, the evidence from both tables suggests that the regulatory-based exposure measure, RG_CC_EXPO, is the most robust and economically meaningful predictor of stock price crash risk across different model specifications and dependent variables. Physical-based and opportunity-based measures, whether framed as exposures or risks, show limited and inconsistent predictive power. These findings emphasize the central role of policy uncertainty in driving crash risk, consistent with theoretical models linking external regulatory shocks to managerial disclosure behavior and market stability.

3.5 The Test of Bad News Hoarding

The mechanism of bad news hoarding is tested in this section. The test follows (Myers et al., 2007; Andreou et al., 2017), who proposed that managers have the incentive to hoard bad news for their own benefit and consequently prefer to maintain a string of earnings increases for as long as possible. According to Myers et al. (2007), the inclination of companies to consistently report earnings growth, often exceeding expectations, suggests that managers may strive to prolong this pattern even at the risk of encountering defaults. During this period, bad news hoarding problems may

arise. Consequently, a price crash risk triggered by a break in the string implies a sudden release of bad news. In this section, this hypothesis will be empirically tested using the following equation:

$$\begin{aligned} CRASH_BREAK_STRINGt_{j,t} =& \beta_0 + \beta_1 CC_EXPO_j \times LEN_t \\ &+ \beta_2 LEN_t + \beta_3 CC_EXPO_j + \gamma X_{i,t} \\ &+ \theta_i + \phi_t + \tau + \epsilon_{i,t} \end{aligned} \tag{3.10}$$

Following Andreou et al. (2017), the dummy dependent variables would be defined as (i) *CRASH_BREAK_STRING1* equals to 1 if a firm experience price crash risk in year t, firm earnings decrease in year t and increases in the previous year, and zero otherwise; (ii) *CRASH_BREAK_STRING2* equals to 1 if a firm experience price crash risk in year t, while its earning increases in year $t-1$ and year $t-2$, and zero otherwise; (iii) *CRASH_BREAK_STRING3* equals to 1 if a firm experience price crash risk in year t, and the firm earnings increases separately in year $t-1$, year $t-2$ and year $t-3$, and zero otherwise. The Eq. (3.10) also includes controls and year-, state-, firm-, and industry-fixed effects. These *CRASH_BREAK_STRING* dummy variables are expected to be related to stock price crash risk and are employed to proxy the sudden release of the hoarding bad news, by estimating the probability of climate change exposure measurements, the hypothesis is tested that climate change exposure leads to the hoarding of negative news. The length of earning strings is also expected to positively affect these proxies, consequently, another independent variable representing the length of earning strings in the corresponding year will be defined and will be controlled in the logit regression with its interaction with climate change exposure. A logistic regression will be utilized to test the

hypothesis, with these dummy variables being employed as separate dependent variables. The same sets of control variables will be included as well as yearly- and industry-fixed effects.

The regression results are reported in Table 3.9. Columns (1), (2), and (3) report the estimation results for three different earning string break measures, each including the interaction term between climate change exposure and the length of the prior earning string. Panel A focuses on the effects of overall climate change exposure (CC_EXPO) on the probability of a break in the earning string, controlling for the length of the string preceding the break. Panel B reports analogous results, replacing overall exposure with regulatory-related climate change exposure (RG_CC_EXPO).

From Panel A, it is evident that climate change exposure (CC_EXPO) increases the probability of stock price crashes following breaks in earnings strings, particularly for *CRASH_BREAK_STRING1* and *CRASH_BREAK_STRING2*. Across all three models including the interaction term with string length, CC_EXPO remains positive, with coefficients of 0.455 ($t = 1.870$) for *CRASH_BREAK_STRING1*, 0.525 ($t = 1.766$) for *CRASH_BREAK_STRING2*, and 0.402 ($t = 0.609$) for *CRASH_BREAK_STRING3*.

The coefficient on the length of the earnings string (len) is consistently positive and significant, indicating that longer prior streaks are associated with a higher likelihood of stock price crashes (e.g., coef. = 0.213, $t = 3.687$ for *CRASH_BREAK_STRING3*). The interaction term between CC_EXPO and string length ($len \times CC_EXPO$) is negative across all specifications (e.g., –0.035, $t = -1.429$ for *CRASH_BREAK_STRING1*; –0.026, $t = -1.164$ for *CRASH_BREAK_STRING2*), though not statistically significant. This pattern suggests that while climate change exposure generally increases crash risk, there is weak evidence that its marginal effect may slightly di-

minish for firms with longer prior earnings streaks, consistent with the notion that sustained prior performance provides a modest buffering effect against exposure-induced crash risk.

Panel B focuses on regulatory-related climate change exposure (*RG_CC_EXPO*) and its interaction with the length of prior earnings streaks (*len*). The main effect of *RG_CC_EXPO* is positive across all three specifications, indicating that higher regulatory exposure tends to increase the probability of stock price crashes following breaks in earnings strings. Specifically, the coefficients are 6.897 ($t = 1.663$), 4.706 ($t = 1.737$), and 3.732 ($t = 1.304$) for *CRASH_BREAK_STRING1*, *CRASH_BREAK_STRING2*, and *CRASH_BREAK_STRING3*, respectively, highlighting that the effect is most pronounced for shorter streaks. The coefficient on *len* is consistently positive and significant (0.039, 0.050, 0.074; $t = 2.390$, 2.702, 3.573), indicating that longer prior earnings streaks themselves are associated with a higher likelihood of subsequent crashes, consistent with the notion that sustained periods of earnings growth can accumulate latent risks. Importantly, the interaction term (*len* × *RG_CC_EXPO*) is negative and significant across all models (–1.708, –1.038, –1.332; $t = -2.041$, –2.080, –2.328), suggesting that the incremental impact of regulatory-related climate exposure on crash probability diminishes as the length of the prior earnings streak increases. In other words, while regulatory exposure raises crash risk, its effect is strongest following shorter sequences of sustained earnings growth and attenuates for longer streaks. Collectively, these results underscore the joint importance of regulatory exposure and the context of prior earnings performance in shaping stock price crash risk.

Overall, these findings indicate two important patterns. First, climate change exposure, both overall and regulatory-specific, increases the likelihood of stock price crashes, particularly when negative news has been ac-

cumulated over multiple years. Second, the length of prior earnings growth plays a dual role: it directly elevates crash probability due to potential bad news hoarding, but it also moderates the effect of exposure, with longer streaks reducing the marginal impact of climate change exposure. These results are consistent with theories of managerial disclosure behavior and the stockpiling of bad news, and they highlight the importance of regulatory risk in driving extreme stock price movements.

3.6 Climate Change Exposure, Price Crash Risk, and Public Attention to Climate Change

According to Choi et al. (2020), surveys show great concern about climate change and the threats of global warming, while the limited attention of human beings causes this concern to be overlooked in normal times, but it is revived in specific periods, especially when extreme weather events such as abnormally high temperatures occur. It is also believed that fluctuations in public attention to global warming affect the financial market. Ilhan et al. (2021) is one of the papers studying the effect of public attention and finds that in periods of high environmental public attention, there is a higher probability of pro-climate regulations, which increases the cost of protecting against policy uncertainty. Stricter regulation would inevitably increase the cost of hoarding bad news and eventually cause a decrease in price crash risk.

To test this hypothesis, the proxy for public attention is the Google Search Volume for the topic “climate change”. The monthly volume ranges from

0 to 100, where 100 represents the period with the highest search volume. The yearly search volume is calculated as the sum of monthly volumes for the years from 2006 to 2020, forming an index with a value of 1 in periods when the yearly volume is larger than the sample median, denoted as SVI_HIGH, and 0 otherwise. This index has been proven useful as a proxy for investor attention according to Da et al. (2011), and Choi et al. (2020) shows it is positively related to abnormally high temperatures.

$$\begin{aligned} CRASH_{j,t+1} =& \beta_0 + \beta_1 HIGH_ATTENTION_t + \beta_2 CC_EXPO_{i,t} \\ &+ \beta_3 \left(HIGH_ATTENTION_t \times CC_EXPO_{i,t}\right) + \gamma X_{i,t} \\ &+ \theta_i + \phi_t + \tau + \epsilon_{i,t} \end{aligned} \tag{3.11}$$

where $HIGH_ATTENTION_t$ is the dummy variables as defined before and other control variables, year-, state-, firm- and industry-fixed effects are included.

The regression results corresponding to this hypothesis are presented in Table 3.10. The key independent variables include CC_EXPO, the proxy for public attention to climate change, its interaction terms with CC_EXPO, and the set of control variables defined previously. The coefficients of the interaction terms are of primary interest, as they capture the differential impact of climate change exposure on stock price crash risk during high- versus low-attention periods.

The regression results using Google Search Volume Index (SVI_HIGH) as the proxy for public attention are reported in Table 3.10. The coefficients on CC_EXPO remain positive across all specifications. Columns (1)–(3) correspond to the crash risk measures $NCSKEW$, $DUVOL$, and $COUNT$, respectively.

The interaction term between public attention and climate change exposure ($SVI_HIGH \times CC_EXPO$) is significantly negative for *NCSKEW* and *DUVOL*, with coefficients of –0.080 (t = –2.504) and –0.097 (t = –3.238), respectively, indicating that heightened public attention reduces the effect of climate change exposure on crash risk. For *COUNT*, the interaction coefficient is –0.048 (t = –1.065) and not statistically significant. A one-standard-deviation increase in the interaction term corresponds approximately to an 8.0% reduction in the effect of *CC_EXPO* on *NCSKEW*, a 9.7% reduction for *DUVOL*, and a 4.8% reduction for *COUNT*. These results suggest that increased public attention generally weakens the influence of climate change exposure on stock price crashes, with the effect most pronounced for *DUVOL*.

Overall, these results suggest that during periods of high public attention, managers face greater scrutiny and reduced discretion in reporting firm performance. As a result, the ability to withhold or delay the disclosure of negative information diminishes, which in turn mitigates the extent to which climate change exposure contributes to stock price crash risk. In particular, heightened attention appears to curb the accumulation of bad news that could otherwise lead to extreme negative returns, especially affecting measures sensitive to downside risk, such as *NCSKEW* and *DUVOL*. This implies that public monitoring and awareness play a significant moderating role in the relationship between environmental exposure and tail risk in stock returns, highlighting the importance of transparency and external oversight in corporate disclosure practices.

3.7 The Causal Effect of President Trump Election

Inspired by Hsu et al. (2022), it is investigated that the causal effect of firm-specific exposure to climate regulation on the risk of stock price crash. Mimicking a natural experiment, Donald Trump's surprise election victory is used as an exogenous source of variation and estimate the difference-in-differences (DiD) models around the 2015–2017 period. Three crash risk measures are applied in the analysis: the difference between the occurrences of price crash and price jump, the negative coefficient of return skewness, and the down-to-up volatility (Chen et al., 2001; Kim et al., 2011a,b; Wu and Lai, 2020). The measure of firm-level exposure to climate policy is obtained from Sautner et al. (2020) who derives a set of climate change bigrams from English-language conference call transcripts of publicly-listed firms using a machine learning technique à la King et al. (2017).[2]

While Trump's election win was unexpected, his position on climate change had been known long before he entered the race for presidency. To illustrate, on 6th November 2012, he tweeted: *"The concept of global warming was created by and for the Chinese in order to make U.S. manufacturing non-competitive."* Six months after he took office in January 2017, he announced that the US would cease all participation in the 2015 Paris Agreement on climate change mitigation. Over the next three and a half years, his administration would reverse nearly 100 climate change rules, including relaxing methane regulation, freezing fuel efficiency standards, eliminating the Clean Power Plan, promoting drilling on public lands, and boosting fossil fuel companies by weakening protections for endangered

[2]Compared to the word-list approach, the approach is advantageous because it only requires a small number of climate-related biagrams as initial input for training purposes which are then used to further locate new bigrams.

species (Schwartz, 2019).

3.7.1 Exposure to Climate Change Regulation and Crash Risk

Firms in the sample are divided into treated and control firms based on their exposure to climate regulation in 2015. Firms with non-zero exposure to climate change regulation are assigned to the treatment group, while those with no exposure to the rules are assigned to the control group. To estimate the causal effect of exposure to climate regulation on stock price crash risk, a difference-in-differences (DiD) specification with firm-level control variables is employed.

Following Chen et al. (2001); Hutton et al. (2009); Li and Zhan (2019), the set of controls includes firm size ($SIZE$), leverage ($LEVERAGE$), the market-to-book ratio ($MARKET_TO_BOOK$), return on assets (ROA), earnings management ($ACCM$), stock return (RET), volatility (VOL), turnover ($DTURN$), skewness ($SKEWNESS$) and kurtosis ($KURTOSIS$) of returns, R&D expenditure to total assets ($R\&D$), CEO characteristics (age LN_CEO_AGE, salary LN_CEO_SALARY, tenure CEO_TENURE, overconfidence $CEO_OVERCONFIDENCE$, and power CEO_POWER), the dummy for change of CEO ($CHANGE$), CEO retirement ($RETIRE$), whether the CEO is the chairman of the board ($CHAIR$), proportion of religious adherents to total population in the state of headquarters ($RELIGION$), annual frequency of natural disasters in the firm's headquarters state ($DISASTER$), and managerial political orientation (POI). These covariates are included to mitigate concerns of omitted variable bias and to capture observable firm characteristics that may influence crash risk.

Table 3.12 reports the top ten sectors in which the treated and the matched control firms in the sample operate. While the majority of the treated firms are in the Industrials (26.27%), Utilities (15.82%), and Energy (13.61%) sectors, large proportions of the control firms operate in the Consumer Discretionary (17.37%), Financials (15.31%), and Industrials (15.27%) sectors. It is worth noting that three out of five industries ranked in the bottom five industries in the treated group, namely Health Care, Technology, and Financials, are ranked among the top five industries in the control group, pointing to the association between industry and exposure to the climate rules.

To investigate the causal effect of exposure to climate change regulation on the stock price crash risk, the DiD model is specified as:

$$\begin{aligned} CRASH_{j,t} = \beta_0 + \beta_1 HIGH_EXP_j + \beta_2 TRUMP_t \\ + \beta_3 \left(HIGH_EXP_j \times TRUMP_t\right) + \beta_4 CONTROL_{j,t} + \varepsilon_{j,t} \end{aligned} \tag{3.12}$$

where j indexes firms and $t \in (2015, 2017)$. $CRASHj, t$ represents one of the three crash risk measures defined in Section 3.3.2: $NCSKEW$, $DUVOL$, or $COUNT$. $HIGH_EXPj$ equals 1 if firm j is exposed to climate regulation and 0 otherwise. $TRUMP$ is a time dummy that equals 0 in 2015 (before the reversal of climate rules) and 1 in 2017 (after Trump's election). The main coefficient of interest is β_3, which captures the causal effect of climate regulation exposure on stock price crash risk. Standard errors are clustered at the firm level to account for serial correlation, and industry fixed effects are alternatively included to control for unobservable industry-level heterogeneity.

Table 3.13 reports the estimation results. Columns (1)–(3) present results without industry fixed effects, while columns (4)–(6) include industry fixed effects. Across both sets of specifications, the interaction term $HIGH_EXP \times TRUMP$ is negative and statistically significant at the 10% level when $NCSKEW$ and $DUVOL$ are used as dependent variables, suggesting that firms exposed to climate regulation experienced larger declines in crash risk relative to control firms after 2015. For example, in column (1), the coefficient of -0.310 for $NCSKEW$ implies that the change in crash risk between 2015 and 2017 for treated firms is lower by approximately 0.310 compared to control firms, representing a substantial fraction of the cross-sectional standard deviation of $NCSKEW$. Similarly, the estimate of -0.241 in column (2) for $DUVOL$ indicates a reduction of comparable economic magnitude.

In contrast, the coefficients on the interaction term in the $COUNT$ regressions are small and statistically insignificant (0.028 in column (3)), indicating no differential effect of climate regulation exposure on the frequency-based measure of crash risk. These results remain robust when industry fixed effects are included, as shown in columns (4)–(6), where the interaction coefficients for $NCSKEW$ and $DUVOL$ are -0.275 and -0.215, respectively, still significant at the 10% level, while the coefficient for $COUNT$ is near zero.

Overall, the findings provide consistent evidence that exposure to climate regulation significantly reduced firms' risk of stock price crashes, particularly when measured by $NCSKEW$ and $DUVOL$.

As discussed in Roberts and Whited (2013), the consistency of a DiD estimator hinges on the parallel trend assumption. To examine whether this assumption holds, it is tested that if the risk of stock price crash for the

treated and control firms followed a common trend prior to the reversal of climate regulation by the Trump administration. The results, reported in Table 3.14, present the differences in the average changes of each crash risk measure between the treated and control firms during the 2013–2014 and 2014–2015 periods. All corresponding p-values, ranging from 0.225 to 0.931, are well above conventional significance levels, indicating that none of the differences are statistically significant. This provides strong evidence that the parallel trend assumption is satisfied for the sample.

The findings support the conjecture that exposure to climate change regulation is associated with the risk of stock price crash and that firms which were exposed to the regulation benefited from the climate policy reversal by the Trump's administration. The results are also consistent with Ilhan et al. (2021) and Hsu et al. (2022). The former found that the cost of option protection against downside tail risks reduced sharply after Trump's election while the latter reported that following Trump's victory, high-emission firms had significantly positive CARs that were higher than their lower counterparts.

3.7.2 Placebo Tests

In this section, two placebo tests are conducted to validate the main findings. In the first test, the DiD model in Eq. (3.12) around the 2015–2017 period is estimated using 10,000 artificial samples, in which firms are randomly assigned to the treatment and control groups. The distribution of the estimates of β_3 is reported in Table 3.15, and the histograms along with the kernel density are shown in Figures 3.1(a)–3.1(c). The distribution of the estimated parameters centers around zero, indicating no meaningful impact of exposure to climate regulation on stock price crash risk when

Eq. (3.12) is estimated using the artificial samples. The 1% and 99% percentiles of the estimates of β_3 when $COUNT$, $NCSKEW$, and $DUVOL$ are used as the dependent variables are $[-0.057, 0.056]$, $[-0.091, 0.093]$, and $[-0.067, 0.067]$, respectively.

The second placebo test focuses on the period during Barack Obama's second term as US President. Eq. (3.12) is estimated for the following event windows: 2012–2013, 2013–2014, and 2014–2015.[3]

Similar to the approach discussed in Section 3.7.1, firms are assigned to the treated and control groups based on their exposure to the climate rules in the first year of each two-year event window. For example, the analysis for 2012–2013 uses the 2012 exposure values to classify firms into treated and control groups.[4] The results for all three crash risk measures, reported in Table 3.16, show that none of the estimates of β_3 are statistically significant, indicating no differences in crash risk between firms with exposure to climate regulation and those without exposure.

3.8 Conclusion

This chapter demonstrates that firm-level exposure to climate change positively affects the risk of stock price crashes, mainly due to breaks in consecutive increasing earnings strings. The empirical results show that firms with higher exposure to climate change are more likely to experience stock price crashes, particularly in years with less than two consecutive years of increasing earnings. In particular, exposure to climate change regulation

[3]President Obama's last Climate Action Plan, issued in June 2013, included regulations targeting industry with the ultimate goal of cutting domestic carbon emissions and preparing the US for the impending effects of climate change.

[4]For clarity, the variable $TRUMP$ is replaced with $TREAT$ to indicate observations in the treatment group, since this analysis is conducted outside the period of Trump's presidency.

significantly influences the occurrence of stock price crashes by prompting the disclosure of adverse news. As prior studies have elucidated, the risks stemming from climate change cascade down to the firm level due to regulatory uncertainty and the costs incurred following the implementation of relevant regulations. Consistent with the hypothesis, heightened public attention to climate change increases awareness, reduces managers' incentives to hoard bad news, and thereby alleviates the extent of stock price crashes.

Utilizing the reversal of US climate policy by the Trump administration as an exogenous source of variation in the DiD framework, this chapter demonstrates that firm-specific exposure to climate change regulation increases stock price crash risk. The empirical analysis shows that firms exposed to climate regulation in the year immediately preceding Trump's shock victory experienced disproportionately lower reductions in crash risk compared to firms with no exposure. To validate the findings, two placebo tests are implemented. The first test uses randomly generated treated and control observations, while the second test examines firms during President Obama's second term. The results of both placebo tests indicate no significant impact of exposure to climate regulation on stock price crash risk, further reinforcing the validity of the main conclusions.

The findings of this chapter have several implications. First, managers should be aware that exposure to climate regulation could potentially elevate stock price crash risk, resulting in higher equity risk premiums. Second, investors are encouraged to adopt risk management strategies to protect their portfolios against potential downside tail risks when investing in companies affected by climate change regulations. Finally, policymakers should be mindful of the unintended consequences of climate regulation, which could potentially destabilize financial markets.

This study also offers implications for investors in evaluating stock price crash risk and provides insights into green finance. Textual analysis of climate change exposure measures indicates their potential in predicting firm-level stock price crashes. Moreover, the results show that attention to climate change affects the stock market, suggesting that investors may reasonably consider a firm's environmental performance when making investment decisions.

3.9 Tables

Table 3.1: Summary Statistics

This table reports the summary statistics for key variables. The definition of variables is provided in Chapter 3.

Variable	N	Mean	25th	Median	75th	std.
NCSKEW	42,576	-0.057	-0.661	0.0153	0.633	1.189
DUVOL	42,576	-0.0519	-0.503	-0.00342	0.460	0.843
COUNT	42,576	-0.109	-1	0	0	0.748
CC_EXPO × 1000	42,576	0.716	0.0821	0.260	0.647	1.475
SIZE	42,576	6.810	5.622	6.804	8.009	1.856
LEVERAGE	42,575	0.691	0.0278	0.401	0.951	2.686
MARKET_TO_BOOK	42,575	3.162	1.328	2.243	3.607	5.926
ROA	42,575	0.006	-0.0552	0.0744	0.156	0.819
R&D	42,576	0.0671	0.0203	0.0341	0.0581	0.105
ACCM	42,575	0.182	0.0643	0.109	0.201	0.219
RET	42,576	-0.128	-0.565	-0.147	0.246	1.007
VOL	42,576	0.0625	0.0359	0.0493	0.0735	0.0463
DTURN	42,576	0.00794	-0.027	0.00221	0.036	0.113
SKEWNESS	42,576	0.481	-0.0899	0.287	0.803	1.037
KURTOSIS	42,576	2.821	0.466	1.338	3.091	4.708
LN_CEO_AGE	21,098	4.017	3.989	4.025	4.043	0.0934
LN_CEO_SALARY	21,098	6.624	6.515	6.664	6.759	0.324
LN_CEO_TENURE	21,098	1.665	1.099	1.792	2.398	0.928
CEO_OVERCONFIDENCE	21,098	0.444	0	0	1	0.497
CEO_POWER	7,416	0.726	0	1	1	0.446
CHANGE	21,098	0.055	0	0	0	0.228
RETIRE	21,098	0.0265	0	0	0	0.161
CHAIR	21,098	0.393	0	0	1	0.488
RELIGION	15,952	0.537	0.466	0.514	0.616	0.0898
DISASTER	16,826	2.324	1	2	3	1.394
POI	6,393	0.150	-0.158	0	1	0.713

Table 3.2: Correlation (Columns 1–6)

This table reports correlation coefficients for the main variables in this chapter 3

	1	2	3	4	5	6
NCSKEW	1.000					
DUVOL	0.929	1.000				
COUNT	0.728	0.617	1.000			
CC_EXPO $*$ 1000	0.012	0.010	0.019	1.000		
SIZE	0.058	0.086	0.060	-0.018	1.000	
LEVERAGE	0.004	0.009	0.005	-0.002	0.138	1.000
MARKET_TO_BOOK	-0.047	-0.049	-0.027	-0.022	0.006	0.529
ROA	-0.001	0.002	0.011	-0.016	0.152	-0.146
R&D	0.001	-0.012	-0.012	-0.044	-0.422	-0.087
ACCM	-0.018	-0.032	-0.026	-0.000	-0.419	-0.081
RET	-0.599	-0.681	-0.274	-0.005	0.036	0.008
DTURN	-0.299	-0.341	-0.171	0.037	-0.360	-0.030
VOL	-0.106	-0.130	-0.040	0.005	0.005	0.016
SKEWNESS	-0.808	-0.747	-0.618	0.017	-0.200	-0.023
KURTOSIS	-0.503	-0.445	-0.304	-0.009	-0.153	-0.015
LN_CEO_AGE	0.018	0.021	0.009	0.024	0.072	0.011
LN_CEO_SALARY	0.014	0.024	0.013	-0.003	0.405	0.053
LN_CEO_TENURE	0.020	0.028	0.005	0.005	-0.066	-0.020
CEO_OVERCONFIDENCE	-0.022	-0.020	-0.022	0.031	0.053	-0.003
CEO_POWER	-0.034	-0.046	-0.006	0.002	-0.036	-0.034
CHANGE	0.022	0.022	0.020	-0.017	0.116	0.008
RETIRE	0.021	0.026	0.024	0.001	0.096	0.007
CHAIR	0.063	0.083	0.046	-0.008	0.387	0.021
RELIGION	0.000	0.007	-0.001	0.023	0.101	0.040
DISASTER	0.022	0.019	0.012	-0.036	-0.087	-0.039
POI	0.012	0.023	-0.007	0.021	0.023	0.006

Table 3.3: Correlation (Columns 7–18)

This table reports correlation coefficients for the main variables in this chapter 3

	7	8	9	10	11	12
NCSKEW						
DUVOL						
COUNT						
CC_EXPO $*$ 1000						
SIZE						
LEVERAGE						
MARKET_TO_BOOK	1.000					
ROA	-0.102	1.000				
R&D	0.094	-0.184	1.000			
ACCM	0.056	-0.106	0.487	1.000		
RET	0.067	0.037	-0.081	-0.039	1.000	
DTURN	-0.034	-0.141	0.248	0.245	0.258	1.000
VOL	0.020	-0.003	0.005	-0.003	0.180	0.258
SKEWNESS	0.007	-0.059	0.112	0.110	0.380	0.552
KURTOSIS	0.000	-0.052	0.109	0.086	0.266	0.554
LN_CEO_AGE	-0.012	0.008	-0.037	-0.049	-0.020	-0.036
LN_CEO_SALARY	0.014	0.036	-0.088	-0.142	-0.008	-0.104
LN_CEO_TENURE	0.011	0.004	0.038	0.012	-0.034	-0.036
CEO_OVERCONFIDENCE	0.102	0.061	0.002	-0.032	0.008	-0.085
CEO_POWER	-0.044	-0.012	-0.006	0.044	0.053	0.048
CHANGE	-0.001	0.015	-0.055	-0.047	0.010	-0.048
RETIRE	-0.003	0.017	-0.040	-0.043	-0.004	-0.061
CHAIR	0.026	0.087	-0.176	-0.193	0.010	-0.254
RELIGION	-0.069	0.050	-0.199	-0.157	0.017	-0.041
DISASTER	0.071	-0.046	0.210	0.136	-0.048	-0.007
POI	-0.011	0.027	-0.056	-0.077	-0.038	-0.063

	13	14	15	16	17	18
NCSKEW						
DUVOL						
COUNT						
CC_EXPO $*$ 1000						
SIZE						
LEVERAGE						
MARKET_TO_BOOK						
ROA						
R&D						
ACCM						
RET						
DTURN						
VOL	1.000					
SKEWNESS	0.423	1.000				
KURTOSIS	0.473	0.742	1.000			
LN_CEO_AGE	-0.050	-0.058	-0.049	1.000		
LN_CEO_SALARY	-0.064	-0.083	-0.073	0.019	1.000	
LN_CEO_TENURE	-0.029	-0.011	-0.012	0.052	-0.031	1.000
CEO_OVERCONFIDENCE	-0.002	-0.006	-0.000	0.027	-0.022	0.008
CEO_POWER	-0.012	0.014	-0.017	-0.005	0.001	-0.026
CHANGE	-0.050	-0.067	-0.046	-0.006	-0.008	-0.024
RETIRE	-0.042	-0.051	-0.051	-0.014	-0.007	-0.021
CHAIR	-0.068	-0.094	-0.090	-0.021	0.010	-0.054
RELIGION	-0.002	-0.013	-0.018	-0.005	-0.002	-0.006
DISASTER	0.005	0.005	0.007	-0.019	-0.021	0.004
POI	-0.036	-0.045	-0.040	-0.004	-0.004	-0.007

Table 3.4: Correlation (Columns 19–26)

This table reports correlation coefficients for the main variables in this chapter 3

	19	20	21	22	23	24
NCSKEW						
DUVOL						
COUNT						
CC_EXPO $*$ 1000						
SIZE						
LEVERAGE						
MARKET_TO_BOOK						
ROA						
R&D						
ACCM						
RET						
DTURN						
VOL						
SKEWNESS						
KURTOSIS						
LN_CEO_AGE						
LN_CEO_SALARY						
LN_CEO_TENURE						
CEO_OVERCONFIDENCE	1.000					
CEO_POWER	-0.020	1.000				
CHANGE	-0.013	0.054	1.000			
RETIRE	-0.011	0.016	0.668	1.000		
CHAIR	-0.013	0.081	-0.123	-0.115	1.000	
RELIGION	-0.006	-0.004	-0.045	-0.061	0.100	1.000
DISASTER	-0.006	0.006	-0.022	-0.023	0.036	0.056
POI	0.000	0.007	0.000	-0.003	-0.011	0.010

	25	26
NCSKEW		
DUVOL		
COUNT		
CC_EXPO $*$ 1000		
SIZE		
LEVERAGE		
MARKET_TO_BOOK		
ROA		
R&D		
ACCM		
RET		
DTURN		
VOL		
SKEWNESS		
KURTOSIS		
LN_CEO_AGE		
LN_CEO_SALARY		
LN_CEO_TENURE		
CEO_OVERCONFIDENCE		
CEO_POWER		
CHANGE		
RETIRE		
CHAIR		
RELIGION		
DISASTER	1.000	
POI	-0.012	1.000

Table 3.5: Results for Climate Change Exposure

This table reports the estimation results of the model with *CC_EXPO* as independent variables as specified in Eq. (3.6). The measures of crash risk are *NCSKEW* in columns (1) and (4), *DUVOL* in columns (2) and (5), *COUNT* in columns (3) and (6). Columns (1), (2) and (3) are univariate regression results, Columns (4), (5) and (6) are regression results with control variables. Basic controls and year- and industry-fixed effects are included. Standard errors are clustered at the firm level and are reported in the parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Univariate			With Controls		
	(1) *NCSKEW*	(2) *DUVOL*	(3) *COUNT*	(4) *NCSKEW*	(5) *DUVOL*	(6) *COUNT*
CC_EXPO	0.013	0.006	0.008	0.019**	0.012*	0.012
	(1.393)	(0.980)	(1.417)	(2.228)	(1.754)	(1.196)
SIZE				-0.019	-0.015	-0.004
				(-1.063)	(-1.210)	(-0.257)
LEVERAGE				0.01	0.014	0.004
				(0.790)	(1.503)	(0.507)
MARKET_TO_BOOK				-0.003	-0.005	-0.002
				(-0.573)	(-1.400)	(-0.500)
ROA				-0.111	-0.057	-0.028
				(-1.528)	(-1.082)	(-0.715)
R&D				0.141	-0.155	-0.269
				(0.394)	(-0.612)	(-0.767)
ACCM				0.214	0.142	0.301**
				(1.215)	(1.096)	(2.427)
RET				-0.465***	-0.453***	-0.052**
				(-8.828)	(-11.581)	(-2.210)
VOL				2.476	0.151	2.013**
				(0.789)	(0.071)	(2.024)
DTURN				0.334*	0.09	0.029
				(1.694)	(0.644)	(0.165)
SKEWNESS				-1.088***	-0.628***	-0.707***
				(-51.870)	(-40.664)	(-30.688)
KURTOSIS				0.048***	0.041***	0.045***
				(5.454)	(6.542)	(7.170)
LN_CEO_AGE				-0.088	-0.024	-0.066
				(-0.720)	(-0.266)	(-0.505)
LN_CEO_SALARY				-0.02	0.007	-0.021
				(-0.434)	(0.193)	(-0.416)
LN_CEO_TENURE				0.021	0.007	0.01
				(1.234)	(0.538)	(0.609)
CEO_OVERCONFIDENCE				-0.001	-0.006	0.027
				(-0.047)	(-0.287)	(0.865)
CEO_POWER				0.012	-0.014	0.052*
				(0.432)	(-0.679)	(1.661)
CHANGE				0.019	-0.057	0.057
				(0.298)	(-1.171)	(0.819)
RETIRE				0.011	-0.046	0.085*
				(0.248)	(-1.386)	(1.776)
CHAIR				0.014	0.03	-0.005
				(0.369)	(1.062)	(-0.120)
RELIGION				0.001	-0.011	0.131*
				(0.014)	(-0.217)	(1.720)
DISASTER				-0.005	0	-0.012
				(-0.328)	(-0.048)	(-0.770)
POI				-0.008	0	-0.021
				(-0.443)	(0.016)	(-1.049)
Year-fixed	Y	Y	Y	Y	Y	Y
Industry-fixed	Y	Y	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y	Y	Y

t-statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: Results for Climate Change Risk Measurements

This table reports the estimation results of the model with CC_RISK as independent variables as specified in Eq. (3.7). The measures of crash risk are $NCSKEW$ in columns (1) and (4), $DUVOL$ in columns (2) and (5), $COUNT$ in columns (3) and (6). Columns (1), (2) and (3) are univariate regression results, Columns (4), (5) and (6) are regression results with control variables. Basic controls and year- and industry-fixed effects are included. Standard errors are clustered at the firm level and are reported in the parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Univariate			With Controls		
	(1)	(2)	(3)	(4)	(5)	(6)
	NCSKEW	*DUVOL*	*COUNT*	*NCSKEW*	*DUVOL*	*COUNT*
CC_RISK	0.903***	0.819***	0.336**	0.172	0.539*	-0.274
	(3.908)	(4.289)	(1.966)	(0.397)	(1.725)	(-0.562)
SIZE				-0.021	-0.016	-0.01
				(-1.260)	(-1.397)	(-0.732)
LEVERAGE				0.004	0.008	0.011*
				(0.419)	(1.445)	(1.670)
MARKET_TO_BOOK				-0.003	-0.004	-0.006
				(-0.537)	(-1.180)	(-1.581)
ROA				0.029	0.025	0.028
				(0.930)	(1.257)	(1.289)
R&D				0.391	-0.101	0.025
				(1.215)	(-0.426)	(0.076)
ACCM				0.192	0.121	0.296**
				(1.121)	(0.969)	(2.435)
RET				-0.438***	-0.432***	-0.043*
				(-7.498)	(-10.310)	(-1.878)
VOL				4.017	1.165	2.162**
				(1.437)	(0.638)	(2.567)
DTURN				0.289	0.054	0.034
				(1.511)	(0.421)	(0.211)
SKEWNESS				-1.090***	-0.635***	-0.706***
				(-51.729)	(-41.357)	(-31.389)
KURTOSIS				0.050***	0.044***	0.046***
				(5.368)	(6.749)	(7.775)
LN_CEO_AGE				-0.089	-0.034	-0.086
				(-0.756)	(-0.388)	(-0.669)
LN_CEO_SALARY				0	0.018	-0.01
				(0.002)	(0.563)	(-0.215)
LN_CEO_TENURE				0.027	0.011	0.013
				(1.528)	(0.858)	(0.778)
CEO_OVERCONFIDENCE				-0.014	-0.011	0.031
				(-0.424)	(-0.485)	(1.036)
CEO_POWER				0.012	-0.016	0.042
				(0.423)	(-0.771)	(1.379)
CHANGE				0.025	-0.042	0.071
				(0.402)	(-0.886)	(1.028)
RETIRE				0.002	-0.054	0.084*
				(0.059)	(-1.634)	(1.758)
CHAIR				0.003	0.023	-0.016
				(0.089)	(0.834)	(-0.396)
RELIGION				0.024	0.005	0.115
				(0.343)	(0.091)	(1.549)
DISASTER				-0.008	-0.004	-0.01
				(-0.612)	(-0.405)	(-0.692)
POI				-0.011	0.001	-0.028
				(-0.636)	(0.062)	(-1.440)
Year-fixed	Y	Y	Y	Y	Y	Y
Industry-fixed	Y	Y	Y	Y	Y	Y
Cluster	Y	Y	Y	Y	Y	Y

t-statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Summary Results for Different Types of Exposure

This table reports the estimation results of the model including different types of climate change exposure measurements as specified in Eq. (3.8). The measures of crash risk are *NCSKEW* in column (1), *DUVOL* in column (2), and *COUNT* in column (3). Basic controls and year- and industry-fixed effects are included. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	NCSKEW	*DUVOL*	*COUNT*
RG_CC_EXPO	0.778*	0.155*	0.686
	(1.831)	(1.897)	(1.625)
PH_CC_EXPO	0.718	-0.424**	-0.701
	(1.075)	(-2.134)	(-1.241)
OP_CC_EXPO	-0.062	0.016	-0.068
	(-0.827)	(1.047)	(-1.211)
SIZE	-0.004	-0.037***	0.002
	(-0.170)	(-4.532)	(0.091)
LEVERAGE	-0.009	0.024***	0.008
	(-0.745)	(3.194)	(0.496)
MARKET_TO_BOOK	-0.002	-0.013***	0.002
	(-0.332)	(-3.667)	(0.384)
ROA	0.216*	-0.105***	0.092
	(1.903)	(-2.930)	(0.794)
R&D	0.477	0.234	1.300*
	(0.725)	(0.681)	(1.958)
ACCM	0.299	0.070	0.547*
	(0.989)	(0.751)	(1.704)
RET	-0.638***	0.001	-0.108*
	(-10.245)	(1.643)	(-1.839)
VOL	3.725**	0.017*	1.107
	(2.095)	(1.651)	(0.577)
DTURN	0.338	0.197	0.409
	(0.786)	(1.307)	(1.151)
SKEWNESS	-0.803***	-0.753***	-0.614***
	(-15.060)	(-37.030)	(-11.579)
KURTOSIS	-0.013	0.036***	0.019
	(-0.798)	(7.220)	(1.349)
LN_CEO_AGE	0.005	-0.001	0.011**
	(1.127)	(-0.491)	(2.102)
LN_CEO_SALARY	0.051***	0.009	0.040**
	(3.441)	(1.195)	(2.508)
LN_CEO_TENURE	-0.003	0.015	-0.008
	(-0.105)	(0.976)	(-0.248)
CEO_OVERCONFIDENCE	-0.038	0.002	-0.030
	(-0.630)	(0.061)	(-0.444)
CEO_POWER	0.019	-0.031	0.097
	(0.333)	(-1.091)	(1.509)
CHANGE	-0.034	-0.073	-0.291*
	(-0.281)	(-1.298)	(-1.943)
RETIRE	0.047	-0.040	0.181*
	(0.527)	(-0.870)	(1.896)
CHAIR	0.007	0.005	0.027

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Table 3.7 (continued)

	(1) *NCSKEW*	(2) *DUVOL*	(3) *COUNT*
	(0.090)	(0.153)	(0.268)
RELIGION	0.018	0.028	0.013
	(0.115)	(0.401)	(0.080)
DISASTER	0.007	-0.013	0.045
	(0.231)	(-0.751)	(1.514)
POI	-0.104**	0.007	-0.094*
	(-2.419)	(0.373)	(-1.960)
Year-fixed	Y	Y	Y
Industry-fixed	Y	Y	Y
Cluster	Y	Y	Y

t-statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8: Summary Results for Different Types of Risk Exposure

This table reports the estimation results of the model including different types of climate change risk measurements as specified in Eq. (3.9). The measures of crash risk are *NCSKEW* in columns (1), *DUVOL* in columns (2) and *COUNT* in columns (3). Basic controls and year- and industry-fixed effects are included. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	NCSKEW	*DUVOL*	*COUNT*
RG_CC_RISK	2.789*	3.016**	0.990
	(1.669)	(1.997)	(1.001)
PH_CC_RISK	1.087	2.169*	2.348**
	(1.003)	(1.841)	(2.408)
OP_CC_RISK	-0.085	-0.090	0.041
	(-0.962)	(-1.304)	(0.558)
SIZE	-0.042***	-0.038***	-0.024**
	(-4.265)	(-4.685)	(-2.231)
LEVERAGE	0.026***	0.025***	0.010
	(2.987)	(3.262)	(1.342)
MARKET_TO_BOOK	-0.012***	-0.013***	-0.005
	(-3.122)	(-3.756)	(-1.344)
ROA	-0.116**	-0.105***	-0.052
	(-2.555)	(-2.909)	(-1.301)
R&D	0.672	0.203	-0.134
	(1.573)	(0.592)	(-0.379)
ACCM	0.114	0.066	0.158
	(0.974)	(0.711)	(1.476)
RET	0.001**	0.001	0.001***
	(2.091)	(1.637)	(2.627)
VOL	0.023**	0.017	0.016***
	(1.968)	(1.623)	(2.887)
DTURN	0.469***	0.198	0.146
	(2.869)	(1.306)	(0.836)
SKEWNESS	-0.878***	-0.754***	-0.669***
	(-27.350)	(-36.988)	(-22.713)
KURTOSIS	0.026***	0.037***	0.038***
	(2.873)	(7.270)	(4.764)
LN_CEO_AGE	-0.001	-0.001	-0.002
	(-0.516)	(-0.311)	(-0.632)
LN_CEO_SALARY	0.015	0.010	0.018
	(1.088)	(1.252)	(1.097)
LN_CEO_TENURE	0.030*	0.014	0.009
	(1.714)	(0.929)	(0.516)
CEO_OVERCONFIDENCE	-0.015	0.001	0.026
	(-0.454)	(0.044)	(0.837)
CEO_POWER	-0.015	-0.031	0.053
	(-0.440)	(-1.094)	(1.639)
CHANGE	0.036	-0.073	0.047
	(0.562)	(-1.294)	(0.670)
RETIRE	0.021	-0.039	0.075
	(0.393)	(-0.848)	(1.576)
CHAIR	-0.039	0.006	-0.017

Continued on next page

Table 3.8 (continued)

	(1)	(2)	(3)
	NCSKEW	*DUVOL*	*COUNT*
	(-0.942)	(0.159)	(-0.403)
RELIGION	0.022	0.027	0.128*
	(0.246)	(0.377)	(1.654)
DISASTER	0.001	-0.011	-0.010
	(0.041)	(-0.633)	(-0.619)
POI	-0.018	0.005	-0.025
	(-0.822)	(0.255)	(-1.252)
Year-fixed	Y	Y	Y
Industry-fixed	Y	Y	Y
Cluster	Y	Y	Y

t-statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9: Estimates of Stock Price Crash Due to Breaks in Earnings String Caused by Climate Change Exposure

This table reports the estimation results of the earning string break models. Panel A reports results as specified in Eq. (3.10), and Panel B reports the same regression with *RG_CC_EXPO* replacing *CC_EXPO*. The *CRASH_BREAK_STRINGt* measurements equal one when a crash occurs and earnings decrease that year, while earnings increased in previous t years. Columns (1), (2), and (3) report the estimation results for *CRASH_BREAK_STRING1*, *CRASH_BREAK_STRING2*, and *CRASH_BREAK_STRING3*, respectively. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	CRASH_BREAK_STRING1 (1)	*CRASH_BREAK_STRING2* (2)	*CRASH_BREAK_STRING3* (3)
Panel A: CC_EXPO			
CC_EXPO	0.455*	0.525*	0.402
	(1.870)	(1.766)	(0.609)
len	0.045*	0.066*	0.213***
	(1.707)	(1.905)	(3.687)
len × *CC_EXPO*	-0.035	-0.026	-0.045
	(-1.429)	(-1.164)	(-0.809)
Panel B: RG_CC_EXPO			
RG_CC_EXPO	6.897*	4.706*	3.732
	(1.663)	(1.737)	(1.304)
len	0.039**	0.050***	0.074***
	(2.390)	(2.702)	(3.573)
len × *RG_CC_EXPO*	-1.708**	-1.038**	-1.332**
	(-2.041)	(-2.080)	(-2.328)
Control	Y	Y	Y
Year-fixed	Y	Y	Y
Industry-fixed	Y	Y	Y
Cluster	Y	Y	Y

t-statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.10: High Attention Effect.

This table reports the estimation results of the model including the high attention index model as specified in Eq. (3.11). The measures of crash risk are *NCSKEW* in column (1), *DUVOL* in column (2), and *COUNT* in column (3). This table reports the regression results when Google search volumes are used to calculate the high attention index. Basic controls and year- and industry-fixed effects are included. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	NCSKEW	*DUVOL*	*COUNT*
CC_EXPO	0.013	0.012	-0.003
	(0.587)	(0.534)	(-0.105)
SVI_HIGH	0.124*	0.103	0.072
	(1.681)	(1.625)	(0.783)
SVI_HIGH × *CC_EXPO*	-0.080**	-0.097***	-0.048
	(-2.504)	(-3.238)	(-1.065)
SIZE	0.059***	0.046**	0.090***
	(2.731)	(2.455)	(3.100)
LEVERAGE	0.007	0.011	-0.003
	(0.627)	(1.076)	(-0.190)
MARKET_TO_BOOK	-0.006	-0.010	0.014
	(-0.379)	(-0.768)	(0.642)
ROA	0.036*	0.040**	-0.005
	(1.725)	(2.025)	(-0.207)
R&D	-0.055*	-0.079***	0.005
	(-1.829)	(-3.320)	(0.133)
ACCM	0.015	0.005	0.024
	(0.730)	(0.234)	(0.903)
RET	-1.022***	-1.075***	-0.446***
	(-36.606)	(-38.263)	(-18.103)
VOL	-0.101***	-0.100***	-0.152***
	(-3.114)	(-2.722)	(-4.241)
DTURN	0.057***	0.048***	0.032*
	(3.789)	(3.575)	(1.834)
SKEWNESS	-0.858***	-0.732***	-0.920***
	(-39.165)	(-33.546)	(-26.256)
KURTOSIS	0.100***	0.130***	0.225***
	(4.168)	(4.364)	(5.880)
LN_CEO_AGE	0.006	0.002	0.013
	(0.741)	(0.263)	(1.128)
LN_CEO_SALARY	-0.021*	-0.019*	-0.029*
	(-1.649)	(-1.740)	(-1.722)
CEO_TENURE	0.019**	0.018**	0.008
	(2.129)	(2.283)	(0.720)
CEO_OVERCONFIDENCE	-0.001	-0.041	0.041
	(-0.066)	(-0.801)	(0.465)
CEO_POWER	0.023	0.004	0.009
	(1.087)	(0.178)	(0.323)
CHANGE	0.045	-0.027	0.028
	(0.038)	(0.049)	(0.040)
RETIRE	0.003	-0.069	0.029
	(0.031)	(0.050)	(0.033)

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Table 3.10 (continued)

	(1)	(2)	(3)
	NCSKEW	*DUVOL*	*COUNT*
CHAIR	-0.011	0.001	-0.000
	(0.019)	(0.024)	(0.021)
RELIGION	-0.012	-0.011	-0.081
	(-0.191)	(-0.197)	(-0.974)
DISASTER	-0.003	0.006	0.003
	(-0.187)	(0.442)	(0.165)
POI	0.003	0.011	-0.004
	(0.212)	(0.923)	(-0.214)
Year-fixed	Y	Y	Y
Industry-fixed	Y	Y	Y
Cluster	Y	Y	Y

t-statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.11: Definition of Variables

This table lists the variables used in the empirical analysis. Column (1) presents the variable names, Column (2) presents the definitions of the variables and Column (3) presents the sources of the variables. Financial data are primarily drawn from Compustat and CRSP; CEO characteristics are drawn from ExecuComp; external variables are from EM-DAT, county religiosity sources, and FEC as noted.

Variable	Definition	Source
SIZE	The natural logarithm of market value, measured as shares outstanding multiplied by the fiscal-year-end closing stock price.	Compustat
LEVERAGE	Financial leverage, defined as the ratio of total long-term debt to total assets.	Compustat
MARKET_TO_BOOK	Market-to-book ratio: market value of equity divided by book value of equity (book value = shareholders' equity + deferred taxes + investment tax credits (if available) book value of preferred stock).	Compustat
ROA	Return on assets, measured as earnings before interest and taxes (EBIT) divided by total assets.	Compustat
R&D	Research and development intensity, measured as R&D expenditures scaled by total assets.	Compustat
ACCM	Accounting opacity measured by discretionary accruals: the three-year moving sum of the absolute value of discretionary accruals estimated using the modified Jones model.	Compustat
RET	Average firm-specific weekly returns during the fiscal year.	CRSP
VOL	Yearly firm-specific volatility, calculated as the annual standard deviation of daily stock returns.	CRSP
DTURN	Change in trading activity: average monthly stock turnover in the current fiscal year minus that in the previous fiscal year; monthly turnover = monthly trading volume / shares outstanding.	CRSP
SKEWNESS	Skewness of firm-specific weekly returns within the fiscal year.	CRSP
KURTOSIS	Kurtosis of firm-specific weekly returns within the fiscal year.	CRSP
LN_CEO_AGE	Natural logarithm of CEO age.	ExecuComp
LN_CEO_SALARY	Natural logarithm of CEO total salary (cash salary).	ExecuComp
LN_CEO_TENURE	Natural logarithm of CEO tenure in the firm (years).	ExecuComp
CEO_OVERCONFIDENCE	CEO overconfidence indicator constructed from option moneyness following Kim et al. (2016): based on realizable value per option and estimated exercise price; coded as an indicator for overconfident CEOs if hold options at least twice during the sample period that are more than 100% in the money.	ExecuComp (option data)
CEO_POWER	Dummy equal to 1 if the CEO simultaneously serves as board chair and president (indicating concentrated CEO power), and 0 otherwise.	ExecuComp / Board records
CHANGE	Dummy variable equal to 1 if there is a CEO change during the fiscal year, and 0 otherwise.	ExecuComp
RETIRE	Dummy variable equal to 1 if the CEO retires during the fiscal year, and 0 otherwise.	ExecuComp
CHAIR	Dummy variable equal to 1 if the CEO serves as board chair, and 0 otherwise.	ExecuComp
RELIGION	County-level religiosity: proportion of religious adherents to total population in the firm's headquarters state (following Callen and Fang (2015a)).	County religiosity data
DISASTER	Annual frequency of natural disasters in the firm's headquarters state as recorded in EM-DAT (capturing disaster shocks that may affect firm stress).	EM-DAT

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Table 3.11 (continued)

Variable	Definition	Source
POI	Firm-level managerial political orientation index: the average personal political orientation (PO) of the five highest-paid managers, constructed from FEC contribution data (POCYCLE = (Rep Dem)/Total; PO averaged across cycles; firms with no contributions set to zero).	FEC

Notes: Definitions follow prior literature (see main text).

Table 3.12: Top Ten Sectors

This table reports the top ten of sectors in which firms in the treated and the control groups operate. Firms in the treated group are those with high exposure to climate regulation. Firms in the control group are those with low exposure to climate regulation. Section 3.3.1 discusses the construction of the exposure to climate regulation.

Treated		Control	
Sector	Composition (%)	Sector	Composition (%)
Industrials	26.27	Consumer Discretionary	17.37
Utilities	15.82	Financials	15.31
Energy	13.61	Industrials	15.27
Consumer Discretionary	12.03	Health Care	14.46
Basic Materials	9.81	Technology	12.57
Health Care	6.65	Energy	6.65
Technology	5.06	Real Estate	6.33
Financials	4.11	Consumer Staples	3.99
Consumer Staples	2.85	Basic Materials	3.55
Real Estate	2.22	Telecommunications	3.38

Table 3.13: The Causal Effect of Exposure to Climate Regulation on the Risk of Stock Price Crash

This table reports the estimation results of the difference-in-differences model as specified in Eq. (3.12) using observations from the sample period 2015–2017. The measures of crash risk are *COUNT*, *NCSKEW*, and *DUVOL*. See Section 3.3.2 for a detailed description of the crash risk measures. *HIGH_EXP* is a dummy variable that takes values of zero for the firms that belong to the control group, and one for the firms that belong to the treated group. *TRUMP* is a dummy variable that takes values of zero for the year 2015 (before Trump's election victory) and one for the year 2017 (after Trump's election victory). Columns (1)–(3) report the estimation results for models without industry fixed effects. Columns (4)–(6) report the estimation results for models with industry fixed effects. Standard errors are clustered at the firm level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	NCSKEW	*DUVOL*	*COUNT*	*NCSKEW*	*DUVOL*	*COUNT*
HIGH_EXP	0.269**	0.184*	-0.018	0.229*	0.164*	-0.028
	(2.207)	(1.772)	(-0.147)	(1.876)	(1.747)	(-0.225)
TRUMP	0.059	0.034	0.082	0.063	0.045	0.102*
	(1.002)	(0.684)	(1.385)	(1.092)	(1.005)	(1.719)
HIGH_EXP × *TRUMP*	-0.310*	-0.241*	0.028	-0.275*	-0.215*	0.008
	(-1.938)	(-1.765)	(0.177)	(-1.751)	(-1.827)	(0.049)
SIZE	-0.059***	-0.058***	0.001	-0.081***	-0.078***	0.004
	(-3.236)	(-3.712)	(0.043)	(-4.318)	(-4.637)	(0.220)
LEVERAGE	0.007**	0.006*	0.003	0.006	0.004	0.002
	(2.048)	(1.849)	(0.725)	(1.590)	(1.137)	(0.487)
MARKET_TO_BOOK	-0.005***	-0.004***	-0.001	-0.004***	-0.003***	0
	(-3.517)	(-2.878)	(-0.435)	(-2.880)	(-2.915)	(-0.196)
ROA	0.035*	0.030*	-0.003	0.023	0.015	-0.01
	(1.774)	(1.760)	(-0.174)	(1.166)	(1.274)	(-0.515)
R&D	0.613	-0.626	-0.49	0.91	-0.32	0.187
	(0.967)	(-1.155)	(-0.771)	(1.317)	(-0.626)	(0.265)
ACCM	-0.375	-0.114	0.242	-0.417	-0.16	0.438
	(-1.251)	(-0.445)	(0.808)	(-1.367)	(-0.545)	(1.403)
RET	-0.157***	-0.227***	0.074**	-0.169***	-0.230***	0.065*
	(-4.557)	(-7.746)	(2.158)	(-4.966)	(-2.640)	(1.883)
VOL	-4.232***	-6.362***	2.380**	-4.849***	-6.715***	2.092**
	(-4.237)	(-7.462)	(2.379)	(-4.884)	(-2.911)	(2.059)
DTURN	0.194	0.117	-0.096	0.300**	0.209	-0.046
	(1.316)	(0.931)	(-0.653)	(2.056)	(0.993)	(-0.308)
SKEWNESS	-1.186***	-0.680***	-0.676***	-1.200***	-0.688***	-0.661***
	(-33.862)	(-22.741)	(-19.251)	(-34.601)	(-14.848)	(-18.613)
KURTOSIS	0.057***	0.041***	0.025***	0.060***	0.043***	0.025***
	(6.466)	(5.375)	(2.773)	(6.912)	(3.815)	(2.824)
LN_CEO_AGE	-0.21	-0.299	-0.071	-0.162	-0.241	0.037
	(-0.856)	(-1.430)	(-0.289)	(-0.663)	(-1.070)	(0.147)
LN_CEO_SALARY	0.017	0.006	0.028*	0.021	0.008	0.027*
	(1.073)	(0.426)	(1.720)	(1.286)	(0.607)	(1.668)
LN_CEO_TENURE	-0.016	0.011	-0.025	-0.006	0.014	-0.026
	(-0.339)	(0.278)	(-0.510)	(-0.129)	(0.332)	(-0.522)

Continued on next page

Table 3.13 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)
	NCSKEW	*DUVOL*	*COUNT*	*NCSKEW*	*DUVOL*	*COUNT*
CEO_OVERCONFIDENCE	-0.096*	-0.031	-0.05	-0.068	-0.001	-0.049
	(-1.655)	(-0.632)	(-0.857)	(-1.181)	(-0.023)	(-0.827)
CEO_POWER	0.052	0.035	-0.022	0.069	0.044	-0.01
	(0.973)	(0.757)	(-0.402)	(1.309)	(0.947)	(-0.179)
CHANGE	0.001	0.023	0.011	0.019	0.024	0.026
	(0.006)	(0.239)	(0.098)	(0.170)	(0.250)	(0.227)
RETIRE	-0.033	-0.026	-0.071	-0.035	-0.02	-0.074
	(-0.321)	(-0.295)	(-0.694)	(-0.348)	(-0.224)	(-0.719)
CHAIR	0.028	0.051	-0.117	0.02	0.037	-0.108
	(0.312)	(0.675)	(-1.322)	(0.231)	(0.514)	(-1.217)
RELIGION	0.04	0.011	0.079	0.045	0.039	0.088
	(0.210)	(0.065)	(0.412)	(0.241)	(0.238)	(0.459)
DISASTER	-0.065*	-0.034	-0.054	-0.055	-0.032	-0.054
	(-1.677)	(-1.020)	(-1.378)	(-1.422)	(-0.876)	(-1.366)
POI	-0.038	0.002	-0.033	-0.063	-0.013	-0.027
	(-0.924)	(0.058)	(-0.804)	(-1.539)	(-0.340)	(-0.645)
Industry Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	432	432	432	432	432	432
R-squared	0.799	0.689	0.530	0.814	0.712	0.546
Firms	221	221	221	221	221	221

t-statistics in parentheses. Standard errors are clustered at the firm level.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3.14: Parallel Trend Tests: Pre-Event Trends in Crash Risk

This table reports the results of the tests of the parallel trend assumption. For each crash risk measure *COUNT*, *NCSKEW*, and *DUVOL*, the difference of the average changes in crash risk is computed between the treated and the matched control group during 2013–2014 and during 2014–2015. Section 3.3.2 provides a detailed description of the crash risk measures. P-values are reported in parentheses. Higher p-values indicate stronger support for the parallel trend assumption.

		Average change during 2013–2014	Difference between treated and control firms	Average change during 2014–2015	Difference between treated and control firms
COUNT	Treated	0.304	0.316 (0.931)	-0.450	-0.438 (0.655)
	Control	-0.012		-0.012	
NCSKEW	Treated	0.472	0.549 (0.225)	-0.572	0.035 (0.796)
	Control	-0.077		0.059	
DUVOL	Treated	0.323	0.272 (0.689)	-0.347	0.016 (0.866)
	Control	0.051		0.031	

Table 3.15: Placebo Tests: Causal Effect of Exposure to Climate Regulation on Stock Price Crash Risk Based on Pseudo-Samples

This table reports the distribution of the estimates of β_3 constructed by estimating the DiD model as specified in Eq. (3.12) using observations from 10,000 pseudo-samples where firms are randomly assigned the treated and the control status. The table reports the distribution of the estimates of β_3 which is used to construct the histograms in Figures 3.1(a)–3.1(c).

Estimate of β_3	(1)	(2)	(3)
	COUNT	*NCSKEW*	*DUVOL*
Min	-0.092	-0.166	-0.114
1%	-0.057	-0.091	-0.067
5%	-0.040	-0.065	-0.047
25%	-0.016	-0.027	-0.019
Median	0.000	0.000	0.000
Mean	0.000	0.000	0.000
75%	0.016	0.027	0.020
95%	0.039	0.065	0.047
99%	0.056	0.093	0.067
Max	0.089	0.153	0.105

Table 3.16: Placebo Test: The Causal Effect of Exposure to Climate Regulation on the Risk of Stock Price Crash during Obama's Second Term

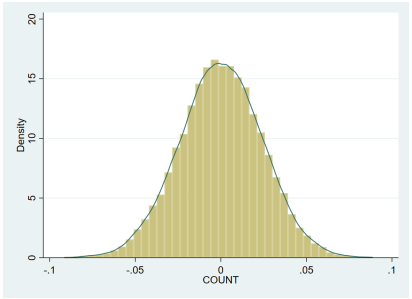
This table reports the estimation results of the difference-in-differences model as specified in Eq. (3.12) using observations from the following sample periods: 2012–2013 (Panel A), 2013–2014 (Panel B), and 2014–2015 (Panel C). The measures of crash risk are *COUNT*, *NCSKEW*, and *DUVOL*. See Section 3.3.2 for a detailed description of the crash risk measures. *HIGH_EXP* is a dummy variable that takes values of zero for the firms that belong to the control group, and one for the firms that belong to the treated group. *TREAT* is a dummy variable which equals zero for observations of firms in the control group and equals one for observations of firms in the treatment group. Columns (1)–(3) report the estimation results for models without industry fixed effects. Columns (4)–(6) report the estimation results for models with industry fixed effects. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	COUNT	*NCSKEW*	*DUVOL*	*COUNT*	*NCSKEW*	*DUVOL*
Panel A: 2012-2013						
HIGH_EXP	0.020	0.045	0.056	0.010	−0.033	−0.009
	(0.315)	(0.514)	(0.950)	(0.152)	(−0.353)	(−0.149)
TREAT	−0.100	−0.208**	−0.207***	−0.100	−0.208**	−0.207***
	(−1.515)	(−2.041)	(−2.989)	(−1.508)	(−2.032)	(−2.975)
HIGH_EXP × *TREAT*	0.003	0.103	0.091	0.003	0.103	0.091
	(0.036)	(0.764)	(0.975)	(0.036)	(0.760)	(0.971)
Industry Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	1,094	1,094	1,094	1,094	1,094	1,094
R-squared	0.004	0.007	0.015	0.02	0.031	0.04
Firms	547	547	547	547	547	547
Panel B: 2013-2014						
HIGH_EXP	0.037	0.144	0.158**	0.019	0.058	0.088
	(0.501)	(1.364)	(2.139)	(0.237)	(0.514)	(1.131)
TREAT	−0.068	−0.124	−0.017	−0.068	−0.124	−0.017
	(−0.896)	(−1.121)	(−0.219)	(−0.892)	(−1.115)	(−0.218)
HIGH_EXP × *TREAT*	−0.046	−0.113	−0.107	−0.046	−0.113	−0.107
	(−0.454)	(−0.747)	(−1.005)	(−0.452)	(−0.743)	(−1.000)
Industry Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	962	962	962	962	962	962
R-squared	0.004	0.007	0.007	0.015	0.038	0.046
Firms	481	481	481	481	481	481
Panel C: 2014-2015						
HIGH_EXP	−0.025	−0.018	0.010	−0.022	−0.073	−0.052
	(−0.354)	(−0.178)	(0.145)	(−0.305)	(−0.674)	(−0.709)
TREAT	0.025	−0.080	−0.100	0.025	−0.080	−0.100
	(0.347)	(−0.735)	(−1.318)	(0.345)	(−0.731)	(−1.312)
HIGH_EXP × *TREAT*	0.014	0.027	0.059	0.014	0.027	0.059
	(0.149)	(0.175)	(0.552)	(0.148)	(0.174)	(0.549)
Industry Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	1,002	1,002	1,002	1,002	1,002	1,002
R-squared	0.001	0.001	0.003	0.014	0.013	0.025
Firms	501	501	501	501	501	501

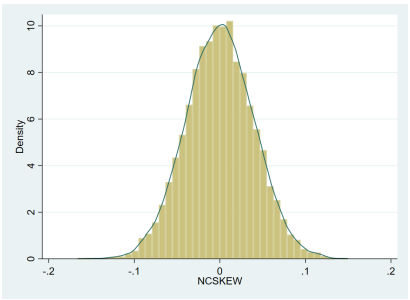
3.10 Figures

Figure 3.1: Placebo Test: Density Estimates of the Impact of Exposure to Climate Regulation on Crash Risk

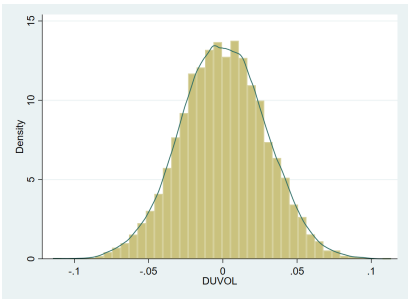
The figures below show the density of the estimates of the impact of exposure to climate regulation on crash risk when the estimation is conducted using 10,000 artificial samples where firms are randomly classified as treated and control. Figures 3.1(a), 3.1(b), and 3.1(c) show the density when the measure of crash risk is *COUNT*, *NCSKEW*, and *DUVOL*, respectively.



(a) *COUNT*



(b) *NCSKEW*



(c) *DUVOL*

Chapter 4

Study two – CEO Versus CFO: Debt-based Compensation and Intangible Assets

4.1 Introduction

Intangible assets have grown rapidly in recent decades and contributed significantly to corporate growth. Numerous examples, such as the patents of Apple and Pfizer, the brand value of Coca-Cola, and Walmart's pioneering supply chain system, demonstrate that intangible assets can enhance organizational creativity and value, thereby improving firm productivity and firm value. To gain stronger core competitiveness, firms often target pioneering innovation and creative products or services, which leads them to outspend industry peers in technology-based intangibles (R&D). According to Corrado et al. (2009), only 8% of economic growth is attributed to traditional tangible assets nowadays. Nakamura (2010) further documents that intangible assets are essential to the U.S. economy: their share rose from 4% of GDP in 1977 to about 10% in 2010, and their total value increased from nearly zero in 1983 to over 80 billion dollars in 2017.

Although intangible assets have been linked to economic growth, many studies highlight their association with information asymmetry. A major concern is that current regulations do not mandate the disclosure of sufficient financial information. The lack of sufficient disclosure requirements reduces managers' incentives to provide value-relevant information in financial reports. Moreover, the uncertain valuation, ambiguous property rights, low market activity, and unreliable estimation methods of intangible assets further contribute to substantial informational complexity. Gu and Wang (2005) shows that such complexity increases analyst forecast errors and reduces the quality of intangible-related information. This complexity also gives managers greater scope to manipulate business behavior and disclosure, meaning that intangible-intensive firms are often subject to agency problems.

A number of studies highlight the information asymmetry associated with intangible assets. For instance, Barth et al. (2001b) finds that higher intangible assets are associated with greater analyst coverage but also higher information costs. Tasker (1998) proposes that the coordination between intangible-intensive firms and analysts through conferences is weaker compared to firms with fewer intangibles. Similarly, Gu and Wang (2005) shows that analyst forecast errors are higher for intangible-intensive firms.

The sources of this information asymmetry are diverse. First, the absence of a physical form makes intangible assets difficult to measure and undermines the reliability of fair valuation for trading purposes. Second, the absence of observable market prices for many intangibles complicates reliable valuation. This raises concerns about the credibility of financial statements that incorporate such valuations (Grüber, 2014; Reilly and Schweihs, 2016). Third, capturing the value of intangibles through M&A activities is one possible approach, but it lacks generality and depends heavily on the financial decisions of managers, auditors, and analysts. Together, these factors amplify the opacity of intangible-intensive firms.

The reliability of value-relevant information on intangible assets disclosed in financial reports has been widely criticized in prior research (Barth et al., 2001a; Dahmash et al., 2009; Kallapur and Kwan, 2004; Boone and Raman, 2001). In practice, empirical studies have often relied on R&D expenditures or patent-based measures as proxies for intangible assets. However, these indicators capture only a narrow subset of the broader spectrum of intangibles, thereby reinforcing concerns about the limited reliability and completeness of reported information. Such disclosure and measurement deficiencies not only constrain the ability of investors and researchers to accurately assess firm value, but also create substantial room for managerial discretion, which can have far-reaching implications for corporate

risk-taking and financial stability.

Because intangible assets are not directly observable on the balance sheet, managers often have strong incentives to overstate their value in order to influence market perceptions and investor beliefs. One common channel is through overpriced acquisitions, where managers can use inflated intangible valuations as justification for aggressive expansion strategies. Such acquisitions can create an appearance of growth, allowing managers to enhance their personal wealth through compensation tied to firm size or stock price performance. At the same time, they may temporarily improve reported corporate performance by signaling confidence to the market. However, these short-term benefits mask substantial long-term risks. Inflated valuations distort resource allocation, reduce the efficiency of capital investment, and ultimately depress firm performance once the overpayment becomes evident. In more severe cases, they may exacerbate financial fragility and increase bankruptcy risk (Li et al., 2011; Gu and Lev, 2011). Consistent with this reasoning, Wu and Lai (2020) documents a positive association between intangible intensity and stock price crash risk, underscoring the role of managerial discretion in shaping financial market outcomes and highlighting the systemic implications of inflated intangible reporting. This motivates the current chapter to examine the link between the level of intangible assets and the risk-taking incentives of top executives.

This chapter examines how the level of intangible assets is influenced by managers' debt-based compensation, applying the direct measurement of intangible assets from Clausen and Hirth (2016) rather than the commonly used proxy of R&D expenditures in prior research. Debt-based compensation is widely considered an incentive for managers to adopt more conservative policies and to reduce the degree of information asymmetry in financial disclosure. Accordingly, managerial incentives constitute a central deter-

minant of firm development and financial policy for firm development and financial decision-making.

According to Jensen and Murphy (1990), the use of equity-based compensation for CEOs has increased as a means to mitigate conflicts of interest between shareholders and managers. By tying executives' wealth to the firm's stock price, equity-based compensation aligns managerial benefits with those of shareholders and helps reduce agency problems, that is, situations in which CEOs' decisions could harm shareholder value. However, while this approach addresses traditional agency concerns, it also creates new challenges: the direct link between CEO wealth and stock prices may motivate executives to prioritize short-term gains.

In contrast, internal debt holdings (such as deferred compensation or pensions) may encourage managers to mitigate firm risk. The agency problem between debt holders and managers arises because managers have incentives to undertake risky projects at the expense of creditors, whose payoffs are fixed and independent of the firm's future value. Debt-based compensation mitigates this conflict by linking managers' benefits to those of external creditors. This alignment discourages excessive risk-taking, since such behavior increases the probability of bankruptcy and thereby endangers the managers' personal wealth. From this perspective, CEOs with substantial inside debt holdings are more likely to protect firm value by pursuing less risky investments and policies (Cassell et al., 2012).

Similarly, as top executives, CFOs may also be influenced by equity-based compensation, which can affect earnings management and give rise to agency problems comparable to those observed with CEOs. These concerns have drawn increasing attention from both academia and policymakers. It has been argued that the disclosure of CFO compensation is vital for reg-

ulation and constitutes "a major benefit" for the SEC. While the majority of research focuses on CEO compensation and its influence on corporate finance and stock market performance, several studies have also examined the implications of CFO compensation and incentives. The dynamics surrounding CFOs can be more complex than those of CEOs, since CEOs typically hold the authority to replace CFOs who do not act in accordance with their preferences, thereby inducing CFOs to conform to CEO expectations (Mian, 2001; Fee and Hadlock, 2004). This factor may partly explain why most research emphasizes CEO-based compensation.

Nonetheless, examining the role of CFO incentives remains crucial. Empirical studies comparing the equity-based compensation and incentives of CEOs and CFOs suggest that CFOs can exert a notable influence on earnings management and contribute to stock price crash risk (Jiang et al., 2010). In addition, (Baker et al., 2019) highlights that the relative power between CEOs and CFOs affects both the type and magnitude of earnings management, while (Hsieh et al., 2018) shows that different combinations of CEO and CFO confidence levels lead to varying degrees of tax avoidance. Collectively, these findings indicate that both CEOs and CFOs shape firms' financial decision-making.

Building on this evidence, the present chapter examines the inside-debt incentives of both CEOs and CFOs to assess their impact on firms' financial policies. Specifically, the analysis investigates the relationship between debt-based incentives of top executives and firm-level intangible asset intensity, while also determining which executive exerts a greater influence in this context. Using data from all firms with available information on both CEOs and CFOs for the period 2006 to 2022, a strong negative relationship is observed between managers' debt-based compensation and intangible assets. This relationship holds after controlling for firm characteristics and

managerial compensation variables.

The research presented in this chapter differs from Lu-Andrews and Yu-Thompson (2015), which employs direct measurement of tangible assets and examines the effects of capital allocation and investment decisions. Tangible assets generally possess a physical form, which makes it easier to quantify investment amounts. Intangible expenses, such as R&D expenditures, share a similarity with tangible assets in that they also represent investment behavior and have been shown to positively relate to market capitalization and investment activity. However, relying solely on R&D as a proxy captures only new investment and overlooks the value generated by previously accumulated intangible assets, therefore being subject to extensive criticism.

To address this limitation, Clausen and Hirth (2016) proposes intangible intensity as an alternative measurement. Unlike traditional proxies, intangible intensity captures the productivity of existing intangible assets rather than merely new investments. This measure reflects not only investment behavior but also the value created by accumulated intangibles. The indirect nature of this approach highlights the inherent difficulty of valuing intangible assets, which contributes to the information complexity of intangible-intensive firms and thereby increases the risk of information asymmetry (Barth et al., 2001b).

Furthermore, Clausen and Hirth (2016) demonstrates that intangible intensity consistently explains a significant portion of acquisition prices. Prior studies (Li et al., 2011; Gu and Lev, 2011; Detzen and Zülch, 2012) indicate that managers often have incentives to inflate certain intangible assets, such as goodwill, through overpriced acquisitions. This behavior generates additional uncertainty and increases information asymmetry regarding future

firm value. In contrast, a higher share of tangible assets has not been found to be positively associated with either market capitalization or acquisition prices (Clausen and Hirth, 2016).

Following Edmans and Liu (2011) and Wei and Yermack (2011), two sets of measures are employed to capture managers' debt incentives. The first measure is the CEO's inside debt relative to equity holdings, scaled by the company's debt-equity ratio. The second measure quantifies the change in the CEO's debt-equity ratio resulting from a one-unit increase in firm value. When scaled by a comparable metric, this ratio provides a standardized measure. It indicates the effect of a uniform increase in firm value on the debt-equity claims within the firm.

A key concern in this analysis is the potential endogeneity between managers' inside debt holdings and intangible intensity. Firms with higher R&D expenditures often exhibit lower levels of information disclosure. This can lead to higher inside gains and may incentivize managers to hold less debt-based compensation (Aboody and Lev, 2000).

To address this issue, two alternative methods are employed. The first method is an instrumental variable (IV) approach. It uses the industry average of managers' inside debt holdings, excluding the firm itself, as well as individual tax rates, long-term capital gains, and the maximum mortgage subsidy rate as instruments. These instruments are correlated with managers' inside debt holdings but are unlikely to be directly related to intangible assets. The second method relies on first-differencing. Specifically, it calculates the change in each variable between the current period and the previous period. Additionally, quantile regression at the median is applied to mitigate the influence of outliers. Using these approaches, the influence of CEO inside debt holdings is found to be stronger than that of CFOs.

The results remain robust across different measures of intangible intensity, including rankings based on year-specific distributions rather than the full sample. Further robustness tests are conducted using bid-ask spreads as an alternative measure of information asymmetry, confirming the consistency of the main findings.

This chapter makes several contributions. First, it enhances the understanding of the relative importance of CEOs and CFOs in financial decision-making. Although debates persist regarding which executive plays a more critical role, the evidence indicates that CEOs exert a dominant influence compared to CFOs. Second, the chapter highlights the significance of debt-based compensation and its relationship with intangible asset intensity. While equity-based remuneration has been recognized as an important mechanism for mitigating agency conflicts, the analysis extends the literature on agency issues between managers and debt holders. Third, the chapter contributes to the understanding of intangible assets. Specifically, it demonstrates that, through their connection with debt-based compensation, intangible assets not only serve as a source of value creation and productivity but also introduce information asymmetry.

The rest of the chapter is organized as follows: Section 4.2 describes related literature and forms the hypotheses of the chapter. Section 4.3 describes the data source, the forming of variables and the methods to be applied. Section 4.4 reports the empirical results used to test the hypothesis and all robustness tests. Section 4.5 is the conclusion of this chapter.

4.2 Related Literature and Hypothesis

4.2.1 Intangible Assets and Information Asymmetry

Intangible assets are widely recognized as critical for fostering corporate innovation and enhancing firm value. Among these assets, R&D-related items and patent holdings serve a crucial function in driving innovation and are expected to generate long-term returns. Despite their importance, intangible assets are frequently characterized by high valuation uncertainty in prior research (Gu and Wang, 2005). Such valuation uncertainty exacerbates information complexity and increases the likelihood that managers may conceal relevant information. Barth et al. (2001b) reports that firms with higher intangible asset holdings face greater costs associated with analyst coverage and effort. In addition, Tasker (1998) suggests that coordination between analysts and intangible-intensive firms is less transparent. This is particularly evident in interactions conducted through conferences, compared with firms exhibiting lower intangible intensity. Similarly, Gu and Wang (2005) finds that intangible-intensive firms experience higher analyst errors, indicating an elevated level of information asymmetry in organizations with abundant intangible assets.

Intangible assets, due to their high valuation uncertainty and associated information complexity, often generate significant information asymmetry within firms. This asymmetry not only complicates external evaluation but also amplifies financial frictions within the firm, increasing agency problems and bankruptcy risk. For example, Alves and Martins (2014) shows that intangible assets affect key financial factors such as non-debt tax shields, bankruptcy costs, agency costs, and transaction costs. Consistent with this view, Myers (1977) demonstrates that firms with high intangible intensity face greater bankruptcy costs.

Information asymmetry theory predicts that the greater the extent of informational frictions within a firm, the more likely managers are to exploit these asymmetries when accessing capital markets (Ross, 1977; Bhattacharya, 1979). A key implication of this theory is that firms characterized by high levels of information asymmetry are more inclined to rely on debt financing, since creditors face greater difficulty in accurately assessing firm value and monitoring managerial actions (Myers, 1977). Consistent with this theoretical prediction, Lim et al. (2020) provides empirical evidence of a positive relationship between intangible asset intensity and financial leverage. In other words, firms with greater reliance on intangible assets tend to adopt more aggressive financial policies, reflecting the strategic use of debt under conditions of heightened informational opacity. These findings further suggest that managerial incentives are closely intertwined with the accumulation and reporting of intangible assets, as agency problems are likely to shape financial decision-making in ways that amplify both leverage and the risks associated with intangible asset holdings.

Moreover, empirically measuring intangible assets remains a challenging task. As Nichita et al. (2019) notes, persistent disagreements exist regarding their definition and classification, while current accounting and reporting systems are ill-suited to capture the value of firms whose worth is primarily driven by intangibles and innovation (Grüber, 2014; Reilly and Schweihs, 2016). Traditional accounting standards that rely on historical costs are particularly unreliable for valuing such firms, since intangible assets, unlike tangible property, plant, and equipment, lack physical form and are difficult to assess in terms of both value and profitability potential. Gu and Wang (2005) emphasizes that these challenges stem from the inherent complexity of information related to intangibles. Unclear property rights, the high risks surrounding innovative assets such as R&D, and the diffuse

benefits of assets like advertising (Dahmash et al., 2009) further exacerbate this complexity, making accurate valuation even more difficult.

Also, as mentioned before, the inconsistency in the classification, definition, and accounting standards of intangible assets complicates their valuation, creating opportunities for earnings manipulation, particularly in financially distressed firms. Several studies support this view, particularly from the perspective of relevance and readability in financial reports (Barth et al., 2001a). For example, Dahmash et al. (2009) examines the value relevance and readability of intangible assets, with a particular focus on reported goodwill, during the period from 1994 to 2003, when accounting regulations for flexible items were relatively restrictive. They find that reported information is largely value relevant but not fully reliable: firms tend to report goodwill conservatively, whereas other intangible assets are reported more aggressively, and the underlying mechanisms behind this pattern remain unclear. Similarly, Kallapur and Kwan (2004) investigates the value relevance and reliability of brand assets in UK firms. By evaluating brand assets in the context of acquisitions rather than in isolation, they show that although brand assets are value relevant, they still lack full reliability despite managerial incentives to overestimate their value. More broadly, these studies suggest that the more reliable the information, the greater its value relevance. In addition, Boone and Raman (2001) shows that the magnitude of off-balance-sheet R&D reduces market liquidity. While their study does not identify a specific mechanism, the intensity of off-balance-sheet R&D is widely regarded as a potential factor contributing to adverse selection in the market.

Extending this perspective, recent researches highlight the potential negative consequences of intangible assets for bankruptcy and financial distress. Because they cannot be easily liquidated or pledged, intangibles

often amplify financing constraints and information asymmetry. Goodwill accounting, with impairment-only testing, creates additional volatility by generating sudden downward shocks that heighten creditors' concerns (Amoros et al., 2023). Empirical work further shows that while advertising and R&D may enhance long-term earnings potential, they can complicate liquidation and creditor negotiations, thus undermining recovery prospects in bankruptcy. Jones (2011) finds that failing firms capitalize intangible assets more aggressively than non-failing firms, that such capitalization is strongly associated with earnings management, and that voluntary capitalization of intangibles has significant predictive power for firm failure. Horsch et al. (2021) shows that patent invalidation leads to an exogenous reduction in firms' intangible capital, which in turn reduces leverage by approximately 14%, with the effect being stronger for smaller or less creditworthy firms.

This evidence suggests that firms that rely heavily on intangible assets for financing are more exposed to shocks affecting leverage and short-term debt management, thereby facing higher bankruptcy risk. Overall, fluctuations in intangible assets not only affect financing capacity but also influence financial stability through changes in capital structure. Jindal and McAlister (2015) finds that although these assets improve bankruptcy prediction models, their protective role holds only under certain firm conditions, and Jindal (2020) stresses that they operate as a double-edged sword: expected cash flows may rise, but distress costs and survival risks often increase when markets turn adverse. Overall, intangible intensity tends to heighten operational and financial fragility, making firms more exposed to bankruptcy and credit risk when external conditions deteriorate.

Building on concerns about the reliability of reported intangible assets, another line of research has focused on the limitations of commonly used

empirical measures. Previous studies have shown that accounting information on intangible assets is generally less accurate than that for tangible assets (Dahmash et al., 2009). According to Wu and Lai (2020), many measures of intangible assets are subject to measurement error.

One commonly used proxy is R&D expenses, which has been criticized in multiple studies. First, R&D expenses primarily reflect current-period investments in R&D activities. They do not capture the cumulative value of previously acquired intangible assets, such as goodwill. Additionally, R&D provides information only on newly acquired intangibles for the current period (Clausen and Hirth, 2016). Moreover, R&D expenses are susceptible to managerial opportunism. Managers may select particular valuation methods or make impairment decisions for intangible assets to serve their own interests, thereby potentially manipulating financial reports (Johnson and Revsine, 1988).

Several studies document these managerial influences. For instance, Brown and Petersen (2011) highlights that firms facing financing constraints often smooth R&D expenses to manage cash holdings, while Lundstrum (2002) examines how managerial myopia distorts R&D expenditures. Furthermore, Adhikari and Agrawal (2016) finds that firms headquartered in regions with a higher "taste for gambling" tend to adopt more adventurous R&D strategies. Finally, even within the available research datasets, however, the recurring incompleteness and irregularity of R&D data pose significant challenges for empirical analysis, further complicating efforts to study the effects of managerial behavior on R&D investment.

Given the challenges and limitations associated with traditional measures of intangible assets, it is necessary to adopt more robust and broadly applicable metrics for empirical analysis. The information complexity of intangible

assets underscores the importance of studying them. It facilitates a more empirical understanding of information asymmetry, while simultaneously posing challenges for accurate measurement.

In this chapter, the intangible intensity measurement proposed by Clausen and Hirth (2016) and Wu and Lai (2020) is employed. This empirical measure evaluates the relative ranking of returns on tangible assets across the entire sample. It has been shown to serve as an additional factor in explaining firm value. Moreover, it effectively captures the growing significance of intangible assets. This approach offers the advantage of producing meaningful results across a wide range of firms and accounting practices, making it broadly applicable. Furthermore, the measure relies exclusively on publicly available data rather than stock market data. This feature helps avoid distortions arising from market bubbles, investor sentiment, and similar factors.

4.2.2 Debt-based Compensation of CEO and CFO

Theoretically, inside debt compensation is unsecured, unfunded, and payable in the future, placing CEOs who hold substantial amounts of debt-based compensation in a position analogous to that of external creditors. The payoff from inside debt is asymmetric with respect to firm performance, as it depends on the likelihood of bankruptcy and the firm's liquidation value in the event of bankruptcy (Jensen and Meckling, 1979; Sundaram and Yermack, 2007; Gerakos, 2010; Cassell et al., 2012). These characteristics align managerial incentives with long-term value maximization and encourage risk-averse decision-making.

Inside debt is often regarded as the counterpart to equity-based compensation, with higher levels incentivizing managers to pursue less risky corpo-

rate management and investment strategies. Empirical evidence supports this perspective. For example, Cassell et al. (2012) finds that CEO inside debt holdings are negatively associated with future stock returns and R&D investment, which is typically considered risky, as well as with financial leverage, while being positively related to firm diversification and asset liquidity. Similarly, Choy et al. (2014) documents a positive association between defined benefit pension plan freezes and both increased credit risk and riskier R&D investment strategies. Taken together, these findings suggest that inside debt is likely to exert a conservative influence on managerial decisions regarding intangible assets, implying a negative relationship.

Building on the theoretical and empirical evidence that inside debt encourages conservative managerial behavior, inside debt holdings are specifically designed to reduce default risk and discourage unethical behavior. Theoretically, debt-based compensation mitigates the agency conflict between debt holders and managers (Edmans and Liu, 2011). Noe (2009) and Nachman and Noe (1995) propose a framework in which fixed executive compensation plays a crucial role in reducing agency costs, contrasting with approaches that rely solely on aggressive, performance-sensitive pay. Within this framework, CEOs act as agents employed by shareholders to enhance the value of corporate assets through diligent management, while simultaneously serving as custodians of these assets with information not readily observable to outsiders. Agency costs arise when executives act both as custodians and authorized users of corporate resources, with the potential to divert resources for personal gain, a practice commonly referred to as "tunneling" and largely depending on information obtained after their appointment. Inside debt compensation mitigates these agency costs by aligning executives' incentives with the long-term interests of creditors and reducing the likelihood of opportunistic behavior.

Based on this framework, the optimal proportion of debt-based compensation varies non-monotonically with firm performance, initially increasing and subsequently decreasing. Edmans and Liu (2011) compares inside debt holdings with fixed compensation, such as salaries and bonuses. Contrary to prior research suggesting that salaries and bonuses could substitute for debt-based compensation, they find that inside debt provides superior alignment of managerial incentives. Fixed compensation instruments, such as pensions, are sensitive only to the incidence of bankruptcy but not to the firm's liquidation value in the event of bankruptcy. Inside debt, in contrast, provides a positive payoff during bankruptcy that is proportional to the firm's liquidation value, thereby aligning managerial incentives with those of outside creditors. Furthermore, the binary nature of bonuses can, in certain contexts, encourage risk-taking behavior. Managers may be incentivized to trade off the firm's liquidation value in pursuit of avoiding bankruptcy, potentially leading to excessive risk exposure. These features highlight the superiority of inside debt in aligning managerial incentives with long-term firm value and mitigating opportunistic or excessively risky behavior.

These theoretical frameworks have prompted empirical studies investigating the influence of inside debt holdings of top executives on management and financial decisions in corporate finance. Overall, these studies indicate that inside debt induces more conservative managerial behavior. For instance, Sundaram and Yermack (2007) documents a negative association between CEO inside debt holdings and default risk. CEOs with higher levels of inside debt are more likely to avoid risky projects, constrain payoffs to equity holders, reduce leverage in the capital structure, and extend the average maturity of outstanding debt. Similarly, Chi et al. (2017) reports that CEO inside debt is associated with reduced tax sheltering behavior.

Specifically, they identify a significant negative relationship between inside debt holdings and the tax shelter score developed by Lisowsky (2010), which encompasses 19 categories of explicitly identified illegal tax avoidance activities. Furthermore, Cassell et al. (2012) finds that CEO inside debt correlates with lower volatility of future stock returns, consistent with more conservative investment and financial policies. In addition, CEO inside debt exhibits a positive relationship with asset liquidation value and diversification, which aligns with the theoretical predictions of Edmans and Liu (2011).

Additionally, CEO inside debt holdings are negatively associated with financial leverage and R&D expenditure. Liu et al. (2014) documents a positive relationship between CEO inside debt and firm cash holdings. Furthermore, as CEO inside debt increases, the marginal value of cash to shareholders decreases, suggesting that debt-based compensation aligns managerial incentives more closely with debt holders than with shareholders. Phan (2014) reports that CEO inside debt causally influences M&A activities, leading to more diversified acquisitions and a reduction in financial leverage. In the short term, this effect is reflected in increased abnormal bond returns and decreased abnormal stock returns. Over the longer term, firms exhibit improved operating performance following M&A activity. He (2015) finds that higher CEO inside debt holdings are associated with enhanced financial reporting quality, evidenced by lower abnormal accruals, higher accrual quality, and a reduced likelihood of earnings misstatements. Additionally, Sheikh (2020) finds that firms with higher CEO debt-based compensation tend to invest more in Corporate Social Responsibility (CSR). Specifically, CEO inside debt positively affects all five CSR dimensions: diversity, community, product, employee relations, and environmental initiatives.

From a corporate finance perspective, the risk-taking characteristics of intangible assets contrast with the incentives created by debt-based compensation for executives. Inside debt holdings align managers' interests with both the probability of bankruptcy and the firm's liquidation value, akin to external debt holders. In contrast, intangible assets, unlike tangible assets, are generally expected to have limited realized value because their worth is closely tied to the firm's going-concern prospects. Lim et al. (2020) demonstrates that intangible assets are positively associated with financial leverage, reflecting their high valuation risk and limited collateralizability. Li et al. (2011) and Gu and Lev (2011) report that intangible assets, such as goodwill, are frequently overpriced in acquisitions. Since intangible assets generate non-interest tax shields, they are often treated as expenses (Alves and Martins, 2014). Collectively, this evidence indicates that inside debt incentivizes managers to adopt more conservative behaviors, reduce unethical or illegal actions, and implement cautious financial reporting policies, including those related to intangible assets.

Moreover, the information-asymmetric nature of intangible assets, partly resulting from their omission from the balance sheet, is likely associated with a higher probability of bankruptcy. Drawing on the existing literature, a negative relationship between inside debt holdings and intangible asset intensity can be hypothesized. Firms with higher levels of intangible assets often adopt more aggressive financial policies, which increases the likelihood of bankruptcy and provides limited liquidation value. This pattern contrasts with the incentives generated by inside debt, which encourage managers to focus on minimizing bankruptcy risk and preserving liquidation value.

Building on the discussion of managerial incentives and debt-based compensation, it is also important to consider the influence of executive power

on financial reporting and decision-making. Several studies investigate how the relative powers of CEOs and CFOs affect top management decisions. In particular, CEOs often have the authority to replace a CFO who does not align with their preferences (Mian, 2001; Fee and Hadlock, 2004). These studies indicate that CEOs with greater power are generally associated with lower earnings quality (Adams et al., 2005; Efendi et al., 2007; Feng et al., 2011). Specifically, Feng et al. (2011) documents that accounting manipulations are more likely when CEO power is high, as CFOs may acquiesce to the CEO's influence. They further find that when the CEO also serves as board chair, board independence is weakened, diminishing oversight of CEO behavior. Consequently, the probability of financial reporting misstatements increases. This evidence underscores the significance of studying CEO incentives in corporate finance research.

From a complementary perspective, recent literature emphasizes the role of CFOs, in addition to CEOs, given their significant influence on financial decisions. Kim et al. (2011a) compares the effects of equity-based compensation on stock price crash risk between CEOs and CFOs. They provide evidence that the sensitivity of CFOs to equity-based compensation is positively associated with the tendency to hoard bad news. Several studies suggest that CFOs play a critical role in corporate finance, sometimes exerting even greater influence than CEOs. For instance, the appointment of a new CFO has been associated with a substantial reduction in discretionary accruals (Geiger and North, 2006). Survey evidence from Graham et al. (2005) indicates that CFOs focus on meeting earnings benchmarks and tend to produce smoother earnings series. This underscores the strong impact of CFOs on financial reporting, which can occasionally lead to default-related concerns. Furthermore, Chava and Purnanandam (2010) documents that CFOs significantly affect debt maturity decisions and con-

tribute to smoother overall financial outcomes.

Given all these related researches, this chapter firstly addresses the hypothesis that both CEO and CFO inside debt holding would reduce intangible assets holding. It gives the hypothesis as follows:

Hypothesis 1 *Both CEO and CFO inside debt holding are negatively related to firm level intangible intensity.*

Secondly, this chapter also would like to try to compare the influence in this link from CEO and CFO, thus giving the hypothesizes as follows:

Hypothesis 2 *The power of CEO and CFO under different conditions:*

(a) CEOs play a more important role in influencing corporate decisions than CFOs.

(b) CFOs play a more important role in influencing corporate decisions than CEOs.

4.3 Data, Variables, and Methodology

The data used to calculate all the variables included in the regressions are obtained from BoardEX, ExecuComp, and Compustat, covering the period from 2006 to 2022. This period is selected because, following the SEC's expansion of executive compensation disclosure requirements on August 29, 2006, reliable information on the present value of pensions and deferred compensation for top management teams became available. CEO and CFO compensation data are specifically sourced from ExecuComp, utilizing the annual CEO and CFO flags. To mitigate sample selection bias, only firms with available CEO and CFO data are included in the regressions, ensuring robust comparisons between the two top executives. Control variables related to CEOs and CFOs, such as age, tenure, time horizon, gender, and

sensitivities to stock price and volatility changes, are collected from ExecuComp and BoardEX. Following Baker et al. (2019), CEO and CFO power is also controlled for, representing the relative internal influence of these top managers. All other firm-level characteristics and dependent variable data are obtained from Compustat, Refinitiv and IBES.

4.3.1 CEO and CFO Inside Debt

As initially discussed by Jensen and Meckling (1976), the use of inside debt to mitigate the debt-based agency problem was subject to debate. Jensen and Meckling (1976) argues that managers' salaries already provide a mechanism to reduce such agency conflicts, thereby diminishing the necessity for inside debt.

Subsequent studies, including Yermack and Chenyang (2009) and Sundaram and Yermack (2007), document that U.S. CEOs hold substantial defined-benefit pensions in addition to equity-based compensation. This evidence contrasts with earlier research advocating for solely equity-based pay. Building on these observations, Yermack and Chenyang (2009) and Edmans and Liu (2011) demonstrate that debt-based compensation ensures top executives hold the same priority as external debt holders in bankruptcy. Simultaneously, it motivates conservative decision-making and risk-averse behavior, rendering inside debt an effective mechanism for addressing debt-related agency costs, in contrast to salaries or bonuses.

According to Edmans and Liu (2011), the degree of incentive alignment depends on the relative weight of debt in an executive's compensation compared with the firm's overall capital structure. A higher ratio, which indicates greater inside debt holdings relative to firm debt, aligns the executive's incentives more closely with those of debt holders, and vice versa.

This framework provides guidance on the optimal level of inside debt and serves as a proxy for measuring executive alignment with debt holders versus shareholders.

Following this theoretical framework, the first measure of CEO and CFO inside debt is the officer-to-firm debt-to-equity ratio, as proposed by Edmans and Liu (2011). It is calculated as the officer's debt-to-equity ratio scaled by the firm's debt-to-equity ratio, as follows:

$$Inside\ Debt = (Officer_IDH / Officer_EH) / (FD/FE) \tag{4.1}$$

Officer inside debt holdings ($OFFICER_IDH$) are calculated as the sum of the present value of accumulated pension benefits and deferred compensation as reported in Execucomp. The value of equity holdings ($OFFICER_EH$) is made up of the value of both stock and stock options. The calculation of the CEO/CFO's stock value involves multiplying the number of shares held, including restricted shares, by the stock price at the end of the firm's fiscal year. The Black and Scholes (1973) option model is applied to value each tranche of options held by the CEO and CFO(e.g., exercisable and unexercisable) and add up the tranche values to get a total value in grand. The CEO's/CFO's debt-to-equity ratio is scaled by the firm's debt-to-equity ratio, measured as the ratio of total debt (FD=current debt plus long-term debt) to the market value of equity (FE). The ratio of total debt ($dlc + dltt$) to the market value of equity ($csho \times prcc_f$) comes from Compustat.

A second variable is adopted to capture changes in debt and equity values, following Wei and Yermack (2011). It measures how much the value of the CEO's inside debt increases relative to inside equity holdings for a one-unit

increase in firm value, compared with a similar measure for changes in the company's external debt relative to external equity. This measure addresses limitations of the relative equity-debt ratio proposed by Edmans and Liu (2011). For instance, in a simple capital structure with plain-vanilla debt and equity, the relative equity-debt ratio may provide little information. Moreover, the duration of inside debt held by managers can differ from that of the company's external debt. The following measurement is designed to account for these differences:

$$\textit{Officer Relative Incentive} = (\Delta \textit{Officer_IDH} / \Delta \textit{Officer_EH}) \,/\, (\Delta FD / \Delta FE) \tag{4.2}$$

This measurement features in capturing the marginal change in inside debt holding of managers relative to the marginal change of equity holding, compared with that relative ratio in the change of firm level debt-equity structure. For the components in Eq. 4.2, $\Delta \textit{Officer_EH}$ can be thought of as the CEO's/CFO's "total delta" and is constructed as follows: $\Delta \textit{Officer_EH} = S + \Sigma_i N_i(\Delta N_i)$, where S is the CEO's/CFO's "total share delta" (equal to the number of shares held times an assumed delta of 1.0) and $\Sigma_i N_i(\Delta N_i)$ is the CEO's/CFO's "total option delta" (N_i is the number of options in tranche i and ΔN_i is the option delta for tranche i). This total delta is used to capture the slope of the change of the value of a managers' equity holding over per unit increase in firm stock price.

The calculation of personal holdings of equity-based compensation is more challenging compared to debt-based compensation. Equity-based compensation for each manager consists of two components: shareholdings and stock option holdings. The value of shareholdings can be obtained by multiplying the number of shares held by the manager by the closing price of

the corresponding security at the end of each period.

The main difficulty lies in calculating the value of stock options. To accurately capture the present value of options held by a single executive, it is necessary to examine the company's proxy statements for up to ten years, due to the ten-year maturities of granted options. Core and Guay (2002) proposes a reliable and practical method that uses precise information for options granted in the current year, and average characteristics for previously granted exercisable and unexercisable options. By summing the values of different tranches calculated separately, the total value of the option portfolio held by a single executive can be obtained.

To calculate both the total option delta and the personal option value held by managers, options are divided into three tranches following the method of Core and Guay (2002): (1) newly granted options in the current year, (2) options granted in previous years but not yet exercisable, and (3) currently exercisable options granted in previous years. The option delta for each tranche is calculated using the Black and Scholes (1973) formula for European call options, with modifications to account for dividend payouts according to Merton (1974), as described below:

$$\text{Option value} = Se^{-dT}N(Z) - Xe^{-rT}N(Z - \sigma\sqrt{T}) \tag{4.3}$$

$$Z = \frac{\ln\left(\frac{S}{X}\right) + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}} \tag{4.4}$$

where,

- S is the current stock price,
- X is the strike price,
- r is the risk-free interest rate,
- σ is the volatility of the stock,
- T is the time to maturity,
- $N(\cdot)$ is the cumulative distribution function of the standard normal distribution.
- d is the natural logarithm of expected dividend yield over the life of the stock option.

Following Core and Guay (2002), the option delta, which is referred to as the sensitivity with respect to a 1% change in stock price is defined as:

$$Delta = \frac{\partial(\text{option value})}{\partial(\text{price})} \times (price/100) \quad = e^{-dT} N(Z) \times (price/100) \tag{4.5}$$

For the parameters applied in the Black and Scholes (1973) formula, the current stock price (S) and risk-free interest rate (r) are obtained from CRSP for all stocks at fiscal year end of each period. The volatility of each stock (σ) is calculated from monthly return over previous 60 months also from CRSP. The natural logarithm of expected dividend yield over the life of the stock option is calculated as the average using data from Compustat for the last three years for each period. To avoid the affect of outliers, both return volatility (σ) and expected dividend yield(d) are winsorised at 1^{st} and 99^{th} percentiles.

The estimation of exercise price of stock options (X) and time-to-maturity (T) differs across the tranches held by managers, following Core and Guay (2002). For options granted in the current period, the exercise price (X) can be directly obtained from ExecuComp disclosures for each manager. The time-to-maturity (T) is calculated as the difference between the expiration date and the grant date. The expiration date is available in ExecuComp, while the grant date is approximated as July 1st of each year in the sample period.

For previously granted options, whether exercisable or unexercisable, no direct data on exercise price or maturity is disclosed in ExecuComp. Thus, the method in Core and Guay (2002) and He (2015) is applied. The idea is to estimate the average realized value of each tranche per option held by the executive. First, the realized value (i.e., stock price minus exercise price) is obtained from ExecuComp. Second, it is divided by the number of exercisable and unexercisable options separately to calculate the average realized value per option. Finally, the average strike price (X) for previously granted options is derived by subtracting this average realized value from the firm's stock price.

The time-to-maturity (T) for previously granted options also follows the "one-year approximation" (OA) method in Core and Guay (2002). For previously granted unexercisable options, T is set as one year less than newly granted options. For previously granted exercisable options, T is set three years less. If no options were granted in a period, T is assigned as 9 years for previously granted unexercisable options and 6 years for previously granted exercisable options. Using these inputs, the present value for each tranche is computed via the Black and Scholes (1973) model. The total option value and delta (sensitivity to a unit change in stock price) is obtained by summing the three tranches: newly granted, previously granted

exercisable, and previously granted unexercisable options.

A similar approach is applied to calculate the firm-level delta, ΔFE, as in $\Delta Officer_EH$ in Eq. 4.2, though not all option tranches are available from Compustat. Inputs such as the fiscal year-end stock price (S), risk-free rate (r), stock return volatility (σ), and natural logarithm of expected dividend yield (d) are obtained as described above. For the exercise price (X), data from the company's 10-K equity compensation footnotes are used to obtain the number of options outstanding and their average exercise price. The remaining life of each option, not available in Compustat, is assumed to be four years following Wei and Yermack (2011).

Finally, the estimation of $\Delta Officer_IDH$ and ΔFD is rather difficult because for most of the firms not financially distressed, the change in debt holding of a company and a single executive tends to be trivial and hard to measure. To simplify, the estimation of proportion of $\Delta Officer_IDH$ over ΔFD is assumed to be the same as the ratio of $Officer_IDH$ over FD. So there is:

$$\frac{\Delta Officer_IDH}{\Delta FD} = \frac{Officer_IDH}{FD} \tag{4.6}$$

And Eq. 4.2 can also be estimated as:

$$Officer_Relative_Incentive = \frac{Officer_IDH}{FD} / \frac{\Delta Officer_EH}{\Delta FE} \tag{4.7}$$

4.3.2 Intangible Intensity

The measurement of intangible assets remains a significant challenge in academia. The valuation of intangible assets is not solely about the information reported in financial statements; more importantly, it concerns capturing the benefits or value generated from the application of such assets. In some cases, the value may even arise from tangible assets. From this perspective, it is crucial to adequately measure the value created by factors such as the efficient use of tangible assets, the contribution of a skilled labor force, and value derived from digital resources, including customer databases or specialized software systems.

Previous proxies used in academic research suffer from substantial limitations. From an empirical perspective, data from Compustat often contains numerous missing values and zeros, and balance sheet information omits many sources of value not reflected in financial reports. Underestimation is another limitation, as noted by Clausen and Hirth (2016) and Corrado et al. (2009). For years without missing values, the ratio of intangible assets to total book value is about 9%, which contrasts with evidence indicating a roughly equal proportion of tangible and intangible asset holdings among firms during the 1990s (Corrado et al., 2009).

Proxies such as the number of patents or trademarks often fail to capture the value generated for corporate profits. R&D expenditures are widely used, but they cover only certain types of intangible assets. Moreover, R&D expenditures reflect the investment amount rather than the actual value created or the portion of value embedded in firm worth. R&D spending can also be easily distorted by earnings management or opportunistic managerial decisions. Adhikari and Agrawal (2016) shows that psychological characteristics, such as a tendency for risk-taking or gambling, can

distort corporate R&D spending, since R&D investments are sometimes lottery-like in nature.

Furthermore, the value or benefits created by innovation activities are rarely captured by traditional financial or non-financial measures, highlighting the limitations of conventional accounting information in valuing intangible assets (Ittner, 2008). Hall (2001a) and Hall (2001b) propose a method to estimate intangible assets as the difference between the total market value of the firm's debt and equity and the book value of tangible assets. However, this approach is sensitive to rapid stock market fluctuations and is affected by external shocks or business cycles, which limits its reliability.

To address the limitations mentioned above, Clausen and Hirth (2016) proposes a measure that captures the aggregated intangibles of a firm, focusing on the relative productivity of intangible assets. Compared with traditional proxies, this measure, denoted as intangible intensity, is able to capture the off-balance sheet value created by intangible assets.

Based on these considerations, the measurement of intangible intensity following Clausen and Hirth (2016) is applied in this study. Moreover, the measurement is theoretically motivated by a stylized Cobb-Douglas production function with two factors, following McGrattan and Prescott (2010) and Kapicka (2012):

$$y = f(I, T) = I^a T^{c-a} \tag{4.8}$$

where y represents the production level, I and T indicate intangible and tangible assets of a firm separately, where labor is not regarded as a production factor. The exponents represent the output elasticity for those two

production factors, where values between 0 and 1 ensure decreasing returns to scale for those factors.

According to the production function, the firm's maximum profit subjects to:

$$max \prod_{I,T}(I,T) = pf(I,\,T) - w_I I - w_T T \tag{4.9}$$

With w_I and w_T denoting the input price, and p represents the output prices. The optimal input level can be obtained, which is $I^* = apy/w_I$ and $T^* = (c-a)py/w_T$.

The ratio of firm's profit and value of tangible assets can be illustrated as:

$$\frac{\prod I^*, T^*}{W_T T^*} = \frac{py - w_I apy/w_I - W_T(c-a)py/w_T}{W_T(c-a)py/W_T} = \frac{1-c}{c-a} \tag{4.10}$$

The Eq. (4.10) demonstrates a positive relation between intangible output elasticity a and this ratio of profit to tangible assets value. Also, the intangible assets' productivity increases with the level of output elasticity a, consequently a higher level of intangible assets input is required. Due to this relationship, the ratio of Eq. (4.10) can be employed to measure intangible intensity, for it captures the increase in profit on the condition that tangible assets is increased, thus means the higher the ratio, the higher the extent of usage of intangible assets.

Following this theory, Clausen and Hirth (2016) proposes an empirical method with easy access to available public data. The method consists of three steps. The first is to calculate the return on tangible assets at firm-year level. The calculation is similar to return on assets, but it only utilizes tangible assets instead of total assets.

$$ROTA = \frac{EBITA}{NetPP\&E} \tag{4.11}$$

This ratio measures how well firms perform according to their profit before interest, tax, depreciation, and amortization scaled by their tangible assets. As explained by previous theory, this ratio describes the extent how efficient a firm uses a highly skilled workforce, computer systems, or well-established brand name, the more intangible assets the firms tend to possess.

The second step is to peel off the factor that is not related to the productivity of intangible assets, including business cycle variation. One of the most influential factors is the variations across industries. The overall intensity of physical assets used in production across different industries would impact individual *ROTA*. Specifically, in the second step, the median and standard deviation of *ROTA* among industries are adjusted from the original *ROTA*.

$$ADJROTA_{i,t} = \frac{ROTA_{i,t} - Median(ROTA_{j,t})}{\sigma(ROTA_{j,t})} \tag{4.12}$$

Where j denotes Fama-French 48 industries, i denotes individual firm and t denotes year.

The last step is to calculate the relative ranking of adjusted *ROTA* over the whole sample, so that the intensity ranges from 0 to 1, avoiding relying on the absolute value of the return, since it is a noisy measure of intangible driven earnings. A higher rank indicates a greater intensity of intangible assets usage, and this relative rank is denoted as *RKROTA*. Furthermore, to ensure the robustness of the results, an alternative method is

also applied for additional validation. Instead of relative ranking adjusted *ROTA* over the whole sample, it is ranked over each year, which is denoted as *RKROTAYR*.The robustness test will be conducted based on this measurement.

4.3.3 Method

To examine the effect between managers' inside debt incentive and intangible intensity, the regression process is applied:

$$\begin{aligned} Intangible\ Intensity_{i,t} = \beta_0 &+ \beta_1 Incentive_{i,t-1} \\ &+ \beta_2 control_{i,t-1} \\ &+ \beta_3 year_t \\ &+ \beta_4 industry_i + \epsilon_{i,t} \end{aligned} \tag{4.13}$$

Where $Intangible\ Intensity_{i,t}$ is the intangible intensity measurement, $Incentive_{i,t-1}$ are the two inside debt measurements for either and both CEO and CFO, $control_{i,t-1}$ are the control variables, and yearly- and industry-fixed effects are included. For each inside debt measurement, there are three columns with the CEO, CFO, and both incentives as independent variables, to study the different effects of distinct top managers and to compare them.

The control variables consist of commonly used factors capturing firm characteristics, officer characteristics, governance, and market environment. Firm-level controls include the natural logarithm of total assets ($SIZE$), market-to-book ratio ($MVBV$) representing firm growth, financial leverage ($LEVERAGE$), return on assets (ROA) indicating current operating performance, Tobin's q (Q), and the ratio of capital expenditure to total assets ($CAPEX$). Two market-wide variables are included: the yearly equal-

weighted market return (*MARKET_RETURN*) and the yearly standard deviation of market returns (*MARKET_STD*), capturing overall market performance and volatility. Number of analysts following the corresponding company is controlled, denoted as *NUM_OF_ANALYSTS*. Creditworthiness is captured by the S&P credit rating category (*S&P_CATEGORY*), coded as one for investment-grade ratings (BBB− or higher) and zero otherwise. The firm's Environmental, Social, and Governance (ESG) performance is also included (*ESG_RATING*). Finally, social capital is controlled for via the *SOCIAL_CAPITAL* variable, constructed as the number of external board members.

Officer-level controls include the natural logarithm of officers' age (*LOG_CEO_AGE/LOG_CFO_AGE*), the natural logarithm of tenure (*LOG_CEO_TENURE/LOG_CFO_TENURE*), the natural logarithm of expected time to retirement(*LOG_CEO_HORIZON/LOG_CFO_HORIZON*), and the logarithm of option delta (*LOG_CEO_DELTA/LOG_CFO_DELTA*) and vega (*LOG_CEO_VEGA/LOG_CFO_VEGA*) for the corresponding officer. CEO and CFO power are represented by dummy variables (*CEO_POWER/CFO_POWER*), equal to one if the officer simultaneously serves as the board chair and the company president. Gender is also controlled for (*CEO_GENDER/CFO_GENDER*), with 1 represents male and 0 otherwise.

Governance- and information-related controls include the total number of directors on the board (*BOARD_SIZE*), the proportion of independent directors (*BOARD_INDEPENDENCE*), the proportion of female directors (*BOARD_DIVERSITY*), and indicator variables for the presence of board committees, including the audit committee (*BOARD_AUDIT_COMMITTEE*) and the compensation committee (*BOARD_COMPENSATION_COMMITTEE*). Here, *BOARD_AUDIT_COMMITTEE* and *BOARD_COMPENSATION_COMMITTEE* equal 1 if the respective committee is

established, and 0 otherwise.

All data for firm-level variables are sourced from Compustat, officer-level variables are obtained from ExecuComp, IBES and BoardEX, and governance, market, and ESG variables are retrieved from Refinitiv Datastream.

Second, to address the endogeneity problem, the instrumental variables (IV) approach is also applied. Several IVs are commonly utilized to approximate inside debt. Following Lin et al. (2018), the first IV is the industry-year average relative inside debt ratio (*IND_AVG_log(CEO_RELA_INCENTIVE) / IND_AVG_log(CFO_RELA_INCENTIVE)*), where industries are classified according to the three-digit SIC code. Prior research, including Lin et al. (2011), suggests that the compensation structure of peer managers within the same industry can influence a CEO's compensation arrangement, as firms often compete for top managers from a limited pool within the industry. However, the compensation structure of managers from other firms is unlikely to directly affect the decision to manage intangible assets. Therefore, the industry-level average manager inside debt level, excluding the specific firm, serves as a valid IV.

The other three IVs are tax-related: the maximum tax rate for wage income (*TAX_RATE_WAGES*), the maximum tax rate for long-term capital gains (*TAX_RATE_LONG*), and the maximum tax rate on mortgage deductions (*TAX_RATE_MOR*), following Lin et al. (2018), Anantharaman et al. (2014), and He (2015). Pension and deferred compensation are important tools for CEOs and CFOs to manage tax plans. During periods of high tax rates, managers tend to defer their compensation to reduce their tax burden. Consequently, managers are likely to choose higher levels of inside debt holding when subject to higher tax rates. These tax-related variables are therefore expected to be positively related to managers' inside debt

measurements, while not directly influencing intangible asset management.

The third method applied is a specification using change-in-variables versions for both dependent and independent variables. All continuous variables in the regression represent the difference between their values in the current period and those in the previous period for the same firm. Following Lin et al. (2018), median regression is applied for the change specification. To ensure robustness, quantile regressions at the 25% and 75% quantiles are also conducted. The change-in-variable specification offers two main advantages. First, the relationship between dependent and independent variables is less likely to be spurious compared to level variables. Second, the estimated effect tends to capture longer-term dynamics. This regression helps control for unobserved or omitted firm-specific factors, thereby addressing endogeneity issues and supporting causal inference over an extended period.

4.3.4 Descriptive Statistics

Table 4.1 reports the summary statistics of both dependent and independent variables. The variable *RKROTA* represents the relative rank of adjusted *ROTA*, with a mean of 0.496 and a standard deviation of 0.284. The mean of the logarithm of one plus the relative debt-equity ratio for CEOs is 0.532 with a standard deviation of 0.797, while the corresponding measure for CFOs is 0.573 with a standard deviation of 0.898. For option-based incentives, the logarithm of CEO and CFO delta has means of 11.89 and 10.41, and standard deviations of 1.683 and 1.652, respectively. The logarithm of CEO and CFO vega averages 5.773 and 4.521, with standard deviations of 3.916 and 3.645. Regarding the relative incentive ratio from Wei and Yermack (2011), the mean of the logarithm of one plus this ratio

is 0.491 for CEOs (SD 0.754) and 0.533 for CFOs (SD 0.859).

SIZE is measured as the logarithm of total assets. The average *SIZE* of the sample firms is 7.911 with a standard deviation of 1.631. For $MVBV$, ROA, $LEVERAGE$, Q, and $CAPEX$, the means are 3.378, 0.0838, 0.773, 1.927, and 0.0441, and the standard deviations are 7.073, 0.0959, 2.485, 1.177, and 0.0455, respectively. The number of analysts following each firm ($NUM_OF_ANALYSTS$) has a mean of 12.68, a standard deviation of 8.229, with the 25th, 50th, and 75th percentiles equal to 6, 11, and 18, respectively, based on 5,839 firm-year observations.

The average age of CEOs is 56.34 with a standard deviation of 6.731, whereas CFOs have an average age of 51.37 with a standard deviation of 6.472. CEOs have an average tenure of 7.077 years (SD 6.789), while CFOs have 3.337 years (SD 2.878). The average CEO horizon is 10.76 (SD 7.114) and the average CFO horizon is 15.64 (SD 3.581). Regarding gender, 97.5% of CEOs and 97.2% of CFOs are male.

For board characteristics, the average proportion of audit committee presence is 0.993 (SD 0.0859), and that of compensation committee presence is 0.988 (SD 0.111). Board diversity has a mean of 16.07 (SD 9.332), board independence 81.34% (SD 11.65), and board size 10.68 members (SD 2.354). The average ESG rating is 44.4 with a standard deviation of 19.94, and 10.3% of firms belong to the high S&P category.

Finally, market-related variables show that the mean market return is 0.105 with a standard deviation of 0.262, and the mean market volatility is 0.049 with a standard deviation of 0.022. The average social capital measure is 0.379 with a standard deviation of 0.714. Overall, these summary statistics are consistent with prior research.

Definitions and data sources for all variables are provided in Table 4.2. In the regression analysis presented in the next section, the natural logarithm of CEO and CFO age is applied to ensure the variables are continuous.

4.4 Empirical Analysis

4.4.1 CEO and CFO Debt-Based Compensation and Intangible Intensity

The regression results of the baseline model from Eq. (4.13) are reported in Table 4.3. Columns (1) and (2) test the effect of *RKROTA* and the natural logarithm of one plus the relative debt-equity ratio for CEOs and CFOs, respectively. Columns (3) and (4) report the corresponding results for the natural logarithm of one plus the relative incentive ratio. The last two columns (5) and (6) compare the respective effects of CEOs and CFOs.

All firms with available data from Compustat and ExecuComp are included in the regression. Yearly- and industry-fixed effects are controlled, with industry defined at the three-digit SIC level, consistent with the approach for constructing instrumental variables in Lin et al. (2018) and Lin et al. (2011). All dependent variables are lagged by one period to mitigate endogeneity concerns arising from simultaneous determination. Continuous independent variables are winsorised at the 1% level to reduce the influence of outliers. The dependent variable, *RKROTA*, represents the relative rank of adjusted return on tangible assets, bounded between 0 and 1, which further limits the effect of outliers.

Standard errors are clustered at the firm level to account for potential correlations across observations of the same firm over time. In columns (1) and (3), only CEO-related variables, including *LOG_CEO_AGE*, *LOG_CEO_-*

TENURE, *LOG_CEO_HORIZON*, *CEO_GENDER*, *LOG_CEO_DELTA*, *LOG_CEO_VEGA*, *CEO_POWER*, and *LOG(1+CEO_RELA_DEBT)*, *LOG(1+CEO_RELA_INCEN)* when applicable, are included to examine the relation with CEO inside debt holding. Columns (2) and (4) include the corresponding CFO variables, including *LOG_CFO_AGE*, *LOG_CFO_TENURE*, *LOG_CFO_HORIZON*, *CFO_GENDER*, *LOG_CFO_DELTA*, *LOG_CFO_VEGA*, *CFO_POWER*, and *LOG(1+CFO_RELA_DEBT)*, *LOG(1+CFO_RELA_INCEN)* when applicable. Columns (5) and (6) include all manager-related variables simultaneously to directly compare the effects of CEOs and CFOs.

According to the theoretical framework, a higher level of inside debt holding indicates a stronger intention of CEOs and CFOs to defer their compensation. This incentive motivates them to mitigate bankruptcy risk, leading to lower managerial risk-taking and reduced likelihood of unethical behavior. Consequently, a smaller value of *RKROTA* is expected. The regression results are consistent with this theoretical prediction.

For the first proxy, log(1 + relative debt-equity ratio), the coefficients in columns (1) and (2) are -0.017^{***} (t = -2.612) for CEOs and -0.013^{**} (t = -2.081) for CFOs, indicating that higher relative inside debt is associated with lower *RKROTA*. For the second proxy, log(1+relative incentive ratio), columns (3) and (4) report -0.017^{**} (t = -2.584) and -0.014^{**} (t = -2.180) for CEOs and CFOs, respectively, both significant at the 5% level. In columns (5) and (6), when CEO and CFO measures are included jointly, the CEO coefficients remain negative (-0.016^{**}, t = -2.055 for debt; -0.014^{*}, t = -1.811 for incentives), while the CFO coefficients are smaller and not statistically significant (debt: -0.003, t = -0.490; incentives: -0.006, t = -0.825). This pattern indicates that CEO measures tend to dominate when both are considered, suggesting a stronger influence of CEOs on firm intangible investment intensity than CFOs.

Regarding control variables, several show consistent and significant patterns. Firm profitability (*ROA*) is positively and strongly associated with *RKROTA* across all models. *CAPEX* is negatively related and highly significant, reflecting that higher capital expenditures are associated with lower intangible investment intensity. Firm size (*SIZE*), market-to-book ratio (*MVBV*), leverage (*LEVERAGE*) and Tobin's q (Q) show mixed or insignificant effects. Market volatility (*MARKET_STD*), however, is consistently negative and statistically significant across specifications, the coefficients range roughly from -0.023 to -0.017 with t-statistics around -2.7 to -2.0, suggesting that higher market volatility is associated with lower *RKROTA*. Market return (*MARKET_RETURN*) remains largely insignificant. Social capital (*SOCIAL_CAPITAL*) and ESG rating (*ESG_RATING*) are not significant in any specification, whereas S&P category shows a positive and significant association, implying that firms in higher S&P categories tend to have higher *RKROTA*, potentially due to better financial conditions to invest in intangibles. The number of analysts following each firm (*NUM_OF_ANALYSTS*) is not significant in any specification.

Board characteristics are generally not significant, including board size (*BOARD_SIZE*), diversity (*BOARD_DIVERSITY*), board independence (*BOARD_INDEPENDENCE*), and the presence of compensation and audit committees (*BOARD_COMPENSATION_COMMITTEE*, *BOARD_AUDIT_COMMITTEE*).

Regarding managerial characteristics, for CEOs, *LOG_CEO_VEGA* shows a negative effect on *RKROTA*, while age, tenure, horizon, gender, and delta are generally insignificant. For CFOs, *LOG_CFO_AGE* is negatively related, *LOG_CFO_HORIZON* is marginally positive and significant when jointly included, and *LOG_CFO_DELTA* is positively significant in separate specifications. Other CFO characteristics, including tenure, gender,

vega, and power, are not consistently significant.

Overall, the findings suggest that both CEO and CFO inside debt and incentive measures are related to *RKROTA* when considered separately, but CEOs exhibit a stronger and more consistent effect when both sets of managerial variables are included jointly. Control variables such as profitability, CAPEX, and S&P category behave as expected, whereas most board characteristics and ESG measures are not influential. These results indicate that CEO decisions are likely more important for shaping firm intangible investment intensity than CFO decisions, highlighting the dominant role of CEOs in strategic investment choices. Further robustness checks, including addressing potential endogeneity via instrumental variables, are warranted to confirm these conclusions.

4.4.2 Results of Instrumental Variable Method

As mentioned earlier, instrumental variables are included in the second-stage two-stage least squares (2SLS) regression to examine the effect while addressing potential endogeneity concerns. Following Lin et al. (2018), Anantharaman et al. (2014), and He (2015), the industry-level average of the natural logarithm of one plus inside debt proxy measurements, along with state-level maximum tax rates for wage income, long-term capital gains, and mortgage deductions, are used as instruments for the baseline dependent variables.

Consistent with the control variables used in the baseline regression, when using a proxy for CEO inside debt holding, only ceo related control variables are included. For CFO inside debt holding, the corresponding CFO variables are included. In the regression comparing the effects of both managers, all manager-related variables are included in the first-stage re-

gression. The first-stage equation is as follows:

$$\begin{aligned} LOG(1 + CEO_INSIDE_DEBT)_{i,t} = \\ \beta_0 + \beta_1 IND_AVE_LOG(1 + CEO_INSIDE_DEBT)_{i,t-1} \\ + \beta_2 TAX_WAGES_{i,t-1} + \beta_3 TAX_LONGS_{i,t-1} \\ + \beta_4 TAX_MOR_{i,t-1} + \beta_5 control_{i,t-1} \\ + \beta_6 year_t + \beta_7 industry_i + \epsilon_{i,t} \end{aligned} \tag{4.14}$$

$$\begin{aligned} LOG(1 + CFO_INSIDE_DEBT)_{i,t} = \\ \beta_0 + \beta_1 IND_AVE_LOG(1 + CFO_INSIDE_DEBT)_{i,t-1} \\ + \beta_2 TAX_WAGES_{i,t-1} + \beta_3 TAX_LONGS_{i,t-1} \\ + \beta_4 TAX_MOR_{i,t-1} + \beta_5 control_{i,t-1} \\ + \beta_6 year_t + \beta_7 industry_i + \epsilon_{i,t} \end{aligned} \tag{4.15}$$

where $IND_AVE_LOG(1 + CEO_INSIDE_DEBT)$ represents the industry level average–excluding firm i– natural logarithm of one plus inside debt measurements for CEO, and $IND_AVE_LOG(1 + CFO_INSIDE_DEBT)$ indicates the same measurement for CFO, which are relative debt ratio from Eq. (4.1), and relative incentive ratio from Eq. (4.2), in which the industry is separated, utilizing three-digit SIC industry codes from Compustat. TAX_WAGES, TAX_LONGS and TAX_MOR demonstrates state maximum tax rate for wage income, the control variables remain the same as those used in the baseline regression, including the state maximum tax rate for long-term capital gains and the state maximum tax rate on mortgage deductions.

In the second-stage, the estimated CEO and CFO inside debt proxy are used as dependent variables following:

$$\begin{aligned} Intangible\ Intensity_{i,t} = \beta_0 + \beta_1 PRE_CEO_Incentive_{i,t-1} \\ + \beta_2 control_{i,t-1} + \beta_3 year_t + \beta_4 industry_i + \epsilon_{i,t} \end{aligned} \tag{4.16}$$

$$\begin{aligned} Intangible\ Intensity_{i,t} = \beta_0 + \beta_1 PRE_CFO_Incentive_{i,t-1} \\ + \beta_2 control_{i,t-1} + \beta_3 year_t + \beta_4 industry_i + \epsilon_{i,t} \end{aligned} \tag{4.17}$$

$$\begin{aligned} Intangible\ Intensity_{i,t} = \beta_0 + \beta_1 PRE_CEO_Incentive_{i,t-1} \\ + \beta_2 PRE_CFO_Incentive_{i,t-1} \\ + \beta_3 control_{i,t-1} \\ + \beta_4 year_t \\ + \beta_5 industry_i \\ + \epsilon_{i,t} \end{aligned} \tag{4.18}$$

where *PRE_CEO_Incentive* and *PRE_CFO_Incentive* are the estimated measurements from first stage, also same sets of control variables and fixed effects are included.

The results of the second-stage regression are reported in Table 4.4 and are consistent with the baseline univariate regressions reported in columns (1)–(4). The Cragg–Donald Wald F statistics and the 10% critical value are reported; in all specifications from columns (1) to (6), the F statistics exceed the critical value, indicating a low likelihood of weak instruments and supporting the validity of the instruments used.

In columns (1) and (2), the coefficients for the instrumented relative debt

ratio (based on Eq. (4.1)) are both significantly negative: -0.064^{***} for CEO inside debt holdings (t = −3.255) and -0.054^{***} for CFO inside debt holdings (t = −2.736), indicating that higher inside debt is robustly associated with lower intangible investment intensity. Similarly, for the instrumented relative incentive ratio in columns (3) and (4) (derived from Eq. (4.2)), the coefficients are -0.057^{**} for CEO (t = −2.512) and -0.059^{**} for CFO (t = −2.559), both statistically significant, confirming that higher managerial incentives are linked to lower *RKROTA*. These results support the first hypothesis that inside debt and incentives of both executives negatively affect intangible asset intensity.

When both instrumented inside debt proxies are included simultaneously in the second-stage regression, the effects attenuate. In column (5), the coefficients are −0.038 (t = −1.094) for CEO and −0.032 (t = −0.980) for CFO, neither statistically significant. Similarly, in column (6), the coefficients are −0.026 (t = −0.751) for CEO and −0.045 (t = −1.279) for CFO, also showing no significant effects. This suggests that when controlling for potential endogeneity and including both measures jointly, the individual effects weaken, although the magnitudes are comparable between CEOs and CFOs.

Regarding control variables, firm profitability (*ROA*) and Tobin's q (Q) are consistently positive and highly significant across all specifications, while CAPEX and market-to-book ratio ($MVBV$) remain negatively significant, reflecting that higher tangible investment is associated with lower intangible intensity. Firm size ($SIZE$), leverage ($LEVERAGE$), and market return ($MARKET_RETURN$) exhibit mixed significance, while market volatility ($MARKET_STD$) is negatively significant in all models. Board characteristics, including size ($BOARD_SIZE$), diversity ($BOARD_DIVERSITY$), independence ($BOARD_INDEPENDENCE$), and the presence of audit and

compensation committees, are mostly insignificant. ESG rating (*ESG_RATING*) is also insignificant, whereas S&P category (*S&P_CATEGORY*) remains positively significant. The number of analysts following each firm (*NUM_OF_ANALYSTS*) is not significant in any specification.

For executive characteristics, CEO variables, including age, tenure, horizon, gender, delta and power, are generally insignificant, except that CEO option vega shows a marginal negative effect. For CFOs, age is negatively significant in some specifications, horizon is positively significant when both proxies are included, and option delta is consistently positive and highly significant, indicating CFOs' incentives may affect intangible investment through option exposure.

Overall, the IV results confirm that both CEO and CFO inside debt and incentives are negatively associated with intangible asset intensity when considered separately. However, when included jointly, the individual effects diminish, suggesting some overlapping influence. In terms of magnitude, CEOs still exhibit slightly larger point estimates for debt-related effects, while CFOs have marginally stronger estimates for incentives. These findings indicate that both executives matter, but CEOs may exert a slightly more pronounced influence on intangible investment decisions, consistent with the notion that CEOs play a dominant role in strategic investment choices.

4.4.3 Change in Variables Regression Results

In this section, regressions based on the changes in both dependent and independent variables are estimated and reported. A key concern regarding endogeneity arises from the influence of unobserved or omitted variables that capture firm characteristics. Although a set of control variables was

included in the previous regressions, the possibility of omitted factors still exists. One way to address this issue is to compute standard errors clustered at the firm level while adjusting for heteroscedasticity. Another approach is to employ regression models based on changes in variables.

The advantage of this method lies in accounting for the impact of time-invariant unobserved or omitted firm characteristics on both managers' debt-based compensation and intangible asset management. By focusing on time-based changes in variables, this approach minimizes the influence of factors that remain constant over time and better illustrates the causal relationship between the independent and dependent variables through their time-series co-variation.

Moreover, this section applies median regression following Wu and Lai (2020) and Lin et al. (2018). To examine the effects across different levels of variables, the 25% and 75% quantiles are also included, with the median regression being the primary focus. As shown in Table 4.1, the natural logarithm of inside debt holdings of both CEOs and CFOs exhibits noticeable skewness, raising concerns about the potential influence of outliers on the robustness of the hypothesis.

To address this issue, in addition to constructing first differences of variables, median regression is employed, which is more robust than the standard linear regression method under such conditions (Li, 2015). Following Lin et al. (2018) and Graham et al. (2008), median regression is applied to estimate the effects of changes in variables. Unlike OLS, median regression is less sensitive to outliers, as it minimizes the influence of extreme values and does not rely on the assumptions of homoscedasticity or normality. To further test the robustness of the hypothesis, regressions at the 25% and 75% quantiles are also conducted to provide a more complete view of the

relationships. The regression proceeds as follows:

$$\begin{aligned}\Delta Intangible\ Intensity_{i,t} = \beta_0 + \beta_1 \Delta CEO_Incentive_{i,t-1} \\ + \beta_2 \Delta control_{i,t-1} + \beta_3 year_t + \beta_4 industry_i + \epsilon_{i,t}\end{aligned} \tag{4.19}$$

$$\begin{aligned}\Delta Intangible\ Intensity_{i,t} = \beta_0 + \beta_1 \Delta CFO_Incentive_{i,t-1} \\ + \beta_2 \Delta control_{i,t-1} + \beta_3 year_t + \beta_4 industry_i + \epsilon_{i,t}\end{aligned} \tag{4.20}$$

and

$$\begin{aligned}\Delta Intangible\ Intensity_{i,t} = \beta_0 + \beta_1 \Delta CEO_Incentive_{i,t-1} \\ + \beta_2 \Delta CFO_Incentive_{i,t-1} \\ + \beta_3 \Delta control_{i,t-1} \\ + \beta_4 year_t \\ + \beta_5 industry_i \\ + \epsilon_{i,t}\end{aligned} \tag{4.21}$$

where $\Delta Intangible\ Intensity_{i,t}$ represents the change in intangible intensity of firm i in period t over $t-1$. Similarly, $\Delta CEO_Incentive_{i,t-1}$ and $\Delta CFO_Incentive_{i,t-1}$ indicates the change in the logarithm of one plus inside debt proxy for CEO and CFO relatively of firm i lagged by one period. The change in other control variables is constructed in the same method. Since panel data is used in the regression, panel median regression is applied, controlling for industry- and year-fixed effects, to report the results. The results reporting the parameter and t-statistics for variables of interest are reported in panel A of table 4.5. Furthermore, to ensure robustness, quantile regression with quantiles of 25% and 75% are also applied and reported in panels B and C separately in Table 4.5.

From the results reported in Panel A of Table 4.5, the median regres-

sion based on the change specification shows a clear distinction between CEO and CFO effects. In columns (1)–(4), where variables related to either the CEO or CFO are included separately, only CEO-related coefficients are statistically significant and negative, consistent with the hypothesis that changes in inside debt-related compensation are negatively associated with changes in intangible intensity. Specifically, in column (1), $d_LOG(1 + CEO_RELA_DEBT)$ is negative and significant at the 5% level (-0.007^{**}, $t = -2.126$), and in column (3), $d_LOG(1 + CEO_RELA_INCEN)$ is negative and significant at the 5% level (-0.008^{**}, $t = -2.049$), whereas the corresponding CFO-related coefficients, $d_LOG(1 + CFO_RELA_DEBT)$ and $d_LOG(1 + CFO_RELA_INCEN)$, are not significant in columns (2) and (4).

When changes in both CEO and CFO inside debt holdings and incentives are included jointly in columns (5) and (6), the CEO variable *d_LOG(1+CEO_RELA_DEBT)* in column (5) remains negative and marginally significant at the 10% level (-0.008^{*}, $t = -1.688$), whereas the corresponding CFO variable is insignificant. In column (6), the CEO variable $d_LOG(1 + CEO_RELA_INCEN)$ remains negative (-0.009, $t = -1.645$), while all CFO-related variables continue to be insignificant. These results reinforce the conclusion that CEO compensation changes exert a stronger influence on intangible asset adjustments than those of the CFO.

Panel B reports the 25th percentile quantile regression results. All coefficients are statistically insignificant. This suggests that at the lower quantile, there is limited evidence of any systematic relationship between inside debt and intangible intensity.

Panel C reports the 75th percentile quantile regression results. Here, *d_LOG(1+CEO_RELA_DEBT)* remains significantly negative in both sep-

arate and joint specifications (-0.010^{**}, $t = -2.238$ in column (1) and -0.010^{**}, $t = -2.011$ in column (5)), while the other CEO and CFO variables are insignificant. This suggests that at higher quantiles, CEO inside debt continues to exert a negative effect, whereas CFO-related measures remain unimportant across the distribution.

Overall, the change-based median and quantile regressions consistently indicate that CEO inside debt and incentive changes have a stronger and more consistent impact on intangible investment intensity than CFO variables, supporting the conclusion that CEOs play a dominant role in influencing firm-level intangible asset decisions.

4.4.4 Robustness Test Using Yearly Relative Rank of Return on Tangible Assets

To mitigate the concern that a single cross-sectional ranking of EBITDA-to-Net PP&E might overweight observations from periods with systematically different capital intensities, we construct an alternative proxy, RKROTAYR, defined as the within-year decile rank of EBITDA/Net PP&E. This procedure effectively purges low-frequency, macro-level shocks to capital intensity while retaining the ordinal information necessary to test the hypotheses. Next step is to re-estimate the baseline OLS, 2SLS, and change-in-variable (quantile) regressions using RKROTAYR in place of RKROTA. The sample size remains virtually unchanged, and all control variables are kept identical to ensure a clean comparison.

Columns (1)–(4) of Table 4.6 present the OLS estimates. In the baseline specification, $LOG(1 + CEO_RELA_DEBT)$ in column (1) is negative and significant at the 5% level (-0.017^{**}, $t = -2.483$), while *LOG(1+CFO_-RELA_DEBT)* in column (2) is also negative and marginally significant

(-0.012^{*}, $t = -1.837$). Turning to incentive-based measures, both CEO and CFO variables are significantly negative: $LOG(1 + CEO_RELA_INCEN)$ in column (3) (-0.018^{**}, $t = -2.550$) and $LOG(1 + CFO_RELA_INCEN)$ in column (4) (-0.013^{**}, $t = -2.045$). However, in the joint specifications of columns (5) and (6), the CEO coefficients remain negative and weakly significant (e.g., -0.016^{**} for debt and -0.014^{*} for incentives), whereas the corresponding CFO coefficients lose statistical significance. This contrast suggests that CEO-related measures dominate when both sets of variables are considered simultaneously.

Taken together, these findings indicate that both CEO and CFO inside debt and incentive ratios are negatively associated with intangible intensity when considered separately. Yet, in joint regressions, the CEO's measures retain explanatory power while CFO coefficients fade, underscoring the comparatively stronger role of the CEO in shaping intangible investment.

To address potential endogeneity from omitted investment opportunities, a two-stage least squares (2SLS) strategy is employed using industry-year median inside debt and its interaction with executive tenure as instruments. The first-stage F-statistics exceed the Stock–Yogo threshold for weak instruments. Table 4.7 reports the second-stage estimates. CEO-related variables are significant in certain specifications: *INS_LOG(1+CEO_RELA_DEBT)* is negative (-0.066^{***}, $t = -3.053$) in column (1), and *INS_LOG(1+CEO_RELA_INCEN)* is negative (-0.059^{**}, $t = -2.562$) in column (3). CFO-related variables, *INS_LOG(1+CFO_RELA_DEBT)* and *INS_LOG(1+CFO_RELA_INCEN)*, are negative and significant in columns (2) and (4), respectively (-0.057^{***}, $t = -2.826$; -0.061^{***}, $t = -2.616$). When both executives are included jointly, the coefficients in column (5) for debt (CEO -0.040, CFO -0.032) and in column (6) for incentives (CEO -0.029, CFO -0.044) are statistically insignificant, although CEO coeffi-

cients remain larger in magnitude. Overall, the IV results indicate that inside debt and incentives reduce intangible investment, with difficulty to tell which one is more influential.

Next, the relationship between inside debt and changes in intangible intensity is examined. The first difference, ΔRKROTAYR, is computed, and median (50th percentile) as well as lower- and upper-quantile (25th and 75th) regressions are estimated. Table 4.8 summarizes the findings.

Columns (1), (3), and (5) of Panel A show that CEOi nside debt and CEO inside incentive load negatively and significantly. Specifically, *d_LOG(1+CEO_RELA_DEBT)* is estimated at -0.008^{*} ($t = -3.056$) in column (1) and -0.008^{**} ($t = -3.017$) in column (5), while *d_LOG(1+CEO_RELA_INCEN)* is -0.009^{*} ($t = -2.396$) in column (3) and -0.009^{*} ($t = -2.534$) in column (6). By contrast, CFO_Inside_Debt and CFO_Inside_Incentive never reach significance across these columns. Hence, the CEO's inside debt and incentive consistently predict the median year-to-year change in RKROTAYR, whereas the CFO's inside debt does not.

Panel B reports the results from the 25% quantile regression. In columns (1) and (5), the CEO's inside debt ($d_LOG(1 + CEO_RELA_DEBT)$) is negative but not statistically significant (-0.001, $t = -0.243$; -0.005, $t = -0.729$), whereas the CFO's inside debt ($d_LOG(1 + CFO_RELA_DEBT)$) is negative and marginally significant in columns (2) and (5) (0.005^{*}, $t = 1.688$; 0.006^{*}, $t = 1.700$). For incentive-based variables, the CEO's inside incentives ($d_LOG(1 + CEO_RELA_INCEN)$) are negative but not significant in columns (3) and (6) (-0.004, $t = -0.728$; -0.007, $t = -1.066$), while the CFO's inside incentives ($d_LOG(1 + CFO_RELA_INCEN)$) are positive and weakly significant in columns (4) and (6) (0.005, $t = 1.529$; 0.007^{*}, $t = 1.691$). These results suggest that in firms with the lowest in-

tangible intensity, the CFO's inside debt and incentives may exert a binding influence, whereas the CEO's compensation variables are largely not predictive.

Panel C presents the 75% quantile regression results. All coefficients for both CEO and CFO inside debt and incentive variables are statistically insignificant ($|t| < 1.37$), including CEO inside debt in columns (1) and (5) (-0.007, $t = -1.141$; -0.009, $t = -1.365$) and CFO inside debt in columns (2) and (5) (0.001, $t = 0.203$; 0.004, $t = 0.850$), as well as CEO and CFO incentive variables in columns (3), (4), and (6). These results indicate that neither executives' inside debt nor incentive variables meaningfully predict movements among firms exhibiting the fastest increases in intangible intensity, which is consistent with a symmetric null effect at the upper tail.

Across all three empirical approaches, which include OLS, 2SLS, and quantile-based change regressions, the negative association between inside debt and intangible intensity remains robust. The estimates consistently indicate that higher CEO inside debt and incentive ratios are linked to lower RKROTAYR. In joint specifications, the CEO coefficients generally retain statistical significance and are larger in magnitude than the CFO coefficients; for example, in the IV head-to-head regressions, the CEO coefficient is 67% larger, with a Wald test providing suggestive evidence in favor of Hypothesis 2. Quantile analyses further reveal that the relative influence of the CEO and CFO may vary across the intangible-intensity distribution, with CFO effects emerging only at the lower tail (25% quantile). Nonetheless, the central insight is clear: inside debt, particularly for the CEO, consistently constrains intangible investment, highlighting the CEO's dominant role in shaping firm-level intangible allocation.

4.4.5 Robustness Test Using Bid-Ask Spread of Stocks

To verify the robustness of the research, an alternative variable, which is the bid-ask spread for each stock-month, is applied in place of intangible intensity. As described in Callahan et al. (1997), the bid-ask spread in the stock market represents the cost of transacting information and can be decomposed into three components: order-processing costs, inventory holding costs, and adverse selection costs, with the last specifically measuring the degree of information asymmetry. Moreover, the bid-ask spread captures both the risk aversion of dealers and market liquidity (Acharya and Pedersen, 2005). Since a higher bid-ask spread indicates poorer liquidity, investors demand higher compensation for bearing such risk, and securities with higher spreads tend to exhibit higher tail beta (Kelly and Jiang, 2014). This mechanism makes the bid-ask spread a suitable alternative variable for testing the robustness of the results.

To assess the robustness of the main findings, the intangible intensity is replaced with the monthly bid-ask spread (matched from Refinitiv) as a market-based proxy for firm risk and perceived information asymmetry. The bid-ask spread captures market-level manifestations of information asymmetry, liquidity risk, and dealer risk aversion (Glosten and Milgrom, 1985; Amihud and Mendelson, 1986), providing a complement to the accounting-based intangible measure. The regression specification, fixed effects (industry at three-digit SIC and year), variable treatment (lagging the dependent variable by one period and winsorising continuous variables at 1%), and firm-level clustering of standard errors remain identical to the baseline models.

The results are reported in Table 4.9 (columns (1)–(6)). Columns (1) and (2) mirror the baseline setup for the relative debt proxy: column (1) reports

the CEO measure, and column (2) reports the CFO measure. Columns (3) and (4) present analogous results for the relative incentive proxy (CEO in (3), CFO in (4)). Columns (5) and (6) include both CEO and CFO measures jointly, facilitating direct comparison.

The main findings are as follows. For the debt-based proxy, the CEO inside-debt measure is negative and statistically significant: *log(1+CEO_RELA_-DEBT)* has a coefficient of -0.016^{**} (t = -2.472) in column (1), indicating that higher CEO inside-debt holdings are associated with lower bid–ask spreads, i.e., lower market-perceived information or transaction risk. By contrast, the CFO debt measure is smaller in magnitude and weakly significant in column (2) (-0.012^{*}, t = -1.960). For the incentive-based proxy, the CEO incentive measure is negative and significant in column (3) (-0.017^{**}, t = -2.509), whereas the CFO incentive measure is negative and significant in column (4) (-0.013^{**}, t = -2.130). When CEO and CFO measures are included jointly (columns (5)–(6)), the point estimates generally attenuate: CEO debt in (5) is -0.015^{*} (t = -1.942), CFO debt in (5) is not significant (-0.003, t = -0.456), CEO incentive in (6) is -0.013^{*} (t = -1.740), and CFO incentive in (6) is not significant (-0.006, t = -0.830). These results suggest that the CEO effect is stronger when analyzed separately but becomes less robust when both executives' measures are controlled simultaneously.

Regarding control variables, several relationships are economically meaningful and statistically robust. Firm size (*SIZE*) is strongly negatively associated with bid–ask spreads in all specifications, consistent with larger firms exhibiting tighter spreads (better liquidity). Market-to-book ratio (*MVBV*) is slightly negative and marginally significant. Leverage shows a small positive association in one specification but is not robust across all columns. Profitability (*ROA*) is consistently negatively related to the spread, consistent with more profitable firms facing lower transaction costs.

The S&P category enters negatively and significantly in several specifications, indicating that firms with higher credit ratings tend to have lower spreads. Most board structure variables show no consistent significance, although *BOARD_DIVERSITY* and *BOARD_INDEPENDENCE* are marginally significant in some specifications.

Regarding executive characteristics, option-based measures display consistent patterns. CEO delta is significantly negative, CEO vega is weakly positive, and CEO power is negative. Similarly, CFO delta is negative and CFO vega is positive and significant in some specifications. These compensation-related controls behave consistently in the spread regressions, lending credibility to the model specification.

In summary, substituting the bid–ask spread for intangible intensity yields largely consistent evidence that inside-debt management, particularly CEO inside-debt holdings, is associated with lower market-perceived information and liquidity risk, as reflected in tighter bid–ask spreads. The effect is strongest and most robust for the CEO when examined separately, but it attenuates when CEO and CFO measures are included jointly, while the effect for the CEO is more robust. These robustness results therefore reinforce the interpretation that inside-debt alignment between managers and creditors reduces downside exposure as perceived by market participants.

4.5 Conclusions

Debt-based executive compensation has been extensively studied for its influence on corporate financial policies (Cassell et al., 2012). Such compensation is typically linked to long-term firm performance, as its deferred nature incentivizes managers to pursue sustainable strategies. In particular, debt-based compensation encourages executives to mitigate unethical

behavior and reduce bankruptcy risk, thereby promoting more conservative and prudent financial policies. This chapter examines the hypothesis that debt-based compensation affects corporate decision-making through the channel of intangible asset management. Intangible assets are especially sensitive to managerial discretion and often exhibit high information asymmetry due to the absence of universally accepted valuation standards. Managers may have incentives to overstate goodwill or other intangible assets to inflate firm valuation or defer impairment, rendering intangible intensity a relevant proxy for evaluating the effects of managerial incentives. While prior literature has predominantly focused on CEO compensation, the analysis here incorporates both the CEO and CFO, the two executives most influential in shaping firm financial policies.

Empirical analyses are conducted using multiple methodological approaches. Baseline ordinary least squares regressions indicate that higher levels of debt-based compensation are associated with lower intangible intensity, suggesting that both CEOs and CFOs with greater debt-based incentives tend to make more conservative investment decisions. The robustness of this conclusion is further supported by alternative measures of intangible intensity, demonstrating that the findings are not sensitive to the choice of proxy. When both CEO and CFO inside-debt measures are included in the same specification to assess their relative influence, only the CEO's inside debt remains statistically significant. To address potential endogeneity concerns and strengthen causal inference, instrumental-variable regressions and change-in-variables specifications are employed. The industry-level average of CEO/CFO inside debt holdings (excluding the firm itself) serves as an instrument, and results remain qualitatively consistent. Change-in-variables regressions corroborate this finding, showing a significant negative relationship between CEO inside debt and intangible intensity, whereas the

CFO effect is not statistically significant.

Overall, these results suggest that debt-based compensation fosters more conservative managerial behavior, with the CEO's incentives exerting a stronger impact on firm investment decisions than those of the CFO. This underscores the importance of distinguishing between executive roles when evaluating the effects of incentive structures on corporate policy, particularly in areas characterized by high informational opacity, such as intangible asset management.

4.6 Tables

Table 4.1: Summary Statistics

This table reports summary statistics of the variables employed in the chapter 4. Panel A reports the variables that are used in the estimation of Eq. (4.13). n denotes the number of observations, Mean is the average return, SD is the standard deviation, p25 stands for the first quartile (25% percentile), p50 denotes the median and p75 stands for the third quartile (75% percentile). Table 4.2 shows the definition of the covariates.

	n	Mean	SD	p25	p50	p75
RKROTA	11,864	0.496	0.284	0.254	0.494	0.739
LOG(1 + CEO_RELA_DEBT)	11,864	0.532	0.797	0	0.136	0.790
LOG(1 + CFO_RELA_DEBT)	11,864	0.573	0.898	0	0.131	0.820
LOG(1 + CEO_RELA_INCEN)	11,864	0.491	0.754	0	0.126	0.697
LOG(1 + CFO_RELA_INCEN)	11,864	0.533	0.859	0	0.118	0.750
SIZE	11,385	7.911	1.631	6.764	7.804	8.961
MVBV	11,574	3.378	7.073	1.363	2.317	3.876
ROA	11,864	0.0838	0.0959	0.0479	0.0864	0.130
LEVERAGE	11,384	0.773	2.485	0.203	0.508	0.971
Q	11,025	1.927	1.177	1.178	1.569	2.226
CAPEX	11,864	0.0441	0.0455	0.0153	0.0298	0.0551
MARKET_RETURN	11,864	0.105	0.262	-0.066	0.159	0.248
MARKET_STD	11,864	0.049	0.022	0.031	0.041	0.056
SOCIAL_CAPITAL	11,864	0.379	0.714	0	0	1
CEO_AGE	11,077	56.34	6.731	52	56	61
CFO_AGE	11,047	51.37	6.472	47	51	56
CEO_TENURE	11,483	7.077	6.789	2	5	10
CFO_TENURE	11,535	3.337	2.878	1	3	5
CEO_HORIZON	7,494	10.76	7.114	6	9	14
CFO_HORIZON	7,494	15.64	3.581	3	5	8
CEO_GENDER	11,864	0.975	0.156	1	1	1
CFO_GENDER	11,864	0.972	0.164	1	1	1
LOG(CEO_DELTA)	10,081	11.89	1.683	10.89	12.05	13.08
LOG(CFO_DELTA)	10,000	10.41	1.652	9.446	10.57	11.57
LOG(CEO_VEGA)	10,069	5.773	3.916	5.264	6.696	7.713
LOG(CFO_VEGA)	9,992	4.521	3.645	3.982	5.326	6.332
BOARD_AUDIT_COMMITTEE	3,632	0.993	0.0859	1	1	1
BOARD_COMPENSATION_COMMITTEE	3,632	0.988	0.111	1	1	1
BOARD_DIVERSITY	3,618	16.07	9.332	10	15.38	22.22
BOARD_INDEPENDENCE	3,243	81.34	11.65	75	83.33	90
BOARD_SIZE	3,630	10.68	2.354	9	11	12
NUM_OF_ANALYSTS	5,839	12.68	8.229	6	11	18
ESG_RATING	3,632	44.4	19.94	28.55	42.62	59.65
S&P_CATEGORY	3,632	0.103	0.304	0	0	1

Table 4.2: Definition of Variables

This table lists the variables used in the empirical analysis. Column (1) presents the variable names, Column (2) presents the definitions of the variables and Column (3) presents the sources of the variables. Financial data are primarily drawn from Compustat and CRSP; CEO and CFO characteristics are drawn from ExecuComp, BoardEX and IBES; governance and external variables are from Refinitiv.

Variable	Definition	Source
RKROTA	The relative rank of industry-adjusted return on tangible assets over the whole sample.	Compustat
SIZE	The natural logarithm of the value of firm's total assets.	Compustat
MVBV	The ratio of the market value of equity to the book value of equity (Market-to-Book ratio).	Compustat
LEVERAGE	The ratio of total liabilities to total equity.	Compustat
ROA	The ratio of income before extraordinary items to the book value of total assets (Return on assets).	Compustat
Q	Tobin's Q measurement.	Compustat
CAPEX	The ratio of capital expenditure to total assets.	Compustat
MARKET_RETURN	The average stock return of the whole market in the fiscal year.	CRSP
MARKET_STD	The standard deviation of the market's annual returns.	CRSP
SOCIAL_CAPITAL	The number of external board members.	BoardEX
LOG(1+CEO_RELA_DEBT)	The logarithm of one plus relative CEO-debt-ratio. CEO-debt-ratio is calculated as the CEO's debt compensation to equity compensation scaled by the firm's debt-to-equity ratio.	Compustat & ExecuComp
LOG(1+CFO_RELA_DEBT)	The logarithm of one plus relative CFO-debt-ratio. CFO-debt-ratio is calculated as the CFO's debt compensation to equity compensation scaled by the firm's debt-to-equity ratio.	Compustat & ExecuComp
LOG(1+CEO_RELA_INCEN)	The logarithm of one plus relative CEO-incentive-ratio. CEO-incentive-ratio is calculated as the CEO's change in one unit of debt compensation to equity compensation, scaled by the same ratio of the firm.	Compustat & ExecuComp
LOG(1+CFO_RELA_INCEN)	The logarithm of one plus relative CFO-incentive-ratio. CFO-incentive-ratio is calculated as the CFO's change in one unit of debt compensation to equity compensation, scaled by the same ratio of the firm.	Compustat & ExecuComp
CEO_AGE	The age of the firm's CEO.	ExecuComp
CFO_AGE	The age of the firm's CFO.	ExecuComp
CEO_TENURE	The tenure of the CEO in the firm.	ExecuComp
CFO_TENURE	The tenure of the CFO in the firm.	ExecuComp
CEO_HORIZON	The number of years remaining until the CEO retires.	ExecuComp
CFO_HORIZON	The number of years remaining until the CFO retires.	ExecuComp
CEO_GENDER	The dummy variable for CEOs' gender, 1 represents male and 0 otherwise.	ExecuComp
CFO_GENDER	The dummy variable for CFOs' gender, 1 represents male and 0 otherwise.	ExecuComp
LOG(CEO_DELTA)	The logarithm of CEO's option delta.	ExecuComp
LOG(CFO_DELTA)	The logarithm of CFO's option delta.	ExecuComp
LOG(CEO_VEGA)	The logarithm of CEO's option vega.	ExecuComp
LOG(CFO_VEGA)	The logarithm of CFO's option vega.	ExecuComp
BOARD_AUDIT_COMMITTEE	Indicator variable equal to 1 if the firm has an established board audit committee, and 0 otherwise.	Refinitiv
BOARD_COMPENSATION_COMMITTEE	Indicator variable equal to 1 if the firm has an established board compensation committee, and 0 otherwise.	Refinitiv

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Table 4.2 (continued)

Variable	Definition	Source
BOARD_DIVERSITY	The proportion of female directors on the board.	Refinitiv
BOARD_INDEPENDENCE	The proportion of independent directors on the board.	Refinitiv
BOARD_SIZE	The total number of directors on the board.	Refinitiv
NUM_OF_ANALYSTS	The number of analysts following the company.	IBES
ESG_RATING	The overall environmental, social, and governance (ESG) performance score of the firm.	Refinitiv
S&P_CATEGORY	Credit ratings category from S&P, coded as a dummy variable equal to 1 if the rating is investment grade (BBB or higher), and 0 otherwise.	S&P

Notes: Definitions follow prior literature (see main text).

Table 4.3: Baseline Regression Results

This table reports the estimation results of the baseline regression model in Eq. (4.13). The measure of intangible intensity is *RKROTA*. See Section 4.3.2 for a detailed description of the intangible intensity measures. Control variables include *SIZE*, the natural logarithm of total assets; *MVBV*, the market-to-book ratio; *LEVERAGE*, the ratio of total liabilities to total equity; *ROA*, the return on assets; *Q*, Tobin's Q; and *CAPEX*, the ratio of capital expenditures to total assets; *MARKET_RETURN*, the average market stock return; *MARKET_STD*, the standard deviation of the market's annual returns. CEO- and CFO-specific characteristics are also included: *CEO_POWER* and *CFO_POWER* are dummy for CEO or CFO being powerful in the board; *CEO_AGE* and *CFO_AGE* are the age of the CEO and CFO; *CEO_TENURE* and *CFO_TENURE* are their firm tenure; *LOG*(*CEO_DELTA*) and *LOG*(*CFO_DELTA*) are the logarithm of option delta; *LOG*(*CEO_VEGA*) and *LOG*(*CFO_VEGA*) are the logarithm of option vega; *CEO_GENDER* and *CFO_GENDER* are indicator variables equal to 1 if the CEO or CFO is female and 0 otherwise. Governance and external control variables include *CEO_HORIZON* and *CFO_HORIZON*, defined as the expected number of years until the CEO or CFO reaches the age of 65; *BOARD_AUDIT_COMMITTEE* and *BOARD_COMPENSATION_COMMITTEE*, indicator variables for the existence of board audit and compensation committees; *BOARD_DIVERSITY*, the proportion of female directors; *BOARD_INDEPENDENCE*, the proportion of independent directors; *BOARD_SIZE*, the total number of directors; *SOCIAL_CAPITAL*, the number of external board members; *NUM_OF_ANALYSTS*, the number of analysts following; *ESG_RATING*, the firm's ESG score; and *S&P_CATEGORY*, an indicator equal to 1 if the firm has an investment-grade rating (BBB− or above) and 0 otherwise. The measurements for CEO and CFO inside debt holdings are: *LOG*(*1 + CEO_RELA_DEBT*) and *LOG*(*1 + CFO_RELA_DEBT*), the logarithm of one plus relative CEO- and CFO-debt ratio; *LOG*(*1 + CEO_RELA_INCEN*) and *LOG*(*1 + CFO_RELA_INCEN*), the logarithm of one plus relative CEO- and CFO-incentive ratio. See Section 4.3.1 for a detailed description of the inside debt holding measures. Columns (1)–(2) report the estimation results for models with either *LOG*(*1 + CEO_RELA_DEBT*) or *LOG*(*1 + CFO_RELA_DEBT*), and column (5) with both included. Columns (3)–(4) report the estimation results for models with either *LOG*(*1 + CEO_RELA_INCEN*) or *LOG*(*1 + CFO_RELA_INCEN*), and column (6) with both included. Year fixed and industry fixed effects are included. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	RKROTA	*RKROTA*	*RKROTA*	*RKROTA*	*RKROTA*	*RKROTA*
SIZE	0.011	0.006	0.010	0.005	0.008	0.007
	(0.652)	(0.367)	(0.602)	(0.319)	(0.464)	(0.406)
MVBV	-0.007*	-0.007	-0.007*	-0.007	-0.007	-0.007
	(-1.667)	(-1.458)	(-1.669)	(-1.493)	(-1.567)	(-1.581)
LEVERAGE	0	0.002	0	0.002	0.001	0.001
	(-0.153)	(0.559)	(-0.136)	(0.556)	(0.262)	(0.276)
ROA	0.115***	0.113***	0.115***	0.113***	0.114***	0.114***
	(10.486)	(11.092)	(10.448)	(11.072)	(10.674)	(10.626)
Q	0.018*	0.018*	0.018*	0.018*	0.017	0.016
	(1.731)	(1.901)	(1.701)	(1.896)	(1.627)	(1.596)
CAPEX	-0.070***	-0.066***	-0.070***	-0.066***	-0.070***	-0.071***
	(-7.047)	(-7.069)	(-7.076)	(-7.102)	(-6.923)	(-6.961)
MARKET_RETURN	0.001	-0.007	0.001	-0.007	-0.003	-0.003
	(0.174)	(-1.035)	(0.209)	(-0.990)	(-0.494)	(-0.444)

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Table 4.3 – continued

	(1)	(2)	(3)	(4)	(5)	(6)
	RKROTA	*RKROTA*	*RKROTA*	*RKROTA*	*RKROTA*	*RKROTA*
MARKET_STD	-0.023***	-0.018**	-0.023***	-0.017**	-0.023**	-0.022**
	(-2.725)	(-2.069)	(-2.642)	(-2.017)	(-2.500)	(-2.406)
SOCIAL_CAPITAL	-0.004	-0.001	-0.003	-0.001	-0.003	-0.003
	(-0.649)	(-0.109)	(-0.633)	(-0.111)	(-0.521)	(-0.535)
BOARD_SIZE	-0.006	-0.007	-0.007	-0.007	-0.006	-0.007
	(-0.837)	(-0.866)	(-0.874)	(-0.889)	(-0.790)	(-0.826)
BOARD_DIVERSITY	-0.005	0.003	-0.005	0.003	-0.003	-0.003
	(-0.657)	(0.462)	(-0.653)	(0.443)	(-0.417)	(-0.434)
BOARD_-COMPENSATION_-COMMITTEE	-0.001	-0.001	-0.001	0	-0.002	-0.002
	(-0.269)	(-0.107)	(-0.272)	(-0.103)	(-0.297)	(-0.314)
BOARD_AUDIT_-COMMITTEE	0.001	0.003	0.001	0.003	0.004	0.004
	(0.201)	(0.866)	(0.220)	(0.857)	(0.957)	(0.966)
BOARD_INDEPENDENCE	-0.011	-0.009	-0.011	-0.010	-0.012	-0.012
	(-1.448)	(-1.149)	(-1.474)	(-1.168)	(-1.440)	(-1.452)
NUM_OF_ANALYSTS	0.002	0.001	0.002	0.001	0	0
	(0.372)	(0.190)	(0.371)	(0.193)	(0.026)	(0.033)
ESG_RATING	0	0	0	0	0	0
	(-0.520)	(-0.549)	(-0.518)	(-0.534)	(-0.363)	(-0.354)
S&P_CATEGORY	0.061***	0.071***	0.061***	0.071***	0.070***	0.070***
	(2.849)	(3.221)	(2.857)	(3.207)	(3.083)	(3.072)
LOG_CEO_AGE	-0.008		-0.008		-0.006	-0.006
	(-1.013)		(-0.988)		(-0.749)	(-0.731)
LOG_CEO_TENURE	0.003		0.004		0.003	0.004
	(0.404)		(0.449)		(0.330)	(0.395)
LOG_CEO_HORIZON	-0.005		-0.005		-0.005	-0.005
	(-0.576)		(-0.573)		(-0.473)	(-0.502)
CEO_GENDER	0.025		0.027		0.007	0.007
	(0.786)		(0.829)		(0.151)	(0.161)
LOG_CEO_DELTA	0.009		0.009		-0.019	-0.019
	(0.778)		(0.729)		(-1.182)	(-1.187)
LOG_CEO_VEGA	-0.009*		-0.009*		-0.01	-0.01
	(-1.676)		(-1.716)		(-1.000)	(-1.016)
CEO_POWER	0.014		0.014		-0.005	-0.006
	(0.518)		(0.512)		(-0.188)	(-0.199)
LOG_CFO_AGE		-0.019**		-0.019**	-0.019**	-0.018*
		(-2.086)		(-2.042)	(-1.985)	(-1.916)
LOG_CFO_TENURE		0.001		0.001	0	0
		(0.159)		(0.164)	(-0.058)	(-0.049)
LOG_CFO_HORIZON		0.005		0.005	0.010**	0.010**
		(0.941)		(0.954)	(2.052)	(2.036)
CFO_GENDER		0.027		0.029	0.025	0.027
		(1.133)		(1.215)	(0.717)	(0.774)
LOG_CFO_DELTA		0.036***		0.036***	0.047***	0.047***
		(4.084)		(4.043)	(3.749)	(3.698)
LOG_CFO_VEGA		-0.009*		-0.009*	-0.002	-0.002
		(-1.740)		(-1.784)	(-0.229)	(-0.249)
CFO_POWER		-0.024		-0.024	-0.015	-0.015
		(-0.686)		(-0.689)	(-0.412)	(-0.409)
LOG(1+CEO_RELA_-DEBT)	-0.017***				-0.016**	
	(-2.612)				(-2.055)	

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Table 4.3 – continued

	(1)	(2)	(3)	(4)	(5)	(6)
	RKROTA	*RKROTA*	*RKROTA*	*RKROTA*	*RKROTA*	*RKROTA*
LOG(1+CFO_RELA_-DEBT)		-0.013**			-0.003	
		(-2.081)			(-0.490)	
LOG(1+CEO_RELA_-INCEN)			-0.017**			-0.014*
			(-2.584)			(-1.811)
LOG(1+CFO_RELA_-INCEN)				-0.014**		-0.006
				(-2.180)		(-0.825)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Cluster	Y	Y	Y	Y	Y	Y
Observations	2,311	2,229	2,311	2,229	2,019	2,019
R-squared	0.600	0.608	0.601	0.609	0.616	0.617

t-statistics in parentheses. Standard errors clustered at firm level.
*, **, *** indicate significance at the 10%, 5%, and 1% levels.

Table 4.4: Stage II Results of Instrumental Variable Methods for CEO and CFO Inside Debt on Intangible Intensity

This table reports the estimation results of the second stage regression model in Eq. (4.16),Eq. (4.17) and Eq. (4.18). The measures of intangible intensity is *RKROTA*. See Section 4.3.2 for a detailed description of the intangible intensity measures. Control variables include *SIZE*, the natural logarithm of total assets; *MVBV*, the market-to-book ratio; *LEVERAGE*, the ratio of total liabilities to total equity; *ROA*, the return on assets; *Q*, Tobin's Q; and *CAPEX*, the ratio of capital expenditures to total assets; *MARKET_RETURN*, the average market stock return; *MARKET_STD*, the standard deviation of the market's annual returns. CEO- and CFO-specific characteristics are also included: *CEO_POWER* and *CFO_POWER* are dummy for CEO or CFO being powerful in the board; *CEO_AGE* and *CFO_AGE* are the age of the CEO and CFO; *CEO_TENURE* and *CFO_TENURE* are their firm tenure; *LOG*(*CEO_DELTA*) and *LOG*(*CFO_DELTA*) are the logarithm of option delta; *LOG*(*CEO_VEGA*) and *LOG*(*CFO_VEGA*) are the logarithm of option vega; *CEO_GENDER* and *CFO_GENDER* are indicator variables equal to 1 if the CEO or CFO is female and 0 otherwise. Governance and external control variables include *CEO_HORIZON* and *CFO_HORIZON*, defined as the expected number of years until the CEO or CFO reaches the age of 65; *BOARD_AUDIT_COMMITTEE* and *BOARD_COMPENSATION_COMMITTEE*, indicator variables for the existence of board audit and compensation committees; *BOARD_DIVERSITY*, the proportion of female directors; *BOARD_INDEPENDENCE*, the proportion of independent directors; *BOARD_SIZE*, the total number of directors; *SOCIAL_CAPITAL*, the number of external board members; *NUM_OF_ANALYSTS*, the number of analysts following; *ESG_RATING*, the firm's ESG score; and *S&P_CATEGORY*, an indicator equal to 1 if the firm has an investment-grade rating (BBB− or above) and 0 otherwise. The measurements for CEO and CFO inside debt holdings are: *INS_LOG*(*1 + CEO_RELA_DEBT*) and *INS_LOG*(*1 + CEO_RELA_DEBT*) are the estimated measurement using instrumental variables of logarithm of one plus relative CEO- and CFO-debt-ratio. *INS_LOG*(*1 + CEO_RELA_INCEN*) and *INS_LOG*(*1 + CEO_RELA_INCEN*) are the estimated measurement using instrumental variables of the logarithm of one plus relative CEO- and CFO-incentive-ratio. See Section 4.3.3 for a detailed description of the instrumental variables. Columns (1)–(2) report the estimation results for models with either *LOG*(*1 + CEO_RELA_DEBT*) or *LOG*(*1 + CFO_RELA_DEBT*), and column (5) with both included. Columns (3)–(4) report the estimation results for models with either *LOG*(*1 + CEO_RELA_INCEN*) or *LOG*(*1 + CFO_RELA_INCEN*), and column (6) with both included. Year fixed and industry fixed effects are included. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	RKROTA	*RKROTA*	*RKROTA*	*RKROTA*	*RKROTA*	*RKROTA*
SIZE	0.016	0.012	0.012	0.009	0.014	0.010
	(-1.455)	(-1.261)	(-1.209)	(-0.930)	(-1.324)	(-0.921)
MVBV	-0.008**	-0.008*	-0.008*	-0.009*	-0.008*	-0.009*
	(-2.086)	(-1.738)	(-1.871)	(-1.907)	(-1.748)	(-1.901)
LEVERAGE	-0.003	0.001	-0.003	0.001	-0.001	0
	(-0.900)	(-0.162)	(-0.609)	(-0.197)	(-0.208)	(-0.038)
ROA	0.133***	0.127***	0.131***	0.126***	0.132***	0.130***
	(-16.051)	(-18.382)	(-17.644)	(-18.220)	(-17.316)	(-17.382)
Q	0.020***	0.021***	0.018**	0.021***	0.019**	0.018**
	(-2.594)	(-3.037)	(-2.538)	(-3.004)	(-2.499)	(-2.389)
CAPEX	-0.068***	-0.062***	-0.070***	-0.063***	-0.069***	-0.070***
	(-9.311)	(-8.956)	(-10.211)	(-9.091)	(-9.328)	(-9.505)

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Table 4.4 – continued

	(1)	(2)	(3)	(4)	(5)	(6)
	RKROTA	*RKROTA*	*RKROTA*	*RKROTA*	*RKROTA*	*RKROTA*
MARKET_RETURN	-0.001	-0.009	0	-0.008	-0.005	-0.004
	(-0.157)	(-1.358)	(-0.067)	(-1.146)	(-0.784)	(-0.620)
MARKET_STD	-0.028***	-0.021**	-0.024***	-0.019**	-0.027***	-0.023***
	(-3.468)	(-2.541)	(-3.148)	(-2.295)	(-3.083)	(-2.707)
SOCIAL_CAPITAL	-0.002	-0.001	-0.002	-0.001	-0.003	-0.003
	(-0.413)	(-0.255)	(-0.446)	(-0.269)	(-0.624)	(-0.761)
BOARD_SIZE	0	-0.002	-0.002	-0.003	0	-0.001
	(-0.001)	(-0.398)	(-0.335)	(-0.550)	(-0.054)	(-0.224)
BOARD_DIVERSITY	-0.003	0.003	-0.003	0.003	-0.003	-0.004
	(-0.466)	(-0.630)	(-0.543)	(-0.488)	(-0.490)	(-0.676)
BOARD_-COMPENSATION_-COMMITTEE	-0.002	-0.003	-0.002	-0.003	-0.004	-0.004
	(-0.488)	(-0.682)	(-0.528)	(-0.651)	(-0.935)	(-0.967)
BOARD_AUDIT_-COMMITTEE	0	0.003	0	0.002	0.004	0.004
	(-0.009)	(-0.682)	(-0.056)	(-0.604)	(-0.857)	(-0.844)
BOARD_INDEPENDENCE	-0.008	-0.008	-0.009*	-0.009*	-0.009	-0.010*
	(-1.403)	(-1.624)	(-1.829)	(-1.723)	(-1.642)	(-1.733)
NUM_OF_ANALYSTS	0.001	0.001	0.001	0.001	0	0
	(-0.245)	(-0.247)	(-0.253)	(-0.275)	(-0.083)	(-0.018)
ESG_RATING	0	0	0	0	0	0
	(-0.237)	(-0.079)	(-0.308)	(-0.023)	(-0.118)	(-0.191)
S&P_CATEGORY	0.065***	0.074***	0.065***	0.073***	0.072***	0.071***
	(-4.978)	(-6.067)	(-5.379)	(-5.997)	(-5.604)	(-5.510)
LOG_CEO_AGE	-0.003		-0.003		-0.001	-0.001
	(-0.519)		(-0.575)		(-0.186)	(-0.192)
LOG_CEO_TENURE	0		0.002		0.002	0.004
	(-0.053)		(-0.376)		(-0.347)	(-0.675)
LOG_CEO_HORIZON	-0.005		-0.005		-0.006	-0.008
	(-0.860)		(-0.874)		(-0.936)	(-1.138)
CEO_GENDER	0.152		0.171		0.016	0.017
	(0.720)		(0.083)		(0.251)	(0.612)
LOG_CEO_DELTA	0.009		0.007		-0.018*	-0.018*
	(-1.118)		(-0.978)		(-1.695)	(-1.699)
LOG_CEO_VEGA	-0.007		-0.008*		-0.008	-0.009
	(-1.552)		(-1.800)		(-0.999)	(-1.126)
CEO_POWER	0.018		0.017		0.001	0
	(-0.682)		(-0.732)		(-0.053)	(-0.015)
LOG_CFO_AGE		-0.011*		-0.009	-0.013*	-0.010
		(-1.695)		(-1.265)	(-1.770)	(-1.281)
LOG_CFO_TENURE		0.004		0.004	0.002	0.002
		(-0.630)		(-0.643)	(-0.267)	(-0.323)
LOG_CFO_HORIZON		0.004		0.005	0.011**	0.010**
		(-1.140)		(-1.228)	(-2.430)	(-2.389)
CFO_GENDER		0.177		0.184	0.166	0.176
		(0.712)		(0.738)	(0.631)	(0.688)
LOG_CFO_DELTA		0.033***		0.031***	0.044***	0.043***
		(-4.979)		(-4.694)	(-4.457)	(-4.292)
LOG_CFO_VEGA		-0.007		-0.008*	-0.003	-0.004
		(-1.534)		(-1.761)	(-0.339)	(-0.466)
CFO_POWER		-0.012		-0.013	-0.011	-0.010
		(-0.264)		(-0.292)	(-0.235)	(-0.225)

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Table 4.4 – continued

	(1)	(2)	(3)	(4)	(5)	(6)
	RKROTA	*RKROTA*	*RKROTA*	*RKROTA*	*RKROTA*	*RKROTA*
INS_LOG(1+CEO_RELA_-DEBT)	-0.064***				-0.038	
	(-3.255)				(-1.094)	
INS_LOG(1+CFO_RELA_-DEBT)		-0.054***			-0.032	
		(-2.736)			(-0.980)	
INS_LOG(1+CEO_RELA_-INCEN)			-0.057**			-0.026
			(-2.512)			(-0.751)
INS_LOG(1+CFO_RELA_-INCEN)				-0.059**		-0.045
				(-2.559)		(-1.279)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Cluster	Y	Y	Y	Y	Y	Y
Observations	2,217	2,134	2,217	2,134	1,933	1,933
R-squared	0.574	0.587	0.580	0.584	0.587	0.588
Cragg Donald Wald F stat	25.290	27.683	22.278	20.683	12.642	12.642
Critical Value (10%)	10.27	10.27	10.27	10.27	10.27	10.27

t-statistics in parentheses. Standard errors clustered at firm level.
*, **, *** indicate significance at the 10%, 5%, and 1% levels.

Table 4.5: Results of Changes in Variables for CEO and CFO Inside Debt on Intangible Intensity

This table reports the estimation results of the quantile regression results of change-in-variable model in Eq. (4.19),Eq. (4.20) and Eq. (4.21). Panel A reports the results of median regression which is quantile regression with quantile of 50%. Panel B reports the results of quantile regression with quantile of 25%. Panel C reports the results of quantile regression with quantile of 75%. This table only reports the parameter and t-statistics of variables of interest. The measures of first difference of intangible intensity along time period is *d_RKROTA*. See Section 4.3.2 for a detailed description of the intangible intensity measures. The measurements for CEO and CFO inside debt holdings are: $d_LOG(1 + CEO_RELA_DEBT)$ and $d_LOG(1 + CEO_RELA_DEBT)$ are the first difference of logarithm of one plus relative CEO- and CFO-debt-ratio. $d_LOG(1 + CEO_RELA_INCEN)$ and $d_LOG(1 + CEO_RELA_INCEN)$ are the first difference of the logarithm of one plus relative CEO- and CFO-incentive-ratio. See Section 4.3.3 for a detailed description of the instrumental variables. Columns (1)–(2) report the estimation results for models with either $LOG(1 + CEO_RELA_DEBT)$ or $LOG(1 + CFO_RELA_DEBT)$, and column (5) with both included. Columns (3)–(4) report the estimation results for models with either $LOG(1 + CEO_RELA_INCEN)$ or $LOG(1 + CFO_RELA_INCEN)$, and column (6) with both included. Year fixed and industry fixed effects are included. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	d_RKROTA	*d_RKROTA*	*d_RKROTA*	*d_RKROTA*	*d_RKROTA*	*d_RKROTA*
Panel A: Median Regression						
$d_LOG(1 + CEO_RELA_DEBT)$	-0.007**				-0.008*	
	(-2.126)				(-1.688)	
$d_LOG(1 + CFO_RELA_DEBT)$		-0.001			0.001	
		(-0.620)			(0.293)	
$d_LOG(1 + CEO_RELA_INCEN)$			-0.008**			-0.009
			(-2.049)			(-1.645)
$d_LOG(1 + CFO_RELA_INCEN)$				-0.002		0.001
				(-0.718)		(0.228)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	3243	3243	3243	3243	3243	3243
Panel B: 25% Regression						
$d_LOG(1 + CEO_RELA_DEBT)$	-0.008				-0.011	
	(-1.082)				(-1.946)	
$d_LOG(1 + CFO_RELA_DEBT)$		0.005			0.005	
		(1.092)			(1.156)	
$d_LOG(1 + CEO_RELA_INCEN)$			-0.008			-0.012
			(-1.080)			(-1.636)
$d_LOG(1 + CFO_RELA_INCEN)$				0.001		0.004
				(0.334)		(1.034)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	3243	3243	3243	3243	3243	3243
Panel C: 75% Regression						
$d_LOG(1 + CEO_RELA_DEBT)$	-0.010**				-0.010**	
	(-2.238)				(-2.011)	
$d_LOG(1 + CFO_RELA_DEBT)$		0.001			0.001	
		(0.161)			(0.410)	
$d_LOG(1 + CEO_RELA_INCEN)$			-0.011			-0.008
			(-1.973)			(-1.509)
$d_LOG(1 + CFO_RELA_INCEN)$				0		0.002
				(0.054)		(0.473)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	3243	3243	3243	3243	3243	3243

Table 4.6: Robustness of CEO and CFO Inside Debt to Intangible Intensity

This table reports the estimation results of the robustness test of baseline regression model in Eq. (4.13). The measures of intangible intensity is *RKROTAYR*. *RKROTAYR* is the relative rank of *ADJROTA* defined in 4.3.2 over each year instead of the whold sample. Control variables include *SIZE*, the natural logarithm of total assets; *MVBV*, the market-to-book ratio; *LEVERAGE*, the ratio of total liabilities to total equity; *ROA*, the return on assets; *Q*, Tobin's Q; and *CAPEX*, the ratio of capital expenditures to total assets; *MARKET_RETURN*, the average market stock return; *MARKET_STD*, the standard deviation of the market's annual returns. CEO- and CFO-specific characteristics are also included: *CEO_POWER* and *CFO_POWER* are dummy for CEO or CFO being powerful in the board; *CEO_AGE* and *CFO_AGE* are the age of the CEO and CFO; *CEO_TENURE* and *CFO_TENURE* are their firm tenure; *LOG*(*CEO_DELTA*) and *LOG*(*CFO_DELTA*) are the logarithm of option delta; *LOG*(*CEO_VEGA*) and *LOG*(*CFO_VEGA*) are the logarithm of option vega; *CEO_GENDER* and *CFO_GENDER* are indicator variables equal to 1 if the CEO or CFO is female and 0 otherwise. Governance and external control variables include *CEO_HORIZON* and *CFO_HORIZON*, defined as the expected number of years until the CEO or CFO reaches the age of 65; *BOARD_AUDIT_COMMITTEE* and *BOARD_COMPENSATION_COMMITTEE*, indicator variables for the existence of board audit and compensation committees; *BOARD_DIVERSITY*, the proportion of female directors; *BOARD_INDEPENDENCE*, the proportion of independent directors; *BOARD_SIZE*, the total number of directors; *SOCIAL_CAPITAL*, the number of external board members; *NUM_OF_ANALYSTS*, the number of analysts following; *ESG_RATING*, the firm's ESG score; and *S&P_CATEGORY*, an indicator equal to 1 if the firm has an investment-grade rating (BBB− or above) and 0 otherwise. The measurements for CEO and CFO inside debt holdings are: *LOG*(*1 + CEO_RELA_DEBT*) and *LOG*(*1 + CEO_RELA_DEBT*) are the logarithm of one plus relative CEO- and CFO-debt-ratio. *LOG*(*1 + CEO_RELA_INCEN*) and *LOG*(*1 + CEO_RELA_INCEN*) are the logarithm of one plus relative CEO- and CFO-incentive-ratio. See Section 4.3.1 for a detailed description of the inside debt holding measures. Columns (1)–(2) report the estimation results for models with either *LOG*(*1 + CEO_RELA_DEBT*) or *LOG*(*1 + CFO_RELA_DEBT*), and column (5) with both included. Columns (3)–(4) report the estimation results for models with either *LOG*(*1 + CEO_RELA_INCEN*) or *LOG*(*1 + CFO_RELA_INCEN*), and column (6) with both included. Year fixed and industry fixed effects are included. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	RKROTAYR	*RKROTAYR*	*RKROTAYR*	*RKROTAYR*	*RKROTAYR*	*RKROTAYR*
SIZE	0.012	0.007	0.011	0.006	0.009	0.008
	(0.719)	(0.449)	(0.671)	(0.405)	(0.526)	(0.472)
MVBV	-0.006	-0.006	-0.006	-0.007	-0.007	-0.007
	(-1.418)	(-1.299)	(-1.423)	(-1.333)	(-1.371)	(-1.384)
LEVERAGE	-0.001	0.001	-0.001	0.001	0	0
	(-0.464)	(0.295)	(-0.448)	(0.290)	(0.005)	(0.017)
ROA	0.118***	0.116***	0.118***	0.116***	0.117***	0.117***
	(10.671)	(11.268)	(10.636)	(11.249)	(10.894)	(10.845)
Q	0.019*	0.020**	0.019*	0.020**	0.018*	0.018*
	(1.777)	(2.051)	(1.748)	(2.049)	(1.729)	(1.701)
CAPEX	-0.073***	-0.070***	-0.073***	-0.070***	-0.074***	-0.074***
	(-7.292)	(-7.449)	(-7.322)	(-7.478)	(-7.255)	(-7.290)
MARKET_RETURN	0.001	-0.006	0.001	-0.006	-0.003	-0.003
	(0.102)	(-0.884)	(0.138)	(-0.839)	(-0.414)	(-0.364)
MARKET_STD	-0.023***	-0.018**	-0.022**	-0.018**	-0.023**	-0.022**
	(-2.612)	(-2.052)	(-2.530)	(-2.008)	(-2.425)	(-2.337)
SOCIAL_CAPITAL	-0.005	-0.002	-0.005	-0.002	-0.004	-0.004
	(-0.881)	(-0.326)	(-0.864)	(-0.329)	(-0.740)	(-0.754)
BOARD_SIZE	-0.007	-0.008	-0.007	-0.008	-0.007	-0.008
	(-0.899)	(-0.995)	(-0.934)	(-1.014)	(-0.881)	(-0.913)
BOARD_DIVERSITY	-0.005	0.004	-0.005	0.003	-0.003	-0.003

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Table 4.6 – continued

	(1)	(2)	(3)	(4)	(5)	(6)
	RKROTAYR	*RKROTAYR*	*RKROTAYR*	*RKROTAYR*	*RKROTAYR*	*RKROTAYR*
	(-0.608)	(0.470)	(-0.603)	(0.452)	(-0.417)	(-0.432)
BOARD_-COMPENSATION_-COMMITTEE	-0.002	-0.001	-0.002	-0.001	-0.002	-0.002
	(-0.388)	(-0.265)	(-0.393)	(-0.266)	(-0.414)	(-0.437)
BOARD_AUDIT_COMMITTEE	0.001	0.003	0.001	0.003	0.005	0.005
	(0.317)	(0.885)	(0.335)	(0.876)	(0.998)	(1.009)
BOARD_INDEPENDENCE	-0.011	-0.009	-0.011	-0.010	-0.012	-0.012
	(-1.353)	(-1.121)	(-1.378)	(-1.137)	(-1.337)	(-1.346)
NUM_OF_ANALYSTS	0.003	0.002	0.003	0.002	0.001	0.001
	(0.528)	(0.381)	(0.527)	(0.385)	(0.178)	(0.186)
ESG_RATING	0	0	0	0	0	0
	(-0.595)	(-0.510)	(-0.593)	(-0.493)	(-0.382)	(-0.372)
S&P_CATEGORY	0.062***	0.072***	0.062***	0.072***	0.071***	0.071***
	(2.834)	(3.208)	(2.844)	(3.195)	(3.087)	(3.077)
LOG_CEO_AGE	-0.008		-0.008		-0.006	-0.006
	(-1.013)		(-0.987)		(-0.759)	(-0.740)
LOG_CEO_TENURE	0.003		0.003		0.003	0.003
	(0.362)		(0.406)		(0.272)	(0.340)
LOG_CEO_HORIZON	-0.005		-0.005		-0.004	-0.004
	(-0.500)		(-0.496)		(-0.415)	(-0.444)
CEO_GENDER	0.009		0.008		-0.021	-0.021
	(0.714)		(0.664)		(-1.249)	(-1.252)
LOG_CEO_DELTA	-0.010*		-0.010*		-0.01	-0.01
	(-1.828)		(-1.869)		(-0.962)	(-0.980)
LOG_CEO_VEGA	0.014		0.014		-0.005	-0.005
	(0.508)		(0.503)		(-0.175)	(-0.184)
CEO_POWER	0.013		0.013		-0.006	-0.007
	(0.483)		(0.478)		(-0.219)	(-0.226)
LOG_CFO_AGE		-0.020**		-0.019**	-0.019**	-0.019*
		(-2.095)		(-2.047)	(-1.989)	(-1.915)
LOG_CFO_TENURE		0		0	-0.003	-0.003
		(0.012)		(0.018)	(-0.329)	(-0.318)
LOG_CFO_HORIZON		0.005		0.005	0.011**	0.011**
		(0.959)		(0.971)	(2.151)	(2.136)
CFO_GENDER		0.027		0.029	0.025	0.027
		(1.133)		(1.215)	(0.717)	(0.774)
LOG_CFO_DELTA		0.035***		0.035***	0.047***	0.047***
		(3.886)		(3.844)	(3.699)	(3.645)
LOG_CFO_VEGA		-0.010*		-0.010*	-0.003	-0.003
		(-1.800)		(-1.842)	(-0.298)	(-0.315)
CFO_POWER		-0.016		-0.016	-0.010	-0.010
		(-0.455)		(-0.458)	(-0.256)	(-0.254)
LOG(1 + CEO_RELA_DEBT)	-0.017**				-0.016**	
	(-2.483)				(-2.028)	
LOG(1 + CFO_RELA_DEBT)		-0.012*			-0.002	
		(-1.837)			(-0.311)	
LOG(1 + CEO_RELA_INCEN)			-0.018**			-0.014*
			(-2.550)			(-1.818)
LOG(1 + CFO_RELA_INCEN)				-0.013**		-0.005
				(-2.045)		(-0.729)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Cluster	Y	Y	Y	Y	Y	Y
Observations	2,311	2,229	2,311	2,229	2,019	2,019
R-squared	0.600	0.610	0.601	0.611	0.616	0.617

t-statistics in parentheses. Standard errors clustered at firm level.
*, **, *** indicate significance at the 10%, 5%, and 1% levels.

Table 4.7: Stage II Instrumental Variable Methods for Robustness Tests

This table reports the estimation results of robustness tests of the second stage regression model in Eq. (4.16),Eq. (4.17) and Eq. (4.18). The measures of intangible intensity is *RKROTAYR*. *RKROTAYR* is the relative rank of *ADJROTA* defined in 4.3.2 over each year instead of the whold sample. for a detailed description of the intangible intensity measures. Control variables include *SIZE*, the natural logarithm of total assets; *MVBV*, the market-to-book ratio; *LEVERAGE*, the ratio of total liabilities to total equity; *ROA*, the return on assets; *Q*, Tobin's Q; and *CAPEX*, the ratio of capital expenditures to total assets; *MARKET_RETURN*, the average market stock return; *MARKET_STD*, the standard deviation of the market's annual returns. CEO- and CFO-specific characteristics are also included: *CEO_POWER* and *CFO_POWER* are dummy for CEO or CFO being powerful in the board; *CEO_AGE* and *CFO_AGE* are the age of the CEO and CFO; *CEO_TENURE* and *CFO_TENURE* are their firm tenure; *LOG*(*CEO_DELTA*) and *LOG*(*CFO_DELTA*) are the logarithm of option delta; *LOG*(*CEO_VEGA*) and *LOG*(*CFO_VEGA*) are the logarithm of option vega; *CEO_GENDER* and *CFO_GENDER* are indicator variables equal to 1 if the CEO or CFO is female and 0 otherwise. Governance and external control variables include *CEO_HORIZON* and *CFO_HORIZON*, defined as the expected number of years until the CEO or CFO reaches the age of 65; *BOARD_AUDIT_COMMITTEE* and *BOARD_COMPENSATION_COMMITTEE*, indicator variables for the existence of board audit and compensation committees; *BOARD_DIVERSITY*, the proportion of female directors; *BOARD_INDEPENDENCE*, the proportion of independent directors; *BOARD_SIZE*, the total number of directors; *SOCIAL_CAPITAL*, the number of external board members; *NUM_OF_ANALYSTS*, the number of analysts following; *ESG_RATING*, the firm's ESG score; and *S&P_CATEGORY*, an indicator equal to 1 if the firm has an investment-grade rating (BBB− or above) and 0 otherwise. The measurements for CEO and CFO inside debt holdings are: *INS_LOG*(*1 + CEO_RELA_DEBT*) and *INS_LOG*(*1 + CEO_RELA_DEBT*) are the estimated measurement using instrumental variables of logarithm of one plus relative CEO- and CFO-debt-ratio. *INS_LOG*(*1 + CEO_RELA_INCEN*) and *INS_LOG*(*1 + CEO_RELA_INCEN*) are the estimated measurement using instrumental variables of the logarithm of one plus relative CEO- and CFO-incentive-ratio. See Section 4.3.3 for a detailed description of the instrumental variables. Columns (1)–(2) report the estimation results for models with either *LOG*(*1 + CEO_RELA_DEBT*) or *LOG*(*1 + CFO_RELA_DEBT*), and column (5) with both included. Columns (3)–(4) report the estimation results for models with either *LOG*(*1 + CEO_RELA_INCEN*) or *LOG*(*1 + CFO_RELA_INCEN*), and column (6) with both included. Year fixed and industry fixed effects are included. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	RKROTAYR	*RKROTAYR*	*RKROTAYR*	*RKROTAYR*	*RKROTAYR*	*RKROTAYR*
SIZE	0.018*	0.014	0.014	0.011	0.016	0.011
	(1.744)	(1.411)	(1.366)	(1.068)	(1.439)	(1.037)
MVBV	-0.007*	-0.008*	-0.007*	-0.008*	-0.008*	-0.008*
	(-1.661)	(-1.660)	(-1.699)	(-1.834)	(-1.649)	(-1.802)
LEVERAGE	-0.004	0	-0.004	0	-0.002	-0.001
	(-1.015)	(-0.059)	(-0.833)	(-0.020)	(-0.421)	(-0.254)
ROA	0.136***	0.130***	0.134***	0.129***	0.135***	0.133***
	(17.733)	(18.511)	(17.742)	(18.345)	(17.414)	(17.489)
Q	0.021***	0.023***	0.020***	0.023***	0.020***	0.019**
	(2.888)	(3.306)	(2.705)	(3.267)	(2.684)	(2.575)
CAPEX	-0.072***	-0.067***	-0.073***	-0.067***	-0.072***	-0.073***
	(-10.275)	(-9.388)	(-10.564)	(-9.540)	(-9.695)	(-9.885)
MARKET_RETURN	-0.001	-0.009	0	-0.008	-0.005	-0.004
	(-0.157)	(-1.358)	(-0.067)	(-1.146)	(-0.784)	(-0.620)
MARKET_STD	-0.028***	-0.021**	-0.024***	-0.019**	-0.027***	-0.023***
	(-3.468)	(-2.541)	(-3.148)	(-2.295)	(-3.083)	(-2.707)
SOCIAL_CAPITAL	-0.003	-0.002	-0.003	-0.002	-0.004	-0.005
	(-0.710)	(-0.550)	(-0.732)	(-0.562)	(-0.895)	(-1.025)

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Table 4.7 – continued

	(1)	(2)	(3)	(4)	(5)	(6)
	RKROTAYR	*RKROTAYR*	*RKROTAYR*	*RKROTAYR*	*RKROTAYR*	*RKROTAYR*
BOARD_SIZE	-0.001	-0.003	-0.002	-0.004	0	-0.002
	(-0.096)	(-0.547)	(-0.433)	(-0.714)	(-0.053)	(-0.334)
BOARD_DIVERSITY	-0.002	0.004	-0.003	0.003	-0.003	-0.004
	(-0.403)	(0.665)	(-0.471)	(0.520)	(-0.468)	(-0.650)
BOARD_COMPENSATION_-COMMITTEE	-0.003	-0.004	-0.003	-0.004	-0.005	-0.005
	(-0.762)	(-0.925)	(-0.705)	(-0.883)	(-1.096)	(-1.121)
BOARD_INDEPENDENCE	-0.008	-0.008	-0.009*	-0.009*	-0.008	-0.009
	(-1.498)	(-1.614)	(-1.726)	(-1.722)	(-1.520)	(-1.614)
BOARD_AUDIT_COMMITTEE	0	0.003	0	0.002	0.004	0.004
	(0.073)	(0.657)	(0.121)	(0.578)	(0.851)	(0.839)
NUM_OF_ANALYSTS	0.002	0.003	0.002	0.003	0.001	0.001
	(0.485)	(0.539)	(0.504)	(0.564)	(0.145)	(0.205)
ESG_RATING	0	0	0	0	0	0
	(-0.392)	(0.003)	(-0.449)	(0.097)	(0.080)	(0.145)
S&P_CATEGORY	0.066***	0.075***	0.066***	0.074***	0.074***	0.073***
	(5.355)	(6.066)	(5.387)	(5.998)	(5.630)	(5.544)
LOG_CEO_AGE	-0.003		-0.003		-0.001	-0.001
	(-0.553)		(-0.579)		(-0.204)	(-0.209)
LOG_CEO_TENURE	0		0.002		0.002	0.004
	(-0.012)		(0.309)		(0.268)	(0.586)
CEO_HORIZON	-0.004		-0.004		-0.006	-0.008
	(-0.747)		(-0.756)		(-0.869)	(-1.060)
CEO_GENDER	0.152		0.171		0.016	0.017
	(0.720)		(0.083)		(0.251)	(0.612)
LOG_CEO_DELTA	0.007		0.006		-0.020*	-0.020*
	(1.020)		(0.809)		(-1.806)	(-1.817)
LOG_CEO_VEGA	-0.007		-0.009*		-0.008	-0.009
	(-1.610)		(-1.923)		(-0.984)	(-1.112)
CEO_POWER	0.017		0.016		0.001	-0.001
	(0.714)		(0.675)		(0.039)	(-0.030)
LOG_CFO_AGE		-0.011*		-0.009	-0.013*	-0.01
		(-1.657)		(-1.242)	(-1.760)	(-1.290)
LOG_CFO_TENURE		0.003		0.003	0	0
		(0.485)		(0.495)	(-0.041)	(0.008)
CFO_HORIZON		0.005		0.005	0.012***	0.011**
		(1.234)		(1.324)	(2.592)	(2.556)
CFO_GENDER		0.12		0.123	0.11	0.117
		(0.486)		(0.498)	(0.446)	(0.478)
LOG_CFO_DELTA		0.032***		0.031***	0.044***	0.043***
		(4.758)		(4.480)	(4.384)	(4.223)
LOG_CFO_VEGA		-0.008		-0.009*	-0.003	-0.004
		(-1.636)		(-1.872)	(-0.404)	(-0.530)
CFO_POWER		-0.002		-0.003	-0.003	-0.003
		(-0.036)		(-0.065)	(-0.069)	(-0.060)
INS_LOG(1+CEO_RELA_-DEBT)	-0.066***				-0.04	
	(-3.053)				(-1.132)	
INS_LOG(1+CFO_RELA_-DEBT)		-0.057***			-0.032	
		(-2.826)			(-0.958)	
INS_LOG(1+CEO_RELA_-INCEN)			-0.059**			-0.029
			(-2.562)			(-0.806)
INS_LOG(1+CFO_RELA_-INCEN)				-0.061***		-0.044
				(-2.616)		(-1.232)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Cluster	Y	Y	Y	Y	Y	Y
Observations	2,217	2,134	2,217	2,134	1,933	1,933
R-squared	0.573	0.586	0.579	0.585	0.586	0.588
Cragg Donald Wald F stat	25.310	27.648	22.118	20.385	11.972	11.973
Critical Value (10%)	10.27	10.27	10.27	10.27	10.27	10.27

t-statistics in parentheses. Standard errors clustered at firm level.
*, **, *** indicate significance at the 10%, 5%, and 1% levels.

Table 4.8: Robustness Test: Results of Changes in Variables for CEO and CFO Inside Debt on Intangible Intensity

This table reports the estimation results of the quantile regression results of robustness test of change-in-variable model in Eq. (4.19), Eq. (4.20) and Eq. (4.21). The measures of intangible intensity is *RKROTAYR*. *RKROTAYR* is the relative rank of *ADJROTA* defined in 4.3.2, and dependent variable *d_RKROTAYR* is the first difference of *RKROTAYR*. Panel A reports the results of median regression which is quantile regression with quantile of 50%. Panel B reports the results of quantile regression with quantile of 25%. Panel C reports the results of quantile regression with quantile of 75%. This table only reports the parameter and t-statistics of variables of interest. The measures of first difference of intangible intensity along time period is *d_RKROTA*. See Section 4.3.2 for a detailed description of the intangible intensity measures. The measurements for CEO and CFO inside debt holdings are: $d_LOG(1 + CEO_RELA_DEBT)$ and $d_LOG(1 + CEO_RELA_DEBT)$ are the first difference of logarithm of one plus relative CEO- and CFO-debt-ratio. $d_LOG(1 + CEO_RELA_INCEN)$ and $d_LOG(1 + CEO_RELA_INCEN)$ are the first difference of the logarithm of one plus relative CEO- and CFO-incentive-ratio. See Section 4.3.3 for a detailed description of the instrumental variables. Columns (1)–(2) report the estimation results for models with either $LOG(1 + CEO_RELA_DEBT)$ or $LOG(1 + CFO_RELA_DEBT)$, and column (5) with both included. Columns (3)–(4) report the estimation results for models with either $LOG(1 + CEO_RELA_INCEN)$ or $LOG(1 + CFO_RELA_INCEN)$, and column (6) with both included. Year fixed and industry fixed effects are included. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	d_RKROTAYR	*d_RKROTAYR*	*d_RKROTAYR*	*d_RKROTAYR*	*d_RKROTAYR*	*d_RKROTAYR*
Panel A: Median Regression						
d_LOG(1 + CEO_RELA_DEBT)	-0.008*				-0.008**	
	(-3.056)				(-3.017)	
d_LOG(1 + CFO_RELA_DEBT)		-0.003			0	
		(-1.054)			(0.081)	
d_LOG(1 + CEO_RELA_INCEN)			-0.009*			-0.009**
			(-2.396)			(-2.534)
d_LOG(1 + CFO_RELA_INCEN)				-0.004		0.000
				(-1.410)		(0.106)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	3243	3243	3243	3243	3243	3243
Panel B: 25% Regression						
d_LOG(1 + CEO_RELA_DEBT)	-0.001				-0.005	
	(-0.243)				(-0.729)	
d_LOG(1 + CFO_RELA_DEBT)		0.005*			0.006*	
		(1.688)			(1.700)	
d_LOG(1 + CEO_RELA_INCEN)			-0.004			-0.007
			(-0.728)			(-1.066)
d_LOG(1 + CFO_RELA_INCEN)				0.005		0.007*
				(1.529)		(1.691)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	3243	3243	3243	3243	3243	3243
Panel C: 75% Regression						
d_LOG(1 + CEO_RELA_DEBT)	-0.007				-0.009	
	(-1.141)				-(-1.365)	
d_LOG(1 + CFO_RELA_DEBT)		0.001			0.004	
		(0.203)			(0.850)	
d_LOG(1 + CEO_RELA_INCEN)			-0.011			-0.011
			(-1.433)			(-1.380)
d_LOG(1 + CFO_RELA_INCEN)				-0.002		0.004
				(-0.424)		(0.817)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	3243	3243	3243	3243	3243	3243

Table 4.9: Robustness of CEO and CFO Inside Debt to Bid-Ask Spread

This table reports the estimation results of the robustness test of baseline regression model in Eq. (4.13). The measures of credit spread is *SPREAD*. *SPREAD* is the relative rank of *ADJROTA* defined in 4.3.2 over each year instead of the whold sample. Control variables include *SIZE*, the natural logarithm of total assets; *MVBV*, the market-to-book ratio; *LEVERAGE*, the ratio of total liabilities to total equity; *ROA*, the return on assets; *Q*, Tobin's Q; and *CAPEX*, the ratio of capital expenditures to total assets; *MARKET_RETURN*, the average market stock return; *MARKET_STD*, the standard deviation of the market's annual returns. CEO- and CFO-specific characteristics are also included: *CEO_POWER* and *CFO_POWER* are dummy for CEO or CFO being powerful in the board; *CEO_AGE* and *CFO_AGE* are the age of the CEO and CFO; *CEO_TENURE* and *CFO_TENURE* are their firm tenure; *LOG*(*CEO_DELTA*) and *LOG*(*CFO_DELTA*) are the logarithm of option delta; *LOG*(*CEO_VEGA*) and *LOG*(*CFO_VEGA*) are the logarithm of option vega; *CEO_GENDER* and *CFO_GENDER* are indicator variables equal to 1 if the CEO or CFO is female and 0 otherwise. Governance and external control variables include *CEO_HORIZON* and *CFO_HORIZON*, defined as the expected number of years until the CEO or CFO reaches the age of 65; *BOARD_AUDIT_COMMITTEE* and *BOARD_COMPENSATION_COMMITTEE*, indicator variables for the existence of board audit and compensation committees; *BOARD_DIVERSITY*, the proportion of female directors; *BOARD_INDEPENDENCE*, the proportion of independent directors; *BOARD_SIZE*, the total number of directors; *SOCIAL_CAPITAL*, the number of external board members; *NUM_OF_ANALYSTS*, the number of analysts following; *ESG_RATING*, the firm's ESG score; and *S&P_CATEGORY*, an indicator equal to 1 if the firm has an investment-grade rating (BBB− or above) and 0 otherwise. The measurements for CEO and CFO inside debt holdings are: *LOG*(*1 + CEO_RELA_DEBT*) and *LOG*(*1 + CEO_RELA_DEBT*) are the logarithm of one plus relative CEO- and CFO-debt-ratio. *LOG*(*1 + CEO_RELA_INCEN*) and *LOG*(*1 + CEO_RELA_INCEN*) are the logarithm of one plus relative CEO- and CFO-incentive-ratio. See Section 4.3.1 for a detailed description of the inside debt holding measures. Columns (1)–(2) report the estimation results for models with either *LOG*(*1 + CEO_RELA_DEBT*) or *LOG*(*1 + CFO_RELA_DEBT*), and column (5) with both included. Columns (3)–(4) report the estimation results for models with either *LOG*(*1 + CEO_RELA_INCEN*) or *LOG*(*1 + CFO_RELA_INCEN*), and column (6) with both included. Year fixed and industry fixed effects are included. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	SPREAD	*SPREAD*	*SPREAD*	*SPREAD*	*SPREAD*	*SPREAD*
SIZE	-0.221***	-0.238***	-0.222***	-0.239***	-0.227***	-0.228***
	(-11.337)	(-6.407)	(-5.552)	(-6.422)	(-5.383)	(-5.421)
MVBV	-0.014*	-0.014*	-0.014*	-0.014*	-0.013	-0.014
	(-1.690)	(-1.836)	(-1.755)	(-1.873)	(-1.487)	(-1.529)
LEVERAGE	0.019**	0.015	0.019	0.015	0.016	0.016
	(2.364)	(0.985)	(1.563)	(0.984)	(0.917)	(0.919)
ROA	-0.088***	-0.072***	-0.088***	-0.072***	-0.073***	-0.073***
	(-7.265)	(-2.912)	(-3.514)	(-2.914)	(-3.214)	(-3.187)
Q	-0.021	-0.025	-0.021	-0.025	-0.024	-0.024
	(-1.493)	(-0.994)	(-0.809)	(-0.994)	(-0.999)	(-1.010)
CAPEX	-0.012	-0.022	-0.012	-0.022	-0.022	-0.022
	(-0.875)	(-1.138)	(-0.569)	(-1.150)	(-1.132)	(-1.155)
MARKET_RETURN	-0.032***	-0.027***	-0.031***	-0.027***	-0.019*	-0.019*
	(-3.971)	(-2.681)	(-3.592)	(-2.666)	(-1.885)	(-1.864)

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Table 4.9 – continued

	(1)	(2)	(3)	(4)	(5)	(6)
	SPREAD	*SPREAD*	*SPREAD*	*SPREAD*	*SPREAD*	*SPREAD*
MARKET_STD	0.053***	0.050***	0.052***	0.049***	0.038**	0.036*
	(3.464)	(3.202)	(3.377)	(3.089)	(2.021)	(1.898)
SOCIAL_CAPITAL	-0.01	-0.017	-0.01	-0.017	-0.016	-0.016
	(-1.254)	(-1.540)	(-0.817)	(-1.541)	(-1.134)	(-1.133)
BOARD_SIZE	0.007	-0.001	0.007	-0.001	0.001	0.001
	(0.710)	(-0.058)	(0.542)	(-0.073)	(0.053)	(0.036)
BOARD_DIVERSITY	-0.020*	-0.029**	-0.02	-0.030**	-0.030*	-0.030*
	(-1.918)	(-2.111)	(-1.317)	(-2.119)	(-1.701)	(-1.709)
BOARD_-COMPENSATION_-COMMITTEE	0.008	0.01	0.008	0.01	0.008	0.008
	(1.030)	(0.864)	(0.666)	(0.864)	(0.610)	(0.611)
BOARD_-INDEPENDENCE	-0.018*	-0.016	-0.018	-0.016	-0.017	-0.017
	(-1.880)	(-0.920)	(-1.211)	(-0.930)	(-0.849)	(-0.860)
BOARD_AUDIT_-COMMITTEE	-0.004	-0.017	-0.004	-0.017	-0.006	-0.006
	(-0.483)	(-0.916)	(-0.328)	(-0.920)	(-0.441)	(-0.445)
NUM_OF_ANALYSTS	0.002	0.003	0.002	0.003	0.005	0.005
	(0.167)	(0.192)	(0.107)	(0.196)	(0.360)	(0.362)
ESG_RATING	0	0.001	0	0.001	0.001	0.001
	(0.688)	(0.828)	(0.419)	(0.839)	(0.644)	(0.651)
S&P_CATEGORY	-0.067***	-0.072*	-0.067	-0.072*	-0.079	-0.079
	(-2.758)	(-1.850)	(-1.638)	(-1.853)	(-1.547)	(-1.551)
LOG_CEO_AGE	0.007		0.007		0.001	0.001
	(0.619)		(0.360)		(0.033)	(0.048)
LOG_CEO_TENURE	0.003		0.003		0.005	0.005
	(0.259)		(0.193)		(0.246)	(0.255)
LOG_CEO_HORIZON	0.001		0.002		-0.012	-0.012
	(0.130)		(0.077)		(-0.441)	(-0.450)
CEO_GENDER	-0.104**		-0.104**		-0.071	-0.071
	(-2.256)		(-2.017)		(-1.441)	(-1.449)
LOG_CEO_DELTA	-0.074***		-0.075***		-0.047	-0.047
	(-5.317)		(-2.853)		(-1.311)	(-1.324)
LOG_CEO_VEGA	0.018**		0.018**		-0.006	-0.006
	(2.055)		(2.122)		(-0.673)	(-0.666)
CEO_POWER	-0.106**		-0.107**		-0.076	-0.077
	(-2.308)		(-2.017)		(-1.475)	(-1.484)
LOG_CFO_AGE		0.018		0.019	0.014	0.015
		(1.087)		(1.119)	(0.641)	(0.668)
LOG_CFO_TENURE		-0.002		-0.002	-0.006	-0.006
		(-0.116)		(-0.114)	(-0.325)	(-0.326)
LOG_CFO_HORIZON		0.007		0.008	0.007	0.007
		(0.622)		(0.632)	(0.532)	(0.544)
CFO_GENDER		0.005		0.007	0.576***	0.573***
		(0.046)		(0.063)	(12.900)	(12.612)
LOG_CFO_DELTA		-0.064***		-0.065***	-0.029	-0.029
		(-2.688)		(-2.710)	(-0.983)	(-0.998)
LOG_CFO_VEGA		0.027**		0.027**	0.031**	0.031**
		(2.585)		(2.551)	(2.171)	(2.135)
CFO_POWER		0.023		0.023	0.039	0.039
		(0.223)		(0.221)	(0.347)	(0.343)
LOG(1+CEO_RELA_-DEBT)	-0.016**				-0.015*	

Continued on next page

Table 4.9 – continued

	(1)	(2)	(3)	(4)	(5)	(6)
	SPREAD	*SPREAD*	*SPREAD*	*SPREAD*	*SPREAD*	*SPREAD*
	(-2.472)				(-1.942)	
LOG(1+CFO_RELA_-DEBT)		-0.012*			-0.003	
		(-1.960)			(-0.456)	
LOG(1+CEO_RELA_-INCEN)			-0.017**			-0.013*
			(-2.509)			(-1.740)
LOG(1+CFO_RELA_-INCEN)				-0.013**		-0.006
				(-2.130)		(-0.830)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Cluster	Y	Y	Y	Y	Y	Y
Observations	2,311	2,229	2,311	2,229	2,019	2,019
R-squared	0.496	0.498	0.496	0.498	0.501	0.501

t-statistics in parentheses. Standard errors clustered at firm level.
*, **, *** indicate significance at the 10%, 5%, and 1% levels.

Chapter 5

Study Three – Economic Policy Uncertainty and Cross-Country Tail Risk

5.1 Introduction

Political regulations play a significant role in shaping the business environment for firms. Their influence stems not only from their impact on the domestic economy but also from their direct effect on corporate operations, such as varying tax regulations. Consequently, political regulations wield considerable influence over corporate governance and financial decision-making. Nonetheless, policy regulations are not always persistent, particularly during extreme events and external shocks, such as the unexpected Brexit of the UK, the surprising election success of Donald Trump in 2016, and the COVID-19 pandemic. These events have heightened global political and financial uncertainty, posing significant challenges for both managers and investors. For instance, the announcement on October 27, 2011, of the proposed Greek debt haircut raised the S&P 500 index by 3.4% and the French and German markets by over 5%, due to increased expectations of eurozone preservation. Market enthusiasm later fell when the Greek prime minister suggested holding a referendum on the deal, and rebounded when his opponent claimed the opposite. Such rapid market fluctuations provide direct evidence of how political uncertainty can shift investor sentiment. These observations underscore that political uncertainty is not merely episodic but systemic, with implications that transcend national borders.

Such uncertainty often arises from unpredictable changes in political and economic regulations, giving rise to the broader notion of Economic Policy Uncertainty (EPU) that has since become central in empirical research. While many illustrative cases originate in Europe, the underlying dynamics are not confined to a single region. Similar patterns of policy-induced market volatility and investor reactions can be observed in other major

economies, especially the United States, where political shocks and abrupt policy shifts have also generated significant financial turbulence. Pástor and Veronesi (2013) notes that political uncertainty has had a significant impact on the U.S. market, as evidenced by Standard & Poor's citing it as a major factor behind the downgrade of U.S. Treasury debt in August 2011. Rapid changes in U.S. policy-making, particularly following the global financial crisis of 2007–2008 and the surprising outcome of the 2016 U.S. presidential election, have amplified uncertainty. These U.S. experiences highlight that political shocks in large economies not only disrupt domestic markets but also serve as a source of contagion for the global financial system. Globalization further magnifies spillover effects: regional events, such as U.S. elections, can propagate worldwide, affecting international stock markets (Brogaard et al., 2020), while phenomena like the Arab Spring and Brexit demonstrate similar cross-border consequences. This motivates a growing literature that systematically explores the economic and financial consequences of policy-related uncertainty.

The growing realization that political uncertainty operates as a global phenomenon has prompted scholars to examine its economic manifestations more rigorously. In particular, the concept of Economic Policy Uncertainty (EPU) has emerged as a key framework for analyzing how uncertainty shapes investment and financial decision-making. Specifically, studies show that policy uncertainty discourages corporate investment because managers delay irreversible projects when future conditions are unclear (Gulen and Ion, 2016; Bernanke, 1983; Handley and Limao, 2015; Dixit and Pindyck, 1994; Marcus, 1981; Julio and Yook, 2012). At the international level, higher policy uncertainty reduces foreign direct investment, while firms increase their use of derivatives to hedge risks (Nguyen et al., 2018). EPU also raises information asymmetry and unethical behavior, as private firms

are more likely to evade taxes while state-owned firms may rely on bribery (Afzali et al., 2021). Policy uncertainty also has a dampening effect on M&A activities, as it reduces transaction volume, prolongs deal completion, and shifts payment structures from cash to stock (Nguyen and Phan, 2017). Similarly, dividend payout policies become more conservative under political crises, with dividend-paying firms suspending distributions and non-dividend firms delaying initiation (Huang et al., 2015). Policy uncertainty also shapes financing choices: firms rely more heavily on bank loans when public debt markets become less attractive (Ben-Nasr et al., 2020). At the same time, banks themselves reduce lending in response to rising EPU, especially those with higher risk profiles, though prudential regulation can moderate this effect (Hu and Gong, 2019). Finally, firms respond to heightened uncertainty by hoarding cash as a precautionary measure, particularly in emerging economies (Demir and Ersan, 2017).

Because EPU varies at the country level, firm-level responses to policy uncertainty often move in concert, producing market-wide co-movements. Therefore, causal effects of policy uncertainty are observed globally on macroeconomic outcomes, raising growing concerns. For example, policy uncertainty has been shown to increase unemployment rates, as firms delay hiring during periods of uncertainty (Shoag and Veuger, 2016; Bloom, 2009). It also reduces domestic output by discouraging investment and consumption, leading to weaker economic activity (Jones and Olson, 2013). Similarly, persistent policy uncertainty lowers the ratio of real capital to GDP by depressing long-term capital formation and growth (Aizenman and Marion, 1993). In financial markets, EPU elevates stock price crash risk, as political events such as elections temporarily suppress negative news that later resurfaces abruptly (Li et al., 2018).

Building on the observed firm- and macro-level consequences of EPU, it is

essential to understand how these effects aggregate and propagate through financial markets. Economic Policy Uncertainty (EPU) operates at the national level, causing firm-level responses to synchronize and propagate into broader market dynamics. At the firm level, heightened uncertainty affects investment, financing, corporate control, dividend policies, and risk management, while at the macro level it depresses output, capital formation, and employment. These synchronized micro- and macro-level adjustments generate correlated exposures across the economy, amplifying market volatility and systemic risk. Theoretical frameworks in asset pricing, such as those by Pastor and Veronesi (2012) and Pástor and Veronesi (2013), formalize this mechanism by modeling political risk as a systematic factor that influences stock valuations and jump risk. In these models, the joint effect of policy uncertainty across firms increases the likelihood of abrupt market-wide movements, while investors demand compensation for bearing this systematic risk. Such frameworks provide a structural explanation for how EPU-induced firm and macro responses propagate through the financial system, affecting asset prices, volatility, and systemic risk.

At a more systematic level, predictable cycles in stock returns are observed around presidential elections (Allvine and O'Neill, 1980; Santa-Clara and Valkanov, 2003), with partisan effects on excess returns (Pastor and Veronesi, 2012; Pástor and Veronesi, 2013) and stronger risk premia during periods of high uncertainty (Li et al., 2016; Dzielinski, 2012). These patterns indicate that policy uncertainty shapes both cross-sectional and aggregate market outcomes, affecting expected returns, pricing of systematic risk, and investor behavior. Moreover, empirical evidence suggests that EPU can influence asset allocation decisions, with investors adjusting portfolios toward safer or hedged positions during periods of elevated uncertainty, further reinforcing co-movement across stocks and amplifying

market-level risk.

EPU also amplifies stock market volatility, with global spillovers transmitting shocks across countries and industries. Evidence shows that volatility responds sharply to uncertainty shocks (Liu and Zhang, 2015; Amengual and Xiu, 2018; Mei et al., 2018; Boutchkova et al., 2012), displays dynamic patterns across markets (Antonakakis et al., 2013), and is particularly pronounced during crises such as the COVID-19 pandemic (Albulescu, 2021). Cross-market and industry-level transmission of uncertainty has been documented (Su et al., 2019), highlighting the interconnectedness of modern financial systems. These findings demonstrate that firm-level and macro-level responses to policy uncertainty collectively generate systemic financial risk, affecting not only asset pricing and volatility but also market liquidity, hedging demand, and the synchronization of downside movements. Collectively, these empirical observations validate the theoretical mechanisms described by Pastor and Veronesi (2012) and Pástor and Veronesi (2013), confirming that policy-driven uncertainty is not merely a local phenomenon but a global determinant of market-wide risk and asset pricing dynamics.

Against this backdrop, it is crucial to clarify why this chapter emphasizes systematic (aggregate) tail risk rather than firm-level stock price crash risk, in contrast to other chapters of this study. Contemporary financial research increasingly recognizes two distinct dimensions of extreme downside risk exposure: systematic tail risk and firm-level crash risk. Although both phenomena manifest as severe negative returns, their origins, transmission mechanisms, and implications for financial stability differ fundamentally. Systematic tail risk originates from macroeconomic or policy-driven shocks with the potential to disrupt the entire financial system. These shocks include global recessions, geopolitical crises, or liquidity spirals that simultaneously affect broad asset classes. For example, during the 2008 finan-

cial crisis, correlated institutional failures created feedback loops in which forced asset liquidations depressed asset prices, which in turn triggered additional rounds of deleveraging across the banking sector. Similarly, the COVID-19 market collapse of March 2020 illustrates how initially localized selloffs escalated into an 18 trillion global equity rout as liquidity evaporated across asset classes. These dynamics reflect the "fat tails" in market return distributions and represent non-diversifiable systemic failures. By contrast, firm-level crash risk arises from idiosyncratic vulnerabilities, particularly the concealment of negative information, which generates asymmetric stock return distributions marked by frequent modest gains and infrequent but severe losses. Unlike systematic shocks, these episodes tend to be largely confined to the affected firm or sector.

Three key differences highlight the distinct economic nature of systematic tail risk and stock price crash risk. First, scope and contagion. Systematic tail risk affects the entire market because assets are correlated and institutions are interconnected. For example, during the COVID-19 market collapse in March 2020, what began as localized selloffs quickly turned into an 18-trillion-dollar global equity decline as liquidity dried up across asset classes. By definition, systematic tail risk is closely linked to systemic crises. In a broad market crash, all stocks lose value, but those with higher tail betas suffer more. During the 2008–09 financial crisis, high-tail-beta stocks lost about two to three times as much as low-tail-beta stocks. In contrast, stock price crash risk is mostly a firm-level phenomenon. Macroeconomic shocks, such as high inflation, sanctions, or other adverse trends, can increase the likelihood of firm-specific crashes, for example by encouraging managers to hoard bad news. However, measures of crash risk (like NCSKEW or DUVOL) mainly reflect residual, firm-specific variation, even during market downturns.

Second, diversifiability. Systematic tail risk cannot be easily reduced through diversification, because it is embedded in market-wide exposures. Firm-specific risks, including stock price crashes, tend to decrease when investors hold diversified portfolios, since the risks are idiosyncratic.

Third, measurement. Systematic tail risk is typically measured using extreme value techniques, tail beta calculations, or macroeconomic left-tail quantile regressions, such as GDP growth tail quantiles. Stock price crash risk, on the other hand, is measured with firm-level indicators, such as negative skewness of returns or the probability of earnings restatements. Systematic tail risk is directly affected by country-level economic conditions, because macro shocks, like GDP contractions, financial crises, or policy uncertainty, impact the entire market and increase the likelihood and severity of extreme losses. Stock price crash risk is influenced by these shocks only indirectly, to the extent that they change the environment in which firm-specific bad news is released or concealed.

Building on these distinctions, the empirical analysis in this chapter relies on country-level measures of systematic tail risk rather than firm-level crash risk indicators. This choice is motivated by the macroeconomic nature of the shocks under investigation. Economic policy uncertainty (EPU) operates primarily through fiscal, monetary, and regulatory channels, and its consequences unfold at the aggregate rather than firm-specific level (Bloom, 2009). Consequently, firm-level crash risk, which is often driven by governance failures or accounting irregularities, would introduce substantial idiosyncratic noise that obscures the policy-relevant transmission of uncertainty. In contrast, country-level systematic tail risk captures non-diversifiable downside exposure embedded in the entire market (Van Oordt and Zhou, 2016), which aligns conceptually with the macro-level character of EPU.

While firm-level political risk measures provide useful insights into cross-firm heterogeneity, they primarily reflect idiosyncratic shocks and do not capture the aggregate, market-wide effects of policy uncertainty that this chapter seeks to evaluate. Hassan et al. (2019) makes an important contribution by constructing the first firm-level political risk series from earnings-call transcripts, they also find that the average of their measure closely tracks the Economic Policy Uncertainty (EPU) measurement *BBD* index introduced by Baker et al. (2016), and concludes that the main advantage of firm-level data is in showing heterogeneity across firms and sectors. Since this study does not aim to explain why some firms are more vulnerable than others, but instead to evaluate how overall uncertainty affects financial system stability, the fact that firm-level averages converge to the *BBD* index is decisive. It shows that national EPU already captures the systematic policy uncertainty that matters for aggregate financial outcomes. Using firm-level measures here would mainly add idiosyncratic noise instead of improving the identification of systemic tail risk.

Moreover, country-level indicators enhance comparability across economies by mitigating firm-specific measurement biases related to disclosure standards or data availability. By focusing on aggregate tail risk, the analysis ensures that the results reflect systemic vulnerabilities to policy uncertainty, rather than idiosyncratic firm-level episodes that can be diversified away in cross-country portfolios.

Also, this approach is consistent with prior research practices. For example, Studies such as Dai et al. (2021) analyze the relationship between U.S. market-wide crash risk and EPU during the COVID-19 pandemic, explicitly focusing on the overall market using the S&P 500 index as a benchmark instead of examining firm-specific returns. Likewise, Chiu et al. (2015) underscores the role of tail dependence in amplifying market-wide co-movements

during extreme events, reinforcing the view that systemic downside risk should be evaluated at the market or country level. These precedents highlight that employing aggregate crash or tail risk measures has become a well-established and effective method for examining the macro-level effects of EPU.

Methodologically, this choice aligns with the design of Kelly and Jiang (2014), whose aggregate downside risk measure is specifically constructed to capture a common market-wide tail factor by pooling information across all listed firms. Applying their framework at the country level maintains consistency with its original purpose. In contrast, a firm-level implementation would diverge from the model's assumptions and fail to isolate the systemic component most relevant to macroeconomic shocks, such as economic policy uncertainty (EPU). Aggregate tail risk captures the systematic channel through which EPU operates, which operates via fiscal, monetary, and regulatory mechanisms, affecting macroeconomic expectations and investor sentiment at the country level, rather than firm-specific fundamentals (Bloom, 2009; Pastor and Veronesi, 2012; Pástor and Veronesi, 2013; Brogaard et al., 2020).

Finally, statistical stability and cross-country comparability further motivate the use of country-level aggregate tail risk. In a cross-country setting, constructing aggregate measures from all listed securities within each market provides a robust and comparable proxy for tail risk, reducing the influence of microstructure noise or firm-specific outliers. By pooling firm-level returns into a market-wide distribution, country-level tail risk offers a consistent metric to evaluate the impact of EPU across economies, enabling coherent analyses that distinguish between developed and emerging markets (Christou et al., 2017; Ko and Lee, 2015; Das and Kumar, 2018; Carrière-Swallow and Céspedes, 2013). In this way, systematic tail risk pro-

vides both economic relevance, as it captures market-wide fragility under policy uncertainty, and methodological robustness for cross-country empirical research.

Taken together, these arguments support the focus on aggregate measures in this chapter. By linking country-level EPU to systemic tail risk, this study directly addresses the goal of understanding financial fragility across countries in the face of global uncertainty. Firm-level measures remain valuable for corporate-finance research, but at the macro-financial level they largely collapse to country indices that better capture the systemic uncertainty at the heart of this analysis.

In order to test the hypothesis that Economic Policy Uncertainty (EPU) affects not only stock market returns but also left-tail risk at the cross-country level, a panel regression framework is employed. The baseline specification uses the *BBD* index as the Economic Policy Uncertainty measurement, introduced by Baker et al. (2016) and obtained from the public Economic Policy Uncertainty database, as the main explanatory variable. The regressions further control for country-specific economic characteristics, along with monthly and country-level fixed effects. The dependent variable, capturing time-varying tail risk, follows the measures developed by Kelly and Jiang (2012) and Kelly and Jiang (2014), which quantify extreme left-tail events in equity markets. This measure is constructed at the country level on a monthly basis by aggregating daily returns of all securities headquartered in the respective country, thereby reflecting market-wide tail risk rather than firm-specific events.

The baseline regression results indicate that the hypothesis, which states that EPU is positively related to financial market tail risk at the cross-country level, is significant across all three groups. To further verify the

robustness of this finding, alternative proxies for global EPU are employed in additional regressions. Given the prominent role of the U.S. in the global economy, U.S. EPU is expected to have spillover effects on other countries (He et al., 2020; Coronado et al., 2020; Istiak and Alam, 2020). Therefore, indicators representing one, three, and six months prior to U.S. election months are incorporated, based on the premise that concerns about potential policy changes increase as elections approach. The results remain robust for the overall sample, while some variation is observed across the developed and emerging market subgroups.

Beyond the baseline regressions with aggregate EPU, additional analyses are conducted using pandemic-related EPU and trade-related EPU indices to capture heterogeneity across different sources of policy uncertainty. These alternative measures allow the study to disentangle whether the left-tail risk effect is driven by specific forms of uncertainty (e.g., health crises or trade disruptions) rather than general macroeconomic policy uncertainty.

To strengthen the causal interpretation, an instrumental variable (IV) approach is further implemented, using political polarization as an instrument for EPU. Polarization, measured by indices of ideological distance, partisan fractionalization, or partisan conflict, has been shown to generate spikes in EPU, especially during highly contested elections. Importantly, polarization evolves gradually and remains largely unaffected by short-term economic shocks, thereby satisfying the exclusion restriction. Structurally, polarization influences EPU through its impact on policy predictability rather than directly affecting contemporaneous economic outcomes. This IV strategy is well-established in related literature. Empirical finance studies confirm these properties in practice. For example, researchers instrument U.S. tax-policy uncertainty with Senate partisan splits and report strong first-stage F-statistics and significant Two-Stage Least

Squares (2SLS) estimates, indicating the instrument's relevance and exclusion (Tosun and Yildiz, 2020). Likewise, work on environmental policy uncertainty uses variations in congressional climate-bill votes or ideological polarization to isolate exogenous EPU shocks (Benlemlih and Yavaş, 2024). In each case, the polarization-based IV yields a clean test of the causal effect: because it isolates truly exogenous uncertainty variation, the estimated impact of EPU on outcomes (such as asset tail risk) can be interpreted as a policy-driven causal effect rather than a spurious correlation.

The regression sample comprises data from 23 countries for the period from January 1985 to the present, consistent with the availability of EPU data. Preliminary analyses indicate a significant relationship between EPU and aggregate tail risk. As discussed previously, the impact of EPU may differ across countries, particularly between developed and emerging markets. To address this concern, the regression is conducted on three separate samples: the full sample including all observations, a subsample of developed countries, and a subsample of emerging markets.

This chapter contributes to the literature in several aspects. First, it expands research on EPU and its influence on financial markets. Previous works have established that EPU functions as a priced risk factor in option markets and predicts future stock market volatility; however, few studies have directly linked EPU to extreme market-wide events. Luo and Zhang (2020) examines the relationship between EPU and firm-level stock price crash risk, but the cross-country validity of this effect remains unclear. By analyzing EPU's effect at the country level and across different country groups, this chapter fills this gap, demonstrating its relevance for both developed and emerging markets. Second, the chapter advances the understanding of factors driving tail risk. Despite its importance, few studies have explored the determinants of time-varying tail risk. Leveraging the

aggregate tail risk measures of Kelly and Jiang (2012) and Kelly and Jiang (2014), which capture infrequent extreme events and aggregate the performance of all securities in each market, this study provides insights into the connection between policy uncertainty and unexpected financial events, offering both practical guidance for investors and theoretical contributions to academia.

The chapter is structured as follows. Section 5.2 reviews the relevant literature on EPU and tail risk, and proposes the chapter's hypotheses. Section 5.3 details the construction of variables and the methodology employed to test these hypotheses quantitatively. Section 5.4 presents summary statistics for the sample, followed by results and analysis of the baseline regressions, robustness checks using U.S. election-period indicators, the 2SLS regression results of instrumental variables method, and further investigations into the two specific channels of policy uncertainty. Finally, Section 5.5 provides a brief summary of the chapter's findings.

5.2 Literature Review

5.2.1 The Influence of Economic Policy Uncertainty

A large body of research has documented the causal effects of policy uncertainty on economic activity. According to business cycle theory, external shocks—including policy shocks—can induce fluctuations in the macroeconomy (Plosser, 1989). Consequently, policy uncertainty can affect the economy through multiple channels, such as investment, employment, and aggregate output.

Building on this theoretical foundation, several studies have empirically examined the impact of policy uncertainty on investment. Handley and Li-

mao (2015) finds that trade-related policy uncertainty influences firm-level investment decisions, while Dixit and Pindyck (1994) shows that managers tend to delay irreversible projects under uncertain policy conditions. Similarly, Bernanke (1983) documents that macroeconomic policy uncertainty discourages firms from committing to long-term capital expenditures. Policy uncertainty can also reduce innovation, as decision-makers may face greater difficulty in assessing the risks associated with R&D investments (Marcus, 1981).

Beyond investment, evidence from labor markets indicates that policy uncertainty can increase unemployment. Shoag and Veuger (2016) finds that state-level policy uncertainty in the U.S. contributed to higher unemployment during the 2007–2009 financial crisis. Policy uncertainty also negatively affects aggregate output: Jones and Olson (2013) demonstrates that uncertainty reduces U.S. domestic output, while Aizenman and Marion (1993) documents similar effects across 46 countries, showing a decline in real capital per GDP during 1970–1985.

To better understand these macroeconomic effects, a structural perspective provides further support. Analyzing major economic and political shocks, including the Cuban Missile Crisis, the assassination of JFK, the OPEC I oil-price shock, and the 9/11 terrorist attack, Bloom (2009) finds that policy uncertainty is associated with declines in employment and output over the six months following these events.

One observable source of policy uncertainty is presidential elections, which can generate shifts in expectations about future fiscal, monetary, and regulatory policies. Therefore, one stream of research has used presidential elections as a proxy for Economic Policy Uncertainty (EPU), given that elections are widely regarded as significant policy shocks, especially when

outcomes are unexpected. Niederhoffer et al. (1970) first develops a model to proxy business cycles, indicating that agents in different sectors tend to vote for distinct parties. Allvine and O'Neill (1980) documents the relationship between U.S. presidential elections and stock market returns over the period 1961–1978. Herbst and Slinkman (1984) examines the effects of political-economic cycles on the stock market based on election cycles.

Julio and Yook (2012) shows that policy uncertainty arising from national elections can introduce cycles in corporate investment. Similarly, Booth and Booth (2003) finds that presidential elections affect stock market returns, with returns generally higher in the last two years of a presidential term than in the first two years. Białkowski et al. (2008) demonstrates that national elections induce higher stock market volatility within a sample of 27 OECD countries. Li et al. (2018) finds that stock markets are less likely to crash during election years, but more likely to experience crashes in the post-election period, based on data from 1982–2012.

While presidential elections represent an observable source of policy uncertainty, they capture only a subset of potential policy-related shocks. To measure uncertainty more comprehensively, researchers have increasingly relied on the Economic Policy Uncertainty (EPU) index, denoted as the *BBD* index, developed by Baker et al. (2016). This news coverage-based measure systematically quantifies policy uncertainty and exhibits pronounced spikes around major events, such as closely contested U.S. presidential elections, the Gulf Wars I and II, the 9/11 attacks, and the failure of Lehman Brothers. Empirical studies using the *BBD* index show that elevated EPU increases firm-level stock price volatility, while also reducing corporate investment and domestic employment, capturing the broader economic consequences of policy uncertainty more effectively than single-event proxies.

The *BBD* index addresses concerns regarding reliability, accuracy, bias, and consistency. First, it shows a strong correlation with other measures of economic uncertainty, including implied volatility. Second, it aligns with alternative indicators, such as the frequency of policy-related mentions in the Federal Reserve System's Beige Books. Third, the index is robust to political slant, and fourth, its reliability has been confirmed through extensive audit studies, demonstrating high correlation between human- and computer-generated indices.

Numerous studies have corroborated the impact of *BBD* index on market participants' behavior. Gulen and Ion (2016) finds that *BBD* index negatively affects corporate investment at both firm and industry levels, accounting for approximately two-thirds of the 32% decline in investment observed during the 2007–2009 financial crisis, thereby significantly depressing U.S. economic growth. Nagar et al. (2019) shows that managerial decision-making is highly sensitive to *BBD* index, which is associated with widening bid-ask spreads and reduced stock price reactions to unexpected earnings announcements, amplifying information asymmetry. Similarly, Afzali et al. (2021) documents that, across multiple countries, high policy uncertainty is linked to increased corruption, including tax evasion and bribery.

Other studies have investigated how EPU affects firms through different corporate and financial channels. Nguyen and Phan (2017) examines the relationship between *BBD* index and M&A activity, while Nguyen et al. (2018) links it to firm-level foreign direct investment. Huang et al. (2015) investigates political risk's effect on dividend payout policy, Ben-Nasr et al. (2020) studies its influence on debt sourcing, Hu and Gong (2019) finds a negative effect on bank lending, and Demir and Ersan (2017) highlights the impact on corporate cash holdings in BRIC countries. Collectively,

these studies illustrate the pervasive influence of policy uncertainty across investment, corporate governance, and financial market outcomes.

From an asset pricing perspective, economic policy uncertainty (EPU) affects stock market performance by influencing investors' expectations of future cash flows and discount rates. Modern finance theory views stock market performance as the sum of the present value of all expected future dividends. Economic activities can influence market participants' expectations of future returns. Consequently, uncertain policymaking is likely to generate pessimistic expectations about future discount rates, which can lead to declines in stock market returns. Governments can also shape the business environment in multiple ways, including levying taxes, providing subsidies, enforcing laws, regulating competition, and defining environmental policies. These policy interventions are reflected in stock prices, especially when the changes are unanticipated (Pastor and Veronesi, 2012). Building on this, Pástor and Veronesi (2013) develops a theoretical model to analyze the relationship between stock prices, return volatility, and policy uncertainty.

Empirical studies have increasingly documented the link between policy uncertainty and stock market performance. Berkman et al. (2011) constructs a crisis index based on 447 international political crises to proxy for perceived disaster probability and finds substantial effects on both the mean and standard deviation of global stock market returns. Li et al. (2016) provides evidence from China and India showing that policy uncertainty influences stock market performance in both the short and long run. Using Google Search Volume Index (SVI) for the word "economy," Dzielinski (2012) finds that elevated economic uncertainty leads to sharp declines in stock returns.

Other research highlights the predictive power of policy uncertainty on market volatility. Liu and Zhang (2015) demonstrates this through a heterogeneous autoregressive realized volatility model. Amengual and Xiu (2018) shows that negative volatility jumps are correlated with the sudden resolution of unexpected political news. More recently, Rungmaitree et al. (2022) finds that political risk significantly reduces hedge fund returns, with the effect varying across different hedge fund strategies within G7 countries.

More specifically, research on economic policy uncertainty (EPU) and financial market volatility has a well-established tradition. Antonakakis et al. (2013) investigates the time-varying relationship between policy uncertainty, implied stock market volatility, and stock returns. The study finds that global oil price shocks and U.S. recessions have substantial effects on this relationship. Albulescu (2021) examines the impact of the COVID-19 pandemic on the realized volatility of the S&P 500, highlighting one of the most significant recent external shocks to the global economy. Mei et al. (2018) shows that the U.S. *BBD* index can predict European stock market volatility. Su et al. (2019) studies the spillover effect of U.S. policy uncertainty on the stock market volatility of six industrialized and three emerging countries, emphasizing its strong global influence. Boutchkova et al. (2012) further finds that both global and local policy uncertainty affect industry-level return volatility. Notably, uncertainty in major trading partners tends to generate particularly high volatility.

Moreover, an increasing number of studies on policy uncertainty now extend beyond the U.S. market and developed countries, focusing instead on its effects on global markets. Bekaert et al. (2016) evaluates global asset prices using "political risk spreads," derived from sovereign spreads and political risk ratings. Le and Zak (2006) examines the impact of three

types of political and economic risk on capital flight across a panel of 45 developing countries over a 16-year period. Chang et al. (2015) investigates the causal relationship between policy uncertainty and stock prices in seven OECD countries from 2000 to 2013, finding that the effect is not uniform across all countries. Liu et al. (2017) treats the Bo Xilai scandal as an exogenous political shock to the Chinese financial market and provides evidence for the existence of political stock risk. Białkowski et al. (2008) shows that elections increase stock market volatility in 27 OECD countries, with index return variance doubling during the week surrounding Election Day. Engelhardt et al. (2021) employs a sample of 47 countries to show that the exogenous shock from COVID-19 affected stock markets differently depending on societal trust and trust in government.

Another strand of research examines the spillover effects of EPU across countries, highlighting its global transmission. Kido (2018) demonstrates how U.S. policy uncertainty propagates to global equity and foreign exchange markets. Gong et al. (2022) analyzes EPU spillovers across 23 countries, employing the theory of global interdependence of policy uncertainty on stock returns. Christou et al. (2017) uses a panel VAR model to examine the role of EPU in seven Pacific Rim countries, while Li et al. (2020b) and Liang et al. (2020) document the spillover of U.S. policy uncertainty to Asian stock markets. Building on these findings, which underscore the potential global significance of Economic Policy Uncertainty, this chapter investigates the impact of policy-related economic uncertainty on all countries with accessible *BBD* index data from Baker et al. (2016).

5.2.2 Tail Risks

Tail risk refers to extreme conditions or events, often described as "low probability, but high impact" occurrences. In financial markets, tail risk is typically associated with extremely negative returns, which can produce exceptionally high utility losses for investors. Consequently, market participants are often willing to pay substantial costs to hedge against such extreme events. Tail risk represents an important feature of financial markets, and numerous studies have documented its relationship with asset pricing. Understanding how investors respond to rare disasters is therefore a central concern in finance. Economic uncertainty is generally regarded as a foundation for investors' confidence in available information; external economic shocks can imply a sudden loss of information, which in turn can generate increased market volatility and severe extreme events, that is, tail risk in financial markets.

The relationship between tail risk and asset pricing has been investigated for decades. Since Fama (1965) established tail risk as a critical feature of financial markets, researchers have proposed various theoretical frameworks to incorporate tail events into asset pricing. For instance, building on the safety-first principle of Telser (1955), Arzac and Bawa (1977) proposes an asset pricing theory that maximizes expected return under a Value-at-Risk (VaR) constraint, introducing an alternative tail "beta" to the traditional CAPM model. Several other methods have been developed to proxy tail risk. Ilhan et al. (2021) demonstrates that options can be used to hedge downside risk, while Bollerslev and Todorov (2014) utilizes a cross-section of short-maturity options to estimate time-varying risk-neutral jump tail risk, finding significant temporal dependencies for both distribution extremes in a panel of S&P 500 index options. Similarly, Bakshi et al. (2003)

employs skewness and kurtosis measures to capture the differential pricing of individual equity options relative to the market index. Bollerslev et al. (2009) estimates both implied and realized variance risk premiums as proxies for tail risk in a model-free framework, while Backus et al. (2011) links the distribution of extreme events to asset prices using equity option data to study tail risk effects. These approaches collectively illustrate the variety of methods available to quantify extreme events in financial markets.

Previous research has motivated this chapter to investigate the impact of policy uncertainty on stock market performance and extreme negative returns. It is widely recognized that investors are concerned about rare disasters and require compensation for bearing such risks in financial markets. This concern makes the study of left-tail risk particularly important. The significance of tail risk originates from two main factors. First, investors exhibit heterogeneous preferences in weighing losses against returns, which affects their risk-taking behavior and portfolio decisions. Second, empirical evidence indicates that security market returns often display fat-tailed distributions, meaning extreme losses occur more frequently than predicted by standard normal assumptions. These features have motivated extensive academic efforts to develop robust measurements of tail risk, particularly focusing on the market-wide, systematic components that cannot be easily diversified through large portfolios. Such measures are essential for understanding not only individual firm exposure but also aggregate market vulnerability to extreme shocks.

A major contribution in this area is provided by Bloom (2009), which offers a framework to analyze the impact of large, temporary uncertainty shocks on the entire economy. This study demonstrates that significant unexpected shocks can cause sharp declines in employment, output, and productivity growth, primarily through the effect on corporate hiring and

investment decisions. Importantly, this work establishes a channel for examining macroeconomic consequences via firm-level behavior, overcoming the difficulty of studying aggregate effects directly. Uncertainty shocks affect the economy at the market-wide level because of adjustment costs in capital and labor: when firms simultaneously reduce investment and hiring, aggregate economic activity declines, as reflected in lower output and productivity growth.

Building on this perspective, Gabaix (2011) proposes a mechanism in which idiosyncratic shocks to individual firms or industries can propagate and contribute to aggregate fluctuations in the economy. Inspired by this idea, Kelly and Jiang (2014) develops a framework that links the aggregation of firm-level tail risks to market-wide uncertainty. In this framework, extreme losses at the firm level can combine to generate systemic tail risk, capturing the broader impact of uncertainty on the market. This theoretical channel underpins the current chapter's investigation of how Economic Policy Uncertainty (EPU) affects market-wide tail risk across different countries. By connecting firm-level vulnerabilities to aggregate outcomes, the approach provides a clearer understanding of how policy-related shocks can trigger extreme negative returns in national stock markets.

A range of measurements has been developed to capture left-tail extreme events. Arzac and Bawa (1977) introduces a model in which investors maximize expected returns under VaR constraints. Bali and Cakici (2004) shows that factors such as VaR and firm-specific characteristics influence expected stock returns, confirming a positive relationship between VaR and market returns at the monthly level. Bollerslev and Todorov (2011b) constructs an Investor Fear Index and demonstrates its association with equity premia. While various studies have explored tail risk predictivity (Dierkes et al., 2024), this chapter prioritizes capturing the common components of

market-wide tail risk, rather than focusing solely on forecasting. Accordingly, the tail risk measurement from Kelly and Jiang (2012) and Kelly and Jiang (2014) is employed.

One challenge in measuring tail risk is the infrequency of extreme events, which makes standard volatility models, such as GARCH, inadequate. Kelly and Jiang (2012) and Kelly and Jiang (2014) address this problem by constructing a time-varying, market-wide tail risk measure that aggregates individual firm tail risks. This approach successfully captures the dynamics of heavy-tailed shocks across the stock market and has been shown to correlate positively with both excess returns and the cross-section of expected returns. Kelly and Jiang (2014) further demonstrates that aggregate market tail risk inherits the dynamics of individual assets, highlighting the importance of considering systemic components rather than firm-level tail risk alone.

Building on these theoretical and empirical foundations, this chapter applies the Kelly and Jiang (2012) and Kelly and Jiang (2014) methodology to measure the aggregate tail risk of stock markets across multiple countries. The analysis then investigates how the *BBD* index developed by Baker et al. (2016) influences market-wide tail risk at the country level, providing insights into the relationship between policy uncertainty and extreme negative returns in international financial markets.

Based on all the previous research, this chapter intends to make the following hypothesis:

Hypothesis 1 *Economy policy uncertainty is positively related to aggregate tail risk of the stock market, and this effect is significant among countries.*

5.3 Data, Variables, and Methodology

The sample employed in this study covers 23 countries, as described in Section 5.3.2, spanning the period from January 1985 to December 2022. This period corresponds to the availability of the *BBD* index provided by the Economic Policy Uncertainty website, and all available observations within this time period are included in the analysis. Daily return data for individual stocks are primarily obtained from the DataStream database, with the exception of U.S. stocks, for which data are sourced from the CRSP database. Macroeconomic variables and other country-level characteristics are collected from the International Monetary Fund (IMF), the World Bank, and the Organisation for Economic Co-operation and Development (OECD).

5.3.1 Dependent Variables

Rare disasters have been shown to play an important role in addressing several longstanding puzzles in asset pricing research. Rietz (1988) extends the framework of Lucas Jr (1978) and Mehra and Prescott (1985) by introducing a low-probability, depression-like "third state," referred to as a rare disaster state. This addition helps explain the observed high equity risk premia alongside the low risk-free rate, a phenomenon that standard models struggled to reconcile.

A key motivation for introducing rare disaster states into asset pricing models is their ability to help explain several longstanding puzzles in equity markets, particularly the unexpectedly high volatility of stock returns. This phenomenon has long attracted academic interest, with early studies linking it to the predictive ability of the price-dividend ratio for excess stock

returns (Fama and French, 1989; Cochrane, 1992; Keim and Stambaugh, 1986). According to this theory, excess returns are driven by realized cash flows, expected future cash flows such as dividends, and variations in the discount rate. Traditional models often attribute stock return volatility primarily to new information about future cash flows or changes in the discount rate. If the discount rate is indeed the main source of variation, it should manifest in the predictive relationship between excess returns and the price-dividend ratio.

The equity volatility puzzle poses a challenge to the predictions of the traditional consumption-based CAPM. Under the assumption of unlevered stock returns, the model predicts that stock return volatility should equal consumption volatility. However, empirical evidence consistently shows that stock market volatility is much higher than predicted.

Based on the framework of the consumption-based CAPM, the stochastic discount factor (SDF) is modeled as a parametric function of consumption growth, as future dividends are assumed to provide cash flows for consumption. This parametric specification treats the random walk component of consumption growth as i.i.d., implying that the volatility of consumption should equal the volatility of stock returns. However, empirical data show that stock return volatility is substantially higher than consumption volatility, even after accounting for leverage and dividend volatility.

Barro (2006) builds on this insight and extends the work of Lucas Jr (1978), Mehra and Prescott (1985), and Rietz (1988) by calibrating the magnitude and probability of rare economic disasters. In Barro's model, when the probability of rare disaster is held constant, the standard consumption-based inference remains, which states that consumption volatility matches stock return volatility, but this is inconsistent with observed twentieth-

century data. Empirically, stock return volatility far exceeds the prediction of the traditional model, exemplifying the equity volatility puzzle. To address this, Barro introduces a stochastic, persistent variation in the probability of rare disasters, combining a standard i.i.d. random walk with a disaster-related term that features time-varying disaster probabilities.

The introduction of stochastic and persistent variation in rare disaster probabilities relaxes the i.i.d. assumption for productivity shocks and extends the frameworks of Lucas Jr (1978), Mehra and Prescott (1985), and Rietz (1988). The findings indicate that assuming a constant disaster probability does little to address the equity volatility puzzle. In contrast, allowing disaster risk to fluctuate over time significantly increases stock return volatility, aligning theoretical predictions more closely with empirical evidence. This line of research has inspired subsequent empirical efforts to quantify time-varying disaster probabilities, which is a technically demanding yet essential step toward understanding stock market dynamics under extreme events.

The theoretical insight that time-varying probabilities of rare disasters can generate heightened stock return volatility naturally motivates empirical efforts to quantify market-level tail risk. In this vein, studies such as Kelly and Jiang (2012) and Kelly and Jiang (2014) develop methods to measure time-varying tail risk by aggregating cross-sectional information from individual stocks. Their approach assumes that the tail distributions of different firms share similar dynamics, allowing common components of tail risk to be extracted at the market level. A major advantage of this measurement is that it overcomes the challenge posed by the rarity of extreme events, which makes traditional proxies less reliable. By capturing the systematic component of tail risk, this methodology provides a practical foundation for studying the impact of extreme economic shocks on

financial markets.

This measurement is based on the assumption of power-law tail behavior in financial markets, as described in Eq. 5.1, a notion supported by extensive literature. Ample evidence indicates that the key parameter of the power law changes over time. This feature makes the approach effective for monitoring the time-series variation of tail risks. The measurement focuses on the reduced form of the tail distribution, which captures return events below a given extreme negative threshold u_t, consistent with the definition of tail risk. By emphasizing the commonality of tail events across individual assets, the method exploits relatively abundant cross-sectional information to estimate the probability of an overall market disaster from individual stock returns.

According to Gabaix (2016), power-law distributions are common not only in physics but also in economics. For example, firm sizes follow a power-law distribution, implying that economic activity is concentrated among a few large firms. This concentration is important because idiosyncratic shocks to large firms can easily propagate to other firms, generating market-wide effects. From a power-law perspective, trades by large institutions exert a price impact proportional to the square root of trade size. Empirical evidence shows that these institutions trade gradually to moderate such impacts, but when trading under time pressure, large trades can cause market declines or crashes.

The application of power-law distributions in economic activity helps explain both the drivers of market crashes and the connection between idiosyncratic shocks and aggregate tail risk. Kelly and Jiang (2014) identifies two mechanisms underlying this relationship. First, the power-law tails of individual firms remain stable under aggregation. As shown by Gabaix

(2009), aggregating power-law tails preserves their properties under addition, multiplication, polynomial transformations, and operations such as min and max. This stability allows measurements to capture market-wide extreme events by summarizing individual firm tails. Second, uncertainty shocks at the firm level can affect real economic outcomes, consistent with Bloom (2009). For example, increased uncertainty raises corporate costs, such as labor expenses, which may lead firms to postpone investment decisions. When many firms experience such shocks simultaneously, these effects propagate across the market, reducing aggregate outcomes including investment and employment. While Bloom (2009) emphasizes volatility effects, this mechanism also shows how firm-level shocks can inform market-wide tail risks.

Therefore, it is reasonable to use aggregate information from individual tails to capture the common dynamics of market-wide tail risk.

Finally, the tail distribution of asset returns in this framework is described by the following formula:

$$P(R_{i,t} < r | R_{i,t} < u_t) \propto (\frac{r}{u_t})^{a_i \zeta_t} \tag{5.1}$$

where $r < u_t < 0$. $R_{i,t}$ is the return of individual stock i on date t, and u_t defines the threshold of the left tail, separating the extreme negative returns from the center of the distribution. It is typically set as the 5^{th} percentile of the cross-section of individual stock returns on date t, following Kelly and Jiang (2012) and Kelly and Jiang (2014).

Eq. (5.1) shows that the left tail of the return distribution follows a power law once returns exceed the threshold u_t. The right-hand side of the equation uses the exponent to quantify the tail risk of an individual stock. Here,

a_i is a constant representing the unconditional tail risk level for each asset, while ζ_t is the key time-varying parameter common to all assets. This parameter determines the shape of the tail distribution, reflecting the dynamic nature of rare disaster risk. A lower exponent produces a fatter tail, whereas a higher ζ_t shifts the left tail further left, indicating higher tail risk. This approach assumes that while firms have different unconditional tail risks, their tail risk dynamics are similar.

According to Kelly and Jiang (2012) and Kelly and Jiang (2014), ζ_t can be estimated by applying Hill (1975) power law estimation method to the pooled cross-section of extreme daily stock return over the month t for all stocks on date t following:

$$\frac{1}{\zeta^{Hill}} = \frac{1}{K_t} \sum_{K=1}^{K_t} ln \frac{R_{K,t}}{u_t} \tag{5.2}$$

where $R_{K,t}$ is the daily return of stock k on date t that exceeds the tail risk threshold u_t during month t, and K_t is the number of daily returns that falls below the threshold in that month. Next the parameter is standardized to usage to proxy for the tail risk:

$$TAIL_t = \frac{\hat{\zeta}_t^{Hill} - \hat{E}(\hat{\zeta}_t^{Hill})}{\hat{\sigma}(\hat{\zeta}_t^{Hill})} \tag{5.3}$$

where $\hat{E}$ and $\hat{\sigma}$ indicate the sample mean and standard deviation over the whole sample of all the monthly tail risk estimators.

The daily stock return data are obtained from the DataStream database, and all securities listed based on the location of headquarters registered are included in the sample to calculate the tail risk measurements. For each country, the data are obtained following the start time of the *BBD* index, starting from January 1985 to December 2022. For the markets that exist

after the starting time, all available observations are included.

5.3.2 Independent Variables

The variable of interest in this study is the Economic Policy Uncertainty (EPU) index developed by Baker et al. (2016), which is adopted to capture the degree of changes in a country's policy and regulatory environment. The monthly index, starting from January 1985, is denoted as the *BBD* index. A higher *BBD* index indicates a greater level of economic policy uncertainty. The index typically spikes during periods of extreme events, such as the 9/11 attacks or tightly contested elections.

In addition to the foundational work of Baker et al. (2016), a series of studies have employed similar methodologies to construct the *BBD* index for 23 countries. Specifically, the indices for Australia, Brazil, Canada, France, Germany, India, Italy, Mexico, South Korea, Russia, the United Kingdom, and the United States are sourced from Baker et al. (2016). Data for Chile are obtained from Cerda et al. (2016), for SMCP China from Baker et al. (2013), for Mainland China from Davis et al. (2019), for Colombia from Gil and Silva (2018), for Greece from Hardouvelis et al. (2018), for Ireland from Zalla (2016), for Japan from Arbatli et al. (2017), for the Netherlands from Kroese et al. (2015), for Singapore from Davis (2016), for Spain from Ghirelli et al. (2019), and for Sweden from Armelius et al. (2017).

This index is constructed by quantifying economy- and policy-related news coverage in newspapers. Collecting data from both government sources and newspapers addresses the conventional challenge posed by the infrequent occurrence of specific uncertain or extreme events. For the U.S. *BBD* index, the measurement reflects the frequency of articles in 10 widely recognized

newspapers, using three sets of word lists representing "economy," "policy," and "uncertainty." The index is observed to spike during major exogenous economic or political shocks, such as tight presidential elections, the 9/11 terrorist attacks, and the Gulf Wars I and II.

Comparable methodologies are applied to construct the index for other countries. Prior studies have demonstrated the relationship between this measure and firm-level stock price volatility, as well as macroeconomic outcomes such as investment, employment, and output. The reliability of the index is further confirmed by the high correlation between computer-generated and human-constructed versions. Data for this metric are sourced from the Economic Policy Uncertainty website. For the purposes of regression analysis, the monthly *BBD* index for each country is multiplied by 100 to maintain appropriate decimal precision for parameter estimation.[1]

According to Baker et al. (2016), the construction of the *BBD* index consists of three components. The first component captures the coverage of policy- and economy-related uncertainty in leading newspapers of each country. For example, in the U.S., ten major newspapers are selected: *USA Today*, *Miami Herald*, *Chicago Tribune*, *Washington Post*, *Los Angeles Times*, *Boston Globe*, *San Francisco Chronicle*, *Dallas Morning News*, *New York Times*, and the *Wall Street Journal*.

Within these newspapers, articles containing keywords related to uncertainty or economic policy are identified. Specifically, terms such as "uncertainty" or "uncertain," "economic" or "economy," and other policy-relevant words including "congress," "deficit," "Federal Reserve," "legislation," "regulation," or "White House" are counted. The frequency of these articles is then scaled by the total number of articles published in

[1]The website of Economic Policy Uncertainty is https://www.policyuncertainty.com/index.html

the corresponding newspapers. The first component of the index is defined as the sum of these normalized values across all selected newspapers on a monthly basis for each country.

The second component of the index captures the federal tax code provisions scheduled to expire in the coming year, with their dollar values obtained from the Congressional Budget Office (CBO). The uncertainty associated with these scheduled tax provisions arises from the common practice of Congress postponing decisions on whether to extend them until the last moment, which undermines the stability and predictability of tax policy for the upcoming year. Additionally, differences between the tax revenue projections of the CBO and those of the Office of Management and Budget (OMB), due to varying assumptions about the treatment of scheduled expiries under current law, further contribute to uncertainty regarding future federal borrowing and lending.

To construct this component, the absolute dollar value of expiring tax provisions over a 10-year horizon is first calculated for each year. These values are then discounted at a rate of 50% per year. The discounted, dollar-weighted tax provisions are summed for each January to produce an index, which is subsequently normalized to have a mean value of 100.

The third component of the index captures disagreement regarding inflation and government purchases. This component is derived from individual-level quarterly forecast data on inflation, federal government purchases of goods and services, and state and local government purchases of goods and services, obtained from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters (SPF). To measure inflation uncertainty, individual forecasts of the quarter-on-quarter annualized CPI inflation rate over the next four quarters are collected, and the cross-sectional interquartile

range of these forecasts is computed as a signal of forecast disagreement. This approach follows the methodology of Zarnowitz and Lambros (1987), Bomberger (1996), Giordani and Söderlind (2003), and Boero et al. (2008).

For government purchases, the interquartile range of four-quarter-ahead forecasts for federal, state, and local government purchases is first divided by the corresponding median four-quarter-ahead forecast. This ratio is then multiplied by a five-year backward-looking moving average of the ratio of nominal federal purchases to nominal GDP. Finally, the resulting measures are summed to produce an overall indicator of forecasting disagreement about future government purchases, expressed as a percentage of GDP.

To construct the overall *BBD* index, each of the three components is first normalized by its standard deviation calculated over the period prior to January 2012. Subsequently, the components are aggregated on a monthly basis using a weighted average, assigning a weight of 1/2 to the news-based index and 1/6 to each of the other components (tax expirations, inflation forecast disagreement, and government purchases forecast disagreement). The resulting overall index is then normalized to have a value of 100.

For countries other than the U.S., a similar procedure is applied, with the exception that the scheduled tax code provisions component is excluded due to its idiosyncratic nature in the U.S. In these cases, the overall index is computed as the equally weighted average of the remaining two components. For the newspaper-coverage component, the word lists are adapted to the native language of local newspapers. The disagreement component relies on individual forecasts of CPI inflation and government budget balance variables collected by Consensus Economics (CE).

5.3.3 Method

To examine the hypothesis listed above, the straightforward panel regression process is applied as following:

$$TAIL_{i,t} = \beta_0 + \beta_1 \times BBD_index_{i,t-1} + \beta_2 \times Control_{i,t-1} + \beta_3 \times Country_i + \beta_4 \times Month_t + \epsilon_{i,t} \quad (5.4)$$

where $TAIL_{i,t}$ represents the tail risk measurements described in Section 5.3.1, BBD_index represents the BBD index adopted to proxy for Economic Policy Uncertainty introduced by Baker et al. (2016), and its parameter β_1 is the variable of interest for testing the hypothesis. $Control$ indicates the control variables.

A set of control variables is included to account for the macroeconomic characteristics of individual countries. The short-term lending interest rate from the OECD database ($LENDING_IR$) is employed, as higher interest rates are expected to depress stock prices and increase stock volatility. The natural logarithm of GDP per capita ($LN_GDP_PER_CA$), calculated in local currency from the World Bank database, proxies the economic development level; in growing economies, higher investor confidence may reduce tail risk. The output gap ($OUTPUT_GAP$), measured as the percentage deviation of actual GDP from potential GDP (IMF data), reflects cyclical conditions: a positive gap signals overheating and potential instability, while a negative gap indicates slack and heightened risk aversion.

Market volatility (VOL), measured by the standard deviation of monthly stock returns, is assumed to be positively related to uncertainty. Inflation is proxied by the year-on-year change in the Producer Price Index

($PPI - YOY$, IMF). Narrow money supply ($M1$, OECD) captures monetary conditions, which can influence interest rates and market risk. The unemployment rate ($UNEMPLOYMENT$, IMF) represents labor market health, with higher unemployment typically associated with lower household income and reduced investment confidence.

Finally, the Caldara and Iacoviello geopolitical risk index ($GEO_POLITICAL$) accounts for adverse geopolitical events that may affect national financial markets. Constructed from article counts on geopolitical threats across ten major newspapers, it captures monthly variations in geopolitical risk and their potential impact on investor sentiment and tail risk.

In order to strengthen the robustness and causal interpretation of the findings in this chapter, a 2SLS regression using instrumental variables (IV) is also considered. This approach addresses potential endogeneity concerns in the relationship between Economic Policy Uncertainty (EPU) and tail risk, which may arise due to omitted variable bias, measurement error, or reverse causality that can bias ordinary least squares (OLS) estimates. By using instruments that are strongly correlated with the endogenous regressor but exogenous to the error term in the outcome equation, the IV method isolates exogenous variation in EPU, allowing for a clearer identification of its causal effect on tail risk. The validity of the instruments is supported by passing the underidentification test, confirming sufficient correlation with the endogenous variable. Importantly, by separating exogenous, policy-induced variation in EPU from confounding macroeconomic or firm-specific shocks, the IV strategy strengthens causal inference, ensuring that the estimated effect of EPU on tail risk reflects the underlying policy mechanism rather than spurious correlations.

A commonly adopted choice for the instrumental variable in Economic

Policy Uncertainty (EPU) studies is a measure of political polarization. Empirical research suggests that high levels of political fractionalization prolong budget finalization and hinder deficit reduction, while strong partisan polarization impedes legislative processes and induces policy instability, thereby elevating EPU (Grier et al., 2015). This measure is arguably exogenous to financial markets, as it captures underlying political dynamics rather than economic shocks.

To operationalise this instrument, data relies on the Varieties of Democracy (V-Dem) dataset, which offers highly granular and globally comprehensive democracy indicators collected via expert surveys. Specifically, we use the variable 'v2cacamps', which estimates the extent to which society is divided into hostile political camps. The V-Dem data is widely regarded as authoritative in political science research: it includes hundreds of indicators across mid- and high-level indices over long time spans, is maintained by an international team of more than 4,000 country experts based at the V-Dem Institute (University of Gothenburg), and enjoys extensive usage in scholarly and policy analyses worldwide.

5.4 Empirical Analysis

5.4.1 Descriptive Statistics

The summary statistics of the variables applied are reported in Table 5.1, and the definitions are recorded in Table 5.2 for 23 countries, with 7,198 observations starting from January 1985 for the earliest available data. For countries where stock market data is available only after 1985, the dataset includes all available data from the respective starting period of the stock market. For instance, in the case of Russia, the data includes

only information after the dissolution of the Soviet Union, as it is regarded as two distinct economies from both political and economic perspectives.

Tail is the standardized tail risk measurement as described in Section 5.3.1, with a sample mean of 0.0436 and a standard deviation of 0.128. *BBD* is the index developed by Baker et al. (2016) used to measure economic policy uncertainty, scaled by 100, with a sample mean of 125.4 and a standard deviation of 83.27. The Caldara and Iacoviello geopolitical risk index, *GEO_POLITICAL*, has a sample mean of 0.409 and a standard deviation of 0.625. *LENDING_IR* represents the short-term lending interest rate reported in percentage, with a sample mean of 8.57 and a standard deviation of 11.42. The natural logarithm of GDP per capita, *LN_GDP_PER_CA*, has a mean of 9.787 and a standard deviation of 1.088. The output gap, *OUTPUT_GAP*, which measures the cyclical position of the economy, has a mean of -0.714 and a standard deviation of 2.891. Market volatility, *VOL*, calculated as the standard deviation of monthly returns of listed stocks, has a mean of 1.207 and a standard deviation of 6.809. The year-on-year Producer Price Index change rate, $PPI - YOY$, has a sample mean of 3.813 and a standard deviation of 13.71. The narrow money supply, *M1*, which is a seasonally adjusted index, with 2015 as the reference year, has a mean of 75 and a standard deviation of 63.03. Finally, the unemployment rate, *UNEMPLOYMENT*, has a mean of 7.47 and a standard deviation of 4.298.

5.4.2 Baseline Regression Results

This section presents the panel regression results used to test the hypothesis that the level of economic and political uncertainty is positively associated with the left-tail risk in stock market returns at the cross-country level, as discussed in the preceding sections. Based on the theoretical frame-

work of Bloom (2009), uncertainty shocks can influence the economy at a market-wide level through their impact on hiring and investment, mediated by capital and labor adjustment costs. These costs lead to simultaneous declines in investment and hiring across the market, which are ultimately reflected in the performance of the stock market, as captured by the tail risk measurement employed in this study. This theoretical reasoning predicts a positive relationship between *BBD* and tail risk in the baseline regression, which is confirmed by the regression results reported in Eq. 5.4.

Table 5.3 reports the baseline regression results for the equation presented in Section 5.3.3. In the regression, the tail risk measurement serves as the dependent variable for country i in month t, while *BBD* is the key explanatory variable for country i in month $t-1$, along with all control variables. Both month- and country-fixed effects are included to account for unobserved heterogeneity.

To examine potential differences across countries at distinct stages of economic development, the regression is conducted for three groups. The first column of Table 5.3 reports results for the full sample. The second column presents results for developed countries only, and the third column shows results for emerging countries. This subgroup analysis is employed to investigate whether the effect of *BBD* on tail risk varies depending on a country's stage of development.

The empirical results are consistent with Hypothesis 1, indicating that the *BBD* index is positively associated with country-level tail risk. For the full sample (column (1) of Table 5.3), the coefficient on *BBD* is 0.001^{**} (coef. $= 0.001$, $t = 2.238$), suggesting that a one standard deviation increase in the *BBD* index corresponds to a 0.096% increase in the tail risk measurement. The effect, however, is heterogeneous across country groups.

In developed countries (column (2)), the coefficient is close to zero and statistically insignificant (coef. = 0.000, $t = 1.362$), whereas in emerging markets (column (3)) the coefficient is stronger and significant 0.001* (coef. = 0.001, $t = 1.733$). This pattern confirms that EPU has a measurable effect on country-level stock-market tail risk, with emerging markets being more sensitive to policy uncertainty, consistent with theory and prior evidence that they are often subject to greater policy instability and financial constraints (Liu and Dong, 2020; Hong et al., 2024).

Regarding control variables, the full-sample results (column (1)) show that geopolitical risk (*GEO_POLITICAL*) is positive and significant (coef. = 0.133, $t = 3.680$), market volatility (*VOL*) is positive and highly significant(coef. = 0.016, $t = 4.678$), and the level of economic development proxied by *LN_GDP_PER_CA* is strongly positive(coef. = 1.265, $t = 12.589$). The output gap is positive and significant(coef. = 0.029, $t = 2.448$). Year-on-year PPI is negative and highly significant in the full sample (coef. = -0.033, $t = -5.923$). Narrow money growth (*M1*) is positive and significant(coef. = 0.001, $t = 2.184$). The unemployment rate is marginally negative(coef. = -0.014, $t = -1.674$). Short-term lending rates are insignificant in the full sample (coef. = -0.006, $t = -0.874$).

For developed countries (column (2)), the principal significant predictors are market volatility(coef. = 0.015, $t = 3.808$), the output gap(coef. = 0.045, $t = 3.240$), and geopolitical risk(coef. = 0.294, $t = 5.792$). Other controls (e.g., lending rates) are also not statistically significant here. For emerging markets (column (3)), tail risk is significantly associated with *LN_GDP_PER_CA*(coef. = 0.805, $t = 9.603$), market volatility(coef. = 0.019, $t = 2.622$), the output gap(coef. = 0.025, $t = 1.988$), and geopolitical risk(coef. = 0.405, $t = 3.680$). Year-on-year PPI is negative and significant(coef. = -0.010, $t = -3.626$), M1 is positive and significant(coef.

= 0.002, t = 2.495), and short-term lending rates are positive and significant(coef. = 0.018, t = 2.726). Unemployment is not significant in the emerging-market sample (coef. = 0.007, t = 0.347).

Taken together, these findings demonstrate that economic policy uncertainty, as captured by the *BBD* index, is an important determinant of stock market downside risk. The results imply that uncertainty shocks amplify vulnerabilities in less mature financial systems, where weaker institutional frameworks and limited policy credibility magnify the adverse effects of uncertainty on market stability. This underscores the broader economic significance of policy uncertainty as not only a short-term risk factor but also a structural driver of financial fragility across countries.

5.4.3 2SLS Regression Results

The results of the 2SLS regression are reported in Table 5.4, revealing patterns similar to the baseline regression results presented in the previous section.The 2SLS estimates confirm that higher Economic Policy Uncertainty significantly increases market-wide tail risk, reinforcing the robustness of the results and supporting a causal interpretation linking policy-related uncertainty to extreme downside risk. Following Chatjuthamard et al. (2020) and Yu et al. (2021), political polarization is employed as the instrumental variable for the *BBD* index in the 2SLS regression.

This variable—measured through ideological distance, partisan fractionalization, or partisan conflict indices—has been empirically shown to drive spikes in EPU, particularly during closely contested elections. For example, Baker et al. (2016) documents a 28% increase in EPU during the U.S. election month. In this study, polarization is proxied using data from the V-Dem dataset, which provides comprehensive democracy indicators

and annual ratings of political polarization across countries. Additionally, polarization evolves gradually over time and is largely unaffected by short-term economic shocks, supporting the exclusion restriction. Structurally, polarization affects EPU exclusively through its impact on policy predictability, rather than through transient economic outcomes.

Using partisan polarization as an instrumental variable not only mitigates endogeneity concerns but also enhances the identification of causal effects of policy uncertainty shocks. Changes in partisan control within highly polarized legislatures generate exogenous fluctuations in policy-making, which include legislative gridlock and abrupt shifts in policy, and these fluctuations systematically increase uncertainty (Agarwal et al., 2018). This ensures a strong correlation between polarization and policy uncertainty, satisfying the relevance condition of the IV. Concurrently, these partisan divides are unlikely to influence outcomes through channels other than policy uncertainty, fulfilling the exclusion restriction. Evidence from empirical finance supports these assumptions: for instance, studies that instrument U.S. tax-policy uncertainty with Senate partisan splits report strong first-stage F-statistics and significant 2SLS estimates (Tosun and Yildiz, 2020), confirming both relevance and exogeneity. By isolating truly exogenous variation in policy-driven uncertainty, the polarization-based IV allows the estimated effect of EPU on outcomes, such as asset tail risk, to be interpreted as a causal impact rather than a spurious association. .

Table 5.4 reports the second-stage results of the two-stage least squares (2SLS) estimation, which examines the effect of economic policy uncertainty (EPU), proxied by the *INS_BBD* index, on tail risk. Political polarization serves as the instrumental variable for EPU. Column (1) reports results for the full sample of 23 countries, while Columns (2) and (3) present estimates for developed and emerging economies, respectively.

For the full sample (column (1) of Table 5.3), the coefficient on *INS_BBD* is 0.003^{*} (coef. $= 0.003$, $t = 1.719$), indicating that higher economic policy uncertainty is associated with an increase in tail risk. The first-stage relevance is supported by the Cragg–Donald Wald F statistic of 23.582, which is well above the 10% critical value of 10.27, suggesting that weak instrument concerns are not an issue in this specification. In developed economies (column (2)), the coefficient is positive but statistically insignificant (coef. $= 0.003$, $t = 1.354$), and the corresponding Cragg–Donald Wald F statistic of 16.593 also exceeds the 10% critical threshold, alleviating weak instrument concerns. In contrast, for emerging markets (column (3)), the estimated coefficient is 0.006^{**} (coef. $= 0.006$, $t = 2.111$), nearly twice as large as in the full sample and significant at the 5% level, with the Cragg–Donald Wald F statistic of 12.153 still above the 10% critical value, further supporting the validity of the instruments. Overall, these results highlight the greater sensitivity of tail risk to policy uncertainty while confirming the robustness of the IV estimates.

Regarding control variables, the output gap is strongly and positively associated with tail risk in both the full sample and developed economies,with coefficients of 0.075^{***} (coef. $= 0.075$, $t = 6.676$) and 0.080^{***} (coef. $= 0.080$, $t = 7.007$), respectively. In emerging markets, however, the effect is small and insignificant (coef. $= 0.012$, $t = 0.577$). Market volatility (VOL) significantly increases tail risk only in emerging markets(coef. $= 0.047$, $t = 4.048$), whereas it is insignificant in the full sample (coef. $= 0.003$, $t = 1.111$) and in developed economies (coef. $= 0.003$, $t = 0.789$). Producer price inflation ($PPI\text{-}YOY$) is negative and significant in emerging markets(coef. $= -0.015$, $t = -3.410$), but insignificant in the other two samples.

Other controls behave largely as expected but are mostly insignificant. In developed economies, short-term lending rates have no effect (coef. $= 0.000$,

$t = 0.029$), whereas in the full sample they are negative and highly significant(coef. $= -0.052$, $t = -4.164$), and in emerging markets also negative and significant(coef. $= -0.049$, $t = -2.028$). Narrow money supply (*M1*) is negative and significant in developed economies (coef. $= -0.001$, $t = -2.547$), but insignificant elsewhere. The level of GDP per capita is insignificant in the full sample (coef. $= 0.019$, $t = 0.326$) and in developed economies (coef. $= 0.418$, $t = 1.450$), but positive and significant in emerging markets(coef. $= 0.182$, $t = 2.059$). Geopolitical risk and unemployment show no significant effect across any group.

Overall, these results indicate that economic policy uncertainty, as measured by *INS_BBD*, amplifies tail risk particularly in emerging markets, whereas its effect in developed economies is muted. The use of *INS_BBD* as an instrumental variable addresses potential endogeneity concerns, reinforcing the interpretation that the observed relationship is causal. By leveraging the exogenous variation in the instrument, the analysis provides robust evidence that economic policy uncertainty systematically influences tail risk across countries, with the strongest effects observed in emerging financial markets.

5.4.4 Robustness Check

In this subsection, the robustness test is conducted using alternative measurements of economic policy uncertainty. According to Brogaard et al. (2020), political uncertainty exerts a global influence on stock market performance. As the largest economy, the United States has a significant impact on the global equity market. This influence is further amplified by the uncertainty surrounding U.S. elections. The effects of U.S. election uncertainty can also propagate internationally, partly through the United

States Security Council.

To examine this claim, this chapter introduces an alternative global political uncertainty measure. The measure is constructed as a set of dummy variables that equal one during periods one month, three months, and six months prior to the U.S. presidential election. These variables are designed to capture the heightened uncertainty associated with electoral outcomes. Empirical results indicate that uncertainty related to U.S. elections significantly reduces stock market returns both in the U.S. and internationally.

Moreover, differing from the domestic *BBD* index used in the previous section, this robustness analysis aims to test whether a proxy for global Economic Policy Uncertainty is also relevant for stock market performance. This approach is motivated by Hong et al. (2024), which provides evidence that both domestic and global EPU indices exert causal effects on equity markets. Consistent with their findings, similar effects are expected in the empirical results presented in this subsection.

Therefore, in line with the hypothesis proposed in this chapter, it is assumed that tail risk will also exhibit a positive relationship with this measure of political uncertainty. Following Brogaard et al. (2020), three dummy variables, denoted as *pre_us_01*, *pre_us_03*, and *pre_us_06*, are set equal to one for periods one month, three months, and six months prior to U.S. election months. These variables are employed as the independent variables in a modified specification of Eq. (5.4), as follows:

$$\begin{aligned} TAIL_{i,t} = \beta_0 + \beta_1 \times pre_us_01_t + \beta_2 \times Control_{i,t-1} \\ + \beta_3 \times Country_i + \beta_4 \times Month_t + \epsilon_{i,t} \end{aligned} \tag{5.5}$$

$$TAIL_{i,t} = \beta_0 + \beta_1 \times pre_us_03_t + \beta_2 \times Control_{i,t-1} + \beta_3 \times Country_i + \beta_4 \times Month_t + \epsilon_{i,t} \quad (5.6)$$

$$TAIL_{i,t} = \beta_0 + \beta_1 \times pre_us_06_t + \beta_2 \times Control_{i,t-1} + \beta_3 \times Country_i + \beta_4 \times Month_t + \epsilon_{i,t} \quad (5.7)$$

Here, the panel regression follows the same specification as Eq. 5.4, except that the independent variables are replaced by *pre_us_01*, *pre_us_03*, and *pre_us_06*, as described above. Similarly, β_1 represents the parameter of interest and is expected to be significantly positive. $TAIL_{i,t}$ denotes the tail risk measurements described in Section 5.3.1. Control includes the macroeconomic control variables: short-term interest rate ($LENDING_IR$), natural logarithm of GDP per capita growth rate ($LN_GDP_PER_CA$), the output gap ($OUTPUT_GAP$), market volatility (VOL), year-on-year PPI index change rate ($PPI\text{-}YOY$), the narrow money supply ($M1$), the unemployment rate($UNEMPLOYMENT$) and the Caldara and Iacoviello geopolitical risk index ($GEO_POLITICAL$). $Country_i$ and $Month_t$ are included to control for country- and month-fixed effects. Standard errors are clustered at the country level to account for potential correlation within a country.

The regression results are reported in Tables 5.5, 5.6, and 5.7 for *pre_us_01*, *pre_us_03*, and *pre_us_06*, respectively. Each set of regressions is conducted for three sample groups, presented in three columns within each table.

According to Tables 5.5–5.7, the month immediately preceding the U.S.

election exhibits a significant positive relationship with country-level tail risk across all countries. Specifically, for the one-month pre-election proxy (*pre_us_01*, Table 5.5), the coefficient is 1.199^{***} (coef. = 1.199, $t = 3.322$) for the full sample, 1.306^{**} (coef. = 1.306, $t = 2.375$) for developed countries, and 0.628^{***} (coef. = 0.628, $t = 18.364$) for emerging markets, indicating a robust increase in tail risk across all groups.

For proxies three months (*pre_us_03*, Table 5.6) and six months (*pre_us_06*, Table 5.7) prior to the election, the coefficients for the full sample remain positive and significant: 1.299^{**} (coef. = 1.299, $t = 1.963$) and 1.344^{**} (coef. = 1.344, $t = 2.031$), respectively. In developed countries, the coefficients are larger and highly significant three and six months before the election: 3.722^{***} (coef. = 3.722, $t = 5.025$) and 3.781^{***} (coef. = 3.781, $t = 5.087$), whereas in emerging markets, the coefficients are either negative or insignificant: -0.191 (coef. = -0.191, t = -0.188) and -0.791 (coef. = -0.791, t = -0.778). These patterns suggest that the month immediately preceding the election is particularly relevant, coinciding with the peak of speculation and debate activity, and driving the strongest impact on tail risk.

Overall, these results demonstrate the robustness of the relationship between U.S. election-related uncertainty and country-level tail risk, particularly in the month immediately preceding the election. The evidence suggests that the observed effects are concentrated in this critical period, consistent with heightened information asymmetry and market speculation. Moreover, the differential patterns across developed and emerging markets highlight the importance of institutional factors and market structure in shaping the sensitivity of tail risk to political uncertainty.

5.4.5 Horse Race Regression: EPU, Pandemic-related Uncertainty, and Trade-related Uncertainty

Beyond the baseline regression with aggregate EPU, this section extends the analysis by jointly considering alternative sources of uncertainty. Specifically, the regression framework incorporates three indices simultaneously: (i) the *BBD* index of Baker et al. (2016), capturing general economic policy uncertainty; (ii) the pandemic-related uncertainty index (*EPI*) developed by Ahir et al. (2022), which measures the frequency of epidemic-related discussions in Economist Intelligence Unit (EIU) country reports; and (iii) the World Trade Uncertainty Index (*WTUI*) of Ahir et al. (2022), constructed from the frequency of uncertainty terms surrounding trade-related keywords such as tariffs, WTO, and protectionism. This "horse race" specification enables a direct comparison of the relative contributions of these different dimensions of uncertainty to country-level tail risk.

The regression is specified as follows:

$$\begin{aligned} TAIL_{i,t} = \beta_0 + \beta_1 \times BBD_{i,t-1} + \beta_2 \times EPI_{i,t-1} + \beta_3 \times WTUI_{i,t-1} \\ + \beta_4 \times Control_{i,t-1} + \beta_5 \times Country_i + \beta_6 \times Month_t + \epsilon_{i,t}, \end{aligned} \tag{5.8}$$

where $TAIL_{i,t}$ is the tail risk measure defined in Section 5.3.1. Control includes the macroeconomic control variables: short-term interest rate (*LENDING_IR*), natural logarithm of GDP per capita growth rate (*LN_GDP_PER_CA*), the output gap (*OUTPUT_GAP*), market volatility (*VOL*), year-on-year PPI index change rate (*PPI-YOY*), the narrow money supply (*M1*), the unemployment rate(*UNEMPLOYMENT*) and the Caldara and Iacoviello geopolitical risk index (*GEO_POLITICAL*). Country and month

fixed effects are included, with standard errors clustered at the country level.

The estimation results are reported in Table 5.8. Several findings emerge. First, the coefficient on aggregate *BBD* index is significantly positive in the full sample (0.001***, coef. = 0.001, t = 2.983) and in emerging markets (0.001***, coef. = 0.001, t = 2.705), consistent with the baseline regressions. This reinforces the view that general policy uncertainty is a robust driver of country-level tail risk.

Second, the pandemic-related uncertainty index (*EPI*) does not exhibit a significant effect in the full sample (coef. = 0, t = -0.587) or in emerging markets (coef. = -0.001, t = -0.584), and is negative and highly significant in developed countries (−0.001***, coef. = -0.001, t = -3.850). This suggests that pandemic shocks, such as COVID-19, influence tail risk primarily through channels captured by broader policy uncertainty, rather than exerting an independent effect.

Third, the trade-related uncertainty index (*WTUI*) shows a marginally significant positive effect in the full sample (0.005*, coef. = 0.005, t = 1.887), but is insignificant in both developed (coef. = 0, t = -0.318) and emerging markets (coef. = 0.002, t = 0.412). This indicates that trade policy shocks, while important in specific episodes, do not consistently explain cross-country variation in tail risk once aggregate policy uncertainty is accounted for.

Taken together, these results indicate that aggregate EPU is the most consistent and robust predictor of country-level tail risk, whereas thematic uncertainty measures, including pandemic- and trade-related indices, provide weaker and less stable explanatory power. The findings suggest that event-specific shocks primarily operate through the amplification of over-

all policy uncertainty, reinforcing the dominant role of EPU in capturing persistent variations in downside risk across countries.

5.5 Conclusions

This chapter provides strong evidence that economic policy uncertainty is an important factor driving country-level stock market tail risk. Across baseline regressions, instrumental variable estimates, robustness checks, and horse race regressions, the results consistently show that higher uncertainty increases the likelihood of extreme negative returns.

The baseline results indicate that the *BBD* index is positively associated with tail risk, especially in emerging markets. This shows that markets with weaker institutions and less mature financial systems are more sensitive to policy shocks, as firms in these countries often face tighter financing constraints and lower investor confidence. In practice, this means that policy uncertainty can quickly lead to sharp declines in stock prices and market instability in these economies.

The 2SLS estimations, which employ political polarization as an instrumental variable, support a causal interpretation of the relationship. The findings suggest that political divisions and policy unpredictability heighten financial risk, whereas stable and predictable policymaking can mitigate market fragility.

Robustness checks using U.S. election-related uncertainty show that global political events can also affect tail risk, with the strongest impact in the month right before the election. This highlights how uncertainty in a major economy like the U.S. can spill over to international markets, affecting investment decisions, capital flows, and market stability worldwide.

Finally, the horse race regressions show that overall economic policy uncertainty is the most consistent predictor of tail risk, while specific shocks from pandemics or trade disputes have weaker and less consistent effects. This suggests that extreme events tend to increase risk mainly by raising general uncertainty rather than creating independent effects.

Overall, the findings show that economic policy uncertainty is a key driver of extreme market risk, both domestically and internationally. Investors and policymakers should monitor uncertainty closely, as periods of heightened unpredictability can amplify market swings. Reducing policy uncertainty and improving institutional credibility can help make markets more stable, especially in emerging economies.

5.6 Tables

Table 5.1: Summary Statistics

This table reports summary statistics of the variables employed in the chapter 5. n denotes the number of observations, Mean is the average return, SD is the standard deviation, p25 stands for the first quartile (25% percentile), p50 denotes the median and p75 stands for the third quartile (75% percentile).

	n	Mean	SD	p25	p50	p75
TAIL	7,198	0.0436	-1.389	-0.11	0.128	0.408
BBD	7,198	125.4	83.27	75.51	103.3	145.2
GEO_POLITICAL	5,906	0.409	0.625	0.0641	0.162	0.422
LENDING_IR	6,098	8.57	11.42	3.25	5.575	9.315
LN_GDP_PER_CA	6,747	9.787	1.088	9.233	10.14	10.59
OUTPUT_GAP	6,899	-0.714	2.891	-1.828	-0.387	0.92
VOL	6,721	1.207	6.809	0.0972	0.135	0.205
$PPI - YOY$	6,280	3.813	13.71	-0.27	2.194	5.155
M1	6,273	75	63.03	30.14	65.56	103.6
UNEMPLOYMENT	6,337	7.47	4.298	4.5	6.879	9.2

Table 5.2: Definition of Variables

This table lists the variables used in the empirical analysis. Column (1) presents the variable names, Column (2) presents the definitions of the variables and Column (3) presents the sources of the variables.

Variable	Definition	Source
TAIL	The standardized tail risk measurement from Kelly and Jiang (2012).	CRSP& DataStream
BBD	The *BBD* index scaled by 100 from Baker et al. (2016).	The Economic Policy Uncertainty
GEO_POLITICAL	The geopolitical risk index from Caldara and Iacoviello (2022).	Caldara and Iacoviello website
OUTPUT_GAP	The difference between the actual output of an economy and its potential output.	IMF
LENDING_IR	The short-term interest rate measured by lending interest rate.	OECD
LN_GDP_PER_CA	The natural logarithm of the growth rate of GDP per capital of different countries.	WorldBank
VOL	The standard deviation of monthly return over all listed securities of each country.	CRSP& DataStream
$PPI - YOY$	The year-on-year Producer Price Index change rate.	IMF
M1	Narrow money supply.	OECD
UNEMPLOYMENT	National unemployment rate in percentage.	IMF

Table 5.3: Baseline Relationship Between the *BBD* Index and Tail Risk

This table reports the estimation results of the baseline regression model in Eq. (5.2). The measures of *TAIL* is the tail risk measurement and see Section 5.3.1 for a detailed description. *BBD* is the *BBD* index scaled by 100 from Baker et al. (2016) proxied for Economy Policy Uncertainty. *LENDING_IR* is the short-term interest rate measured by lending interest rate. *LN_GDP_PER_CA* is the natural logarithm of GDP per capita of different countries. *OUTPUT_GAP* is the the percentage deviation of actual GDP from its potential level of different countries. *VOL* is The standard deviation of monthly return over all listed securities of each country. $PPI - YOY$ is the year-on-year Producer Price Index change rate. *M1* is the narrow money supply. *UNEMPLOYMENT* is the unemployment rate of different countries. Columns (1) reports the estimation results for models with all samples included. Columns (2) reports the estimation results with samples of developed countries, and column (3) with both countries of emerging markets. Month Fixed and country fixed effects are included. Standard errors are clustered at the firm level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(All)	(Dev.)	(Emer.)
	TAIL	*TAIL*	*TAIL*
GEO_POLITICAL	0.133**	0.294***	0.405***
	(3.680)	(5.792)	(3.680)
LENDING_IR	-0.006	-0.016	0.018***
	(-0.874)	(-1.345)	(2.726)
LN_GDP_PER_CA	1.265***	0.026	0.805***
	(12.589)	(0.358)	(9.603)
OUTPUT_GAP	0.029**	0.045***	0.025**
	(2.448)	(3.240)	(1.988)
VOL	0.016***	0.015***	0.019***
	(4.678)	(3.808)	(2.622)
$PPI - YOY$	-0.033***	0	-0.010***
	(-5.923)	(-0.081)	(-3.626)
M1	0.001**	0	0.002**
	(2.184)	(0.094)	(2.495)
UNEMPLOYMENT	-0.014*	-0.012	0.007
	(-1.674)	(-1.175)	(0.347)
BBD	0.001**	0	0.001*
	(2.238)	(1.362)	(1.733)
Country Fixed Effects	Y	Y	Y
Month Fixed Effects	Y	Y	Y
Cluster	Y	Y	Y
Observations	3,140	2,367	773
R-squared	0.353	0.063	0.37

Table 5.4: 2SLS Results of the *BBD* Index and Tail Risk

This table reports the 2SLS regression estimation results of the baseline regression model in Eq. (5.2). The measures of *TAIL* is the tail risk measurement and see Section 5.3.1 for a detailed description. The key explanatory variable, *INS_EPU*, refers to the instrumented economic policy uncertainty measure: the fitted values of the *BBD* index (Baker et al., 2016), scaled by 100, obtained from the first-stage regression using political polarization as an instrument. *LENDING_IR* is the short-term interest rate measured by lending interest rate. *LN_GDP_PER_CA* is the natural logarithm of GDP per capita of different countries. *OUTPUT_GAP* is the the percentage deviation of actual GDP from its potential level of different countries. *VOL* is The standard deviation of monthly return over all listed securities of each country. $PPI - YOY$ is the year-on-year Producer Price Index change rate. *M1* is the narrow money supply. *UNEMPLOYMENT* is the unemployment rate of different countries. Columns (1) reports the estimation results for models with all samples included. Columns (2) reports the estimation results with samples of developed countries, and column (3) with both countries of emerging markets. Month Fixed and country fixed effects are included. Standard errors are clustered at the firm level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(All)	(Dev.)	(Emer.)
	TAIL	*TAIL*	*TAIL*
GEO_POLITICAL	-0.029	-0.061	0.060
	(-0.755)	(-1.410)	(0.278)
LENDING_IR	-0.052***	0.000	-0.049**
	(-4.164)	(0.029)	(-2.028)
LN_GDP_PER_CA	0.019	0.418	0.182**
	(0.326)	(1.450)	(2.059)
OUTPUT_GAP	0.075***	0.080***	0.012
	(6.676)	(7.007)	(0.577)
VOL	0.003	0.003	0.047***
	(1.111)	(0.789)	(4.048)
PPI − YOY	-0.008	-0.008	-0.015***
	(-1.444)	(-0.881)	(-3.410)
M1	-0.001	-0.001**	0.001
	(-1.627)	(-2.547)	(0.292)
UNEMPLOYMENT	-0.004	0.013	-0.006
	(-0.745)	(0.712)	(-0.290)
INS_BBD	0.003*	0.003	0.006**
	(1.719)	(1.354)	(2.111)
Country Fixed Effects	Y	Y	Y
Month Fixed Effects	Y	Y	Y
Cluster	Y	Y	Y
Observations	3,558	2,959	599
R-squared	0.234	0.256	0.655
Cragg Donald Wald F stat	23.582	16.593	12.153
Critical Value (10%)	10.27	10.27	10.27

Table 5.5: Robustness Test Using Indicator for One Month Prior to U.S. Election

This table reports the estimation results of the baseline regression model in Eq. (5.2). The measures of *TAIL* is the tail risk measurement and see Section 5.3.1 for a detailed description. *pre_us_01* is the indicator of months one period prior U.S. election. *LENDING_IR* is the short-term interest rate measured by lending interest rate. *LN_GDP_PER_CA* is the natural logarithm of GDP per capita of different countries. *OUTPUT_GAP* is the the percentage deviation of actual GDP from its potential level of different countries. *VOL* is The standard deviation of monthly return over all listed securities of each country. $PPI - YOY$ is the year-on-year Producer Price Index change rate. *M1* is the narrow money supply. *UNEMPLOYMENT* is the unemployment rate of different countries. Columns (1) reports the estimation results for models with all samples included. Columns (2) reports the estimation results with samples of developed countries, and column (3) with both countries of emerging markets. Month fixed and country fixed effects are included. Standard errors are clustered at the firm level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(All)	(Dev.)	(Emer.)
	TAIL	*TAIL*	*TAIL*
GEO_POLITICAL	0.135*	-0.049	0.127
	(1.794)	(-0.477)	(0.675)
LENDING_IR	-0.005	-0.170**	0.025**
	(-0.178)	(-3.304)	(2.983)
LN_GDP_PER_CA	0.766*	1.746*	0.536**
	(2.070)	(2.325)	(3.385)
OUTPUT_GAP	0.006	0.038	-0.006
	(0.170)	(0.658)	(-0.158)
VOL	0.015**	0.013*	0.024***
	(2.332)	(2.155)	(4.244)
PPI − YOY	-0.047	0.11	-0.075**
	(-1.646)	(1.234)	(-2.697)
M1	0	-0.001**	-0.003
	(-0.262)	(-2.904)	(-0.243)
UNEMPLOYMENT	-0.065	-0.055	-0.123*
	(-1.533)	(-0.916)	(-2.552)
pre_us_01	1.199***	1.306**	0.628***
	(3.322)	(2.375)	(18.364)
Country Fixed Effects	Y	Y	Y
Month Fixed Effects	Y	Y	Y
Cluster	Y	Y	Y
Observations	3,140	2,367	773
R-squared	0.352	0.374	0.689

Table 5.6: Robustness Test Using Indicator for Three Months Prior to U.S. Election

This table reports the estimation results of the baseline regression model in Eq. (5.2). The measures of *TAIL* is the tail risk measurement and see Section 5.3.1 for a detailed description. *pre_us_03* is the indicator of months three periods prior U.S. election. *LENDING_IR* is the short-term interest rate measured by lending interest rate. *LN_GDP_PER_CA* is the natural logarithm of GDP per capita of different countries. *OUTPUT_GAP* is the the percentage deviation of actual GDP from its potential level of different countries. *VOL* is The standard deviation of monthly return over all listed securities of each country. $PPI - YOY$ is the year-on-year Producer Price Index change rate. *M1* is the narrow money supply. *UNEMPLOYMENT* is the unemployment rate of different countries. Columns (1) reports the estimation results for models with all samples included. Columns (2) reports the estimation results with samples of developed countries, and column (3) with both countries of emerging markets. Month fixed and country fixed effects are included. Standard errors are clustered at the firm level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(All)	(Dev.)	(Emer.)
	TAIL	*TAIL*	*TAIL*
GEO_POLITICAL	0.140**	0.005	0.318**
	(2.545)	(0.085)	(2.497)
LENDING_IR	-0.004	-0.142***	0.015**
	(-0.541)	(-7.176)	(2.067)
LN_GDP_PER_CA	1.259***	1.613***	0.867***
	(12.531)	(8.861)	(4.688)
OUTPUT_GAP	0.033***	0.046**	0.039**
	(2.778)	(2.505)	(1.982)
VOL	0.016***	0.015***	0.026**
	(4.738)	(3.989)	(2.191)
$PPI - YOY$	-0.001	0.016	-0.010***
	(-0.247)	(1.612)	(-2.914)
M1	-0.001**	-0.001**	0.004
	(-2.207)	(-2.206)	(1.009)
UNEMPLOYMENT	-0.013	-0.024**	0.017
	(-1.544)	(-2.130)	(0.737)
pre_us_03	1.299**	3.722***	-0.191
	(1.963)	(5.025)	(-0.188)
Country Fixed Effects	Y	Y	Y
Month Fixed Effects	Y	Y	Y
Cluster	Y	Y	Y
Observations	3,140	2,367	773
R-squared	0.352	0.374	0.689

Table 5.7: Robustness Test Using Indicator for Six Month Prior to U.S. Election

This table reports the estimation results of the baseline regression model in Eq. (5.2). The measures of *TAIL* is the tail risk measurement and see Section 5.3.1 for a detailed description. *pre_us_06* is the indicator of months six periods prior U.S. election. *LENDING_IR* is the short-term interest rate measured by lending interest rate. *LN_GDP_PER_CA* is the natural logarithm of GDP per capita of different countries. *OUTPUT_GAP* is the the percentage deviation of actual GDP from its potential level of different countries. *VOL* is The standard deviation of monthly return over all listed securities of each country. $PPI - YOY$ is the year-on-year Producer Price Index change rate. *M1* is the narrow money supply. *UNEMPLOYMENT* is the unemployment rate of different countries. Columns (1) reports the estimation results for models with all samples included. Columns (2) reports the estimation results with samples of developed countries, and column (3) with both countries of emerging markets. Month fixed and country fixed effects are included. Standard errors are clustered at the firm level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(All)	(Dev.)	(Emer.)
	TAIL	*TAIL*	*TAIL*
GEO_POLITICAL	0.140**	0.005	0.318**
	(2.545)	(0.085)	(2.497)
LENDING_IR	-0.004	-0.142***	0.015**
	(-0.541)	(-7.176)	(2.067)
LN_GDP_PER_CA	1.259***	1.613***	0.867***
	(12.531)	(8.861)	(4.688)
OUTPUT_GAP	0.033***	0.046**	0.039**
	(2.778)	(2.505)	(1.982)
VOL	0.016***	0.015***	0.026**
	(4.738)	(3.989)	(2.191)
$PPI - YOY$	-0.001	0.016	-0.010***
	(-0.247)	(1.612)	(-2.914)
M1	-0.001**	-0.001**	0.004
	(-2.207)	(-2.206)	(1.009)
UNEMPLOYMENT	-0.013	-0.024**	0.017
	(-1.544)	(-2.130)	(0.737)
pre_us_06	1.344**	3.781***	-0.791
	(2.031)	(5.087)	(-0.778)
Country Fixed Effects	Y	Y	Y
Month Fixed Effects	Y	Y	Y
Cluster	Y	Y	Y
Observations	4,320	2,662	1,658
R-squared	0.352	0.374	0.689

Table 5.8: Robustness Test Using the Index of Discussion on Epidemics and World Trade Policy Uncertainty

This table reports the estimation results of the baseline regression model in Eq. (5.2). The measures of *TAIL* is the tail risk measurement and see Section 5.3.1 for a detailed description. *BBD* is the *BBD* index scaled by 100 from Baker et al. (2016) proxied for Economy Policy Uncertainty. *EPI* is the index of discussion about epidemic. *WTUI* is the index of world trade uncertainty. See Section 5.4.5 for detailed description. *LENDING_IR* is the short-term interest rate measured by lending interest rate. *LN_GDP_PER_CA* is the natural logarithm of GDP per capita of different countries. *OUTPUT_GAP* is the the percentage deviation of actual GDP from its potential level of different countries. *VOL* is The standard deviation of monthly return over all listed securities of each country. $PPI - YOY$ is the year-on-year Producer Price Index change rate. *M1* is the narrow money supply. *UNEMPLOYMENT* is the unemployment rate of different countries. Columns (1) reports the estimation results for models with all samples included. Columns (2) reports the estimation results with samples of developed countries, and column (3) with both countries of emerging markets. Month fixed and country fixed effects are included. Standard errors are clustered at the firm level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(All)	(Dev.)	(Emer.)
	TAIL	*TAIL*	*TAIL*
GEO_POLITICAL	0.127***	0.162***	0.302***
	(5.169)	(3.003)	(3.801)
LENDING_IR	-0.006***	-0.068***	-0.011***
	(-2.789)	(-4.107)	(-3.932)
LN_GDP_PER_CA	0.088***	0.166**	0.373***
	(4.120)	(2.137)	(10.112)
OUTPUT_GAP	0.077***	0.037**	0
	(8.683)	(2.398)	(-0.030)
VOL	0.011***	0.012***	0.027**
	(3.303)	(3.200)	(2.321)
PPI − YOY	-0.001	-0.028***	-0.015***
	(-0.404)	(-4.890)	(-4.581)
M1	0.001*	0	0.013***
	(1.650)	(1.282)	(4.700)
UNEMPLOYMENT	-0.006	-0.024**	0.036***
	(-1.378)	(-2.301)	(3.051)
BBD	0.001***	0	0.001***
	(2.983)	(-0.181)	(2.705)
EPI	0	-0.001***	-0.001
	(-0.587)	(-3.850)	(-0.584)
WTUI	0.005*	0	0.002
	(1.887)	(-0.318)	(0.412)
Country Fixed Effects	Y	Y	Y
Month Fixed Effects	Y	Y	Y
Cluster	Y	Y	Y
Observations	2,845	2,072	773
R-squared	0.268	0.123	0.682

Chapter 6

Conclusions

6.1 Overview

This chapter aims at describing the findings of each chapter which consist of the research aims of this thesis, from which a overall summary for this thesis can be drawn. After the main findings and summaries of each chapter, the contribution related to each research topic and its limitation will be discussed, in order to motivate further investigation into related research work. Recommendations about related fruitful areas will be then given.

6.2 Main Findings

This thesis investigates several critical factors influencing tail risk in stock markets and explores the mechanisms underlying the causal relationships between these factors and extreme market outcomes.

6.2.1 Study One

The first study examines the effect of firm-level exposure to climate change on the risk of stock price crashes, grounded in the theory of bad news hoarding. The empirical evidence indicates that firms with greater exposure to climate-related risks are more likely to experience stock price crashes, particularly in periods of consecutive positive earnings, suggesting that managers may withhold adverse information to maintain short-term performance. Consistent with the theoretical framework, public attention to climate change mitigates the tendency to hoard bad news, thereby alleviating the extent of stock price crashes.

The causal impact of the unexpected election of President Trump on firms exposed to climate regulations is confirmed through a difference-in-differences

framework. Firms with regulatory exposure in the year preceding the shock experienced a disproportionate reduction in crash risk relative to unaffected firms. The findings are further reinforced through two placebo tests: one using randomly assigned treated and control groups, and another examining the Obama administration period. Both tests show no significant effect, enhancing the credibility of the main results.

The findings carry several implications. Managers should recognize that regulatory exposure may increase stock price crash risk, prompting the need for prudent risk management. Investors can use climate exposure information to assess downside-tail risk and implement protective portfolio strategies. Policymakers, in turn, should consider the unintended market consequences of climate regulations, ensuring that interventions do not destabilize financial markets. Overall, this study provides valuable insights for investors and regulators, highlighting the role of climate-related information in shaping firm-level financial risk.

6.2.2 Study Two

The second study investigates the relationship between debt-based incentives for CEOs and CFOs and information asymmetry, with a particular focus on intangible asset intensity. Debt-based compensation is believed to motivate managers to reduce bankruptcy risk, thereby discouraging unethical behavior and fostering more conservative financial decisions. Empirical results show a negative relationship between debt-based compensation for both CEOs and CFOs and intangible intensity, suggesting that higher deferred incentives encourage prudent management.

Multiple methods are employed to validate these findings. Baseline OLS regressions demonstrate the negative effect of debt-based compensation on in-

tangible intensity, while instrumental variable (IV) and change-in-variables quantile regressions address potential endogeneity concerns and reinforce causal inference. To further ensure robustness, the bid–ask spread is employed as an alternative measure of information asymmetry, and the results remain consistent. Notably, considering all methods applied, a particularly strong effect for CEOs is applied when both executive roles are considered simultaneously, indicating that CEO incentives may carry more weight in driving conservative corporate decisions than those of CFOs.

6.2.3 Study Three

The third study explores the impact of Economic Policy Uncertainty (EPU) on country-level stock market tail risk. Using the *BBD* index as a proxy for EPU, the analysis reveals a robust positive relationship between policy uncertainty and tail risk across all countries, with consistent results for emerging markets. The robustness of these findings is confirmed using alternative indicators, including periods one, three, and six months before U.S. presidential elections, capturing the temporal dynamics of political uncertainty. To address potential endogeneity and establish causality, an additional test is conducted using political polarization as an instrumental variable, further confirming the robustness of the results.

Furthermore, this study examines the influence of global shocks, including pandemics and trade policy uncertainty. The weighted discussion of epidemics and the World Trade Uncertainty Index (WTUI) are both positively associated with tail risk, demonstrating that extreme events affecting the real economy also amplify financial market risk. Emerging markets, in particular, exhibit heightened sensitivity to these shocks, reflecting differences in institutional quality, market depth, and economic resilience. These

findings underscore the importance for investors to consider global and domestic uncertainty when evaluating market risk, especially in the context of highly disruptive events such as the COVID-19 pandemic and trade conflicts.

Overall, the results of Study Three highlight that tail risk in national equity markets is not only influenced by domestic policy uncertainty but also by global economic and political shocks. This emphasizes the necessity for investors and policymakers to adopt comprehensive risk assessment frameworks that account for both local and international sources of uncertainty. The findings provide empirical support for the theoretical view that uncertainty affects the macroeconomy at both the firm and market levels, reinforcing the importance of monitoring extreme events for financial decision-making.

6.2.4 Overall Implications

Taken together, the three studies offer a comprehensive understanding of the determinants of tail risk in financial markets. They reveal that both firm-specific factors, such as climate regulation exposure and managerial incentives, and macro-level uncertainties, including economic policy, pandemics, and trade shocks, significantly shape the likelihood of extreme negative market outcomes. For investors, this research underscores the necessity of incorporating these risk factors into portfolio management and strategic decision-making. For managers, it highlights the importance of aligning incentives to promote conservative and transparent decision-making. Finally, for policymakers, the findings emphasize that regulatory and policy interventions can have unintended consequences on market stability, necessitating careful consideration of their broader financial impacts.

6.3 Contributions

6.3.1 Study One

This chapter makes multiple contributions to the field of green finance and financial risk research. Firstly, it enriches the understanding of green finance by providing empirical evidence on the direct link between climate-related risks and stock market performance. While previous studies have demonstrated that climate change can affect corporate performance and influence policy-making, thereby indirectly impacting financial markets (Ilhan et al., 2021; Ryan, 2012; Seltzer et al., 2022), this chapter establishes a more concrete connection at the firm level, showing that exposure to climate change increases the risk of stock price crashes. Moreover, it emphasizes the role of managerial behavior in amplifying such risks: managers, faced with the possibility of market devaluation and potential costs associated with climate-related exposure, may hoard negative information. This behavioral channel provides a nuanced understanding of how environmental risks translate into financial tail risk, offering insights not only for investors in managing climate-related financial risk but also for policymakers in evaluating the broader market consequences of environmental regulations. In addition, the chapter highlights the mitigating effect of public attention to climate change, which reduces managers' incentive to conceal bad news, suggesting that information transparency and societal awareness can play a stabilizing role in financial markets.

Secondly, this chapter contributes to the literature on stock price crash risk by integrating environmental exposure as a determinant of firm-level crashes. Previous theoretical and empirical research has examined multiple channels affecting crash risk, including earnings opacity (Hutton et al., 2009), executive incentives (Kim et al., 2011a; Andreou et al., 2017), firm

innovation strategies (Jia, 2018), and product market threats (Li and Zhan, 2019). Building on these foundations, this study adds climate-related exposure as a novel factor motivating managers to hoard adverse firm-specific news. It demonstrates that the anticipation of negative financial consequences associated with climate change can directly influence managerial decision-making, thereby exacerbating the likelihood of stock price crashes. By doing so, the chapter extends the theoretical understanding of the interplay between environmental risk, managerial incentives, and financial market stability, offering both predictive insights for investors and a foundation for further research on environmental factors as drivers of extreme market events.

6.3.2 Study Two

This chapter contributes to the literature in several important ways. Firstly, it expands the understanding of the relative importance of CEOs and CFOs in corporate decision-making. While the role of CFOs is often considered secondary to that of CEOs, as CEOs have the authority to replace CFOs who may act in accordance with their directives (Mian, 2001; Fee and Hadlock, 2004), existing research also suggests that CFOs can exert influence equal to or even greater than CEOs in certain corporate finance contexts (Kim et al., 2011a; Chava and Purnanandam, 2010). By analyzing the interaction between executive incentives and corporate risk-taking, this study demonstrates that CEOs tend to maintain dominance over CFOs in shaping financial policies, particularly in decisions related to the management of intangible assets and the control of information asymmetry. This provides a nuanced understanding of how the dynamics between top executives can influence corporate governance and strategic decision-making, highlighting the differential impact of executive roles in shaping firm behavior and

financial outcomes.

Secondly, this chapter provides significant insights into the importance of debt-based compensation, particularly inside debt, and its relationship with intangible asset intensity. While traditional literature emphasizes the role of equity-based incentives in aligning managerial interests with shareholders, this chapter highlights that debt-based compensation plays a critical and complementary role in motivating conservative managerial behavior. By tying managerial rewards to the avoidance of bankruptcy and the protection of corporate liquidation value (Edmans and Liu, 2011; Noe, 2009; Nachman and Noe, 1995), inside debt directly influences executives' risk-taking decisions. The findings show that higher levels of debt-based compensation are associated with a reduction in the intensity of intangible assets held by the firm, suggesting that managers with substantial inside debt are incentivized to make more cautious investment choices. This underscores the relevance of inside debt in corporate finance research and demonstrates its importance as a mechanism to mitigate agency problems, particularly in firms with significant intangible asset holdings.

Thirdly, this chapter contributes to the broader understanding of intangible assets as both a source of firm value and a potential driver of information asymmetry. Intangible assets, such as R&D investments, patents, and proprietary technologies, have become central to firm competitiveness and economic growth over recent decades. However, the lack of physical form and observable market prices complicates their valuation and creates opportunities for managerial discretion, which can exacerbate agency problems (Noe, 2009). By linking the structure of debt-based compensation to managerial decisions regarding intangible assets, this study illuminates a previously underexplored determinant of intangible asset holdings. It shows that executives' risk-taking incentives significantly influence both

the quantity and quality of intangible investments, offering critical insights for investors, policymakers, and researchers concerned with innovation, corporate governance, and financial reporting transparency.

6.3.3 Study Three

This chapter contributes to the literature in multiple important ways. Firstly, it extends research on the topic of Economic Policy Uncertainty (EPU) and its impact on financial markets. While prior studies have established that EPU can serve as a priced risk factor in option markets and a predictor for future stock market volatility, relatively few works have systematically linked EPU to extreme market events at an aggregated, market-wide level. Luo and Zhang (2020) examines the relationship between EPU and firm-level stock price crash risk, but the extent to which these findings hold at the country level remained unclear. This chapter addresses this gap by conducting cross-country analyses that examine the influence of EPU on country-level tail risk. By considering different country groups, including developed economies and emerging markets, the study provides robust evidence that policy uncertainty is a significant determinant of extreme market outcomes across diverse institutional and economic settings, highlighting the global relevance of EPU for financial stability and risk management.

Secondly, this chapter advances the understanding of the determinants of aggregated tail risk. Tail risk, representing the likelihood of extreme adverse outcomes in financial markets, has long been recognized as a critical component of systemic risk. However, identifying the drivers of time-varying tail risk has proven challenging, as most theoretical frameworks treat rare economic disasters as exogenous shocks while focusing on mar-

ket volatility to explain asset pricing anomalies. This study demonstrates that EPU can serve as a fundamental source of uncertainty that drives aggregated tail risk by affecting the economic environment and shaping investor expectations. By analyzing the common components of firm-level tail risks, the research captures the systematic concerns of market participants, offering a deeper understanding of how policy-induced uncertainty propagates through financial markets and manifests as extreme events at the country level.

Thirdly, this chapter contributes methodologically by leveraging the tail risk measurement proposed by Kelly and Jiang (2014), which captures the aggregate components of infrequent extreme events while accounting for their time-varying nature. Unlike firm-level analyses that focus on idiosyncratic failures, this approach integrates stock market performance across all securities within a country, providing a comprehensive view of market-wide tail risk. By doing so, the study offers practical insights for investors, portfolio managers, and policymakers, emphasizing that monitoring EPU is essential for understanding and mitigating extreme financial outcomes. The results provide empirical evidence that policy uncertainty is not merely a theoretical risk factor but a measurable source of systematic risk that can influence investment decisions, market regulation, and broader financial stability considerations.

6.4 Limitations and Recommendations for Future Studies

The limitations of this research arise from several aspects, which can be considered separately for each study. A primary limitation of the research is that the empirical samples used in Chapters 3 and 4 are exclusively

drawn from the U.S. market. As the largest and most developed economy in the world, the U.S. market provides a suitable context to test theoretical frameworks due to its high market efficiency and data availability. However, this focus also constrains the generalizability of the empirical findings. Evidence from Chapter 5 suggests that the influence of key economic and policy factors on tail risk is not uniform across countries with different levels of economic development. Unique policy-making processes, institutional structures, and market regulations in other countries may interact with firm- and country-level factors in ways that differ from the U.S. context. As a result, there is no certainty that the relationships identified in the first two chapters would hold in other markets.

Expanding the empirical analysis to a global context presents several challenges, primarily related to the measurement of key determinants that influence firm-level and country-level tail risks. For instance, previous studies have measured managerial political orientation through corporate political contributions to different parties in the U.S.; however, such data are generally unavailable or inapplicable in many other countries. Differences in political systems across nations further complicate the use of analogous proxies, making it difficult to identify a commonly accepted measure of political orientation in a cross-country setting. Similar challenges arise when considering cultural or religious factors, as well as other important determinants that have been shown in prior research to significantly affect financial outcomes. Although these factors are crucial for a comprehensive understanding of tail risk, their measurement limitations constrain the feasibility of extending the analysis beyond the U.S., thereby highlighting an important direction for future research.

Secondly, specifically for Chapter 4, the inference regarding the linkage between top executive teams' inside debt holdings and a firm's intangible

asset intensity relies on the assumptions that inside debt motivates risk-averse behavior and that intangible assets inherently introduce information asymmetry. However, the underlying channel through which these relationships are formed remains somewhat unclear due to the limited research on determinants of corporate intangible asset holdings. Accurately identifying and classifying intangible assets is inherently challenging because of their lack of physical form and the difficulty of measuring the future economic value generated by activities such as R&D. The intangible intensity metric employed, as introduced by Clausen and Hirth (2016), is an indirect proxy that reflects the efficiency of tangible asset utilization relative to total assets. Future research could build on this study by investigating the precise mechanisms linking executive incentives to intangible asset accumulation or by providing direct evidence of how these incentives affect agency costs and information asymmetry within firms.

Thirdly, from the perspective of the empirical methodology, the analyses in Chapter 5 employed panel regressions using country-level EPU and aggregated market-level tail risk, but did not fully account for the time-varying nature of tail risk. As described in Kelly and Jiang (2014), the construction of the tail risk measure is based on a time-varying threshold of extremely negative returns, which implies that the tail risk series may be influenced by contemporaneous volatility dynamics. Kelly and Jiang (2012) models this threshold as an autoregressive process updated by recent extreme return observations and develops the properties of maximum likelihood estimation under this assumption, emphasizing that the tail risk measure is fundamentally a time-dependent function. Future studies could incorporate time series methodologies or dynamic panel techniques to better account for these temporal dependencies, thereby providing more robust estimates of the effect of policy uncertainty on aggregated tail risk.

6.5 Summary

This thesis aims to investigate several determinants of left-tail extreme events in security markets, spanning from firm-specific idiosyncratic factors to market-wide tail risks, thereby contributing to the study of rare disasters in financial markets from multiple perspectives. The overarching goal is to provide a comprehensive understanding of the drivers of extreme negative returns and to highlight the implications for investors, policymakers, and researchers.

Chapter 3 explores the relationship between firm-level exposure to climate change and the risk of firm-specific stock price crashes. The analysis reveals a significant positive relationship, suggesting that firms more exposed to climate-related risks are more susceptible to extreme downside events. Drawing on the theory of bad news hoarding, this effect arises because managers of exposed firms are more likely to conceal adverse information, which eventually amplifies the likelihood of a stock price crash when such information is inevitably revealed. The effect is further strengthened when public attention to climate change increases, as measured by the Google Search Volume index (SVI), indicating that greater societal concern can moderate managerial behavior by discouraging the concealment of negative information. Furthermore, the chapter incorporates an external policy shock—the surprising election of President Trump—to examine the causal impact of climate-related policy reversals on stock price crash risk. By implementing a Difference-in-Differences (DiD) framework, the analysis demonstrates that firms highly exposed to climate policies, particularly those reliant on traditional energy sources, benefited from the policy shift, experiencing a reduced likelihood of stock price crashes.

Chapter 4 shifts focus to the corporate internal decision-making process,

specifically examining the relationship between top executive teams' risk-taking incentives and the level of intangible assets held by a firm. Intangible assets, as critical drivers of innovation and economic growth, are inherently difficult to value and classify due to their lack of physical form, which also introduces information asymmetry and potential agency costs. Motivated by prior research linking intangible assets to managerial opacity, this chapter investigates how CEO and CFO debt-based compensation influences firms' decisions regarding intangible asset intensity. Employing panel regression, instrumental variable techniques, and quantile regression using first differences of relevant variables, the findings consistently indicate a negative relationship between executives' inside debt holdings and the intensity of intangible assets. This suggests that debt-based incentives encourage more conservative corporate investment decisions, limiting excessive accumulation of hard-to-value assets. Comparative analysis between CEOs and CFOs further indicates that CEO incentives generally have a stronger influence on intangible asset policy, highlighting the differential impact of top executives on strategic corporate choices.

Chapter 5 examines the determinants of market-wide tail risk, focusing on the role of Economic Policy Uncertainty (EPU). Building on the literature that aggregates firm-level shocks into market-level tail risk, such as Gabaix (2011), this chapter applies the tail risk measurement developed by Kelly and Jiang (2014) to capture extreme downside movements across 23 national markets. The empirical analysis investigates the impact of country-level EPU, proxied by the *BBD* index, on aggregate tail risk. Panel regressions provide robust evidence that higher EPU is associated with increased market-wide tail risk, confirming that macroeconomic policy uncertainty is a significant driver of extreme market outcomes. Further investigation distinguishes between different dimensions of EPU, includ-

ing concerns about the pandemic, which surged following the outbreak of COVID-19, and trade policy uncertainty, which escalated during the trade tensions between China and the U.S. Both dimensions are found to have less substantial effects on aggregate tail risk than EPU proxy, referred to as *BBD* index, highlighting the global relevance of policy-driven uncertainty and its implications for financial stability.

Overall, this thesis contributes to a deeper understanding of extreme negative events in financial markets by integrating analyses at the firm level, corporate governance level, and macroeconomic level. It provides insights into the mechanisms through which environmental exposure, managerial incentives, and policy uncertainty shape the risk of tail events, offering practical implications for risk management, corporate strategy, and policy evaluation.

Bibliography

Abel, A. B. (1983). Optimal investment under uncertainty. *The American Economic Review*, 73(1):228–233.

Abeysekera, I. (2016). Does the classification of intangibles matter? an equivalence testing. *Advances in accounting*, 35:135–142.

Aboody, D. and Lev, B. (2000). Information asymmetry, r&d, and insider gains. *The journal of Finance*, 55(6):2747–2766.

Acharya, V. V. and Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of financial Economics*, 77(2):375–410.

Adams, R. B., Almeida, H., and Ferreira, D. (2005). Powerful ceos and their impact on corporate performance. *The Review of Financial Studies*, 18(4):1403–1432.

Addoum, J. M., Ng, D. T., and Ortiz-Bobea, A. (2021). Temperature shocks and industry earnings news. *Available at SSRN 3480695*.

Adhikari, B. K. and Agrawal, A. (2016). Religion, gambling attitudes and corporate innovation. *Journal of Corporate Finance*, 37:229–248.

Adrian, T., Boyarchenko, N., and Giannone, D. (2019). Vulnerable growth. *American Economic Review*, 109(4):1263–1289.

Afzali, M., olak, G., and Fu, M. (2021). Economic uncertainty and cor-

ruption: Evidence from public and private firms. *Journal of Financial Stability*, 57:100936.

Agarwal, V., Aslan, H., Huang, L., and Ren, H. (2018). Policy uncertainty and household stock market participation. *SSRN Scholarly Paper*, 3068792.

Agrawal, A. and Mandelker, G. N. (1987). Managerial incentives and corporate investment and financing decisions. *The journal of finance*, 42(4):823–837.

Ahir, H., Bloom, N., and Furceri, D. (2022). The world uncertainty index. Technical report, National bureau of economic research.

Aizenman, J. and Marion, N. P. (1993). Policy uncertainty, persistence and growth. *Review of international economics*, 1(2):145–163.

Al Mamun, M., Balachandran, B., and Duong, H. N. (2020). Powerful ceos and stock price crash risk. *Journal of Corporate Finance*, 62:101582.

Al-Thaqeb, S. A. and Algharabali, B. G. (2019). Economic policy uncertainty: A literature review. *The Journal of Economic Asymmetries*, 20:e00133.

Albulescu, C. (2020). Coronavirus and financial volatility: 40 days of fasting and fear. *arXiv preprint arXiv:2003.04005*.

Albulescu, C. T. (2021). Covid-19 and the united states financial markets' volatility. *Finance research letters*, 38:101699.

Allvine, F. C. and O'Neill, D. E. (1980). Stock market returns and the presidential election cycle: Implications for market efficiency. *Financial Analysts Journal*, 36(5):49–56.

Alves, S. and Martins, J. (2014). The impact of intangible assets on financial and governance policies: A simultaneous equation analysis. *Journal of Applied Finance and Banking*, 4(1):61.

Amengual, D. and Xiu, D. (2018). Resolution of policy uncertainty and sudden declines in volatility. *Journal of Econometrics*, 203(2):297–315.

Amihud, Y. and Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of financial Economics*, 17(2):223–249.

Amoros, A., Cavero Rubio, J., and Gonzalez, M. (2023). Accounting for goodwill: A literature review. *Accounting*, 9:17–44.

Anantharaman, D., Fang, V. W., and Gong, G. (2014). Inside debt and the design of corporate debt contracts. *Management Science*, 60(5):1260–1280.

Andersen, T. G., Fusari, N., and Todorov, V. (2020). The pricing of tail risk and the equity premium: Evidence from international option markets. *Journal of Business & Economic Statistics*, 38(3):662–678.

Andreou, P. C., Antoniou, C., Horton, J., and Louca, C. (2016). Corporate governance and firm-specific stock price crashes. *European Financial Management*, 22(5):916–956.

Andreou, P. C., Louca, C., and Petrou, A. P. (2017). CEO Age and Stock Price Crash Risk. *Review of Finance*, 21(3):1287–1325.

Ang, A. and Bekaert, G. (2002). International asset allocation with regime shifts. *The review of financial studies*, 15(4):1137–1187.

Antonakakis, N., Chatziantoniou, I., and Filis, G. (2013). Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. *Economics Letters*, 120(1):87–92.

Antonakakis, N., Gabauer, D., and Gupta, R. (2019). Greek economic policy uncertainty: Does it matter for europe? evidence from a dynamic connectedness decomposition approach. *Physica A: Statistical Mechanics and Its Applications*, 535:122280.

Arbatli, E. C., Davis, S. J., Ito, A., and Miake, N. (2017). Policy uncertainty in japan. Technical report, National Bureau of Economic Research.

Armelius, H., Hull, I., and Köhler, H. S. (2017). The timing of uncertainty shocks in a small open economy. *Economics Letters*, 155:31–34.

Arzac, E. R. and Bawa, V. S. (1977). Portfolio choice and equilibrium in capital markets with safety-first investors. *Journal of Financial Economics*, 4(3):277–288.

Avramov, D., Cheng, S., Lioui, A., and Tarelli, A. (2021). Sustainable investing with esg rating uncertainty. *Journal of Financial Economics*.

Aye, G. C., Balcilar, M., Demirer, R., and Gupta, R. (2018). Firm-level political risk and asymmetric volatility. *The Journal of Economic Asymmetries*, 18:e00110.

Backus, D., Chernov, M., and Martin, I. (2011). Disasters implied by equity index options. *The journal of finance*, 66(6):1969–2012.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4):1593–1636.

Baker, S. R., Bloom, N., Davis, S. J., and Wang, X. (2013). Economic policy uncertainty in china. *unpublished paper, University of Chicago*.

Baker, T. A., Lopez, T. J., Reitenga, A. L., and Ruch, G. W. (2019). The influence of ceo and cfo power on accruals and real earnings management. *Review of Quantitative Finance and Accounting*, 52:325–345.

Bakshi, G., Kapadia, N., and Madan, D. (2003). Stock return characteristics, skew laws, and the differential pricing of individual equity options. *The Review of Financial Studies*, 16(1):101–143.

Balcilar, M., Gupta, R., and Segnon, M. (2016). The role of economic policy uncertainty in predicting us recessions: A mixed-frequency markov-switching vector autoregressive approach. *Economics*, 10(1):20160027.

Bali, T. G. and Cakici, N. (2004). Value at risk and expected stock returns. *Financial Analysts Journal*, 60(2):57–73.

Bali, T. G., Demirtas, K. O., and Levy, H. (2009). Is there an intertemporal relation between downside risk and expected returns? *Journal of financial and quantitative analysis*, 44(4):883–909.

Ball, R. (2009). Market and political/regulatory perspectives on the recent accounting scandals. *Journal of accounting research*, 47(2):277–323.

Bansal, R., Kiku, D., and Ochoa, M. (2016). Price of long-run temperature shifts in capital markets. Technical report, National Bureau of Economic Research.

Bansal, R., Ochoa, M., and Kiku, D. (2017). Climate change and growth risks. Technical report, National Bureau of Economic Research.

Bansal, R. and Shaliastovich, I. (2011). Learning and asset-price jumps. *The Review of Financial Studies*, 24(8):2738–2780.

Barnea, A., Haugen, R. A., and Senbet, L. W. (1980). A rationale for debt maturity structure and call provisions in the agency theoretic framework. *the Journal of Finance*, 35(5):1223–1234.

Barnett, M., Brock, W., and Hansen, L. P. (2020). Pricing uncertainty induced by climate change. *The Review of Financial Studies*, 33(3):1024–1066.

Barrero, J. M., Bloom, N., and Wright, I. (2017). Short and long run uncertainty. Technical report, National Bureau of Economic Research.

Barro, R. J. (2006). Rare disasters and asset markets in the twentieth century. *The Quarterly Journal of Economics*, 121(3):823–866.

Barro, R. J. (2015). Environmental protection, rare disasters and discount rates. *Economica*, 82(325):1–23.

Barro, R. J., Ursúa, J. F., and Weng, J. (2020). The coronavirus and the great influenza pandemic: Lessons from the "spanish flu" for the coronavirus's potential effects on mortality and economic activity. Technical report, National Bureau of Economic Research.

Barth, M. E., Beaver, W. H., and Landsman, W. R. (2001a). The relevance of the value relevance literature for financial accounting standard setting: another view. *Journal of accounting and economics*, 31(1-3):77–104.

Barth, M. E., Kasznik, R., and McNichols, M. F. (2001b). Analyst coverage and intangible assets. *Journal of accounting research*, 39(1):1–34.

Bartram, S. M., Hou, K., and Kim, S. (2021). Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics*, page S0304405X21002853.

Basu, S. and Waymire, G. (2008). Has the importance of intangibles really grown? and if so, why? *Accounting and business research*, 38(3):171–190.

Bekaert, G., Harvey, C. R., Lundblad, C. T., and Siegel, S. (2016). Political risk and international valuation. *Journal of Corporate Finance*, 37:1–23.

Ben-Nasr, H., Bouslimi, L., Ebrahim, M. S., and Zhong, R. (2020). Political uncertainty and the choice of debt sources. *Journal of International Financial Markets, Institutions and Money*, 64:101142.

Benlemlih, M. and Yavaş, Ç. V. (2024). Economic policy uncertainty and climate change: Evidence from co2 emission: M. benlemlih, çiğdem vural yavaş. *Journal of Business Ethics*, 191(3):415–441.

Benmelech, E., Kandel, E., and Veronesi, P. (2010). Stock-based compensation and ceo (dis) incentives. *The Quarterly Journal of Economics*, 125(4):1769–1820.

Bennett, R. L., Güntay, L., and Unal, H. (2015). Inside debt, bank default risk, and performance during the crisis. *Journal of Financial Intermediation*, 24(4):487–513.

Berkman, H., Jacobsen, B., and Lee, J. B. (2011). Time-varying rare disaster risk and stock returns. *Journal of Financial Economics*, 101(2):313–332.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The quarterly journal of economics*, 98(1):85–106.

Bhattacharya, S. (1979). Imperfect information, dividend policy, and" the bird in the hand" fallacy. *The bell journal of economics*, pages 259–270.

Białkowski, J., Gottschalk, K., and Wisniewski, T. P. (2008). Stock market volatility around national elections. *Journal of Banking & Finance*, 32(9):1941–1953.

Black, F. and Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of political economy*, 81(3):637–654.

Blair, M. and Wallman, S. (2003). The growing intangibles reporting discrepancy. *Intangibles: Management, Measurement, and Reporting, Washington: Brooking Institution Press, John Hand and Baruch Lev (Ed.)*, pages 449–468.

Bleck, A. and Liu, X. (2007). Market transparency and the accounting regime. *Journal of Accounting Research*, 45(2):229–256.

Bloom, N. (2009). The impact of uncertainty shocks. *econometrica*, 77(3):623–685.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of economic Perspectives*, 28(2):153–176.

Boero, G., Smith, J., and Wallis, K. F. (2008). Uncertainty and disagreement in economic prediction: the bank of england survey of external forecasters. *The Economic Journal*, 118(530):1107–1127.

Bollerslev, T., Tauchen, G., and Zhou, H. (2009). Expected stock returns and variance risk premia. *The Review of Financial Studies*, 22(11):4463–4492.

Bollerslev, T. and Todorov, V. (2011a). Estimation of jump tails. *Econometrica*, 79(6):1727–1783.

Bollerslev, T. and Todorov, V. (2011b). Tails, fears, and risk premia. *The Journal of Finance*, 66(6):2165–2211.

Bollerslev, T. and Todorov, V. (2014). Time-varying jump tails. *Journal of Econometrics*, 183(2):168–180.

Bollerslev, T., Todorov, V., and Xu, L. (2015). Tail risk premia and return predictability. *Journal of Financial Economics*, 118(1):113–134.

Bolton, P. and Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, 142(2):517–549.

Bomberger, W. A. (1996). Disagreement as a measure of uncertainty. *Journal of Money, Credit and Banking*, 28(3):381–392.

Bonaime, A., Gulen, H., and Ion, M. (2018). Does policy uncertainty affect mergers and acquisitions? *Journal of Financial Economics*, 129(3):531–558.

Bond, S. R., Cummins, J. G., Eberly, J., and Shiller, R. J. (2000). The stock market and investment in the new economy: Some tangible facts and intangible fictions. *Brookings Papers on Economic Activity*, 2000(1):61–124.

Boone, J. P. and Raman, K. K. (2001). Off-balance sheet r&d assets and market liquidity. *Journal of accounting and public policy*, 20(2):97–128.

Booth, J. R. and Booth, L. C. (2003). Is presidential cycle in security returns merely a reflection of business conditions? *Review of Financial Economics*, 12(2):131–159.

Boutchkova, M., Doshi, H., Durnev, A., and Molchanov, A. (2012). Precarious politics and return volatility. *The Review of Financial Studies*, 25(4):1111–1154.

Brogaard, J., Dai, L., Ngo, P. T., and Zhang, B. (2020). Global political uncertainty and asset prices. *The Review of Financial Studies*, 33(4):1737–1780.

Brown, J. R. and Petersen, B. C. (2011). Cash holdings and r&d smoothing. *Journal of Corporate Finance*, 17(3):694–709.

Buhagiar, R., Cortis, D., and Newall, P. W. (2018). Why do some soccer bettors lose more money than others? *Journal of Behavioral and Experimental Finance*, 18:85–93.

Burke, M., Hsiang, S. M., and Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239.

Caldara, D. and Iacoviello, M. (2022). Measuring geopolitical risk. *American economic review*, 112(4):1194–1225.

Callahan, C. M., Lee, C., and Yohn, T. L. (1997). Accounting information and bid-ask spreads. *Accounting horizons*, 11(4).

Callen, J. L. and Fang, X. (2013). Institutional investor stability and crash risk: Monitoring versus short-termism? *Journal of Banking & Finance*, 37(8):3047–3063.

Callen, J. L. and Fang, X. (2015a). Religion and stock price crash risk. *Journal of Financial and Quantitative Analysis*, 50(1-2):169–195.

Callen, J. L. and Fang, X. (2015b). Short interest and stock price crash risk. *Journal of Banking & Finance*, 60:181–194.

Cao, C., Xia, C., and Chan, K. C. (2016). Social trust and stock price crash risk: Evidence from china. *International Review of Economics & Finance*, 46:148–165.

Carney, M. (2015). Breaking the tragedy of the horizon—climate change and financial stability.

Carrière-Swallow, Y. and Céspedes, L. F. (2013). The impact of uncertainty shocks in emerging economies. *Journal of International Economics*, 90(2):316–325.

Cassell, C. A., Huang, S. X., Sanchez, J. M., and Stuart, M. D. (2012). Seeking safety: The relation between ceo inside debt holdings and the riskiness of firm investment and financial policies. *Journal of Financial Economics*, 103(3):588–610.

Cerda, R., Silva, A., and Valente, J. T. (2016). Economic policy uncertainty indices for chile. *Economic Policy Uncertainty working paper*.

Chang, T., Chen, W.-Y., Gupta, R., and Nguyen, D. K. (2015). Are stock prices related to the political uncertainty index in oecd countries? evidence from the bootstrap panel causality test. *Economic Systems*, 39(2):288–300.

Chang, X., Chen, Y., and Zolotoy, L. (2017). Stock Liquidity and Stock Price Crash Risk. *Journal of Financial and Quantitative Analysis*, 52(4):1605–1637.

Chapman, D. A., Gallmeyer, M. F., and Martin, J. S. (2018). Aggregate tail risk and expected returns. *The Review of Asset Pricing Studies*, 8(1):36–76.

Chatjuthamard, P., Wongboonsin, P., et al. (2024). Climate policy shocks and corporate value: Evidence from the 2016 us presidential election. *Journal of Corporate Finance*.

Chatjuthamard, P., Wongboonsin, P., Kongsompong, K., and Jiraporn, P. (2020). Does economic policy uncertainty influence executive risk-taking incentives? *Finance Research Letters*, 37:101385.

Chava, S. and Purnanandam, A. (2010). Ceos versus cfos: Incentives and corporate policies. *Journal of financial Economics*, 97(2):263–278.

Chen, C., Kim, J.-B., and Yao, L. (2017). Earnings smoothing: does it

exacerbate or constrain stock price crash risk? *Journal of Corporate Finance*, 42:36–54.

Chen, F., Dou, Y., and Wang, X. (2010). Executive inside debt holdings and creditors' demand for pricing and non-pricing protections. *Unpublished working paper, University of Toronto and the Chinese University of Hong Kong*.

Chen, J., Hong, H., and Stein, J. C. (2001). Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of financial Economics*, 61(3):345–381.

Chen, W., Jin, H., and Luo, Y. (2022). Managerial political orientation and stock price crash risk. *Journal of Accounting, Auditing & Finance*, 37(4):829–847.

Chen, X. and Chiang, T. C. (2020). Empirical investigation of changes in policy uncertainty on stock returns—evidence from china's market. *Research in International Business and Finance*, 53:101183.

Chenari, H., Darabi, R., and Chaharmahali, S. (2025). The impact of bankruptcy risk on stock price crash risk by emphasis on debt maturity. *Iranian Journal of Accounting, Auditing & Finance (IJAAF)*, 9(1).

Chi, S., Huang, S. X., and Sanchez, J. M. (2017). Ceo inside debt incentives and corporate tax sheltering. *Journal of Accounting Research*, 55(4):837–876.

Chiu, W.-C., Peña, J. I., and Wang, C.-W. (2015). Measuring systemic risk: Common factor exposures and tail dependence effects. *European Financial Management*, 21(5):833–866.

Choi, D., Gao, Z., and Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, 33(3):1112–1145.

Chollete, L. and Lu, C.-C. (2011). The market premium for dynamic tail risk. *Unpublished working paper. University of Stavanger, Norway.*

Choy, H., Lin, J., and Officer, M. S. (2014). Does freezing a defined benefit pension plan affect firm risk? *Journal of Accounting and Economics*, 57(1):1–21.

Christoffersen, P., Jacobs, K., and Ornthanalai, C. (2012). Dynamic jump intensities and risk premiums: Evidence from s&p500 returns and options. *Journal of Financial Economics*, 106(3):447–472.

Christou, C., Cunado, J., Gupta, R., and Hassapis, C. (2017). Economic policy uncertainty and stock market returns in pacificrim countries: Evidence based on a bayesian panel var model. *Journal of Multinational Financial Management*, 40:92–102.

Clausen, S. and Hirth, S. (2016). Measuring the value of intangibles. *Journal of Corporate Finance*, 40:110–127.

Cochrane, J. H. (1992). Explaining the variance of price–dividend ratios. *The Review of Financial Studies*, 5(2):243–280.

Çolak, G., Durnev, A., and Qian, Y. (2017). Political uncertainty and ipo activity: Evidence from us gubernatorial elections. *Journal of Financial and Quantitative Analysis*, 52(6):2523–2564.

Coles, J. L., Daniel, N. D., and Naveen, L. (2006). Managerial incentives and risk-taking. *Journal of financial Economics*, 79(2):431–468.

Core, J. and Guay, W. (2002). Estimating the value of employee stock option portfolios and their sensitivities to price and volatility. *Journal of Accounting research*, 40(3):613–630.

Coronado, S., Martínez, J., and Venegas-Martínez, F. (2020). Spillover effects of the us economic policy uncertainty in latin america. *Estudios de economía*, 47(2):273–293.

Corrado, C., Hulten, C., and Sichel, D. (2009). Intangible capital and us economic growth. *Review of income and wealth*, 55(3):661–685.

Cremers, M., Halling, M., and Weinbaum, D. (2015). Aggregate jump and volatility risk in the cross-section of stock returns. *The Journal of finance*, 70(2):577–614.

Da, Z., Engelberg, J., and Gao, P. (2011). In search of attention. *The journal of finance*, 66(5):1461–1499.

Da, Z., Engelberg, J., and Gao, P. (2015). The sum of all fears investor sentiment and asset prices. *The Review of Financial Studies*, 28(1):1–32.

Dahmash, F. N., Durand, R. B., and Watson, J. (2009). The value relevance and reliability of reported goodwill and identifiable intangible assets. *The British Accounting Review*, 41(2):120–137.

Dai, P.-F., Xiong, X., Liu, Z., Huynh, T. L. D., and Sun, J. (2021). Preventing crash in stock market: The role of economic policy uncertainty during covid-19. *Financial Innovation*, 7(1):31.

Daniel, K. and Titman, S. (2006). Market reactions to tangible and intangible information. *The Journal of Finance*, 61(4):1605–1643.

Daniel, K. D., Litterman, R. B., and Wagner, G. (2016). Applying asset pricing theory to calibrate the price of climate risk. Technical report, National Bureau of Economic Research.

Das, D. and Kumar, S. B. (2018). International economic policy uncertainty and stock prices revisited: Multiple and partial wavelet approach. *Economics Letters*, 164:100–108.

Davis, S. J. (2016). An index of global economic policy uncertainty. Technical report, National Bureau of Economic Research.

Davis, S. J., Liu, D., and Sheng, X. S. (2019). Economic policy uncertainty in china since 1949: The view from mainland newspapers. In *Fourth Annual IMF-Atlanta Fed Research Workshop on China's Economy Atlanta*, volume 19, pages 1–37.

Dechow, P. M., Sloan, R. G., and Sweeney, A. P. (1995). Detecting earnings management. *Accounting Review*, pages 193–225.

DeFond, M. L., Hung, M., Li, S., and Li, Y. (2015). Does mandatory ifrs adoption affect crash risk? *The Accounting Review*, 90(1):265–299.

Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.

Demir, E. and Ersan, O. (2017). Economic policy uncertainty and cash holdings: Evidence from bric countries. *Emerging Markets Review*, 33:189–200.

Derrien, F., Kecskés, A., and Mansi, S. A. (2016). Information asymmetry, the cost of debt, and credit events: Evidence from quasi-random analyst disappearances. *Journal of Corporate Finance*, 39:295–311.

Detzen, D. and Zülch, H. (2012). Executive compensation and goodwill recognition under ifrs: Evidence from european mergers. *Journal of International Accounting, Auditing and Taxation*, 21(2):106–126.

Dierkes, M., Hollstein, F., Prokopczuk, M., and Würsig, C. M. (2024). Measuring tail risk. *Journal of Econometrics*, 241(2):105769.

Dimson, E. (1979). Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics*, 7(2):197–226.

Dittmar, R. F. (2002). Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns. *The Journal of Finance*, 57(1):369–403.

Dixit, A. K. and Pindyck, R. S. (1994). *Investment under uncertainty*. Princeton university press.

Dzielinski, M. (2012). Measuring economic uncertainty and its impact on the stock market. *Finance Research Letters*, 9(3):167–175.

Edmans, A. and Liu, Q. (2011). Inside debt. *Review of finance*, 15(1):75–102.

Efendi, J., Srivastava, A., and Swanson, E. P. (2007). Why do corporate managers misstate financial statements? the role of option compensation and other factors. *Journal of financial economics*, 85(3):667–708.

Elkemali, T. (2024). Intangible and tangible investments and future earnings volatility. *Economies*, 12(6):132.

Engelhardt, N., Krause, M., Neukirchen, D., and Posch, P. N. (2021). Trust and stock market volatility during the covid-19 crisis. *Finance Research Letters*, 38:101873.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., and Stroebel, J. (2020). Hedging Climate Change News. *The Review of Financial Studies*, 33(3):1184–1216.

Eyraud, L., Clements, B., and Wane, A. (2013). Green investment: Trends and determinants. *Energy Policy*, 60:852–865.

Fama, E. F. (1963). Mandelbrot and the stable paretian hypothesis. *The journal of business*, 36(4):420–429.

Fama, E. F. (1965). The behavior of stock-market prices. *The journal of Business*, 38(1):34–105.

Fama, E. F. and French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of financial economics*, 25(1):23–49.

Fama, E. F. and French, K. R. (2004). New lists: Fundamentals and survival rates. *Journal of financial Economics*, 73(2):229–269.

Fang, L., Chen, B., Yu, H., and Qian, Y. (2018). The importance of global economic policy uncertainty in predicting gold futures market volatility: A garch-midas approach. *Journal of Futures Markets*, 38(3):413–422.

Fang, L., Yu, H., and Li, L. (2017). The effect of economic policy uncertainty on the long-term correlation between us stock and bond markets. *Economic Modelling*, 66:139–145.

Fedderke, J., Kularatne, C., and Mariotti, M. (2007). Mark-up pricing in south african industry. *Journal of African Economies*, 16(1):28–69.

Fee, C. E. and Hadlock, C. J. (2004). Management turnover across the corporate hierarchy. *Journal of Accounting and Economics*, 37(1):3–38.

Feng, M., Ge, W., Luo, S., and Shevlin, T. (2011). Why do cfos become involved in material accounting manipulations? *Journal of accounting and economics*, 51(1-2):21–36.

Gabaix, X. (2009). Power laws in economics and finance. *Annu. Rev. Econ.*, 1(1):255–294.

Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econometrica*, 79(3):733–772.

Gabaix, X. (2016). Power laws in economics: An introduction. *Journal of Economic Perspectives*, 30(1):185–206.

Galbraith, J. W. and Zernov, S. (2004). Circuit breakers and the tail index of equity returns. *Journal of Financial Econometrics*, 2(1):109–129.

Gao, G. P., Gao, P., and Song, Z. (2018). Do hedge funds exploit rare disaster concerns? *The Review of Financial Studies*, 31(7):2650–2692.

Geiger, M. A. and North, D. S. (2006). Does hiring a new cfo change things? an investigation of changes in discretionary accruals. *The accounting review*, 81(4):781–809.

Gerakos, J. (2010). Ceo pensions: disclosure, managerial power, and optimal contracting.

Ghirelli, C., Perez, J., and Urtasun, A. (2019). A new economic policy uncertainty index for spain. bank of spain. In *Working Paper No. 1906*.

Giglio, S., Kelly, B., and Pruitt, S. (2016). Systemic risk and the macroeconomy: An empirical evaluation. *Journal of Financial Economics*, 119(3):457–471.

Giglio, S., Kelly, B., and Stroebel, J. (2020). Climate Finance.

Giglio, S., Maggiori, M., Rao, K., Stroebel, J., and Weber, A. (2021). Climate change and long-run discount rates: Evidence from real estate. *The Review of Financial Studies*, 34(8):3527–3571.

Gil, M. and Silva, D. (2018). Economic policy uncertainty indices for colombia. *Deutch Bank Research. Available online: http://www. policyuncertainty. com/methodology. html (accessed on 7 September 2021)*.

Gilchrist, S., Sim, J. W., and Zakrajšek, E. (2014). Uncertainty, financial frictions, and investment dynamics. Technical report, National Bureau of Economic Research.

Gilli, M. and Këllezi, E. (2006). An application of extreme value theory for measuring financial risk. *Computational Economics*, 27:207–228.

Giordani, P. and Söderlind, P. (2003). Inflation forecast uncertainty. *European Economic Review*, 47(6):1037–1059.

Glosten, L. R. and Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of financial economics*, 14(1):71–100.

Gong, Y., He, Z., and Xue, W. (2022). Epu spillovers and stock return predictability: A cross-country study. *Journal of International Financial Markets, Institutions and Money*, 78:101556.

Gormsen, N. J. and Jensen, C. S. (2022). Higher-moment risk. *Available at SSRN 3069617*.

Gourio, F. (2012). Disaster risk and business cycles. *American Economic Review*, 102(6):2734–2766.

Graham, J. R., Harvey, C. R., and Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of accounting and economics*, 40(1-3):3–73.

Graham, J. R., Li, S., and Qiu, J. (2008). Corporate misreporting and bank loan contracting. *Journal of Financial Economics*, 89(1):44–61.

Grier, K., Lin, S., and Ye, H. (2015). Political fractionalization and delay in fiscal stabilizations: a duration analysis. *Public Choice*, 164(1):157–175.

Grüber, S. (2014). *Intangible values in financial accounting and reporting: an analysis from the perspective of financial analysts*. Springer.

Gu, F. and Lev, B. (2011). Overpriced shares, ill-advised acquisitions, and goodwill impairment. *The accounting review*, 86(6):1995–2022.

Gu, F. and Wang, W. (2005). Intangible assets, information complexity, and analysts' earnings forecasts. *Journal of Business Finance & Accounting*, 32(9-10):1673–1702.

Guimón, J. (2005). Intellectual capital reporting and credit risk analysis. *Journal of Intellectual Capital*, 6(1):28–42.

Gulen, H. and Ion, M. (2016). Policy uncertainty and corporate investment. *The Review of Financial Studies*, 29(3):523–564.

Guo, M., Kuai, Y., and Liu, X. (2020). Stock market response to environmental policies: Evidence from heavily polluting firms in china. *Economic Modelling*, 86:306–316.

Habib, A. and Hasan, M. M. (2016). Auditor-provided tax services and stock price crash risk. *Accounting and Business Research*, 46(1):51–82.

Habib, A., Hasan, M. M., and Jiang, H. (2018). Stock price crash risk: review of the empirical literature. *Accounting & Finance*, 58:211–251.

Hall, R. E. (2001a). The stock market and capital accumulation. *American Economic Review*, 91(5):1185–1202.

Hall, R. E. (2001b). Struggling to understand the stock market. *American Economic Review*, 91(2):1–11.

Handley, K. and Limao, N. (2015). Trade and investment under policy uncertainty: theory and firm evidence. *American Economic Journal: Economic Policy*, 7(4):189–222.

Hansen, L. P., Heaton, J. C., and Li, N. (2005). Intangible risk. In *Measuring Capital in the New Economy*, pages 111–152. University of Chicago Press.

Hardouvelis, G. A., Karalas, G., Karanastasis, D., and Samartzis, P. (2018). Economic policy uncertainty, political uncertainty and the greek economic crisis. *Political Uncertainty and the Greek Economic Crisis (April 3, 2018)*.

Harper, J., Johnson, G., and Sun, L. (2020). Stock price crash risk and ceo power: Firm-level analysis. *Research in International Business and Finance*, 51:101094.

Harvey, C. R. and Siddique, A. (2000). Conditional skewness in asset pricing tests. *The Journal of finance*, 55(3):1263–1295.

Hassan, T. A., Hollander, S., Van Lent, L., and Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The quarterly journal of economics*, 134(4):2135–2202.

He, F., Wang, Z., and Yin, L. (2020). Asymmetric volatility spillovers between international economic policy uncertainty and the us stock market. *The North American Journal of Economics and Finance*, 51:101084.

He, G. (2015). The effect of ceo inside debt holdings on financial reporting quality. *Review of Accounting studies*, 20:501–536.

Heo, Y. (2021). Climate change exposure and firm cash holdings. *Available at SSRN 3795298*.

Herbst, A. F. and Slinkman, C. W. (1984). Political-economic cycles in the us stock market. *Financial Analysts Journal*, 40(2):38–44.

Hill, B. M. (1975). A simple general approach to inference about the tail of a distribution. *The annals of statistics*, pages 1163–1174.

Hoepner, A. G., Oikonomou, I., Sautner, Z., Starks, L. T., and Zhou, X. (2018). Esg shareholder engagement and downside risk.

Hong, H., Li, F. W., and Xu, J. (2019). Climate risks and market efficiency. *Journal of econometrics*, 208(1):265–281.

Hong, Y., Zhang, R., and Zhang, F. (2024). Time-varying causality impact of economic policy uncertainty on stock market returns: global evidence from developed and emerging countries. *International Review of Financial Analysis*, 91:102991.

Horsch, P., Longoni, P., and Oesch, D. (2021). Intangible capital and leverage. *Journal of financial and quantitative analysis*, 56(2):475–498.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the caribbean and central america. *Proceedings of the National Academy of sciences*, 107(35):15367–15372.

Hsieh, T.-S., Wang, Z., and Demirkan, S. (2018). Overconfidence and tax avoidance: The role of ceo and cfo interaction. *Journal of Accounting and Public Policy*, 37(3):241–253.

Hsu, P.-H., Li, K., and Tsou, C.-Y. (2020). The pollution premium. *Available at SSRN 3578215*.

Hsu, P.-H., Li, K., and Tsou, C.-Y. (2022). The Pollution Premium. *The Journal of Finance, Forthcoming*.

Hu, S. and Gong, D. (2019). Economic policy uncertainty, prudential regulation and bank lending. *Finance Research Letters*, 29:373–378.

Huang, S. and Liu, H. (2021). Impact of covid-19 on stock price crash risk: Evidence from chinese energy firms. *Energy Economics*, 101:105431.

Huang, T., Wu, F., Yu, J., and Zhang, B. (2015). Political risk and dividend policy: Evidence from international political crises. *Journal of International Business Studies*, 46:574–595.

Huang, W., Liu, Q., Rhee, S. G., and Wu, F. (2012). Extreme downside risk and expected stock returns. *Journal of Banking & Finance*, 36(5):1492–1502.

Hutton, A. P., Marcus, A. J., and Tehranian, H. (2009). Opaque financial reports, R2, and crash risk. *Journal of Financial Economics*, 94(1):67–86.

Huynh, T. D. and Xia, Y. (2021). Climate change news risk and corporate bond returns. *Journal of Financial and Quantitative Analysis*, 56(6):1985–2009.

Ilhan, E., Sautner, Z., and Vilkov, G. (2021). Carbon Tail Risk. *The Review of Financial Studies*, 34(3):1540–1571.

Im, H. J., Park, H., and Zhao, G. (2017). Uncertainty and the value of cash holdings. *Economics Letters*, 155:43–48.

Istiak, K. and Alam, M. R. (2020). Us economic policy uncertainty spillover on the stock markets of the gcc countries. *Journal of Economic Studies*, 47(1):36–50.

Ittner, C. D. (2008). Does measuring intangibles for management purposes improve performance? a review of the evidence. *Accounting and business research*, 38(3):261–272.

Jens, C. E. (2017). Political uncertainty and investment: Causal evidence from us gubernatorial elections. *Journal of financial economics*, 124(3):563–579.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4):305–360.

Jensen, M. C. and Meckling, W. H. (1979). Rights and production functions: An application to labor-managed firms and codetermination. *Journal of business*, pages 469–506.

Jensen, M. C. and Murphy, K. J. (1990). Ceo incentives: It's not how much you pay, but how.

Jia, N. (2018). Corporate innovation strategy and stock price crash risk. *Journal of Corporate Finance*, 53:155–173.

Jiang, J. X., Petroni, K. R., and Wang, I. Y. (2010). Cfos and ceos: Who have the most influence on earnings management? *Journal of financial economics*, 96(3):513–526.

Jin, L. and Myers, S. C. (2006). R2 around the world: New theory and new tests. *Journal of Financial Economics*, page 36.

Jindal, N. (2020). The impact of advertising and r&d on bankruptcy survival: A double-edged sword. *Journal of Marketing*, 84(5):22–40.

Jindal, N. and McAlister, L. (2015). The impacts of advertising assets and r&d assets on reducing bankruptcy risk. *Marketing Science*, 34(4):555–572.

Jinshuai, H., KIM, J. B., and Zhang, W. (2014). Insider trading and stock price crash risk: International evidence from a natural experiment. In *2014 FMA Asian Conference*.

Johnson, W. B. and Revsine, L. (1988). Financial reporting standards, agency costs, and shareholder intervention. *Journal of Accounting Literature*, 7(1):95–124.

Jones, P. M. and Olson, E. (2013). The time-varying correlation between uncertainty, output, and inflation: Evidence from a dcc-garch model. *Economics Letters*, 118(1):33–37.

Jones, S. (2011). Does the capitalization of intangible assets increase the predictability of corporate failure? *Accounting Horizons*, 25(1):41–70.

Julio, B. and Yook, Y. (2012). Political uncertainty and corporate investment cycles. *The Journal of Finance*, 67(1):45–83.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105(3):1177–1216.

Kahle, K. M. and Stulz, R. M. (2013). Access to capital, investment, and the financial crisis. *Journal of Financial economics*, 110(2):280–299.

Kallapur, S. and Kwan, S. Y. (2004). The value relevance and reliability of brand assets recognized by uk firms. *The accounting review*, 79(1):151–172.

Kapicka, M. (2012). How important is technology capital for the united states? *American Economic Journal: Macroeconomics*, 4(2):218–248.

Karolyi, G. A. and Stulz, R. M. (1996). Why do markets move together? an investigation of us-japan stock return comovements. *The Journal of Finance*, 51(3):951–986.

Keim, D. B. and Stambaugh, R. F. (1986). Predicting returns in the stock and bond markets. *Journal of financial Economics*, 17(2):357–390.

Kelly, B. and Jiang, H. (2014). Tail risk and asset prices. *The Review of Financial Studies*, 27(10):2841–2871.

Kelly, B. T. and Jiang, H. (2012). Tail risk and hedge fund returns. *Chicago Booth Research Paper*, (12-44).

Khalidi, M. A. (2013). *Natural categories and human kinds: Classification in the natural and social sciences*. Cambridge University Press.

Kido, Y. (2018). The transmission of us economic policy uncertainty shocks to asian and global financial markets. *The North American Journal of Economics and Finance*, 46:222–231.

Kim, C., Wang, K., and Zhang, L. (2019). Readability of 10-k reports and stock price crash risk. *Contemporary accounting research*, 36(2):1184–1216.

Kim, J.-B., Li, Y., and Zhang, L. (2011a). CFOs versus CEOs Equity incentives and crashes. *Journal of Financial Economics*, 101(3):713–730.

Kim, J.-B., Li, Y., and Zhang, L. (2011b). Corporate tax avoidance and stock price crash risk: Firm-level analysis. *Journal of Financial Economics*, 100(3):639–662.

Kim, J.-B., Liao, S., and Liu, Y. (2022). Married ceos and stock price crash risk. *European Financial Management*, 28(5):1376–1412.

Kim, J.-B., Wang, Z., and Zhang, L. (2016). Ceo overconfidence and stock price crash risk. *Contemporary Accounting Research*, 33(4):1720–1749.

Kim, J.-B. and Zhang, L. (2014). Financial reporting opacity and expected crash risk: Evidence from implied volatility smirks. *Contemporary Accounting Research*, 31(3):851–875.

Kim, J.-B. and Zhang, L. (2016). Accounting conservatism and stock price crash risk: Firm-level evidence. *Contemporary accounting research*, 33(1):412–441.

Kim, Y., Li, H., and Li, S. (2014). Corporate social responsibility and stock price crash risk. *Journal of Banking & Finance*, 43:1–13.

King, G., Lam, P., and Roberts, M. E. (2017). Computer-assisted keyword and document set discovery from unstructured text. *American Journal of Political Science*, 61(4):971–988.

King, M. A. and Wadhwani, S. (1990). Transmission of volatility between stock markets. *The review of financial studies*, 3(1):5–33.

Ko, J.-H. and Lee, C.-M. (2015). International economic policy uncertainty and stock prices: Wavelet approach. *Economics Letters*, 134:118–122.

Kothari, S., Lewellen, J., and Warner, J. B. (2006). Stock returns, aggregate earnings surprises, and behavioral finance. *Journal of Financial Economics*, 79(3):537–568.

Kothari, S. P., Shu, S., and Wysocki, P. D. (2009). Do managers withhold bad news? *Journal of Accounting research*, 47(1):241–276.

Kowalewski, O. and Śpiewanowski, P. (2020). Stock market response to potash mine disasters. *Journal of Commodity Markets*, 20:100124.

Kroese, L., Kok, S., and Parlevliet, J. (2015). Beleidsonzekerheid in nederland. *Economisch Statistiche Berichten*, 4715:464–467.

Krueger, P., Sautner, Z., and Starks, L. T. (2020). The Importance of Climate Risks for Institutional Investors. *The Review of Financial Studies*, 33(3):1067–1111.

Kruttli, M. S., Roth Tran, B., and Watugala, S. W. (2021). Pricing poseidon: Extreme weather uncertainty and firm return dynamics.

Kumar, A., Xin, W., and Zhang, C. (2019). Climate sensitivity and predictable returns. *Available at SSRN 3331872*.

Le, Q. V. and Zak, P. J. (2006). Political risk and capital flight. *Journal of International Money and Finance*, 25(2):308–329.

Lee, W. and Wang, L. (2017). Do political connections affect stock price crash risk? firm-level evidence from china. *Review of Quantitative Finance and Accounting*, 48:643–676.

Lemoine, D. (2021). The climate risk premium: how uncertainty affects the social cost of carbon. *Journal of the Association of Environmental and Resource Economists*, 8(1):27–57.

Lev, B. (2000). *Intangibles: Management, measurement, and reporting*. Rowman & Littlefield.

Li, D. (2011). Financial constraints, r&d investment, and stock returns. *The Review of Financial Studies*, 24(9):2974–3007.

Li, K. (2018). Reaction to news in the chinese stock market: A study on xiong'an new area strategy. *Journal of Behavioral and Experimental Finance*, 19:36–38.

Li, M. (2015). Moving beyond the linear regression model: Advantages of the quantile regression model. *Journal of Management*, 41(1):71–98.

Li, Q., Li, S., and Xu, L. (2018). National elections and tail risk: International evidence. *Journal of Banking & Finance*, 88:113–128.

Li, Q., Shan, H., Tang, Y., and Yao, V. (2020a). Corporate climate risk: Measurements and responses. *Available at SSRN 3508497*.

Li, R., Li, S., Yuan, D., and Yu, K. (2020b). Does economic policy uncertainty in the us influence stock markets in china and india? time-frequency evidence. *Applied Economics*, 52(39):4300–4316.

Li, S. and Zhan, X. (2019). Product Market Threats and Stock Crash Risk. *Management Science*, 65(9):4011–4031.

Li, X. (2020). The impact of economic policy uncertainty on insider trades: A cross-country analysis. *Journal of Business Research*, 119:41–57.

Li, X.-l., Balcilar, M., Gupta, R., and Chang, T. (2016). The causal relationship between economic policy uncertainty and stock returns in china and india: Evidence from a bootstrap rolling window approach. *Emerging Markets Finance and Trade*, 52(3):674–689.

Li, X.-M., Zhang, B., and Gao, R. (2015). Economic policy uncertainty shocks and stock–bond correlations: Evidence from the us market. *Economics Letters*, 132:91–96.

Li, Z., Shroff, P. K., Venkataraman, R., and Zhang, I. X. (2011). Causes and consequences of goodwill impairment losses. *Review of accounting studies*, 16:745–778.

Liang, C. C., Troy, C., and Rouyer, E. (2020). Us uncertainty and asian stock prices: Evidence from the asymmetric nardl model. *The North American Journal of Economics and Finance*, 51:101046.

Lim, S. C., Macias, A. J., and Moeller, T. (2020). Intangible assets and capital structure. *Journal of Banking & Finance*, 118:105873.

Lin, C., Officer, M. S., and Shen, B. (2018). Managerial risk-taking incentives and merger decisions. *Journal of Financial and Quantitative Analysis*, 53(2):643–680.

Lin, C., Officer, M. S., and Zou, H. (2011). Directors' and officers' liability insurance and acquisition outcomes. *Journal of Financial Economics*, 102(3):507–525.

Lisowsky, P. (2010). Seeking shelter: Empirically modeling tax shelters using financial statement information. *the accounting review*, 85(5):1693–1720.

Litterman, B. (2021). *Climate Risk: Tail Risk and the Price of Carbon Emissions-Answers to the Risk Management Puzzle*. John Wiley & Sons.

Liu, L. and Zhang, T. (2015). Economic policy uncertainty and stock market volatility. *Finance Research Letters*, 15:99–105.

Liu, L. X., Shu, H., and Wei, K. J. (2017). The impacts of political uncertainty on asset prices: Evidence from the bo scandal in china. *Journal of financial economics*, 125(2):286–310.

Liu, P. and Dong, D. (2020). Impact of economic policy uncertainty on trade credit provision: The role of social trust. *Sustainability*, 12(4):1601.

Liu, Y., Mauer, D. C., and Zhang, Y. (2014). Firm cash holdings and ceo inside debt. *Journal of Banking & Finance*, 42:83–100.

Lonergan, W. (2009). Discussion of bloom. *Abacus*, 45(3):390–396.

Longin, F. and Solnik, B. (1995). Is the correlation in international equity returns constant: 1960–1990? *Journal of international money and finance*, 14(1):3–26.

Longin, F. and Solnik, B. (2001). Extreme correlation of international equity markets. *The journal of finance*, 56(2):649–676.

Low, A. (2009). Managerial risk-taking behavior and equity-based compensation. *Journal of financial economics*, 92(3):470–490.

Lu, Z. and Murray, S. (2019). Bear beta. *Journal of Financial Economics*, 131(3):736–760.

Lu-Andrews, R. and Yu-Thompson, Y. (2015). Ceo inside debt, asset tangibility, and investment. *International Journal of Managerial Finance*, 11(4):451–479.

Lucas Jr, R. E. (1978). Asset prices in an exchange economy. *Econometrica: journal of the Econometric Society*, pages 1429–1445.

Luft, J. L. and Shields, M. D. (2001). Why does fixation persist? experimental evidence on the judgment performance effects of expensing intangibles. *The Accounting Review*, 76(4):561–587.

Lundstrum, L. L. (2002). Corporate investment myopia: a horserace of the theories. *Journal of Corporate Finance*, 8(4):353–371.

Luo, Y. and Zhang, C. (2020). Economic policy uncertainty and stock price crash risk. *Research in International Business and Finance*, 51:101112.

Maheu, J. M., McCurdy, T. H., and Zhao, X. (2013). Do jumps contribute to the dynamics of the equity premium? *Journal of Financial Economics*, 110(2):457–477.

Mandelbrot, B. (1963). The variation of certain speculative prices. *The Journal of Business*, 36(4):394–419.

Marcus, A. A. (1981). Policy uncertainty and technological innovation. *Academy of Management Review*, 6(3):443–448.

Martins, J., Alves, S., et al. (2010). The impact of intangible assets on financial and governance policies: A literature review. *Portuguese Journal of Management Studies*, 15(1):87–107.

Masayuki, M. et al. (2012). Credit constraints in intangible investments (japanese). Technical report.

McGrattan, E. R. and Prescott, E. C. (2010). Technology capital and the us current account. *American Economic Review*, 100(4):1493–1522.

McKenzie, R. and Levendis, J. (2010). Flood hazards and urban housing markets: The effects of katrina on new orleans. *The Journal of Real Estate Finance and Economics*, 40:62–76.

Mehra, R. and Prescott, E. C. (1985). The equity premium: A puzzle. *Journal of monetary Economics*, 15(2):145–161.

Mei, D., Zeng, Q., Zhang, Y., and Hou, W. (2018). Does us economic policy uncertainty matter for european stock markets volatility? *Physica A: Statistical Mechanics and its Applications*, 512:215–221.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, 29(2):449–470.

Mian, S. (2001). On the choice and replacement of chief financial officers. *Journal of Financial Economics*, 60(1):143–175.

Muir, T. (2017). Financial crises and risk premia. *The Quarterly Journal of Economics*, 132(2):765–809.

Murata, R. and Hamori, S. (2021). Esg disclosures and stock price crash risk. *Journal of Risk and Financial Management*, 14(2):70.

Myers, J. N., Myers, L. A., and Skinner, D. J. (2007). Earnings momentum and earnings management. *Journal of Accounting, Auditing & Finance*, 22(2):249–284.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of financial economics*, 5(2):147–175.

Nachman, D. C. and Noe, T. H. (1995). Operating efficiency and output insensitive employment contracts for capital management. *Economic Theory*, 5:315–335.

Nagar, V., Schoenfeld, J., and Wellman, L. (2019). The effect of economic policy uncertainty on investor information asymmetry and management disclosures. *Journal of Accounting and Economics*, 67(1):36–57.

Nakamura, L. I. (2010). Intangible assets and national income accounting. *Review of Income and Wealth*, 56:S135–S155.

Nguyen, N. H. and Phan, H. V. (2017). Policy uncertainty and mergers and acquisitions. *Journal of Financial and Quantitative Analysis*, 52(2):613–644.

Nguyen, Q., Kim, T., and Papanastassiou, M. (2018). Policy uncertainty, derivatives use, and firm-level fdi. *Journal of International Business Studies*, 49:96–126.

Nichita, M. E. et al. (2019). Intangible assets–insights from a literature review. *Journal of Accounting and Management Information Systems*, 18(2):224–261.

Niederhoffer, V., Gibbs, S., and Bullock, J. (1970). Presidential elections and the stock market. *Financial Analysts Journal*, pages 111–113.

Nobes, C. (2018). Lessons from misclassification in international accounting. *The British Accounting Review*, 50(3):239–254.

Noe, T. H. (2009). Tunnel-proofing the executive suite: transparency, temptation, and the design of executive compensation. *The Review of Financial Studies*, 22(12):4849–4880.

Pankratz, N., Bauer, R., and Derwall, J. (2019). Climate change, firm performance, and investor surprises. *Firm Performance, and Investor Surprises (May 21, 2019)*.

Pastor, L. and Veronesi, P. (2012). Uncertainty about government policy and stock prices. *The journal of Finance*, 67(4):1219–1264.

Pástor, L. and Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of financial Economics*, 110(3):520–545.

Phan, H. V. (2014). Inside debt and mergers and acquisitions. *Journal of Financial and Quantitative Analysis*, 49(5-6):1365–1401.

Plosser, C. I. (1989). Understanding real business cycles. *Journal of Economic Perspectives*, 3(3):51–77.

Qiao, L., Adegbite, E., and Nguyen, T. H. (2022). Chief financial officer overconfidence and stock price crash risk. *International Review of Financial Analysis*, 84:102364.

Quintos, C., Fan, Z., and Phillips, P. C. (2001). Structural change tests in tail behaviour and the asian crisis. *The Review of Economic Studies*, 68(3):633–663.

Reilly, R. F. and Schweihs, R. P. (2016). *Guide to intangible asset valuation*. John Wiley & Sons.

Riddick, L. A. and Whited, T. M. (2009). The corporate propensity to save. *The Journal of Finance*, 64(4):1729–1766.

Rietz, T. A. (1988). The equity risk premium a solution. *Journal of monetary Economics*, 22(1):117–131.

Roberts, M. R. and Whited, T. M. (2013). Endogeneity in empirical corporate finance1. In *Handbook of the Economics of Finance*, volume 2, pages 493–572. Elsevier.

Ross, S. A. (1977). The determination of financial structure: the incentive-signalling approach. *The bell journal of economics*, pages 23–40.

Rungmaitree, P., Boateng, A., Ahiabor, F., and Lu, Q. (2022). Political risk, hedge fund strategies, and returns: Evidence from g7 countries. *Journal of International Financial Markets, Institutions and Money*, 81:101678.

Ryan, S. P. (2012). The costs of environmental regulation in a concentrated industry. *Econometrica*, 80(3):1019–1061.

Santa-Clara, P. and Valkanov, R. (2003). The presidential puzzle: Political cycles and the stock market. *The Journal of Finance*, 58(5):1841–1872.

Sautner, Z., van Lent, L., Vilkov, G., and Zhang, R. (2020). Firm-level climate change exposure. *European Corporate Governance Institute–Finance Working Paper*, (686).

Sautner, Z., Van Lent, L., Vilkov, G., and Zhang, R. (2023). Pricing climate change exposure. *Management Science*.

Schwartz, J. (2019). Major climate change rules the trump administration is reversing. *New York Times*, 29.

Scotti, C. (2016). Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises. *Journal of Monetary Economics*, 82:1–19.

Seltzer, L., Starks, L. T., and Zhu, Q. (2022). Climate regulatory risks and corporate bonds. *FRB of New York Staff Report*, (1014).

Setzer, J. and Higham, J. (2021). Global trends in climate change litigation: 2021 snapshot (policy report). *Grantham Research Institute on Climate Change and the Environment and Centre for Climate Change Economics and Policy*.

Sheikh, S. (2020). Ceo inside debt and corporate social responsibility. *International Journal of Managerial Finance*, 16(4):525–546.

Shoag, D. and Veuger, S. (2016). Uncertainty and the geography of the great recession. *Journal of Monetary Economics*, 84:84–93.

Skinner, D. J. (2008). Accounting for intangibles–a critical review of policy recommendations. *Accounting and business research*, 38(3):191–204.

Starks, L. T., Venkat, P., and Zhu, Q. (2017). Corporate esg profiles and investor horizons. *Available at SSRN 3049943*.

Steiger, F. (2010). The impact of credit risk and implied volatility on stock returns. *arXiv preprint arXiv:1005.5538*.

Stein, L. C. and Stone, E. (2013). The effect of uncertainty on investment, hiring, and r&d: Causal evidence from equity options. *Hiring, and R&D: Causal Evidence from Equity Options (October 4, 2013)*.

Straetmans, S. and Chaudhry, S. M. (2015). Tail risk and systemic risk of us and eurozone financial institutions in the wake of the global financial crisis. *Journal of International Money and Finance*, 58:191–223.

Su, Z., Fang, T., and Yin, L. (2019). Understanding stock market volatility: What is the role of us uncertainty? *The North American Journal of Economics and Finance*, 48:582–590.

Sundaram, R. K. and Yermack, D. L. (2007). Pay me later: Inside debt and its role in managerial compensation. *The Journal of Finance*, 62(4):1551–1588.

Taghizadeh-Hesary, F. and Yoshino, N. (2019). The way to induce private participation in green finance and investment. *Finance Research Letters*, 31:98–103.

Tasker, S. C. (1998). Bridging the information gap: Quarterly conference calls as a medium for voluntary disclosure. *Review of Accounting Studies*, 3:137–167.

Telser, L. G. (1955). Safety first and hedging. *The Review of Economic Studies*, 23(1):1–16.

Tosun, M. S. and Yildiz, S. (2020). How does aggregate tax policy uncertainty affect default risk? *Journal of Risk and Financial Management*, 13(12):319.

Van Oordt, M. R. and Zhou, C. (2016). Systematic tail risk. *Journal of Financial and Quantitative Analysis*, 51(2):685–705.

Wagner, A. F., Zeckhauser, R. J., and Ziegler, A. (2018). Political uncertainty and the 2016 us election: Evidence from the stock market. *Journal of Financial Economics*, 130(2):428–451.

Wang, C., Xie, F., and Xin, X. (2010). Managerial ownership of debt and bank loan contracting. *Available at SSRN 1703473*.

Wang, Y. and Zhi, Q. (2016). The role of green finance in environmental protection: Two aspects of market mechanism and policies. *Energy Procedia*, 104:311–316.

Wei, C. and Yermack, D. (2011). Investor reactions to ceos' inside debt incentives. *The Review of Financial Studies*, 24(11):3813–3840.

Weitzman, M. L. (2014). Fat tails and the social cost of carbon. *American Economic Review*, 104(5):544–546.

Wu, K. and Lai, S. (2020). Intangible intensity and stock price crash risk. *Journal of Corporate Finance*, 64:101682.

Yallwe, A. H. and Buscemi, A. (2014). An era of intangible assets. *Journal of Applied Finance and Banking*, 4(5):17.

Yermack, D. and Chenyang, W. (2009). Stockholder and bondholder reactions to revelations of large ceo inside debt holdings: An empirical analysis.

Yu, J., Shi, X., Guo, D., and Yang, L. (2021). Economic policy uncertainty (epu) and firm carbon emissions: evidence using a china provincial epu index. *Energy economics*, 94:105071.

Yuan, R., Sun, J., and Cao, F. (2016). Directors' and officers' liability insurance and stock price crash risk. *Journal of Corporate Finance*, 37:173–192.

Zalla, R. (2016). Economic policy uncertainty in ireland." working paper, 20 september.

Zarnowitz, V. and Lambros, L. A. (1987). Consensus and uncertainty in economic prediction. *Journal of Political economy*, 95(3):591–621.

Zhao, R., Zhang, D., and Guo, M. (2024). Do natural disasters affect stock price crash risk? evidence from emerging markets. *Journal of International Financial Markets, Institutions and Money*, 93:102001.

Zhu, S., Liu, Q., Wang, Y., Wei, Y., and Wei, G. (2019). Which fear index matters for predicting us stock market volatilities: Text-counts or option based measurement? *Physica A: Statistical Mechanics and its Applications*, 536:122567.

Zhu, W. (2016). Accruals and price crashes. *Review of Accounting Studies*, 21:349–399.