Firms' Information Quality and Its Effects on Corporate Finance

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Thesis Submitted in Partial Fulfilment of the Requirements for the Degree of Doctor of Philosophy

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October 2022

Declaration of Original Authorship

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Acknowledgement

First and foremost, I would like to express my sincere gratitude to my supervisors Prof. Carol Padgett and Dr. Chao Yin for all their guidance, supports, and encouragements during my four-year study. I would like to thank Carol for all her encouragements in any aspects of my research, and her patient in revising all my stupid grammar mistakes in each paper. I would like to thank Chao for all his selfless efforts for training me to grow to be a professional researcher. I still remember how you teach me to present the research work, to review a paper, and to discuss a topic in a research seminar.

Secondly, I want to express my thanks to ICMA Centre for providing me a scholarship to carry out this study. I would like also thank both academic and administrative staff for supporting all the issues I met during the four-year study. I particularly thank Ivan Sangiorgi, Lisa Schopohl, Andrew Urqhuart, Vu Tran, Mike Clements, Mohammad Shehub Bin Hasan, Yueting Cui, and Charles Sutcliffe for their insightful comments and suggestions.

My sincere thanks also go to all my friends and colleagues. I want to especially express my appreciation to Xiaohan, Zhenghong, Shuyuan and Ran. You are the climbers in front who have already built the stairs for me. I would not accomplish my projects without your experience and help. I also would like to thank to Ning, Xiaoman, Jennifer, Siqi, Yongyi, Yi, Jing, Jingqi, Alex, Stepthen, Moustafa, Evripidis, Erick, Millie, Corina, Victoria, Ana and Zhiguo for all their help and support.

Finally yet importantly, I want to express my gratitude to my family. My faithful thanks go to my father and my mother for all your supports, trust, and understanding through my life. You give me steady support and brave to choose a road full of thorns. I would like to thank my wife Zhenni for your companionship and console during this important part of my life. Meeting you is my fortune in my life.

Abstract

Information quality is crucial for firms' operations and financial markets' efficiency. The internal information quality within the organization determines the efficiency and quality of headquarters' decision making, while the quality of information disclosed to the public will impact the interests of both shareholders and stakeholders. This thesis attempts to explore the determinants of firms' information quality and its economic consequences.

The first empirical chapter answers the question of how firms' internal information quality (IIQ) impacts their capital structure peer effects. The results indicate that when firms' internal information is worse, they are more likely to mimic peers' capital structure. This mimicking behaviour will impair the future profitability for those firms with bad IIQ. Our further analyses show that the effect is more exhibited in firms with lower corporate governance, which indicates that IIQ's moderating role on peer effects is driven by the agency problem between managers and shareholders.

The second empirical chapter studies how firms' dividend smoothing behaviour affect the quality of information disclosed to the public, and then affect the crash risk of the firm. The results suggest that the higher level of dividend smoothing will lead to higher crash risk. In further analysis, the results also show that the effect is driven by dividend smoothing's direct influence on firms' information asymmetry instead of its influence on earnings management. In addition, the effect is exhibited more in economies with a lower level of investor protection and weaker institutional quality.

The last empirical chapter explores how customer bargaining power affects firms' IIQ. The results indicate that firms with more powerful customers are associated with better IIQ. This association is driven by the causal effect between customer bargaining power and suppliers' IIQ. The results also show that the effects are more exhibited in suppliers, whose customers have higher monitoring incentives.

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List of Abbreviations

2SLS: two-stage least squares

CEO: chief executive officer

CSR: corporate social responsibility

DID: Difference in Difference

EPS: Earnings per share

IFRS: international financial reporting standard

HHI: Herfindahl-Hirschman Index

IIQ: internal information quality

IV: instrumental variable

JGTRRA: Jobs and Growth Tax Relief Reconciliation Act of 2003

M&A: merger and acquisition

NAICs: North American Industry Classification System

OLS: ordinary least squares

PSM: Propensity score matching

SIC: Standard Industrial Classification code

SOX: Sarbanes Oxley Act

1. Introduction

Information quality plays an important role not only in firms' effective operations, but also in the efficiency of information transmission within the financial markets. Research emphasizing firms' information quality is mainly focused on two aspects: the internal information quality acquired by managers (Gallemore and Labro 2015; Heitzman and Huang 2019), and the external information quality disclosed to investors and external stakeholders (Hutton, Marcus, and Tehranian 2009; Armstrong et al. 2011; Bissessur and Veenman 2016). Firms' internal information quality captures "the accessibility, usefulness, reliability, accuracy, quantity, and signal-to-noise ratio of the data and knowledge collected, generated, and consumed within an organization" (Gallemore and Labro 2015). The quality of information within an organization is essential for the efficiency of firms' decision making (Gallemore and Labro 2015), the quality of financial reporting (Feng, Li, and McVay 2009), and the effectiveness of corporate policy (Harp and Barnes 2018; Lai, Liu, and Chen 2020), etc. Inaccurate and noisy internal information can mislead manager to make bad decisions. For the quality of information disclosed to the public, low-quality information means that firms' financial reporting disclosure cannot reflect firms' real situation. It will increase the information asymmetry between insiders and outsiders, which will amplify the difficulty for investors to get access to the real operational conditions of the firm. Considering that firms' information quality is vital for both insiders and outsiders, it is meaningful to investigate what determines firms' information quality, as well as the economic consequences brought by low-quality information.

This thesis intends to extend the existing literature by investigating the determinants and economic consequences of firms' information quality through three new aspects. First, information may play a moderating role in corporate peer effects. As a crucial external stakeholder, industry peers exhibit a significant influence on focal firms' financial policies. According to prior economic and psychological studies, information is a basic factor that will affect individual's peer mimicking (Bikhchandani, Hirshleifer, and Welch 1992, 1998). Consequently, information may also exert an influence on firms' peer effects. The first empirical chapter of the thesis therefore explores whether firms' internal information quality can moderate their capital structure peer mimicking behaviour.

Specifically, to understand whether firms' internal information quality is a determinant for their capital structure peer effects, following previous studies, we use the number of days the firm needed to announce earnings (*EAS*) and the difference of insider trading profitability between top managers and divisional managers (*Dret*) as internal information quality proxies. By applying to all U.S. firms with non-missing data from 1965 to 2017, the results exhibit a significant negative effect between internal information quality and capital structure peer effects. These results are not driven by the correlation effects of firms in the same industry, or the confounding factors which simultaneously impact both internal information quality and peer mimicking behaviour. This effect is in line with traditional herding theory (Bikhchandani, Hirshleifer, and Welch 1992; Devenow and Welch 1996), that when individuals/ firms' private information is scarce, they are more willing to mimic peers' choice to acquire information. It also supports the implication of agency theory that firms' herding behaviour indicates managers' incentives to share punishment (Scharfstein and Stein 1990). Bad internal information quality will impede internal monitoring and amplify any agency problem.

To identify the background mechanisms driving our findings, we conduct several further tests. We find that for those firms with low internal information quality, mimicking behaviour will lead to lower future profitability, but this effect is not significant for firms with good internal information quality. These results support the agency theory rather than the information theory. Finally, we find the peer effects only exist in firms with bad corporate governance and bad internal information quality, which further supports the argument that internal information quality affects firms' peer effect because of agency problems within the firm.

While the first chapter studies the consequences of firms' internal information quality, the second and third empirical chapters focus more on the determinants of information quality. Specifically, the second chapter investigates how dividend smoothing, which indicates that firms' dividend payments are much less volatile than earnings, will affect firms' bad news hoarding and stock price crash risk. By adopting dividend payers from 30 economies around the world, we find a significant positive association between dividend smoothing and crash risk. As high stock price crash risk indicates that firms are concealing information, the results also suggest that the quality of information received by external investors is untimely or inaccurate. The findings indicate that dividend smoothing will lead to a deterioration in the quality of firms' external information quality and then increase firms' future stock price crash risk.

Regarding the channel through which dividend smoothing can impact firms' future crash risk, we find that the effect is driven by dividend smoothing's direct influence on firms' information quality and information asymmetry, but not through its impact on firms' earnings announcement level. These findings are consistent with the signalling theory that dividend changes, instead of smoothed dividends, contain useful information about future earnings (Ham, Kaplan, and Leary 2020). It is also in line with the theory that dividend payments can be an information substitute for earnings announcements (Ham, Kaplan, and Utke 2021). In further analysis, we also find that dividend smoothing's influence on crash risk is more pronounced in economies with a lower level of investor protection and weaker institutional quality.

In the third empirical chapter, we explore whether customer power is a determinant of suppliers' internal information quality. As one of the most influential stakeholders, customers can influence suppliers' production and operations through their bargaining power. By employing all manufacturing firms with major customer data (those customers who account for more than 10 percent of suppliers' sales) in the U.S. market, we find that customer bargaining power has a significant positive effect on firms' internal information quality. Specifically, by using customer concentration as a bargaining power measurement, we find that firms with more concentrated customers have higher earnings announcement speed and lower probability of disclosing any material weakness of internal control over financial reporting. These results are in line with the argument that customers play a monitoring role in suppliers' production and operations.

We also investigate whether the effect is driven by customers' monitoring incentives. By applying relationship-specific investment, unique product producer, and customer internal information quality as measurements for customers' monitoring incentives, we find that firms with higher level of customers' monitoring incentives are more likely to have higher internal information quality.

In first and third empirical chapters, we focus on U.S. market instead of international markets. The main reason is that the internal control data is only available for U.S. market. We think the effect of these two chapters may also exists in international market. According to Francis, Hasan, and Kostova (2016), corporate financial policy peer effects, which had been found by Leary and Roberts (2014) in U.S. market, are also been found 47 different countries. In addition, scholars also find that the customers-supplier relationship in America are also similar with international market (Ma et al. 2020; Dai, Liang, and Ng 2021). In the future, when the data from international market is available, it is worthwhile to extend our study to different financial markets all around the world.

The thesis provides a deeper understanding of firms' information environment and information transmission, from both internal and external aspects. As the information transmission is critical for effective capital allocation, efficiency of financial markets and firm productivity, it is essential to understand what factors will affect the efficiency and accuracy of it. Previous studies provide a set of basic determinants of firms' internal and external information environment. The thesis systematically reviews the research which investigating the determinants of firms' internal and external information environment, and discusses the research gap of existing literature. More importantly, the thesis fills in the gap of firm's information environment research by supplementing two important determinants to the existing studies. Specifically, the thesis finds that dividend smoothing behaviour will increase information asymmetry between internal managers and external investors, while the customer bargaining power can improve suppliers' IIQ.

Moreover, the thesis also contributes to the understanding the economic consequences of efficient information transmission. Investigation of economic consequences matters of why efficient information transmission is important for corporate operations and financial markets efficiency. The thesis systemically discusses the effects brought by ineffective information transmission, and provides evidence that inefficient information environments can also alter managers' herding behaviour.

In summary, the thesis contributes to the existing literature by exploring new determinants and the economic consequence of firms' information quality. It provides evidence of the economic connection between information quality and firms' financial policies, such as capital structure and dividend policy. It also shows the economic influence of information quality along the supply chain. The thesis is significant for understanding information's role in corporate operations, and contributory to understanding the factors that will impact firms' information quality.

2. Literature review

In this chapter, we review the literature focusing on topics related to firms' information quality, as well as other research topics related to the thesis. In first two sections of this chapter, we summarize the mainstream literature investigating the determinants and economic consequences of firms' internal information quality and the quality of information reported to external investors and stakeholders (quality of information disclosed). For the quality of information disclosed, in this chapter, we emphasize the studies related to bad news hoarding and stock price crash risk, which are more relevant to the empirical studies in the thesis. In the following three sections, we briefly review other research topics related to this thesis – corporate peer effects, dividend smoothing, and supplier-customer relationship.

2.1 Internal information quality

Firms' internal information quality, which is defined as "the accessibility, usefulness, reliability, accuracy, quantity, and signal-to-noise ratio of the data and knowledge collected, generated, and consumed within an organization" (Gallemore and Labro 2015) is a critical characteristic for firms' decision making. Although this concept was first developed by Gallemore and Labro (2015), studies related to firms' internal information system have been attracting researchers' attention for a long time. Since the accounting frauds surrounding the beginning of the 21st century (e,g, the Enron scandal), and the passage of SOX 302 and SOX 404, researchers started to pay more attention to firms' internal control quality over financial reporting. Firms' internal control quality has a deep and close relationship with internal information quality. Internal control quality, to a great extent, measures the efficiency of firms' internal information system. According to Feng, Li, and McVay (2009), material weakness in an internal control system indicates that the internal financial information of a firm is inaccurate or even erroneous. A group of subsequent studies directly applied the disclosure of material weakness on internal control as one of the measurements of firms' internal information quality (Gallemore and Labro 2015; Harp and Barnes 2018; Heitzman and Huang 2019). Consequently, the studies focusing on an internal control system are highly related to the research on firms' internal information quality.

We divide the internal control and internal information quality studies into two groups. One strand of studies focusing on exploring the factors that will affect firms' internal information quality. The other group of studies tries to examine the economic consequence of bad internal information quality. For the first group of studies, Doyle, Ge, and McVay (2007) , in their seminal research, provide a set of basic determinants of firms' internal control systems, which lay the foundation for future research. They suggest that firms which are smaller in size, less profitable, more complex, experiencing high growth rate, and which are undergoing restructuring, are more likely to suffer from a weak internal control system. The subsequent research also explored multiple other internal or external factors that could affect firms' internal control quality and internal information system. For internal determinants, Hoitash, Hoitash, and Bedard (2009) find a positive relationship between corporate governance and internal control quality. Guo et al. (2016) find that employee welfare can also improve the efficiency of firms' internal control system. Chen, Feng, and Li (2020) indicate that family entrenchment negatively impacts internal control quality. For external determinants, Krishnan

(2005) argues that audit quality has a critical influence on the possibility of disclosing material weakness over financial reporting. In addition, other research also finds that internal control quality has significantly positive correlation with former audit partners on the audit committee (Naiker and Sharma 2009), auditor-provided tax services (De Simone, Ege, and Stomberg 2015), and audit committee expertise (Sterin 2020).

It is essential to explore the factors that will affect firms' internal information quality, because inefficient internal information system will lead to serious consequences. Compared with studies focusing on the determinants of internal information quality and internal control, more research topics are emphasizing the need to investigate the economic consequences of low-quality internal information.

The majority of research articles focusing on the economic consequences of internal control quality argue that bad internal control quality will lead to inefficient managerial decisions. This influence is reflected in several ways. First, the efficiency of internal control system will affect firms' investment policy. According to Cheng, Dhaliwal, and Zhang (2013), firms disclosing material weakness of internal control are more likely to make inefficient investment decisions – they are more prone to underinvest when financially constrained and overinvest when unconstrained. They also argue that the disclosure of material weakness will push them to improve their internal information quality, which will significantly increase investment efficiency. Lai, Liu, and Chen (2020) find a similar association between firms' internal control quality and investment efficiency. Harp and Barnes (2018) investigate a unique type of firms' investment – merger and acquisition (M&A) –

and find that firms with low-quality internal information are more likely to make bad M&A choices and are associated with worse post-acquisition performance. Apart from investment efficiency, internal control weakness can also decrease investment expenditure (Sun 2016) and M&A expenditure (Chen et al. 2020).

Second, the internal control weakness and internal information quality will affect firms' financial reporting quality. For instance, Feng, Li, and McVay (2009) argue that firms with material internal control weakness will also provide inaccurate management guidance on earnings. Altamuro and Beatty (2010) find that the improvement in internal control systems will significantly increase the quality of financial reporting in the banking industry. An internal control weakness can also affect financial reporting quality through amplifying agency problems, which will increase the real earnings management of the firm (Cheng, Lee, and Shevlin 2016). Dowdell Jr, Herda, and Notbohm (2014) and Myllymäki (2014)'s research also provide similar evidence of the positive relationship between internal control quality and financial reporting quality. From the financial market aspect, the deficiency of internal control systems will increase the opaqueness of firms, which will increase the stock price crash risk (Chen et al. 2017).

In addition, previous literature has also investigated the economic consequences of internal information quality and internal control quality from other aspects, including tax avoidance (Gallemore and Labro 2015; Bauer 2016), investment sensitivity to market price (Heitzman and Huang 2019), innovation efficiency (Huang, Lao, and McPhee 2020), and managerial conservatism (Goh and Li 2011).

All these studies prove that internal information quality is vital for both firms' operations and performance.

2.2 Quality of information disclosed

According to the efficient market hypothesis, the financial markets can fully reflect the information about the value of a stock (Malkiel 2003). This hypothesis requires that there is no information asymmetry between firms' insiders (e.g., managers) and outsiders (e.g., investors). As entrepreneurs hold more information about firms' operations and profitability than outside investors, the quality of information disclosed is important for the transparency and efficiency of the market.

Firms have various ways to disclose private information to the public. The most important way is through regulated financial reports, such as annual financial statements, reporting about internal control over financial reporting, and other report filings (Healy and Palepu 2001). Alternatively, firms can also voluntarily disclose information through management guidance, conference calls, and social media, etc. In addition, the information intermediators, such as analysts, news companies, and auditor offices, can also contribute to firms' information transparency.

The different types of ways of information disclosure means that researchers can evaluate firms' information quality from different aspects. The research topics, therefore, can be divided into two groups based on the types of information disclosed. First, most of the studies focus more on the quality of regulated financial reporting, such as earning management level and misstatement. These studies include topics which are trying to find the determinants of firms' financial reporting quality, such as board characteristics (Klein 2002), legal expertise on the audit committee (Krishnan, Wen, and Zhao 2011), social trust (Garrett, Hoitash, and Prawitt 2014), and internal audit quality (Abbott et al. 2016), and also include topics investigating economic consequences, such as higher crash risk (Hutton, Marcus, and Tehranian 2009) and low-quality financial reporting. Apart from regulated financial reporting, a group of studies also measures firms' quality of information disclosed using voluntary disclosure. For instance, Chen et al. (2018) indicate that more accurate managers' earnings forecasts suggest a better information quality. Feng, Li, and McVay (2009) explore the association between internal control quality and management forecast accuracy.

Based on the types of factors that will impact the quality of information disclosed, we can also divide the existing studies into several groups. The first group of studies emphasizes examining the effect of an accounting regulation on firms' financial reporting quality. For instance, Cohen, Dey, and Lys (2008) investigate the level of earnings management before and after the passage of SOX 404.[1] They suggest that firms switched their accrual based earnings management to real earnings management after SOX. Landsman, Maydew, and Thornock (2012) and Byard, Li, and Yu (2011) examine the effect brought by the International Financial Reporting Standards (IFRS) on the quality of financial information disclosed by firms. [2]Landsman, Maydew, and Thornock (2012) find that the adoption of IFRS will increase the information contained in the earnings announcement. Byard, Li, and Yu (2011) indicate that the passage of IFRS 16 will significantly decrease analyst

[1] The Sarbanes-Oxley Act of 2002 require all publicly traded companies to access and report the quality of their internal accounting controls to the SEC for compliance.
[2] IFRS Accounting Standards provide the structure of how firms prepare and report financial statement. It is the combination of old IAS standards and new IFRS standards.

forecast dispersion and analyst forecast error. The second strand of the literature focuses on how firm characteristics can affect the quality of information disclosed. These determinants include corporate governance (Xie, Davidson III, and DaDalt 2003), board characteristics (Klein 2002), dividend payments (Daniel, Denis, and Naveen 2008), and internal audit quality (Abbott et al. 2016). Lastly, researchers also care about how managerial characteristics and incentives impact the quality of information disclosed by firms. As noted by Healy and Palepu (2001), managers have incentives to distort the information to extract benefit for themselves. For example, Bergstresser and Philippon (2006) indicate that CEOs whose compensation is more related to stocks and options are more likely to manage earnings.

Apart from the traditional proxies for information quality, the recent literature also studies the quality of information disclosed by investigating the probability of stock price crash and bad news hoarding. For stock price crash risk research, the early studies mainly focus on how the stock market environment will cause financial market crashes. For example, Hong and Stein (2003) argue that outside short sell constraints lead to bad news hoarding, which can explain the stock market crashes. Huang and Wang (2009) suggest that the liquidity need in the market will increase the crash risk exposure of firms.

In contrast to the papers mentioned above, Jin and Myers (2006) start to explore firms' internal characteristics' influence on stock price crash risk. Based on the finding that crash risk is more pronounced in countries with less investor protection, Jin and Myers (2006) argue that conflicts between insiders and outsiders are the reason that more developed financial markets are associated with a more opaque information environment. In their model, the bad news will be hoarded if insiders are continuously concealing negative information, and after the bad news exceeds a certain threshold, it will come out all at once, which causes the stock price crashes.

Following Jin and Myers (2006) research, Hutton, Marcus, and Tehranian (2009) test how firm-specific characteristics can influence stock price crash risk. They find that firms with higher crash risk are associated with lower stock price informativeness and higher level of earnings management. Based on this evidence that crash risk can indicate the opaqueness of a firm, a growing number of studies have begun to investigate different firm-level determinants of stock price crash risk. A strand of the literature argues that earning management determinants can also impact crash risk through their influence on earnings quality. For example, Kim, Li, and Zhang (2011b) find that tax avoidance can provide a tool for managers in earnings manipulation which increases the opaqueness and stock price crash risk in the future. Ben-Nasr and Ghouma (2018) argue that employee welfare also impacts crash risk through its influence on earnings management. On the contrary, other studies indicate that some factors can affect crash risk because they have a direct influence on firms' information environment. For instance, An et al. (2020) find that media coverage will decrease crash risk because it can improve the information transparency of the firm. Similarly, Xu, Xuan, and Zheng (2021) suggest that more powerful internet searching systems can also mitigate crash risk, as it will increase the quantity of information acquired by investors. In sum, these studies indicate that firms which disclose lower-quality information are associated with higher crash risk.

2.3 Corporate peer effects

Theoretical researches in finance have long assumed that an individual's action will be influenced by its peers (Bikhchandani, Hirshleifer, and Welch 1992). This effect is also applied to firms in the same industry. According to the survey evidence from Graham and Harvey (2001), CFOs admit that they will cite the importance of peers when making their own capital structure decisions. However, empirical work on proving the existence of a peer effect is challenging because of the reflection problem (Manski 1993).[3] Leary and Roberts (2014) solve this problem by using peer firms' idiosyncratic stock return as an instrumental variable and prove that financial policy peer effects indeed exist in financial markets. The subsequent literature finds that peer influence is exhibited in many aspects, such as stock splitting (Kaustia and Rantala 2015), dividend policy (Adhikari and Agrawal 2018; Grennan 2019), corporate social responsibility (Cao, Liang, and Zhan 2019), taxes paying (Bird, Edwards, and Ruchti 2018), and voluntary information disclosure (Lin, Mao, and Wang 2018). These peer effects can be driven by various mechanisms, such as market competition (Grennan 2019), learning (Bikhchandani, Hirshleifer, and Welch 1992; Foucault and Fresard 2014; Leary and Roberts 2014), or reputational concern (Scharfstein and Stein 1990).

Apart from these traditional explanations, some recent articles focus on finding new factors which will influence corporate peer effects. Fairhurst and Nam (2020) find that firms with weaker external corporate governance are more likely to imitate

[3] According to Manski (1993), the reflection problem refers to the issue that arises when the scholars intend to investigate how the average behaviour within a group will influence the behaviour of a unique individual that comprise the group. For instance, the observed co-movement between a firm and its peers does not necessarily indicate that the focal firm is following its peers. It can also suggest that the focal firm's peers are mimicking this firm.

peers' financial policy. In addition, Im, Liu, and Park (2021) suggest that a firm's investment peer effect is more pronounced when political uncertainty is high. However, in contrast to the studies exploring corporate peer effects in different areas, the amount of research focusing on the explanation of the peer effect is comparably small.

2.4 Dividend smoothing

Dividend smoothing, a phenomenon that firms' dividend adjustments are much smoother than earnings change, is an important puzzle in corporate finance research. This phenomenon is quite robust and significant in the U.S. market (Lintner 1956; Fama and Babiak 1968; Brav et al. 2005; Leary and Michaely 2011), and also exists in international markets (Javakhadze, Ferris, and Sen 2014; Ellahie and Kaplan 2021). The concept of dividend smoothing was first developed by Lintner (1956), who finds that firms are extremely reluctant to change dividends. Lintner mainly provides the survey evidence of this effect from 28 typical companies, but does not suggest a clear explanation for it. However, the widespread dividend smoothing behaviour makes it meaningful to investigate why firms are willing to smooth their dividend payments.

During the past half century, scholars have tried to use different theories to explain the reason why firms smooth dividends. First and foremost, a group of studies believe that dividend smoothing is a rational decision of a firm, which should enhance shareholders' wealth. For example, some traditional signalling theories believe firms pay stable dividends to disclose private information about the stability of future earnings (Bhattacharya 1979; Miller and Rock 1985). Also, Kumar (1988) argues that firms sustain dividend payments at a certain level to distinguish themselves from competitors who cannot maintain dividend payments at this level. These theories indicate that dividend smoothing should decrease the levels of information asymmetry between insiders and outsiders. In addition, Allen, Bernardo, and Welch (2000) argue that high and smoothed dividend payments can be treated as a tool for firms to attract institutional investors, which is helpful for firms' external financing.

On the contrary, another strand of literature disagrees with the idea that dividend smoothing is a rational behaviour of a firm to maximize shareholders' value. Fudenberg and Tirole (1995) indicate that dividend smoothing can result from the agency problems within the firm. They argue that managers smooth dividends to avoid punishment following a dividend cut. As financial markets have an asymmetric reaction toward dividend increase and decrease, managers have incentives to smooth dividend payments to avoid cutting dividends. Wu (2018) finds empirical evidence that dividend smoothing will indeed lower managers' turnover risk, which supports Fudenberg and Tirole (1995)'s argument. In addition, Lambrecht and Myers (2012) suggest dividend smoothing is a strategy for managers to maximize the rent they extract from the firm. Consequently, we can find, until now, that there is no agreed conclusion as to why firms smooth dividends.

2.5 Supplier-customer relationship

Corporate customers, who are important stakeholders for suppliers, can exert significant influence on firm operations and corporate decisions. The fear of losing potential sales with principal customers will drive suppliers to engage in customer-benefit activities to please these stakeholders. The prior literature investigates why firms' major customers will put pressure on them to adjust their corporate policies to satisfy customers' demands. This effect has been proved to be influential for many corporate policies. For instance, Cen et al. (2017) find that customers will affect suppliers' tax avoidance behaviour. Dai, Liang, and Ng (2021) indicate that socially responsible customers will also push suppliers to engage in corporate social responsibility (CSR) investment.

However, it is still unclear whether the pressure from customers is a good or a bad thing for suppliers. The literature which argues that customers' pressure will impair firm value suggests that powerful customers will extract benefits from suppliers. According to Lustgarten (1975), the market concentration of buyers will decrease the price cost margin of suppliers. Ravenscraft (1983) supports this view by showing that powerful buyer will decrease the sellers' profit margin. These findings are supported by some recent studies which find that customer power can also impair suppliers' benefits in some different ways. For instance, Campello and Gao (2017) indicate that higher customer concentration will increase the interest rate and the number of restrictive covenants for new bank loans. Ma et al. (2020) find that concentrated customers will lead to higher future crash risk. Dong, Li, and Li (2021) suggest that target firms with more concentrated customers are also associated with lower post-merger performance.

On the contrary, some articles related to the customer–supplier relationship argue that a more concentrated customer base can enhance suppliers' performance. In contrast with Lustgarten (1975) and Ravenscraft (1983)'s industry-level research, Kalwani and Narayandas (1995) investigate firm-level data, and find that a more concentrated customer base is associated with a higher profit margin. They argue that firms can enjoy collaborative marketing and economics of scale from big customers. Consistent with this finding, Patatoukas (2012) finds evidence showing that larger customers will increase the accounting return of suppliers. Different from the collaborative theory, some recent research also argues that customers can play a monitoring role to help them improve themselves. For instance, Cai and Zhu (2020) find that customer bargaining power will decrease the cost of debt of firms. Chen et al. (2021) introduce a disciplinary role for a firm's major customers in reducing suppliers' misconduct relating to social and environmental responsibility. According to all these studies, customers may impair suppliers' interests in some aspects while, at the same time, they can also be beneficial for suppliers in some other aspects.

3. Internal information quality and financial policy peer effects

This chapter investigates how firms' internal information quality (IIQ) influences the peer effects of their financial policies. Using earnings announcement speed and insider trading profitability difference as measurements, we find that when IIQ is low, firms are more likely to change their leverage following a similar change made by peer firms in the same industry. Our further analysis shows that this mimicking behaviour hurts firms' operating performance, and is more prevalent when firms are also characterized by poor corporate governance. Overall, our results indicate that poor information quality could amplify the agency problem, therefore leading to stronger peer effects in corporate financial policies.

3.1 Introduction

It has long been known that the actions and endorsements of some agents often influence others' behaviour (Bikhchandani, Hirshleifer, and Welch 1998). A recent strand of literature also discovered that when peer firms change their financing, investment, or dividend policies, firms tend to follow and adjust their own policies accordingly (Graham and Harvey 2001; Foucault and Fresard 2014; Francis, Hasan, and Kostova 2016; Grennan 2019; Bustamante and Frésard 2020). This is known as "peer effects". In this study, we investigate how firms' internal information quality (IIQ) influences peer effects on their financial policies.

Gallemore and Labro (2015) define the IIQ as "accessibility, usefulness, reliability, accuracy, quantity, and signal-to-noise ratio of the data and knowledge collected, generated, and consumed within an organization". IIQ is important for corporate decision-making for two reasons. First, the quality of internal information will influence the quality of corporate decisions and their outcomes (Gallemore and Labro 2015). Low IIQ can prevent firms from making optimal corporate decisions. Second, the quality of internal information influences the efficacy of monitoring (Harp and Barnes 2018; Laux, Lóránth, and Morrison 2018). In organizations characterized by poor IIQ, monitoring is more costly and agency costs are exacerbated.

Peer effects in corporate financial policy are closely related to a firm's internal information quality. First, according to Bikhchandani, Hirshleifer, and Welch (1998)'s observational learning model, if a firm is confident about the precision of its self-collected information, it will rely less on the information generated by external sources. Consequently, firms' reliance on the signals implied by peer firms' financial policy will be influenced by their IIQ. Secondly, a firm's IIQ will impact its corporate governance as information plays a crucial role in corporate monitoring (Laux, Lóránth, and Morrison 2018). Since the quality of internal control is also related to the peer effects of corporate policies (Fairhurst and Nam 2020), IIQ could potentially influence leverage peer effects through the corporate governance channel.

To understand the effect of IIQ on financial policy peer effects, following Gallemore and Labro (2015) and Chen et al. (2018), we adopt two internal information quality measurements to test the moderating effects of internal information quality on firms' mimicking behaviour. The first measurement is earnings announcement speed (EAS), which is the number of days between the earnings announcement date and fiscal year-end, divided by 365. Intuitively, effective internal information-sharing mechanisms should enable firms to quickly integrate information from different parts of the organization. Therefore, a more efficient internal information system should be able to narrow the time gap between the earnings announcement date and fiscal year-end date (Gallemore and Labro 2015). The second measurement is the difference in insider trading profitability (Dret), which is the difference between the trading profit on their own company's stock achieved by divisional managers and top managers. Higher Dret indicates a more severe information asymmetry between managers at different levels and implies poorer internal information quality possessed by top managers (Chen et al. 2018).

By using these two measurements, we find that, when internal information quality is low (high EAS and high Dret), firms' capital structure is more likely to move in line with the capital structure of their industry peer firms. This effect is both statistically and economically significant. For a firm with IIQ ranked in the top 25% of the sample, a one standard deviation increase in peer leverage would, on average, lead to a 1.81% or 0.97% increase in the firm's own leverage depending on which measure we are using. However, for firms with IIQ in the bottom 25%, the same increase in peer leverage would lead to a leverage increase of 3.35% (EAS) or 1.38% (Dret), which indicates an 85% and 42% increase in magnitude. Our robustness tests adopting different leverage measurements (market leverage or book leverage) and industry classification (both SIC and TNIC) confirm these findings.

Our findings are unlikely to suffer from reverse causality- Firms' internal information quality is unlikely to be driven by peer effects on their financial policy. However, we still need to address the potential endogeneity issue caused by unobservable omitted variables that simultaneously drive both firms' IIQ and leverage peer effects. We adopt a difference-in-difference test to mitigate this concern. In 2004, Section 404 of the Sarbanes-Oxley Act (SOX404) was enacted. The Act mandates firms to evaluate the adequacy of their internal controls and to disclose material weaknesses. To avoid reputational loss due to the disclosure of material internal control weaknesses, firms have incentives to improve their internal information quality. Since the enactment of the Act is exogenous to the decision of the firm, we can exploit this shock and design difference-in-difference tests to validate our findings.[4] Consistent with the main conjecture, firms that experience a distinct improvement in internal information quality (disclosed a material weakness in 2004 and revised it in the year after) significantly reduce mimicking behaviour after the event.

We investigate two potential motivations that drive firms to mimic the capital structure of their peers. First, firms can acquire information both internally and externally. When internal information quality is poor, we expect firms to be more reliant on external sources of information. One important external information source is industry peers (Leary and Roberts 2014). Considering peer firms are not likely to reveal all the information in their possession to the market, actual corporate decisions may convey implied signals that the firms of interest use in their decision-making. Since the signal that the focal firm receives originated from its peers, they are likely to make similar decisions to those made by their peers. Therefore, we can observe a peer effect in financial policies. This behaviour is consistent with the prediction of the information cascade model by Bikhchandani, Hirshleifer, and

[4] A similar approach has been applied in previous studies, such as Gallemore and Labro (2015); Huang, Lao, and McPhee (2020)

Welch (1992) and Bikhchandani, Hirshleifer, and Welch (1998). We call this the information acquisition channel.

On the other hand, poor internal information quality will reduce the monitoring efficacy of the board of directors and weaken corporate governance (Harp and Barnes 2018; Laux, Lóránth, and Morrison 2018). An inefficient internal information system will make it harder for boards to detect managers' self-interested behaviour. Also, firm performance is frequently measured against peer firms. Therefore, incompetent CEOs could simply follow the decisions made by their peers to "play it safe" so that they could attribute any potential failure to industry-level shocks rather than to their lack of competence (Scharfstein and Stein 1990). Therefore, stronger peer effects in corporate policies may also imply the presence of severe agency problems (Fairhurst and Nam 2020). With poor internal information quality, monitoring becomes more costly and agency costs can be amplified, resulting in stronger peer effects in firms' financial policy. We call this the agency cost channel.

We conduct further tests to investigate which of these two potential channels is the main driver of our findings. First, the information acquisition channel implies that peer mimicking provides an important channel through which firms can learn new information. Peers' action may contain information about market trends and investment opportunities (Leary and Roberts 2014; Foucault and Frésard 2014). As suggested by Larcker, So, and Wang (2013) and El-Khatib, Fogel, and Jandik (2015), the quality of information acquired by firms' headquarters is critical for firms' performance.[5] Therefore, following peers should improve the firm's information set and eventually be positively reflected in the firm's performance. On the contrary, agency issues are value-destroying to the shareholders. Scharfstein and Stein (1990) suggest that mimicking peers' investment is inefficient for firms but can protect managers' reputation. If the amplified peer effects are the results of amplified agency costs associated with poor IIQ, we should expect a negative impact of peer effects on the firm's performance. To investigate these predictions, we follow Fairhurst and Nam (2020) and identify firms that are subject to stronger leverage peer effect as mimickers and other firms as non-mimickers. Then we look at the performance of these firms under different levels of IIQ. Our results show that the performance of mimickers is significantly worse when they operate in a poor IIQ environment. Compared with the average performance of non-mimickers, mimickers' return on equity (ROE) is 51.3% lower while return on assets (ROA) is 40.7% worse when IIQ is low. These results indicate that on average when IIQ is poor, the stronger peer effects in leverage are value-destroying. Therefore, the agency cost channel, rather than the information acquisition channel, is more likely to be the main driver of the amplified peer effect.

The tests of firm performance provide indirect evidence on the potential channel of our main findings. However, to further verify our claim that our main findings can be attributed to the agency cost channel, we conducted further tests. The previous literature has long established that effective corporate governance can significantly mitigate agency costs. Therefore, for a well-governed firm with effective monitoring

[5] Larcker, So, and Wang (2013) argue that firm with higher level of board network centrality earn higher risk-adjusted stock return. Similarly, El-Khatib, Fogel, and Jandik (2015) find firms with higher CEO network centrality are associated with more value creating acquisition deals.

in place, we expect the agency cost amplified by the poor IIQ to be moderate. In other words, if strong leverage peer effects are indeed the results of agency costs, we should observe that the effects would only be significant for firms without strong corporate governance. To test this hypothesis, we use the takeover index and CEO-Chair duality as proxies to further divide our samples into well-governed firms and poorly governed firms before estimating our baseline regression in each of the subsamples. Our results show that stronger peer effects in leverage are mainly driven by firms without good corporate governance, and confirm our hypothesis that our main findings are driven by the agency cost channel.

We also conduct a battery of robustness checks to further mitigate various potential concerns with our findings. First, although the contemporaneous specification of our baseline model could limit the time for firms to respond to other firms (Leary and Roberts 2014), one may argue that this would also amplify the potential reverse causality issue. While we believe the 2SLS estimation approach can largely mitigate this concern, we also conducted further tests by using lagged independent variables. Second, to further control for potential omitted variable issues, we conducted further tests by replacing the industry fixed effects with stricter firm fixed effects and high dimensional fixed effects in the panel regressions. Third, to make sure that our results are robust to different proxies, we conducted further tests using alternative internal information quality proxies, book leverage, and an alternative peer definition. Lastly, to mitigate the concerns that our results might be driven by the size, financial distress, cash flow volatility, or the idea that IIQ is a proxy for corporate governance, we conduct further tests by including interaction terms between IIQ and relative size, Z-score, industry level cash flow volatility and corporate governance proxies to our baseline model. Our results remain robust to all these additional tests.

This chapter of the thesis contributes to the literature in several ways. First, it enriches the recent literature studying peer effects in corporate policies. The extant studies focus mainly on identifying the existence of peer effects in firm behaviours such as financial policies (Leary and Roberts 2014), dividend policies (Grennan 2019), investment policies (Bustamante and Frésard 2020), trade credit policy (Gyimah, Machokoto, and Sikochi 2020), or innovation (Machokoto, Gyimah, and Ntim 2021). However, we focus on identifying the background mechanisms that drive the peer effects. We find that poor internal information quality increase peer mimicking, and these effects are more pronounced in firms with higher agency costs. Our findings also support previous literature that the peer effects are related to corporate governance level and are value-destroying (Fairhurst and Nam 2020).[6]

Second, the chapter contributes to the studies that investigate the influence of information quality on corporate decision-making. Some pioneering work has been done in this area. For example, Gallemore and Labro (2015) find that firms with good internal information quality enjoy a lower effective tax rate. Heitzman and Huang (2019) argue that when IIQ is high, corporate investments are more sensitive to internal signals. Huang, Lao, and McPhee (2020) find that higher IIQ could have a positive effect on innovation. However, to the best of our knowledge, our study is the first to investigate the effect of IIQ on the peer effects of corporate policies, and it provides new insights into the real effects of internal information quality.

[6] Our results stay robust after controlling for several corporate governance measurements.

The rest of the chapter proceeds as follows. Section 3.2 presents the methodology and variable definitions. Section 3.3 displays the sample used in this study and empirical results. Section 3.4 describes the further analysis and robustness checks. Section 3.5 provides conclusions and implications.

3.2 Research design and variable definition

3.2.1 Research design

Following Leary and Roberts (2014), we estimate the leverage peer effects by applying the model below:

$$Leverage_{it} = \alpha + \beta Peer\ Leverage_{-it} + \gamma Controls_{-it-1} + \delta Controls_{it-1} + \mu_j + \nu_t + \varepsilon_{it} \quad (3.1)$$

The dependent variable $Leverage_{it}$ indicates the leverage ratio of firm *i*, in year *t*. $Peer\ Leverage_{-it}$ is the average leverage ratio of all the firms with the same 3-digit industry SIC code, excluding firm *i*, at year *t*. $Controls_{it-1}$ indicates a set of firm characteristics which are determinants of the firm's capital structure and $Controls_{-it-1}$ indicates the average value of these characteristics for industry peers. The terms μ_j and ν_t are the industry and year fixed effects, respectively. In this model, the value of β indicates the reaction of a firm's leverage in response to the change in the average peer leverage. A positive and statistically significant β, therefore, indicates the existence of peer effects in that firms will change their leverage in the same direction as changes made by peer firms in the same industry.

To identify the incremental effect of internal information quality on the peer effect in financial policy, we extend Leary and Roberts's model by including internal information quality proxies and their interaction with peer leverage into the model (3.1):

$$Leverage_{it} = \alpha + \beta_1 Peer\ Leverage_{-it} \times IIQ_{it} + \beta_2 Peer\ Leverage_{-it} + \beta_3 IIQ_{it} + \gamma Controls_{-it-1} + \delta Controls_{it-1} + \mu_j + \nu_t + \varepsilon_{it} \quad (3.2)$$

where IIQ_{it} indicates a proxy for internal information quality. In this augmented model, β_3 will capture the effect of internal information quality on firm leverage, while the coefficient of interaction term (β_1) will identify the incremental effect of internal information quality on the leverage peer effect. We use a contemporaneous measure which means the firms have less time to react to on another makes. The contemporaneous term makes it more difficult to identify peer mimicking, which also mitigate the influence of reverse causality and confounding factors. It also mitigates the scope for confounding effects by reducing the likelihood of other capital structure relevant changes. A similar approach has been adopted by other studies, such as Francis, Hasan, and Kostova (2016).

3.2.2 Identification of peer mimicking

The identification of peer effects is not straightforward. According to Manski (1993) and Leary and Roberts (2014), correlation between the characteristics of a firm and its peers can also be caused by other factors. For example, a common shock to an industry may cause all the firms in that industry to simultaneously change their financial policy, and therefore leads to a positive correlation between their leverage. This challenge arises when we try to identify the effect of group characteristics on the group member firms and it is essentially an endogeneity problem that needs to be addressed.

To address this concern, we follow Leary and Roberts (2014) and adopt a two-stage least squares (2SLS) approach to estimate the model. Specifically, before we run the second stage regression that identifies the peer effect, we use peer equity shock, which is measured by the idiosyncratic component of stock return, as an instrumental variable (IV) to extract the fitted value of peer leverage. The construction of this IV is based on the following augmented market model:

$$r_{ijt} = \alpha_{ijt} + \beta_{ijt}^{M}(rm_t - rf_t) + \beta_{ijt}^{IND}(\bar{r}_{-ijt} - rf_t) + \eta_{ijt} \qquad (3.3)$$

$$\hat{r}_{ijt} = \hat{\alpha}_{ijt} + \hat{\beta}_{ijt}^{M}(rm_t - rf_t) + \hat{\beta}_{ijt}^{IND}(\bar{r}_{-ijt} - rf_t)$$

$$Equity\ shock = r_{ijt} - \hat{r}_{ijt}$$

In equation (3.3), the r_{ijt} is the stock return of firm *i* in industry *j* in month *t*. $(rm_t - rf_t)$ is the market excess return. $(\bar{r}_{-ijt} - rf_t)$ is the return of an equally weighted portfolio consisting of all firm *i*'s peer firms in industry j. η_{ijt} refers to the idiosyncratic part of firm *i*'s stock returns. Model (3.3) is then estimated annually for each firm with a 60-month (minimum 24-month) rolling window. For instance, to estimate the coefficient β_{ijt}^{M} and β_{ijt}^{IND} for a firm in 2010, we need at least 24 monthly stock return observations for this firm from January 2005 to December 2009. We then calculate the firm's equity shock by extracting the idiosyncratic part of this firm's stock return using equation (3.3). Specifically, we first estimate the expected stock return $\hat{r}_{ijt}$ for each firm in each month using the rolling estimation method introduced above. Then, we calculate the idiosyncratic return by deducting the expected value of stock return from its actual value. Finally, we compound the monthly idiosyncratic stock returns to obtain the annually equity return shock. The detailed estimation results of model (3.3) are reported in Appendix (Table 3.A.2).

The validity of equity return shock as an instrumental variable rests on two grounds. First, a firm's stock return is known to be an important determinant of capital structure (Marsh 1982; Loughran and Ritter 1995). Therefore, the IV satisfies the relevance condition. Second, when estimating the idiosyncratic return, the common factors that influence the return of the entire market and the return of specific industry have been absorbed by the two independent variables: $(rm_t - rf_t)$ and $\left(\bar{r}_{-ijt} - rf_t\right)$. Since η_{ijt} is net of these common factors, it captures the variation of return that is independent of the market or industry-wide shock, and the exclusion condition is also satisfied (Leary and Roberts 2014).

3.2.3 Internal information quality measurements

We use two variables to measure a firm's internal information quality. The first is earnings announcement speed (EAS), which is the number of days between the firm's fiscal year-end and earnings announcement date, divided by 365. Intuitively, a higher value of EAS indicates that a firm takes more time to prepare the financial statements and indicates a lower internal information quality. EAS is widely used as a proxy for a firm's internal information quality (Gallemore and Labro 2015; Heitzman and Huang 2019; Huang, Lao, and McPhee 2020). Jennings, Seo, and Tanlu (2013) argue that firms with better internal information systems can report earnings information more quickly. Gallemore and Labro (2015) also argue that an accounting system that eliminates manual intervention, reduces redundancy, and streamlines reporting can also improve the efficiency of financial disclosure and accelerate the earnings announcement speed.

The second variable we use to measure internal information quality is the difference between the insider trading profitability for divisional managers and top managers (Dret).[7] Chen et al. (2018) suggest that the disparity between the profitability of insider trading for different levels of managers reflects the asymmetry of information within the management hierarchy. Higher trading profitability of the divisional managers (higher Dret) not only indicates their information advantage over top managers but also reveals that information does not flow smoothly up the hierarchy and business units. The obstructed information transmission will amplify the difficulties faced by top managers in accessing the information on the firm's financial health and limit their ability to make strategic decisions.

For robustness checks, we also adopt two alternative indicators to measure a firm's internal information quality. The first one is Restatement- a dummy variable that equals one if firms report any restatement due to unintentional errors and zero otherwise. Those unintentional errors arise mainly because of basic accounting errors. Such restatements indicate the information reported is unreliable or inaccurate, which also suggests poor internal information quality (Gallemore and Labro 2015; Heitzman and Huang 2019). The second variable is Weakness- a dummy variable that equals one if firms disclose a material weakness in internal controls in the current year and zero otherwise. According to Feng, Li, and McVay (2009) and Gallemore and Labro (2015), firms with material weakness are more likely to decide their strategy based on untimely or even inaccurate financial information. In principle, firms which disclose a material weakness in the current year are more likely to face lower internal information quality.

[7] Chen et al. (2018) treated the CEO, CFO and COO as top managers and other lower-level managers as divisional managers. Detailed definitions are provided in table 3.A.1.

3.2.4 Control variables

To eliminate the possibility that our findings are driven by heterogeneity in firms' basic characteristics, we include a set of control variables in the model. For our main analysis, we include several most influential determinants of firms' leverage ratio following previous studies (Frank and Goyal 2009; Leary and Roberts 2014). These variables include firm size (log(sales)), market to book ratio, profitability (EBITDA/ Total Assets), and asset tangibility (Net PP&E/ Total Assets).[8] In addition to the firms' characteristics, the average values of these characteristics for peer firms are also included in the model. In our further robustness checks, we also control for additional factors which may impact our results, such as corporate governance, relative size and information asymmetry level.

3.3 Sample selection and empirical findings

3.3.1 Sample selection and descriptive statistics

Our analysis is focused on a large sample of listed firms in the US. To construct our sample, we extract accounting data and earnings announcement data from the Compustat database, stock price data from the CRSP database, and insider trading data from Thomson Financial. In addition, we download data about firms' restatements and internal control weakness from Audit Analytics. Consistent with Leary and Roberts (2014), all financial firms (SIC code from 6000-6999), utilities (SIC code from 4900-4999), and government entities (SIC code greater than or equal to 9000) are excluded. For additional tests, the CEO duality information

[8] Frank and Goyal (2009) indicate that these four variables are reliably important for firms' capital structure. They argue that larger firms and firms with more tangible assets have relatively higher leverage, while firms with higher market to book ratio and higher profitability ratio have lower leverage ratio.

comes from the ExecuComp database, and the takeover index data comes from Dr Stephen McKeon's webpage.[9] All variable definitions are given in detail in Appendix (Table 3.A.1).

Due to differences in data availability, our samples for the two main internal information quality proxies span two different periods - EAS is available from 1965 to 2017, while Dret is available from 1989 to 2017.[10] Table 1 presents summary statistics for our sample. Our full sample contains 100,745 firm-year observations with non-missing data for all firm characteristic variables. All variables are presented after winsorizing at the 1st and 99th percentiles. Variables without "peer" in the name refer to the characteristics of a single firm, while the variables starting with "peer" stand for average characteristics of firms within the same 3-digit SIC industry, excluding the firm in question. The summary statistics in our tables are very similar to the ones reported in previous papers, such as Leary and Roberts (2014), Gallemore and Labro (2015), and Chen et al. (2018).

3.3.2 *Internal information quality and financial policy peer effects*

In this section, we investigate the impact of firms' IIQ on their capital structure peer effects. First, we estimate model (3.1) to identify the existence and magnitude of the leverage peer effect. Column (1) of Table 3.2 shows that average peer leverage is positive and significantly related to firms' leverage, indicating the existence of leverage peer effects. Then we estimate model (3.2) with the interaction terms between IIQ and peer leverage. In columns (2) and (3), the coefficients of both

[9] https://pages.uoregon.edu/smckeon/.

[10] Our *Dret* sample covers a shorter period because the insider trading data is only available after 1989. Our results are staying robust if the *EAS* sample also starts from 1989.

interaction terms, EAS × peer leverage, and Dret × peer leverage, are positive and statistically significant. The result indicates that as IIQ deteriorates (when EAS or Dret are higher), an increase in average peer leverage has a stronger positive impact on firms' leverage. This is consistent with our main conjecture that lower internal information quality will enhance the firm's propensity to mimic peer behaviour.

As discussed in section 3.2.2, the positive correlation between firm leverage and peer firms' leverage might also be driven by the "reflection-problem" or the "self-selection" issue. In other words, the OLS estimation of leverage peer effect might be subject to an endogeneity problem. To address this issue, following Leary and Roberts (2014), we use the instrumental variable approach introduced in section 3.2.2 to estimate the model. Specifically, we run a two-stage least squares (2SLS) regression for equation (3.2). In the first stage, we use peer equity shock as the instrumental variable. In the second stage, we replace the peer leverage with its fitted value obtained from the first stage model. A similar approach has been adopted in related research (Leary and Roberts 2014; Francis, Hasan, and Kostova 2016; Fairhurst and Nam 2020).

The results of our 2SLS estimation are presented in Table 3.3. In columns (1) and (2), we first check how peers' leverage influences a firm's financing decisions. Consistent with previous studies (e.g., Leary and Roberts, 2014), we find that peer equity shock is a negative and statistically significant predictor of peer leverage in the first-stage regressions. In addition, the coefficient of fitted peer leverage in the second-stage regression is positive and statistically significant. These results confirm our finding of the leverage peer effects in our OLS regression. Columns (3) - (6) present estimation results including the interaction between IIQ and peer leverage.

In columns (4) and (6), we find positive and statistically significant coefficients for the interaction between IIQ and peer leverage (EAS× Peer leverage and Dret× Peer leverage). The coefficients of the interaction terms are also economically significant. A one standard deviation increase in peer leverage would lead to a 1.81% increase in firms' leverage for a firm with 25% EAS while the same change in peer leverage will induce a 3.35% increase in leverage for a firm with 75% EAS.[11] For the Dret sample, a one standard deviation increase in peer leverage would lead to a 0.97% increase of firms' leverage for a firm with 25% Dret while the same change in peer leverage will induce a 1.38% increase in leverage for a firm with 75% Dret.[12] These results indicate that poor IIQ would amplify the peer effects of firm leverage.

3.3.3 Endogeneity and Identification

3.3.3.1 Difference-in-Difference approach.

Although our results show a significant relationship between firms' internal information quality and mimicking behaviour, it is still hard to say the relationship indicates a causal effect between these two factors. In other word, we need to find ways to identify that bad internal information quality is the reason drives firms to mimic others.

For the reverse causality concern, firms' internal information quality is mainly determined their size, corporate governance, and firm structures (Doyle, Ge, and McVay 2007), which are characteristics with comparably little variance over time.

[11] The standard deviation of estimated peer leverage ratio is 0.089 for EAS sample and 0.080 for Dret sample. Based on the standard deviation of estimated peer leverage, the 1.81% is calculated as 0.089×(0.099×2.035+0.002), while the 0.97% is calculated as 0.080×(-0.091×0.295+0.149).

[12] Based on the standard deviation of estimated peer leverage, the 3.35% is calculated as 0.089×(0.184×2.035+0.002), while the 1.38% is calculated as 0.080×(0.083×0.295+0.149).

Consequently, firms' internal information environment should not be influenced directly by managers' short-term choices, such as peer mimicking. Although our finding is not likely to be driven by reverse causality, it is still reasonable to expect that some omitted factors could simultaneously influence both internal information quality and the leverage peer effects. To address this endogeneity concern, following Gallemore and Labro (2015) and Huang, Lao, and McPhee (2020), we designed a difference-in-difference test by exploiting the enactment of the Sarbanes-Oxley Act (SOX) as an exogenous shock to firms' internal information quality.

Section 404 of SOX requires firms to evaluate their internal controls on financial reporting and to disclose if there is a material weakness. Since the disclosure of material weakness sends a negative signal to the market, firms are incentivized to improve their internal information quality. Because the SOX 404 is an act which aims to improve firms' internal control quality and internal information environment, it should directly impact firms' internal information quality, but exogenous to other confounding factors. Therefore, the enactment of SOX 404 could be used as a shock for our identification (Gallemore and Labro 2015).[13]

In our difference-in-difference design, following Gallemore and Labro (2015) and Huang, Lao, and McPhee (2020), we defined firms that disclosed material weaknesses in the year 2004 but revised it in the following years as treated firms, and all other firms with Audit Analytics database coverage as control firms. A dummy variable "Treated" is then generated to indicate the treated firms and to capture the difference in characteristics between two sets of firms. We also treat

[13] A similar strategy has also been adopted by Huang, Lao, and McPhee (2020) and McGuire, Rane, and Weaver (2018)

three years before the enactment (2001, 2002, and 2003) as the pre-event period and three years after the enactment (2005, 2006, and 2007) as the post-event period, and generated a dummy variable "Post" to indicate the post-event change of leverage of all firms. The interaction term "Treated× Post" identifies the incremental effect of the SOX 404 enactment on the treated firms' leverage. To capture the impact of SOX 404 enactment on the financial policy peer effect, we follow the design of Edmans, Jayaraman, and Schneemeier (2017) and Jayaraman and Wu (2019) by interacting the "Treated× Post" with the fitted peer leverage obtained by estimating the first-stage regression of our 2SLS model and generating a triple interaction term $Peer\ Leverage_{-it} \times Treated \times Post$.[14] Since treated firms are expected to improve their internal information quality as a result of SOX 404 enactment, our hypothesis predicts a negative coefficient on the triple interaction term: the leverage peer effect of the treated firms would become less prominent after the event. After adding the same set of control variables as used in the baseline model and fixed effects, our full model can be displayed as follows:

$$Leverage_{it} = \alpha + \beta_1 Peer\ Leverage_{-it} \times Treated \times Post + \beta_2 Peer\ Leverage_{-it} \times Treated + \beta_3 Peer\ Leverage_{-it} \times Post + \beta_4 Treated \times Post + \beta_5 Peer\ Leverage_{-it} + \beta_6 Treated + \gamma Controls_{-it-1} + \delta Controls_{it-1} + \mu_j + \nu_t + \varepsilon_{it} \tag{3.4}$$

Table 3.4 presents the results of our difference-in-difference tests. Columns (1) and (2) of Panel A display the results with industry fixed effects and firm fixed effects, respectively. Since the SOX-404 enactment event would lead to an improvement of IIQ, we would expect weaker peer effects of the financial policy after the SOX-404

[14] We use the fitted peer leverage to alleviate the endogeneity concern in identifying leverage peer effect. The test using peer leverage variable directly, yields very similar findings.

enactment, if the peer effects on financial policy are indeed amplified by low IIQ. Consistent with our prediction, in both columns, the coefficients β_1 of the triple interaction term $Peer\ Leverage_{-it} \times Treated \times Post$ in equation (3.4) are negative and statistically significant.

We then apply the propensity score matching (PSM) procedure to mitigate the influence brought by heterogeneity in firm-specific characteristics between treated and control firms. Considering that the number of treated firms is small, we match each of them with three control firms in the year before the event (the year 2003).[15] Panel B displays the difference of firm-specific characteristics between treated firms and control firms after the matching. We can see that the differences in the average value of all the matching variables are statistically insignificant, showing that the matching procedure largely eliminates the heterogeneity between treated and control firms. Panel C presents the difference-in-difference test results using the matched sample. The coefficient β_1 on the triple interaction term is still negative and statistically significant. These findings indicate that the influence of peer firms' leverage on the treated firms' leverage is significantly weaker after the enactment of SOX 404 and support our main conjecture that the peer effect on firm leverage weakens when internal information quality improves.

3.3.3.2 Lagged explanatory variables and firm fixed effects

To be consistent with the existing studies (Leary and Roberts 2014; Francis, Hasan, and Kostova 2016; Fairhurst and Nam 2020), we used a contemporaneous setting in

[15] We also try 1-to-1 match and 1-to-2 match methods, but the matched control firms have higher differences in some characteristics for treated firms, compared with all the control firms in the full sample.

our baseline model. While the contemporaneous model is a stricter setting to test peer mimicking as it allows less time for firms to react (Leary and Roberts 2014), it is also more likely to be contaminated by the common omitted factors that lead to the endogeneity problem. A dynamic model with lagged independent variables could partially alleviate this concern, therefore, in this section, we adopt a robustness check by using lagged estimated peer leverage and internal information quality proxies in our tests.

Panel A of Table 3.5 presents the results of our baseline model estimated by using lagged explanatory variables. Consistent with the baseline results, the coefficients of the interaction term are still positive and statistically significant. The results could, at least partially, mitigate the concern that the results are driven by firms' co-movement in response to the contemporaneous shock.

Our baseline model has already incorporated several firm characteristics and industry fixed effects. To further alleviate the concern that omitted time-invariant factors may also drive our findings, we also conducted a test including firm fixed effects. Compared with industry fixed effects, firm fixed effects can better control for unobserved factors that may influence our results. In panel B of Table 3.5, we present the results of baseline tests after replacing industry fixed effects with the firm fixed effects. The positive and statistically significant coefficients of the interaction terms (EAS/ Dret× Peer leverage) provide evidence that our results are not driven by time-invariant fixed effects.

3.4 Potential mechanisms and further analysis

In this section, we explore the effects of, and potential channels for peer mimicking under poor internal information quality.

3.4.1 Information acquisition vs. agency cost

After documenting the amplified financing policy peer effects under poor internal information quality, we shift our focus to an attempt to identify the potential mechanisms that drive the effect. Firms are likely to mimic the behaviour of their product market peers because they believe that peer firms have better information. Consequently, when a firm observes that peer firms change their leverage, they may assume that this would also be a good option for them too, therefore they adjust their own capital structure following the lead of their peers. This hypothesis is consistent with the informational cascade model developed by Bikhchandani, Hirshleifer, and Welch (1998), which predicts that decision-makers are likely to follow the behaviours of their peers as long as they believe their peers' decisions contain new information. Banerjee (1992)'s herding model also implies that uninformed individuals will be more likely to follow predecessors.[16] Similar arguments are also supported by more recent literature. For example, Foucault and Frésard (2014) suggest that firms will learn from their peers' stock prices when making investment decisions because peers' stock prices contain useful information about future

[16] In Banerjee's (1992) model, all individuals can observe the choices of their predecessors, and they know that their predecessors have their own signals. However, they do not know the contents of their predecessor's signals and have no idea of whether the signals are correct. Also, they do not know how the predecessors make their decisions (based on their own signals or mimicking others).

demand in the industry. We define this potential explanation as “the information acquisition channel”.

On the other hand, firms may also mimic the behaviour of their product market peers due to agency problems. For example, managers are concerned about their reputation in the labour market. A “follow the herd” strategy enables them to attribute their failure to uncontrollable systematic risk, instead of lack of competence (Bolton and Scharfstein 1990). Therefore, when corporate governance is weak, managers would be more likely to choose to optimize their career outcome by ignoring their private information and mimicking the behaviour of their peers. Also, good internal information quality is essential for shareholders to mitigate agency problems. Low internal information quality reduces the efficacy of the board of directors’ monitoring and amplifies the agency problem (Harp and Barnes 2018; Laux, Lóránth, and Morrison 2018). Therefore, a low IIQ environment would enable managers to ignore private information and choose to follow peers’ decisions. We define this explanation the “the agency cost channel”.

Although both the information acquisition and agency cost hypothesis predict that with low internal information quality, firms are more likely to mimic the financial policy of their product market peers, the implications of the two hypotheses are different. If mimicking behaviour reflects managers’ incentives to learn, then the consequence of such learning should in general be positively reflected in the firms' future performance. On the other hand, if mimicking is the consequence of amplified agency cost, then the firms’ performance would be likely to suffer.

To improve our understanding of this issue, we classify firms as mimickers and non-mimickers and investigate the difference in their performance under different levels of information quality. Specifically, we follow the approach taken by Belsley, Kuh, and Welsch (2005, p. 13-14) and use DFBETA statistics as the basis of the mimicker classification. DFBETA describes how the coefficient estimates change if an observation is excluded. In this study, for each firm-year observation, DFBETA is the difference between the coefficient of peer leverage estimated using all data and the coefficient estimated by deleting this observation (Belsley, Kuh, and Welsch 2005). Essentially, the leverage of firms that follow their peers' financial policy more closely should exhibit a higher correlation with the peer leverage. Therefore, deleting this observation should lead to a significant change in coefficient estimates, and the difference between the coefficient estimates with and without this observation will be high. On the other hand, firms that do not follow their peers contribute less to the overall goodness of fit of the model, by excluding them, the difference between the coefficients will be small. This approach has also been used by Fairhurst and Nam (2020) and following their specification, we define a firm as a mimicker in year *t* if its DFBETA value falls in the top tercile of the industry-year observations and as a non-mimicker otherwise.

Next, to test the heterogeneity of firms’ performance with different levels of internal information quality (IIQ), we split our sample into a high IIQ group and a low IIQ group using the level of internal information quality in the current year. The high IIQ group contains firms whose internal information quality is above the median level of the industry-year, and the low IIQ group contains firms with IIQ below the median. Then we run the following regression for each subsample:

$$Profitability_{t+1} = \alpha + \beta Mimicker_t + \delta Controls_t + \mu_j + \nu_t + \varepsilon_{it} \quad (3.5)$$

We measure a firm's future profitability using return on equity (ROE) and return on assets (ROA) in year *t+1*. $Mimicker_t$ is an indicator variable which equals one if the firm is a mimicker and zero otherwise. Firm size, market to book ratio, leverage ratio, and the current year's profitability are included to control for firm-specific characteristics. Industry and year fixed effects are also included.

Table 3.6 displays the regression results of equation (3.5). In this table, columns (1) - (4) present the effect of mimicking behaviour on firms' future profitability for the low IIQ group, while columns (5) - (8) present the influence for firms in the high IIQ group. The negative and statistically significant coefficient of Mimicker in the first four columns indicates that when suffering from low IIQ, firms that are more accustomed to mimic are usually worse performers. This effect is also economically significant, compared to the average ROE_{t+1} (-0.076) and ROA_{t+1} (-0.027) of low IIQs (high EAS) firms, mimickers' ROE and ROA are 51.3% and 40.7% lower.[17] Our results indicate that mimicking behaviour is value-destroying, contradicting the prediction of the information acquisition hypothesis while agreeing with the prediction of the agency cost hypothesis.

3.4.2 Agency problem and peer effects

So far, our empirical tests show that with poor IIQ, mimicking peer firms' corporate financial policy would impair shareholder value and lead to worse future performance. To further investigate whether such effects can be directly attributed to

[17] For firms with Dret above the median (low IIQ), mimickers on average earn 43.3% and 56.8% lower ROE_{t+1} and ROA_{t+1} respectively, compared with non-mimickers.

the amplified agency cost, we exploit the cross-sectional heterogeneity of firms' corporate governance and conduct further analysis. If the amplified peer effect caused by low IIQ is coming from agency costs, we expect that better corporate governance can mitigate the effect.[18]

We choose two proxies to measure a firm's corporate governance level: Takeover index and CEO entrenchment. The Takeover index measures the effectiveness of state law in encouraging hostile takeovers (Cain, McKeon, and Solomon 2017). By integrating the information of takeover law legislation at the state level with several key characteristics of the firm, the takeover index could positively predict the likelihood of hostile takeover and therefore measure the effectiveness of the market for corporate control (Cain, McKeon, and Solomon (2017) This measurement has been widely used as a corporate governance proxy in recent studies (Boulton and Campbell 2016; Ferris, Javakhadze, and Rajkovic 2017; Atanassov and Liu 2020; Fairhurst and Nam 2020). Our second proxy for corporate governance is a dummy variable that indicates the presence of an entrenched CEO. Following Baginski et al. (2018), we define a CEO as entrenched if she is also the chair of the board. When the CEO also serves as the board chair, the monitoring role of the board could be partially compromised, and the shareholders' interests could suffer (Rechner and Dalton 1991).

Our objective is to identify the effect of corporate governance in mitigating the agency cost associated with leverage peer effects. To do so, we first split our sample into two subsets: low IIQ firms with EAS above the industry median and high IIQ

[18] A large strand of literature has long argued that effective corporate governance can mitigate agency costs.(John, Knyazeva, and Knyazeva 2015; Cain, McKeon, and Solomon 2017; Morellec, Nikolov, and Schürhoff 2018)

firms with below industry median EAS. Then we further split each subsample based on the quality of corporate governance. We classify the firms with entrenched CEOs (CEOs that are not serving as chair of the board) or with an above industry median takeover index as well-governed firms and other firms as poorly governed firms. This procedure gives us four samples: high IIQ firms with poor corporate governance, high IIQ firms with good corporate governance, low IIQ firms with poor corporate governance, and low IIQ firms with good corporate governance. Then we estimated the baseline model for each subsample.

Table 3.7 displays our estimation results. Within the four groups of firms, we find that when IIQ is low (columns 1, 2, 5, and 6), the coefficients of peer leverage are positive and statistically significant only when firms exhibit weak corporate governance, this applies with both measures of governance quality, CEO duality (column 1) and takeover index (column 5). These findings confirm our conjecture that prominent financial policy peer effects are likely to be the consequence of severe agency problems. Meanwhile, we also find that when the IIQ is high (columns 3, 4, 7, and 8), even though the estimated coefficients of peer leverage for weak corporate governance firms (columns 3 and 7) are still larger than the well-governed firms (columns 4 and 8), it is not statistically significant. These results show that agency cost-related peer mimicking is much less severe when the IIQ is high.

3.4.3 Further robustness checks

We conduct a battery of further tests to ensure our results are robust. First, to make sure that our findings are not unique to the measures we use for internal information quality, we employ two alternative internal information quality proxies following Gallemore and Labro (2015). The first proxy is Restatement, which is an indicator variable which equals one if firms disclose a restatement because of unintentional error and zero otherwise. The second one is Weakness, which is also an indicator variable which equals one when firms disclose a material weakness and a zero otherwise. Panel A of Table 3.8 presents the results of using these two proxies for equation (3.2). The coefficients of the interaction terms (Restatement× Peer leverage and Weakness× Peer leverage) are both positive and statistically significant, confirming our main findings that firms which suffer from bad internal information quality are more willing to adjust their leverage by following their industry peer firms.

Second, since the market value of equity is used to calculate market leverage, one may argue that the identified leverage peer effect might simply reflect the co-movement of the market value of equity of firms in the same industry. Although the use of instrumental variable analysis in our main analysis should alleviate this concern, the use of book leverage could further address this issue as its construction will not rely on the market value of equity. Panel B of Table 3.8 presents the results using book leverage ratio as the dependent variable for equation (3.2). Our results are consistent with our baseline results in section 3.4.

Third, Hoberg and Phillips (2016) argue that frequently used industry classifications such as SIC or NAICs may not be able to accurately reflect the evolution of the product market structure and account for the similarities in products both across and within the industry. To mitigate the concern that our peer firms are inappropriately defined by the traditional industry classification codes, we conduct further robustness tests by adopting the Text-based Network Industry Classifications (TNIC) of Hoberg and Phillips (2016) as an alternative to define peer firms. As an alternative way of defining industry peers, TNIC has two major advantages. First, TNIC classifications are updated on an annual basis, therefore could capture the most up-to-date product linkage between firms. Second, TNIC is constructed based on textual analysis of firms' product descriptions from their 10-K files, therefore ensuring that the peer firms selected are all relevant product-market competitors. Panel C of Table 3.8 presents the results of baseline tests using the TNIC classification as the definition of the peer group. The coefficients of interaction terms (EAS× Peer leverage and Dret× Peer leverage) in the panel are qualitatively similar to the coefficients reported in the baseline regression (Table 3.3).

Another potential concern is that the peer effects identified in our model may result from common systematic shocks that influence all industries simultaneously. If this is the case, then our identified co-movement of capital structure may not be industry specific. The co-movement of leverage would be observed among firms, even if they are not real peers, if the peer effects are in fact a reflection of a systematic common shock. To address this concern, we follow Bustamante and Frésard (2020)'s paper and conduct a set of placebo tests. In each year, for each firm with n peer firms in the same 3-digit SIC industry, we randomly select n firms from the entire sample universe to form the sets of pseudo-peer firms and use the average leverage of these pseudo-peers to rerun our baseline regression (column (4) and (6) of Table 3.3). After repeating this process 1000 times, we plot the distribution of the coefficients of interest (β_1 in equation 3.2) in Figure 3.1. The average value of these coefficients from placebo tests is significantly smaller than our baseline results (0.004 vs 2.035

and 0.007 vs 0.295). The insignificant coefficients from the tests indicate that our results are unlikely to be driven by the omit factors that influence the entire market.

In panel D of Table 3.8, we include high dimensional fixed effects (industry× year) to further control for unobserved time-variant heterogeneity across industries. We also include firm fixed effects to control for time-invariant confounding factors. Our results remain significant after adding stricter fixed effects.

Finally, we conduct further robustness checks by controlling for some additional factors that may simultaneously influence IIQ and leverage peer effects. First, smaller firms are more likely to follow big firms (Leary and Roberts 2014). Since firm size is also an important determinant for its internal information quality (Doyle, Ge, and McVay 2007; Guo et al. 2016), it is possible that our result might be driven by the size effect. Second, information asymmetry could increase the cost of capital (Armstrong et al. 2011) which increases the likelihood of financial distress, while financial distress in one firm may change managers' risk aversion in peer firms, providing incentives for them to adjust leverage in response (Kalda 2020). If this adjustment coincides with leverage adjustment in the focal firms, we could also observe amplified peer effects in firms' financial policy. Finally, existing studies find that corporate governance is another factor that can impact a firm's mimicking behaviour (Fairhurst and Nam 2020). One may argue that since IIQ is related to corporate governance, our findings are simply another way to look at the effect of corporate governance on leverage peer effects.

To mitigate those concerns, we conduct further analysis by adding interaction terms between firms' relative size (firm size scaled by peer's average size), the Altman

(1968) Z-score, takeover index, and CEO entrenchment to our baseline model.[19] Our estimation results in panel E of Table 3.8, show that the coefficient of both EAS × Peer leverage and Dret × Peer leverage remain positive and statistically significant in all specifications. These results show that our findings are not driven by size effect, financial distress-related leverage adjustment, or corporate governance quality.

3.5 Conclusion

This chapter investigates how a firm's internal information quality influences its financial policy peer effects. We find that firms that operate in a low IIQ environment tend to follow the financial policy of their industry peer firms more closely. We also adopt a difference-in-difference test to address the potential endogeneity concern. By exploiting the exogenous shock to the IIQ resulting from the enactment of SOX 404 as our setting, we find that improvement in IIQ leads to weaker financial policy peer effects.

We also investigate the implication of financial policy peer effects on firm performance. We find that when IIQ is low, mimicking the financial policy of peer firms will have a negative impact on firm performance, showing that peer effects are value-destroying. Our further analysis provides evidence that poor IIQ exacerbates agency costs, which enables managers of the firm to follow the strategy of their industry peers even though this is not beneficial to the shareholders.

[19] In unreported tests, we also control for industry level cash flow volatility. Fairhust and Nam (2020) argue that industry level cash flow volatility will increase the difficulty that managers set an optimal capital structure. In addition, Zhang (2006) indicates that cash flow volatility will lead to higher information uncertainty of the firm. Our results stay quantitively similar after controlling for industry level cash flow volatility.

Overall, this empirical chapter contributes to the literature by exploring a new economic consequence of poor internal information quality. It first provides empirical evidence that bad internal information quality will increase firms' capital structure peer effects, and proves that this mimicking will hurt firms' performance. For future studies related to corporate peer effects, internal information quality could be treated as a potential channel to explain why CEOs and CFOs choose to mimic peers but ignore private information.

4. Dividend smoothing and Stock Price Crash Risk

This chapter investigates how dividend smoothing impacts firms' future stock price crash risk. By employing a large sample from 30 economies during the period 1987–2018, we find that dividend smoothing amplifies firms' crash risk. This effect is robust after addressing potential endogeneity issues, using stricter fixed effects models, difference-in-difference estimation, and two-stage least squares regressions. We find that dividend smoothing amplifies future crash risk because it increases the level of information asymmetry between managers and investors. In addition, this effect is more pronounced in economies with weaker shareholder protection or lower institutional quality.

4.1 Introduction

Firms adjust their payouts so that dividend payments are less volatile than earnings-so-called dividend smoothing has been widely documented in both U.S. and international markets after it was first identified by Lintner (1956).[20] The extant literature has provided comprehensive evidence on the managerial incentives and firm characteristics associated with dividend smoothing. For example, Fudenberg and Tirole (1995) argue that managers intend to smooth dividends to avoid being fired. Similarly, Wu (2018) provides empirical evidence suggesting that dividend smoothing is driven by managers' incentives to improve their own benefits. Existing literature also suggests that the dividend smoothing phenomenon is associated with

[20] For the U.S. market, smoothed dividend payments have been observed in both empirical evidence (Fama and Babiak 1968; Leary and Michaely 2011; Wu 2018), and survey studies (Brav et al. 2005). For financial markets outside the U.S., dividend adjustments have also proved to be smoother than earnings change (Javakhadze, Ferris, and Sen 2014; Ellahie and Kaplan 2021).

various firm characteristics, such as size (Leary and Michaely 2011; Javakhadze, Ferris, and Sen 2014), age (Leary and Michaely 2011; Javakhadze, Ferris, and Sen 2014), cash holding (Leary and Michaely 2011), and institutional ownership (Allen, Bernardo, and Welch 2000; Larkin, Leary, and Michaely 2017). By comparison, fewer studies investigate the consequences of dividend smoothing.[21]

However, dividend smoothing is not purely a passive financial policy or just a residual of other corporate strategies. Managers also actively adjust dividend payment (Lintner 1956; Wu 2018), and dividend policy can also impact other corporate decisions. For example, Brav et al. (2005) find that firms' dividend policies have a direct impact on their capital structure and investment decisions. Daniel, Denis, and Naveen (2008) and He et al. (2017) indicate that firms' dividend policy will influence their earnings management behaviour. Our study aims to extend this line of literature by examining the effect of dividend smoothing on firms' stock price crash risk.

A stock price crash is usually the consequence of bad news hoarding. Firms that release a sequence of bad news as it happens should expect a series of moderate price adjustments. In contrast, firms that try to hide the same set of bad news will inevitably need to release the information at some point in bulk, leading to a much more violent price adjustment. (Jin and Myers 2006; Hutton, Marcus, and Tehranian 2009). Earlier literature studied the factors that impact firms' crash risk from many

[21] To our knowledge, the only paper treating dividend smoothing as an explanatory variable is Larkin, Leary, and Michaely (2017), which explores whether dividend smoothing will enhance a firm's institutional environment.

different perspectives.[22] However, the association between dividend smoothing and crash risk has still been unexplored.

The effect of dividend smoothing on crash risk is not self-evident. On the one hand, dividend smoothing could have a negative association with future crash risk. According to (Kumar 1988) and Kumar and Lee (2001), managers could project their confidence in a firm's operation by maintaining a stable level of dividend payments, especially when other firms are less able to do so. In that sense, dividend smoothing is a way of disclosing information so could mitigate crash risk. In addition, smoothed dividends are an attractive feature for institutional investors (Allen, Bernardo, and Welch 2000), and higher institutional ownership could bring more effective external monitoring, consequently reducing firms' opaqueness and crash risk (Callen and Fang 2013).

On the other hand, dividend smoothing could also increase the future crash risk. A stable payout policy could help managers to avoid shareholder attention and interference, therefore, reducing the risk of managerial turnover (Fudenberg and Tirole 1995; Wu 2018). By applying dividend smoothing, managers are able to avoid bad news releases resulting from dividend cuts. This means that dividend smoothing can be treated as way for managers to hoard bad news, which will increase crash risk. Moreover, payout smoothing requires managers to perform accounting adjustments, which may further induce earnings management in both accrual based and real terms (Daniel, Denis, and Naveen 2008; Liu and Espahbodi

[22] There are numerous studies investigating the factors that will influence crash risk, such as earnings management (Hutton, Marcus, and Tehranian 2009), tax avoidance (Kim, Li, and Zhang 2011b), corporate social responsibility (Kim, Li, and Li 2014), individualism (An et al. 2018), production market competition (Li and Zhan 2019), CFO gender (Li and Zeng 2019), media coverage (An et al. 2020), and internet searching (Xu, Xuan, and Zheng 2021).

2014). Combined with the evidence that earnings management will increase future crash risk (Hutton, Marcus, and Tehranian 2009; Khurana, Pereira, and Zhang 2018), dividend smoothing could also amplify crash risk if it indicates a higher level of earnings management.

Following previous studies (Kim, Li, and Li 2014; Xu et al. 2014; Li, Wang, and Wang 2017; Hu et al. 2020; Xu et al. 2020; Xu, Xuan, and Zheng 2021), we use negative skewness of firm-specific weekly returns (Ncskew) and down-to-up volatility (Duvol) as our measures of crash risk. By construction, a higher value of these measurements indicates a lower crash risk. We employ two measurements for dividend smoothing. The first is the speed of adjustment of dividend payments (SOA), which was developed by Leary and Michaely (2011). The SOA measures how fast a firm adjusts its dividend toward its target payout ratio. The second measurement is adjustment frequency (Adjfreq), which is the number of times the firm significantly changed its dividends during the last five years.[23] Higher SOA and Adjfreq suggest that a firm changes its payout level more frequently, and therefore exhibits a lower level of dividend smoothing.

To make sure that our studies are able to be generalised to different countries, we collect our data from international financial market. Our sample consists of more than 6,000 firms across 30 economies from 1987 to 2018.[24] The results of our baseline model indicate a positive association between dividend smoothing and firms' future crash risk. The results are both statistically (at the 1% level) and

[23] Following Grennan (2019), we define "significant change" as more than one percentage change in absolute value.
[24] Following Leary and Michaely (2011), we require at least ten years' dividend payment observations to estimate the *SOA* of the firm, but we only require five year' observations to construct *Adjfreq*. Consequently, the sample size for *Adjfreq* is larger than for *SOA*.

economically significant. Specifically, a one-standard-deviation increase in SOA will reduce firms' crash risk by 7.80% (6.91%) measured by Ncskew (Duvol), while a one-standard-deviation increase in Adjfreq will reduce firms' crash risk by 7.08% (6.28%) measured by Ncskew (Duvol). Because a larger SOA and Adjfreq suggest a lower level of dividend smoothing, these results indicate that dividend smoothing will exacerbate crash risk.

Our baseline results are not free from identification challenges. On the one hand, firms with a higher level of crash risk may be reluctant to adjust dividends, because dividend changes will cause market reactions (Ham, Kaplan, and Leary 2020), which makes it harder to conceal bad news. On the other hand, the relationship between dividend smoothing and crash risk could also be driven by unobservable confounding factors which might cause biased estimation results. We apply three different approaches to address potential endogeneity concerns. First, we perform a difference-in-difference (DiD) estimation by exploiting the exogenous shock to firms' dividend smoothing associated with the Jobs and Growth Tax Relief Reconciliation Act (JGTRRA). The JGTRRA substantially cut dividend tax for U.S. firms and firms domiciled in economies that have tax treaties with the U.S. from 38.6% to 15% and the passage of the act drove firms to adjust their dividend payments (Chetty and Saez 2005; Blouin, Raedy, and Shackelford 2011). Our empirical results suggest that a higher level of dividend adjustment associated with the Act leads to significantly lower crash risk while a similar effect was not identified for control firms that are not influenced by the Act. Second, using peer firms' average level of dividend smoothing as an instrumental variable, we conduct a set of two-stage least squares (2SLS) regressions to validate our baseline results. We believe firms' average dividend smoothing is a valid instrument because it is correlated with the payout of its peer firms (Adhikari and Agrawal 2018; Grennan 2019), while there is no ex-ante reason to believe the latter should have a direct impact on a firm's crash risk. The results of the 2SLS regressions are consistent with the baseline OLS results. Lastly, we apply models with stricter fixed effects to further mitigate the omitted variable concern. Our results show that the inclusion of firm, year, and higher-dimensional fixed effects do not change our conclusion.

We then test the potential channels through which dividend smoothing can amplify a firm's crash risk. As noted previously, dividend smoothing can increase crash risk in two ways. First, dividend smoothing can increase the level of information asymmetry between insiders and outsiders (Guttman, Kadan, and Kandel 2010). Smoothing dividend payments could be a reflection that managers are avoiding the release of negative news. It means less valuable information will be conveyed to outsiders, so that the signaling effect of dividend payment is weakened. Therefore, dividend smoothing will increase the level of information asymmetry, which in turn will lead to higher crash risk (Chen, Hong, and Stein 2001; Jin and Myers 2006; Hutton, Marcus, and Tehranian 2009). We call this the information asymmetry channel. Second, dividend smoothing involves inevitable balance sheet adjustments. Firms might need to manage earnings to achieve a stable level of dividend payout (Daniel, Denis, and Naveen 2008; Liu and Espahbodi 2014), which could consequently exacerbate crash risk (Hutton, Marcus, and Tehranian 2009; Khurana, Pereira, and Zhang 2018). We call this the earnings management channel.

We designed further tests to distinguish the effect through both channels. First, we look at the effect of dividend smoothing on the information asymmetry level between a firm's managers and investors. We use analyst forecast dispersion and analyst forecast error to measure the firm's information asymmetry level. A higher level of forecast dispersion and forecast error suggest a higher level of information asymmetry. Our results show that firms exhibit higher forecast dispersion and forecast error when SOA and Adjfreq are higher, indicating that dividend smoothing is positively related to firms' information asymmetry level. Second, we investigate how dividend smoothing influences earnings management. We find no significant link between dividend smoothing and both accrual-based or real earnings management, measured by discretionary accruals, and production costs/discretionary expense, respectively. These results indicate that the effect of dividend smoothing on crash risk is more likely to be driven by the information asymmetry channel than the earnings management channel.

Our comprehensive international dataset allows us to further reveal the potential heterogeneity of the dividend smoothing-crash risk relationship in different institutional settings. According to Jin and Myers (2006) and An et al. (2018), the institutional and legal environment of an economy is associated with firms' crash risk. The level of dividend smoothing, and its subsequent effects also differ across different economies (Javakhadze, Ferris, and Sen 2014; Ellahie and Kaplan 2021). Inspired by these works, we estimated our model for subsamples of firms operating in economies with different investor protection and institutional quality. We find that the amplification effect of dividend smoothing on crash risk is more pronounced in economies with a lower level of investor protection or weaker institutional quality. These findings are consistent with Hail, Tahoun, and Wang (2014)'s argument that the signalling effect of dividends is stronger for firms operating in a financial market with a weaker environment, and Ellahie and Kaplan (2021)'s argument that dividend adjustment is more important for corporate governance in economies with weak institutional quality.

Finally, we conduct a battery of robustness tests to further address any potential issues that may influence our findings. First, the SOA estimation might be sensitive to the model used to calculate the speed of adjustment. To mitigate this concern, we apply three models used in previous studies as alternative measurements.[25] Similarly, we also use several models with different rolling windows and alternative definitions of significant dividend change for Adjfreq to make sure our results are not dependent on a specific way of measuring this variable. Second, to mitigate the concern that our findings may be driven by a few countries, namely the US and Japan, that constitute a large proportion of the sample, we rerun our baseline tests excluding firms from these countries. Lastly, we also test our model using the sample without observations from 2008 and 2009 to eliminate the extreme event caused by the global financial crisis. Our results are robust to all these additional tests and remain qualitatively similar to our baseline results.

This chapter contributes to the literature in three ways. First, while there are many studies investigating the underlying drivers of dividend smoothing, there is relatively little research on the consequence of dividend smoothing.[26] Our study provides empirical evidence that dividend smoothing is associated with deteriorating

[25] Specifically, we use three alternative models: (1) we estimate the target payout ratio of SOA using the median payout ratio of last ten years (Larkin, Leary, and Michaely 2017; Wu 2018), instead of median payout ratio of sample period (Leary and Michaely 2011). (2) We set the value of SOA which is above one to one, and value which is below zero to zero (Wu 2018; Ellahie and Kaplan 2021). (3) We use the total payout instead of cash dividend payment in estimating SOA (Ellahie and Kaplan 2021).

[26] Previous studies have widely explored the determinants of dividend smoothing and why firms tend to pursue a smoothed dividend policy, from both theorical perspectives (Kumar 1988; Fudenberg and Tirole 1995; Allen, Bernardo, and Welch 2000) and empirical studies (Aivazian, Booth, and Cleary 2006; Leary and Michaely 2011; Javakhadze, Ferris, and Sen 2014).

information transparency in firms, which leads to amplified stock price crash risk. Second, the chapter also contributes to the literature on crash risk. Previous studies have documented that a firm's crash risk is associated with factors such as information opaqueness (Hutton, Marcus, and Tehranian 2009), managers' equity incentives (Kim, Li, and Zhang 2011a), tax avoidance (Kim, Li, and Zhang 2011b), corporate social responsibility (Kim, Li, and Li 2014), religion (Callen and Fang 2015a), social trust (Li, Wang, and Wang 2017), individualism (An et al. 2018), employee welfare (Ben-Nasr and Ghouma 2018), product market competition (Li and Zhan 2019), manager gender (Li and Zeng 2019), media coverage (An et al. 2020), eco-innovation (Zaman et al. 2021). This chapter contributes by investigating the effect of payout policy on the crash risk. Third, our study highlights the signaling effects of dividends. Dividend payouts are believed to be an important signaling tool for firms' insiders (Bhattacharya 1979; John and William 1985). Firms disclose information about future earnings through dividend change (Nissim and Ziv 2001; Ham, Kaplan, and Leary 2020). The chapter provides additional empirical support for this argument that dividend adjustments can provide investors with information about future profitability.

The remainder of the chapter proceeds as follows. Section 4.2 presents the sample description and variable definitions. We then report the research design, main empirical findings, and endogeneity tests in Section 4.3, and the further analysis and robustness checks in section 4.4. Section 4.5 presents our conclusions.

4.2 Sample and variable definition

4.2.1 Sample selection

Our initial sample consists of all publicly listed firms with available stock return data from Datastream and accounting data from Worldscope. We use the weekly return index (RI) in Datastream as our return measure. This variable has been adjusted for stock splits and dividend payments. To eliminate the fundamental difference between dividend-paying and non-dividend-paying firms which might lead to biased estimation, following Leary and Michaely (2011), we only retain the firm-year observations from the first year a firm starts to pay dividends until the last year they pay dividends. For example, if a firm paid its first dividend payment in 2010 and the last one in 2018, we retain all the firm-year observations between 2010 and 2018. Additionally, to avoid those firms which suspend their dividend payments during the sample period, we exclude firms that have continuous zero dividend payment from the first year to the last year they pay dividends.[27] For each firm, we require at least ten years of observations to estimate our SOA measurement, and five years to estimate the Adjfreq measurement, therefore firms with fewer than the required number of observations are dropped. We collect country-level macro-economic variables from the World Development Indicator database, and analyst forecast data from the I/B/E/S database.[28] Country-level investor protection data is

[27] The suspension of firm's dividend payment may make the SOA estimation biased. For instance, if a firm pays dividends for three years and suspends its dividend payment for five years, and then pays dividends for the next three years, we will find the firm applies an extremely smoothed dividend policy during the five years in the middle. However, it is unreasonable to say that the firm applies a smoothed dividend policy because there is no dividend payment in this period. Consequently, we exclude those firms to reduce estimation bias.
In unreported analyses, our main findings are quantitatively similar if we exclude all firms with zero dividend payments from the first year to the last year it pays dividends.
[28] https://databank.worldbank.org/source/world-development-indicators.

from La Porta, Lopez - de - Silanes, and Shleifer (2006) and country-level institutional quality data is from Ellahie and Kaplan (2021).

To ensure that the firms in our sample are comparable across countries, following An et al. (2018)'s work, we use additional filters: first, we exclude all financial firms (SIC code between 6000 and 6999) and utility firms (SIC code between 4900 and 4999) from our sample. Second, we exclude American Depository Receipts (ADR) firms because those firms are traded outside their home countries but disciplined by their own countries' policies, rules, and culture.[29] Third, we exclude firm years with fewer than 26 weekly stock returns which may indicate initial public offering, delisting, or suspension of trading. Fourth, we require all countries to have at least 100 firm-year observations for all variables in our main regression analysis. This leads to a sample of 54,463 firm-year observations for the SOA sample and 83,788 firm-year observations for the Adjfreq sample, respectively, from 30 economies, spanning the period 1987–2018.

Table 4.1 reports the descriptive statistics and sample distributions across economies. In panel A of Table 4.1, the mean (median) values of Ncskew and Duvol are -0.140 (-0.132) and -0.079 (-0.082), which are comparable with the related literature (An, Li, and Yu 2015; An et al. 2018; Hu et al. 2020). Panel B and C display the distribution of crash risk and dividend smoothing across economies. In general, firms in developed markets exhibit a higher dividend smoothing level than those from developing countries. For instance, the mean value of SOA (Adjfreq) for the U.S., Canada, and Japan are 0.124 (3.384), 0.187 (3.296), and 0.188 (2.248),

[29] In unreported analyses, our main findings are qualitatively similar if we include those financial, utility, and ADR firms.

while the same statistics for firms in China, Malaysia, and Thailand are 0.661 (3.960), 0.478 (3.720), and 0.694 (4.185). This is consistent with Ellahie and Kaplan (2021)'s analysis which indicates firms in developing markets benefit more from adjusting dividends.

4.2.2 Crash risk measurements

To investigate the effect of dividend smoothing on firms' stock price crash risk, we choose two proxies to measure firms' crash risk: negative skewness (Ncskew) and down-to-up volatility (Duvol). These two measurements are widely used in empirical studies related to crash risk (Kim, Li, and Zhang 2011a, 2011b; Callen and Fang 2015a; An et al. 2018; Li and Zhan 2019; Li and Zeng 2019; Xu, Xuan, and Zheng 2021).

The construction of these variables starts with the calculation of firm-specific weekly stock returns. Following previous studies (Hutton, Marcus, and Tehranian 2009; Kim, Li, and Zhang 2011a; An et al. 2018), we estimate the following regression model:

$$r_{i,\tau} = \alpha_i + \beta_{1,i} r_{m,\tau} + \beta_{2,i} r_{m,\tau-1} + \beta_{3,i} r_{m,\tau-2} + \beta_{4,i} r_{m,\tau+1} + \beta_{5,i} r_{m,\tau+2} + \varepsilon_{i,\tau} \quad (4.1)$$

where $r_{i,\tau}$ denotes the weekly stock return of firm i in week τ. The $r_{m,\tau}$ refers to the value-weighted market weekly return in week τ. One- and two-period lead and lag terms of market return are included to allow for nonsynchronous trading (Dimson 1979). The regression is run for each fiscal year and the firm-specific weekly return is calculated as $\ln(1 + \varepsilon_{i,\tau})$.

Our first proxy of crash risk is negative coefficient skewness (Ncskew), which is calculated by applying the following equation (4.2):

$$Ncskew_{i,t} = -(n_{i,t}\left(n_{i,t}-1\right)^{\frac{3}{2}}\sum_{t=1}^{n_{i,t}} r_{i,\tau}^{3})/(n_{i,t}-1)(n_{i,t}-2)(\sum_{t=1}^{n_{i,t}} r_{i,\tau}^{2})^{\frac{3}{2}} \quad (4.2)$$

where the $n_{i,t}$ is the number of weekly return observations for firm *i* in fiscal year *t*. A higher value of Ncskew indicates that the stock return is more negatively distributed, which means that the stock is more prone to crash.

Our second proxy for crash risk is down-to-up volatility (Duvol). Following Chen, Hong, and Stein (2001) and Kim, Li, and Zhang (2011a), we calculate Duvol by applying equation (4.3):

$$Duvol_{i,t} = ln\ ((n_{u,i,t}-1)\sum_{t=1}^{n_{d,i,t}} r_{i,t}^{2}/(n_{d,i,t}-1)\sum_{t=1}^{n_{u,i,t}} r_{i,t}^{2}) \quad (4.3)$$

where $n_{u,i,t}$ refers to the number of firm-specific weekly returns above the mean return value of the fiscal year, while $n_{d,i,t}$ refers to the number of firm-specific weekly returns below the mean return value of the fiscal year for firm *i* in year *t*. As noted by Chen, Hong, and Stein (2001), a higher value of Duvol suggest the stock returns are more left-skewed. Thus, a higher value of Duvol indicates that the stock prices are more inclined to crash.

4.2.3 *Dividend smoothing measurements*

We use two proxies to measure firms' dividend smoothing level. The first one is the speed of adjustment of dividend payments (SOA). It reflects how quickly firms adjust their cash dividends to the target level. To construct this variable, we follow

Leary and Michaely (2011) by estimating firms' speed of adjustment for dividends using the beta coefficient of the following regression:

$$D_{it} - D_{it-1} = \alpha + \beta \times dev_{it} + \varepsilon_{it} \tag{4.4}$$

where

$$dev_{it} = TPR_i \times E_{it} - D_{it-1}$$

The D_{it} refers to firm i's cash dividend per share in year t. dev_{it} refers to the deviation of a firm's true dividend payment in the last period from its target dividend payout of this period. TPR_i is the target payout ratio, which is the median payout ratio of the firm over the sample period. E_{it} is the earnings per share for firm i in year t, and D_{it-1} is last year's cash dividend per share. The SOA is the β coefficient of the 10-year rolling regression of equation (4.4). Because the β indicates how a firm's dividend change reacts to the deviation of the firm's dividend from the target level, a larger β indicates a quicker change of dividends towards the target level and a lower level of dividend smoothing.

Our second proxy is the adjustment frequency of dividend payment (Adjfreq), which is the number of times the firm significantly changed its dividends during the last five years. Following Grennan (2019), we treat a dividend change of more than one percent in absolute value as a significant change. We choose this proxy as a complementary measurement for two reasons. First, in reality, there is a significant proportion of firms that do not change their dividend level at all (Guttman, Kadan, and Kandel (2010). The SOA measure is unable to explicitly capture this type of payout policy, as it assumes firms adjust their dividend towards a target level.

Second, SOA is estimated from 10-year rolling window regressions. This means that the firms we can investigate are only those with more than 10 years' dividend payment history, which significantly reduces our sample size, excluding younger firms. We calculate Adjfreq by counting the number of times firms changed their dividends during the last five years. A higher value of Adjfreq also indicates a more frequent dividend adjustment and a lower level of dividend smoothing.

4.2.4 Control variables

Following the previous crash risk literature (Kim, Li, and Zhang 2011a; An et al. 2018; Xu, Xuan, and Zheng 2021), we control for the following variables which may influence a firm's future crash risk: firm size ($Size_{t-1}$), leverage ratio (Lev_{t-1}), return on assets (ROA_{t-1}), market-to-book ratio (MTB_{t-1}), stock return volatility ($Sigma_{t-1}$), mean of weekly stock returns (Ret_{t-1}), discretionary accruals ($Accm_{t-1}$), change in turnover rate ($Dturn_{t-1}$), earnings volatility ($SD\ (EPS)_{t-1}$), and dividend per share (DPS_{t-1}). Additionally, following earlier research using international data (An, Li, and Yu 2015; An et al. 2018; Ben-Nasr and Ghouma 2018), we also include several country-level controls in our regression analysis: annual GDP growth rate (GDP_grow_{t-1}), GDP per capita ($GDP/Captia_{t-1}$), and stock market capitalization scaled by GDP ($Mcap/GDP_{t-1}$).

4.3 Main empirical analysis and findings

4.3.1 Empirical model

The objective of this chapter is to investigate how dividend smoothing influences firms' future crash risk. Our baseline regression specification is described as follows:

$$CrashRisk_{it} = \beta_0 + \beta_1 Smooth_{it-1} + \beta_2 FirmControls_{it-1} + \beta_3 CountryControls_{it-1} + CountryFE + IndustryFE + YearFE + \varepsilon_{it} \quad (4.5)$$

The dependent variable $CrashRisk_{it}$ is firm i's stock price crash risk in year t. $Smooth_{it-1}$ is the main independent variable of interest, firm i's dividend smoothing level. All the firm-level and country-level controls introduced in section 2 are included in the regression to mitigate the influence of any confounding effects. Country, industry, and year fixed effects are also included.[30] Consistent with previous crash risk research (Kim, Li, and Zhang 2011a; An et al. 2018; Li and Zhan 2019; Xu, Xuan, and Zheng 2021), we lag the main independent variables as well as control variables by one period to better indicate how historical factors can influence future crash risk.

Table 4.2 presents the ordinary least squares (OLS) regression results for equation (4.5). The coefficients for SOA_{t-1} and $Adjfreq_{t-1}$ for both crash measurements are negative and statistically significant. The results indicate that a higher level of dividend smoothing (smaller value of SOA_{t-1} and $Adjfreq_{t-1}$) will increase firms' crash risk. In other words, adjusting the dividend level more frequently will reduce

[30] Industry is defined by 2-digit SIC code.

firms' future crash risk. The effect is also economically significant: a one-standard-deviation increase in SOA will reduce firms' crash risk by 7.80% (6.91%) measured by Ncskew (Duvol), while a one-standard-deviation increase in $Adjfreq_{t-1}$ will reduce firms' crash risk by 7.09% (6.28%) measured by Ncskew (Duvol).[31] The result that dividend smoothing amplifies crash risk supports the view that sticky dividend payments indicate managers' incentives to smooth bad news release (Fudenberg and Tirole 1995; Wu 2018), and the view that dividend commitment will encourage managers to engage in earnings management (Daniel, Denis, and Naveen 2008; Liu and Espahbodi 2014).

Turning to the control variables, we find most firm characteristics, such as $Size_{t-1}$, ROA_{t-1}, and MTB_{t-1}, are positively related to future crash risk. This is consistent with other comparable studies (An et al. 2020; Hu et al. 2020), which concentrate on crash risk in international financial markets. In line with the idea that crash risk is persistent over time (Chen, Hong, and Stein 2001), we find a positive relationship between last year's crash risk ($Ncskew_{t-1}$) and the current year's crash risk. To summarize, the coefficients of crash risk determinants in our results are consistent with the majority of comparable crash risk studies.

4.3.2 Endogeneity

The baseline regression results indicate that dividend smoothing leads to higher crash risk. However, one may be concerned that the effect is driven by endogenous factors. First, our findings might be influenced by reverse causality. The positive

[31] The magnitude of economic influence is calculated as the product of the absolute value of the coefficient and the standard deviation of the independent variable, divided by the absolute mean value of the independent variable. For instance, the number 7.80% is calculated as 0.321×0.034/ 0.079.

association between dividend smoothing and crash risk may actually mean that firms with higher crash risk are more inclined to pursue conservative dividend policies. Second, although we have controlled for a set of widely known crash risk determinants, some unobservable confounding factors could still influence our findings. To address these endogeneity concerns, we adopt three econometric approaches, which are difference-in-difference (DiD) estimation, two-stage least squares regression (2SLS), and alternative fixed effects models.

4.3.2.1 Difference-in-differences approach

We first employ a difference-in-difference approach (DiD) by exploiting the Jobs and Growth Tax Relief Reconciliation Act (JGTRRA) as an exogenous shock for dividend smoothing. This Act was passed in 2003, and it substantially cut cash dividend tax rates (from 38.6% to 15%) for U.S. investors who invest in firms domiciled in both the U.S. and countries/economies which have tax treaties with the U.S. JGTRRA can be treated as an exogenous shock for dividend smoothing because tax is a known determinant of a firm's dividend policy (Chetty and Saez 2005; Pattenden and Twite 2008; Hanlon and Hoopes 2014). A change in tax rate can drive firms to adjust payout policy. According to Blouin, Raedy, and Shackelford (2011), the passage of the JGTRRA drove firms to adjust their dividend policy to be consistent with the new, tax-based incentives facing investors. If the Act encourages firms to adjust their dividend payments to satisfy shareholders, it will decrease the level of dividend smoothing. Thus, we expect the JGTRRA would be a negative shock to firms' dividend smoothing behaviour.

Because most investors prefer to invest in domestic financial markets (Coval and Moskowitz 1999; Sialm, Sun, and Zheng 2020), we expect that the Act will be most influential for U.S. firms therefore we classify them as treatment firms. We select firms domiciled in economies that have no tax treaties with the U.S. as control firms, as they will not be affected by the Act. In our sample, these economies are Hong Kong, Malaysia, Singapore, and Chile. However, according to Castillo and Jakob (2006), Chile adjusted its dividend tax rate multiple times around the time of the passage of the JGTRRA. They state that "Until 1997 dividends in Chile were taxed at the regular personal income tax rates. From 1998 to 2002 a tax rate reduction was applied to dividends, and they were taxed at half the regular personal income tax rates. Starting in 2003 this tax rate reduction was eliminated." To avoid the influence of Chile's dividend tax policies, we exclude the observations on Chilean firms from our DiD tests. Our results remain qualitatively similar if we include Chilean firms in our control group. For those firms in economies which have tax treaties with the U.S., however, it is hard to confirm whether they will actively adjust their dividend policy to cater for foreign institutional investors. Consequently, we exclude those firms to avoid them influencing our tests. The sample period of our DiD tests is from 1999–2006, with 1999–2002 as the pre-event period, and 2004–2006 as the post-event period.[32] The DiD tests are based on the following model:

$$CrashRisk_{it} = \beta_0 + \beta_1 Treat \times Post + \beta_2 FirmControls_{it-1} + \beta_3 CountryControls_{it-1} + Fixed\ Effects + \varepsilon_{it} \quad (4.6)$$

[32] Because the JGTRRA was passed in May of 2003, it is hard to identify whether 2003 should be the pre- event period or post- event period. Thus, we exclude this year to avoid interference.

where $Treat$ is an indicator variable equal to one if the firm is domiciled in the U.S. and zero otherwise. $Post$ is an indicator variable equal to one for the years after the event year (2003), and zero for years before the event year. We include all firm-level and country-level controls used in the baseline regression. Country, industry, and year (or firm and year) fixed effects are also included. Considering that the JGTRRA will drive U.S. firms to actively adjust their dividends, we expect that the crash risk of U.S. firms will significantly decrease after the passage of the JGTRRA, compared with firms domiciled in economics that have no tax treaties with the U.S.

Panel A of Table 4.3 presents the regression results of the DiD model. Columns (1) and (2) refer to models which include country, industry, and year fixed effects, while columns (3) and (4) present models including firm and year fixed effects. The negative coefficients of all the interaction terms indicate that after the passage of the JGTRRA, firms domiciled in the U.S. exhibit a significant decrease in crash risk , compared to firms domiciled in economics with no tax treaties with the U.S. Considering that the JGTRRA is a shock that drives U.S. firms to adjust their dividend policy (negative shock for dividend smoothing), the negative coefficients are consistent with our main finding, that dividend smoothing will increase firms' crash risk.

Because the validity of the DiD approach is based on the parallel-trend assumption, we adopt a diagnostic test to make sure that the assumption is satisfied. Following Bertrand and Mullainathan (2003), we develop a dynamic model by replacing the $Post$ dummy with several year-by-year indicator variables, which are Beforet-3, Beforet-2, Beforet-1, Aftert+1, Aftert+2, and Aftert+3, to examine the impact of the JGTRRA on firms' crash risk. These six indicator variables are equal to one if the year is three (Beforet-3), two (Beforet-2), or one (Beforet-1) year before the event year, or three (Aftert+3), two (Aftert+2), or one (Aftert+1) year after the event year, and zero otherwise. Panel B of Table 4.3 presents the results of the diagnostic test. According to the coefficients of the interaction terms, we find that the effect is only pronounced after the passage of the JGTRRA, which indicates that the treatment firms and control firms exhibit a similar crash risk trend before the event year. This test confirms that the parallel trend assumption is not violated.

In addition, we apply propensity score matching (PSM) to mitigate the possibility that the results are driven by the heterogeneity of treated and control firms. Because the number of treated firms is larger than the number of control firms, we match each control firm with one treated firm based on all firm-level controls. Panel C of Table 4.3 displays the results of the DiD test after the PSM procedure. The results are consistent with panel A when we apply the two alternative fixed effects models.

4.3.2.2 Two-stage least squares regression

In addition to the DiD design, we employ an instrumental variable approach and perform a 2SLS regression to further address the endogeneity concern. The instrumental variable used in this chapter is peer firms' average level of dividend smoothing. The peer firms are defined as all firms in the same country and the same industry, excluding the firm itself. We choose peer firms' dividend strategies as the instrumental variable for two reasons. First, peer firms' dividend changes have a significant influence on the firm's own financial policy (Adhikari and Agrawal 2018; Grennan 2019). Grennan (2019) suggests that firms will speed up the time taken for dividend adjustment, and change their dividend payment by 16% in response to peers' changes. This effect is also found outside the U.S. market (Lee 2020). The significance of peer influence indicates that our instrumental variable meets the relevant restriction. Second, Adhikari and Agrawal (2018)'s and Grennan (2019)'s papers also prove that the effect is brought by peer pressure on dividend payments, rather than correlation effects for firms in the same industry. Consequently, peer firms' cash distribution choices should not directly influence focal firms' crash risk, and our instrumental variable also meets the exclusion restriction.

We perform the test in two stages, in the first stage, we regress the firm's dividend smoothing on peer firms' dividend smoothing and all the control variables used in our baseline test. Columns (1) and (4) of Table 4.4 present the results of our first-stage regression, which show that the peer firms' dividend smoothing is positive and significantly related to the focal firm's level of dividend smoothing.[33] The F-statistics of the instrumental variables for SOA and Adjfreq are 36.07 and 152.11, respectively, which are higher than the rule of thumb threshold of 10. The results in the first stage reject the null hypothesis that our instrumental variables are weak.

We then use the predicted value of firm dividend smoothing from the first-stage regression to perform the second stage regression. In Table 4.4, column (2) and (3) present the second-stage results for the SOA measurement, while columns (5) and (6) present the second-stage results for the Adjfreq measurement. Consistent with our baseline regression, the coefficients of interest are still negatively significant,

[33] Because some country-industry peer groups only have one firm in our sample, we need to discard those firms because they have no peer firms based on our definition. Thus, the sample size of the tests is smaller than the baseline regression.

which means that our results are less likely to be affected by the endogeneity issue mentioned above.

4.3.2.3 Alternative fixed effects models

As an alternative way to control for the influence of omitted factors, we also apply two stricter fixed effects models. Considering that firms from different economies and industries exhibit significantly different crash risk and dividend smoothing behaviour, we include country, industry, and year fixed effects in our baseline regression. However, to further alleviate the confounding factors' influence, we also employ a firm and year fixed effects model as a robustness check. Additionally, Gormley and Matsa (2014) suggest implementing a high-dimensional fixed effects model to further eliminate the influence of time varying heterogeneity across countries and industries. Thus, following their approach, we apply two alternative models which include firm and year fixed effects, and country× year, industry× year, and firm fixed effects, respectively.

In Table 4.5, we rerun our baseline regression using the two fixed effects models described above. Columns (1)– (4) display the results using the model including firm and year fixed effects, while columns (5)– (8) indicate the results for the model with country× year, industry× year, and firm fixed effects. The country-level controls are omitted for tests in columns (5)– (8) because they are subsumed by country-year effects. According to the results shown in Table 4.5, our main findings hold for all these alternative fixed effects models. These tests alleviate the concern that our results are driven by omitted factors.

4.3.3 Robustness checks

In this section, we adopt several further robustness tests to ensure that our results are not driven by the specific ways that our variables are defined. We apply three alternative models to estimate SOA. In the first, we follow Larkin, Leary, and Michaely (2017) and Wu (2018) by estimating the target payout ratio using a ten year rolling window ending one year before the time t . In the second model, we set the value of the SOA equal to one if its value is bigger than one, and to zero if its value is below zero, to reduce the extreme value (Wu 2018; Ellahie and Kaplan 2021). Wu (2018) argues that, in reality, the speed of adjustment usually lies between zero and one. For the third model, we use total payout (cash dividend + repurchase) to estimate the speed of adjustment instead of the cash dividend only. Panel A of Table 4.6 presents the results using the alternative SOA estimation model. The results indicates that our findings are not sensitive to the model used.

For our Adjfreq estimation, we conduct several robustness tests to ensure that the results are not sensitive to the definition of significant dividend change and rolling window size. Specifically, we define significant change using several alternative thresholds, such as 0% to 2%, or 5%.[34] In addition, we apply several larger rolling windows, for instance, six-year and seven-year rolling windows, to calculate the Adjfreq measurement. Panel B of Table 4.6 reports the results using alternative thresholds and rolling windows for the Adjfreq calculation. The results shown in the Table indicates that our findings remain robust to the use of alternative estimation models.

[34] In our main analysis, following Grennan (2019), we define a dividend change as significant if the absolute value of percentage is higher than 1%. Here, we treat a dividend change as significant if the absolute value of percentage change is bigger than 0%, 2%, or 5%, respectively.

4.4 Further analysis

4.4.1 Why does dividend smoothing influence crash risk?

In this section, we investigate the background mechanisms through which dividend smoothing impacts a firm's future stock price crash risk. Based on existing theories and empirical evidence, we develop two potential explanations for the finding that dividend smoothing increases crash risk.

4.4.1.1 Information asymmetry channel

The first explanation is that dividend smoothing can increase information asymmetry between managers and investors. Based on the evidence that dividend changes contain useful information about future profitability (Nissim and Ziv 2001; Ham, Kaplan, and Leary 2020), dividend smoothing means less information can be conveyed to outsiders. This is supported by Guttman, Kadan, and Kandel (2010)'s finding that firms which are reluctant to adjust dividends exhibit higher level of information asymmetry than firms with frequently dividend adjustments. The reluctance to adjust dividends might be driven by managers' incentives to keep their position or avoid interference (Fudenberg and Tirole 1995). Because of investors' asymmetric reaction toward dividend increases and decreases, managers have incentives to under-report income when profit is high, so that they can over-report income when profit is low.[35] These arguments mean dividend smoothing will

[35] Fudenberg and Tirole (1995) suggest that the utility managers gain from dividend increases is smaller than the loss from dividend cuts. So, managers are willing to sacrifice the award from dividend increases to avoid punishment brought by dividend cuts. The argument is supported by Wu (2018)'s finding that the mechanism that drives managers to smooth dividends is to mitigate the release of bad news and to lower the risk of managerial turnover.

increase firms' information asymmetry level, which can increase firms' future crash risk (Hutton, Marcus, and Tehranian 2009; Callen and Fang 2015b; Li and Zhan 2019).

If dividend smoothing implies that managers are hoarding bad news, there should be a relationship between dividend smoothing and a firms' information asymmetry level. We apply the following model to test this conjecture:

$$IA_{it} = \beta_0 + \beta_1 Smooth_{it} + \beta_2 FirmControls_{it} + \beta_3 CountryControls_{it} + Country\ FE + Industry\ FE + Year\ FE + \varepsilon_{it} \tag{4.7}$$

In equation (4.7), IA_{it} is the information asymmetry level of firm i in year *t*. $Smooth_{it}$ is the dividend smoothing level for firm *i* in year *t*. We use two proxies, analyst forecast dispersion and analyst forecast error, to measure firms' information asymmetry. Following earlier studies (Bissessur and Veenman 2016; Callen and Fang 2015b; Cheng, Chu, and Ohlson 2020), we measure analyst forecast dispersion as the standard deviation of analyst forecasts of earnings per share (EPS), and analyst forecast error as the absolute difference between analysts' forecasts and the actual EPS. Both variables are scaled by the absolute value of the median level of analysts' EPS forecasts during the year (Callen and Fang 2015b). Higher values of analyst forecast dispersion and analyst forecast error indicate a higher level of information asymmetry.

Table 4.7 presents the results for the tests of equation (4.6). We can see from the table that the coefficients of both the SOA measurements and Adjfreq are negative and statistically significant. The results indicate that dividend smoothing (lower SOA and Adjfreq) will amplify the forecast error and dispersion of analysts following the firm. In other words, it shows dividend smoothing is associated with a higher level of information asymmetry. The result suggests that dividend smoothing will reduce firms' information disclosure and weaken dividend's signalling effect. It also supports the conjecture that dividend smoothing will increase crash risk because it implies that managers are smoothing the release of bad news.

4.4.1.2 Earnings management channel

Dividend smoothing can also amplify crash risk by pushing managers to engage in accrual-based and real earnings management. Managers may do more accrual-based earnings management if they need to meet short-term "dividend obligations". To make it more reasonable to keep the dividend level the same as last year, firms with earnings lower than last year's cash payout will tend to manage earnings upward to meet this dividend threshold (Daniel, Denis, and Naveen 2008). Kasanen, Kinnunen, and Niskanen (1996) also suggest that accrual-based earnings management is partly driven by the implicit commitment to pay a smooth dividend stream. Moreover, the pressure to maintain a historical dividend level will also drive managers to perform a higher level of real earnings management (Liu and Espahbodi 2014).

If the incentives to meet a high and smoothed dividend policy encourage managers to perform more earnings management, we can also expect that it will increase crash risk, as earnings management is a widely known factor causing firms' stock prices to crash. On the one hand, Hutton, Marcus, and Tehranian (2009) find direct evidence showing that accrual-based earnings management will lead to higher crash risk. Accrual-based earnings management has also been treated as a basic channel through which many other factors impact crash risk (Andreou et al. 2016; An et al.

2018; Wu and Lai 2020; Xu, Xuan, and Zheng 2021). On the other hand, real earnings management can enhance crash risk though concealing real operational conditions (Khurana, Pereira, and Zhang 2018). If the higher likelihood of stock price crash results from earnings management, we should expect that dividend smoothing should be positively related to firms' earnings management level. We develop the following empirical model to test this conjecture:

$$EM_{it} = \beta_0 + \beta_1 Smooth_{it} + \beta_2 FirmControls_{it} + \beta_3 CountryControls_{it} + Country\ FE + Industry\ FE + Year\ FE + \varepsilon_{it} \quad (4.8)$$

In equation (4.8), EM_{it} is the earnings management level of firm *i* in year *t*. In line with related research (Hutton, Marcus, and Tehranian 2009; Kim, Kim, and Zhou 2017), we construct the accrual-based earnings management variable (DisAccrualsit) by applying a modified Jones model (Dechow, Sloan, and Sweeney 1995):

$$\frac{TACC_t}{TA_{t-1}} = \alpha_0 + \alpha_1 \frac{1}{TA_{t-1}} + \alpha_2 \frac{\Delta REV_t - \Delta REC_t}{TA_{t-1}} + \alpha_3 \frac{PPE_t}{TA_{t-1}} + \alpha_4 \frac{NI_t}{TA_{t-1}} + \varepsilon_t \quad (4.9)$$

$TACC_t$ refers to total accruals, which is the difference between net income and operating cash flow. TA_{t-1} is total assets in year *t-1*. ΔREV_t is the change in sales. ΔREC_t is the change in accounts receivables. PPE_t is property, plant, and equipment, and NI_t is net income. We run the regression of equation (4.9) for each industry-year, and require at least ten observations for each regression. Earnings management (DisAccrualsit) is measured by the absolute value of discretionary accruals, which is the residual of equation (4.9). Because the ACCM term also captures the level of accruals-based earnings management, we do not control for it in the regression.

Following prior studies (Roychowdhury 2006; Cheng, Lee, and Shevlin 2016; Kim, Kim, and Zhou 2017), we apply two widely used real earnings management measurements, the abnormal level of production costs (AbnProdit), and discretionary expense (DisExpit).[36] Specifically, AbnProdit is derived using the following model:

$$\frac{Prod_t}{TA_{t-1}} = \alpha_0 + \alpha_1 \frac{1}{TA_{t-1}} + \alpha_2 \frac{Sales_t}{TA_{t-1}} + \alpha_3 \frac{\Delta Sales_t}{TA_{t-1}} + \alpha_4 \frac{\Delta Sales_{t-1}}{TA_{t-1}} + \varepsilon_t \qquad (4.10)$$

where $Prod_t$ is the production costs, which are the sum of the cost of goods sold and the change in inventories. TA_{t-1} is total assets in year *t-1*. $Sales_t$ and $\Delta Sales_t$ refer to sales and the change in sales of the firm in year *t*, respectively. We run the regression of equation (4.10) for each industry-year, and require at least ten observations for each regression. AbnProdit is defined as the absolute value of the residual term ε_t.

Discretionary expense (AbnDisExpit) is derived using the following model:

$$\frac{DisExp_t}{TA_{t-1}} = \alpha_0 + \alpha_1 \frac{1}{TA_{t-1}} + \beta \frac{Sales_{t-1}}{TA_{t-1}} + \varepsilon_t \qquad (4.11)$$

where $DisExp_t$ is discretionary expenses in year *t*. We run the regression of equation (4.11) for each industry-year, and require at least ten observations for each regression. AbnDisExpit is defined as the absolute value of the residual term ε_t. We take the absolute value for DisAccrualsit, AbnProdit, and AbnDisExpit, for two reasons: first, Khurana, Pereira, and Zhang (2018) indicate that when earnings are smoothed through real activities this leads to a higher crash risk in the future, so

[36] According to Roychowdhury (2006), the net effect on abnormal operating cash flow is ambiguous, therefore we discard it as our earnings management proxy.

both managing earnings upward and downward will impact crash risk. Second, following the majority of crash risk research, we calculate the accrual-based earnings management using the absolute value of discretionary accruals. For earnings management based on real activities, we also take the absolute value to be consistent with the definition of accrual-based earnings management.

Table 4.8 presents the regression results of equation (4.8). In all columns in Table 4.8, the coefficients for both SOA and Adjfreq are statistically insignificant and close to zero. These results suggest that dividend smoothing has no significant influence on the firm's earnings management behaviour, for both accrual-based and real activity-based earnings management. Since there is no evidence that dividend smoothing significantly changes the level of earnings management, the amplified crash risk is also unlikely to result from the earning management channel.

In summary, in this subsection, we conduct two tests to investigate the potential background mechanism that drives our main findings. The results of the tests support the conclusion that the information asymmetry channel rather than the earnings management channel explains why dividend smoothing affects future crash risk. It means that dividend smoothing can increase crash risk because it weakens the signaling effects of dividend payments, rather than because it can exert pressure on managers to manage their earnings.

4.4.2 Country-level analysis

In section 4.3, we find that dividend smoothing has a positive impact on crash risk. However, there is little reason to believe the effect would be the same in every country. Earlier studies indicate that the institutional and legal environment of an economy will influence investors' behaviour and firms' financial policies and stock performance (La Porta et al. 1998; Burgstahler, Hail, and Leuz 2006; La Porta, Lopez-de-Silanes, and Shleifer 2006). Inspired by these works, we investigate how the effect of dividend smoothing on crash risk varies in economies with different level of investor protection and institutional quality.

The level of investor protection may influence our findings for two reasons. First, investor protection laws are essential to the information disclosure and the information transparency of the financial market (La Porta, Lopez-de-Silanes, and Shleifer 2006). A more transparent financial market is usually associated with lower information asymmetry which means that investors do not have to infer private information by looking at dividend payments (Hail, Tahoun, and Wang 2014) or earnings announcements (Hung, Li, and Wang 2015). Second, the level of investor protection may have a direct influence on firms' policy and performance, such as dividend payments and crash risk (La Porta et al. 1998; Jin and Myers 2006; Javakhadze, Ferris, and Sen 2014). Thus, the investor protection environment may influence the relationship between dividend smoothing and firms' future crash risk.

We use two measures of investor protection, the Disclosure index and Liability index from La Porta, Lopez-de-Silanes, and Shleifer (2006). The Disclosure index is the arithmetic mean of six sub- indices which measure the strength of disclosure requirements from six perspectives. The Liability index is the arithmetic mean of three sub- indices which measure the difficulty that investors have in recovering the loss from suppliers who provide misleading information. The detailed definition of these two variables is presented in Table 4.A.2. These two indices can capture the level of investor protection and the information transparency of the economies. We split our sample into sub-samples including countries with a disclosure (liability) index above and below the sample median. Panel A and panel B of Table 4.9 present the results of the sub-sample analysis. We find the dividend smoothing strategy has a significant impact on crash risk only for firms domiciled in economies with a lower level of investor protection. These findings are consistent with previous literature arguing that a more transparent information environment reduces the information content of dividend changes (Hail, Tahoun, and Wang 2014), making the signaling effect of dividend change less relevant.

The second country-level factor we investigate is the institutional quality of the financial market. Institutional quality is a broad concept that refers to law, individual rights and the provision of government regulation and services (Barbier and Burgess 2021). Firms in economies with lower institutional quality may change dividends more often to alleviate any agency conflict (Ellahie and Kaplan 2021), therefore reducing bad news hoarding and subsequent stock crash. Therefore, we expect that dividend smoothing will have a more significant influence on crash risk for firms in economies with weak institutional quality. Following Ellahie and Kaplan (2021), we measure institutional quality using four factors, which are control of corruption, regulatory quality, rule of law, and government effectiveness, collected from the World Bank's Worldwide Governance Indicator dataset.[37] As shown in panel C of Table 4.9, after splitting the sample into economies with institutional quality above and below the sample median, we find that dividend smoothing has a significant

[37] http://info.worldbank.org/governance/wgi/.

influence on crash risk only for firms domiciled in economies with weaker institutional quality, which is consistent with our expectation.

4.4.3 Further robustness checks

We conduct a battery of robustness checks to further validate our findings. First, since the number of listed firms is not evenly distributed around the world, a large proportion of firms in our sample is from two developed countries: The U.S. and Japan. Firms from these two countries account for more than half of our observations, which may raise the concern that the effects we find are driven by those two countries' economies. To address this issue, we employ two robustness checks by first excluding all Japanese firms then excluding U.S. firms. Columns (1)– (2) of Table 4.10 present our baseline tests with the non-Japan sample, and columns (3)– (4) present tests with the non-U.S. firms. The results are consistent with our main findings, which indicates that our results are not dominated by those big economies.

Additionally, An and Zhang (2013) indicate that the crash risk during the financial crisis period is significantly higher than during the non-crisis period, which will make it harder to identify whether the crashes are driven by dividend smoothing or other market reactions toward the crisis. Also, according to Ben-Nasr and Ghouma (2018), the market crash in 2008 may cause a statistical bias for crash risk studies. To address these concerns, in columns (5)- (6) of Table 4.10, we rerun our baseline regression by excluding observations from 2008 and 2009. Our results remain robust using all alternative samples.

4.5 Conclusion

Although the extant literature provides ample evidence on the existence of dividend smoothing and its potential drivers, the impact of dividend smoothing on a firm's performance remains relatively unexplored. In this study, we investigate whether, and how, dividend smoothing can influence firms' future stock price crash risk. Using data from more than six thousand firms from 30 countries in 1987–2018, we find that firms with a higher dividend smoothing level are associated with a higher crash risk in the following year. This effect is both statistically and economically significant. This finding is robust to several endogeneity tests and alternative dividend smoothing measurements. Furthermore, we find that the effect is driven by dividend smoothing's direct influence on firms' information asymmetry level, rather than its influence on managers' earnings management behaviour. We find dividend smoothing weakens the signalling effect of dividend policy. Firms with a higher dividend smoothing level are associated with higher analyst forecast dispersion and higher forecast error. Lastly, we also find that the effect of dividend smoothing on crash risk is more pronounced in economies with a lower level of investor protection and weaker institutional quality.

This chapter enriches the crash risk literature by proving that dividend smoothing is a determinant of firms' bad news hoarding and crash risk. Studies related to crash risk may also need to consider the influence brought by firms' payout policy. In addition, the chapter also provides empirical evidence that dividend smoothing will directly affect firms' information transparency, although this effect will be mitigated by the transparency level of the whole financial market. All these findings are not only significant for us to better understand signalling role of firms' dividend policy, but also provide novel evidence that why stock price crash risk vary across different firms.

5. Will Powerful Customers Push Suppliers to Improve Their Internal Information Quality?

This chapter investigates how customer bargaining power impacts suppliers' internal information quality. By collecting data on all U.S. manufacturing firms with major customer data from 2004–2020, we find that suppliers with more powerful customers are associated with better internal information quality. We use the instrumental variable approach to mitigate any potential endogeneity concern. The results are also robust to alternative measurements, different sample selection, and additional controls. In addition, we find the effect is only exhibited in firms with higher relationship-specific investment, unique product producer, and firms whose customers have higher internal information quality themselves, indicating that the effect is driven by customers' monitoring incentives.

5.1 Introduction

As one of the most influential groups of stakeholders, big and powerful customers play important roles in firms' productions and operations. Prior studies find that customers may use their bargaining power to interfere with suppliers' behaviour in order to meet their own objectives, which means that customers may extract benefit from suppliers (Porter 1974; Fee and Thomas 2004; Murfin and Njoroge 2015). In this sense, customer power could impair firms' own profits and lower future performance.[38] The most typical example is Walmart's history of squeezing out the

[38] In additional to firm's profitability, previous studies also argue that a more powerful customer base is associated with higher risk and cost of capital (Chen et al. 2022), higher cost of external financing (Campello and Gao 2017), higher stock price crash risk (Ma et al. 2020), lower post-M&A performance (Dong, Li, and Li

last penny of its independent suppliers (PBS 2004). In contrast, however, powerful customers can also be beneficial to suppliers. Suppliers can benefit from the effectiveness of collaboration with big and concentrated customers (Patatoukas 2012; Irvine, Park, and Yildizhan 2013). The discipline and monitoring from customers can also help them to improve themselves (Cai and Zhu 2020; Chen et al. 2021). Following prior studies which discuss the advantages and disadvantages of customer bargaining power, this study investigates the effect of customer bargaining power on suppliers' internal information quality.

Firms' internal information quality, which captures the speed, accuracy, and effectiveness of firms' internal information systems to compile and report useful internal information, is not only essential for firms' decision making (Gallemore and Labro 2015; Heitzman and Huang 2019), but also influential for external stakeholders to get access to the information about firms' operational conditions (Cheng, Cho, and Yang 2018). For those major customers, the efficiency of suppliers' internal information systems also matters in two aspects. First, the quality of suppliers' internal information is vital for their decision on internal asset allocation and investment (Shroff 2017; Cheng, Cho, and Yang 2018; Heitzman and Huang 2019), which can impact the efficiency of their production. Because of the interdependent relationships along the supply chain, the suppliers' efficiency of production is also closely related to the stability of customers' material supply. Second, the quality of suppliers' internal information system can also affect the accuracy and effectiveness for customers to get access to the information about suppliers' operations (Baiman and Rajan 2002; Bauer, Henderson, and Lynch 2018).

2021), and lower level of public information disclosure (Crawford et al. 2020).

Consequently, we argue that customers should place importance on suppliers' internal information quality and be more willing to cooperate with suppliers with better internal information quality.

As customers are prone to intervene in suppliers' behaviour to protect their benefits (Wang 2012; Cai and Zhu 2020), they will also exert influence on suppliers' internal information quality if they think it is important.[39] We believe that customers with higher bargaining power are more likely to affect suppliers' internal information quality, because the bargaining power determines whether customers can exert significant influence on suppliers. This influence might be rooted in two aspects. First, customers can directly use their bargaining power to align suppliers to follow their own objectives, such as CSR (Dai, Liang, and Ng 2021), or corporate misconduct (Chen et al. 2021). In that sense, if customers are unsatisfied about a supplier's internal information quality, they should have incentives to use their power to discipline suppliers to improve it. Second, bad internal information quality may make suppliers lose important customers. According to Bauer, Henderson, and Lynch (2018), bad internal control quality will increase the probability of terminating the relationship with major customers. The fear of losing major customers may drive suppliers to actively improve their internal information quality.

To understand the effect of customer bargaining power on the quality of suppliers' internal information, we adopt two proxies to measure a firm's internal information quality. The first one is earnings announcement speed, which is the number of days

[39] Powerful customers will influence suppliers' operations to protect their own benefits in many ways. First, they will monitor suppliers to confirm that their supply chains are stable (Patatoukas 2012; Wang 2012). In addition, they will also drive suppliers to produce unique products to fit their own production, to shift profits to tax haven subsidiaries (Cen et al. 2017), or to perform better on corporate social responsibility to protect their own reputation (Chen et al. 2021; Dai, Liang, and Ng 2021).

between the earnings announcement date and the fiscal year-end date, scaled by 365. An effective internal information environment could enable firms to shorten the period of time needed to integrate information from different divisions of organizations (Jennings, Seo, and Tanlu 2013). Therefore, a more efficient internal information system should be capable of narrowing the time gap between the earnings announcement date and fiscal year-end (Gallemore and Labro 2015). The second measurement used is the indicator of disclosure of the material weakness of internal control over financial reporting. An ineffective internal control system means that a manager is relying on erroneous internal management reports when making decisions or forming public reports (Feng, Li, and McVay 2009).[40] In addition, we also apply two widely used measurements to capture firms' customer bargaining power, which are the sum of sales from all of major customers and the Herfindahl–Hirschman Index (HHI) of all firms' major customers.[41] These two variables measure the concentration level of the firm's customers, which have proved to be highly related to customer bargaining power (Patatoukas 2012; Fabbri and Klapper 2016; Hribar et al. 2020).

By applying these measurements, we find that firms with stronger customer bargaining power are associated with better internal information quality of suppliers. Firms with more powerful customers need a shorter period of time for earnings announcements, and are associated with a significantly lower probability of disclosing any material weakness of internal control. These results are also

[40] Gallemore and Labro (2015) also suggest that internal control weakness will make the information acquired by firm's headquarters untimely and inaccurate.
[41] Statement of Financial Accounting Standards (SFAS) (No. 14 before 1997, and No. 131 after 1997) mandate firms to disclose all customers that account for more than 10 % of the firm's totals sales for the year. To be consistent with the precious literature, we define all customers which accounts for at least 10 % of the focal firm's sales as major customers.

economically significant. In detail, a one standard deviation increase in the sum of major customers' sales and major customer HHI will reduce by 4.2% and 3% the time needed for suppliers to announce earnings, respectively. For material weakness disclosure, a one standard deviation increase in the sum of major customers' sales (major customer HHI) will decrease the probability of disclosure of material weakness by 1.87% (2.46%). Considering that the average probability of disclosing material weakness for the full sample is 8%, the magnitude of this effect is quite influential. The results support the hypothesis that firms' information quality is higher when their customers' bargaining power is stronger.

While the baseline test indicates a significant association between customer bargaining power and firms' internal information quality, it is still not enough to prove that the effect is causal. The significant association may be driven by customers' incentives to select better suppliers (reverse causality), or other unobserved factors which relate to both customer bargaining power and suppliers' internal information quality. To solve these problems, we conduct an instrumental variable (IV) approach to identify the causal effects between customers' bargaining power and their internal information quality. The first instrumental variable we use is the aggregated M&A level in customer industries (downstream merger wave), which is developed by Campello and Gao (2017). The downstream merger wave will increase the relative size of customer firms, and decrease the market competition in customer industries, which can enhance customers' bargaining power over suppliers. Also, merger wave in customer industry should be exogenous for suppliers' internal information quality because it is not a policy variable for suppliers (Campello and Gao 2017). Therefore, a downstream merger wave can be a valid instrumental variable which can impact suppliers' internal information quality only through its influence on customer bargaining power.

The second instrumental variable used in this study is the restriction regulation index of customer industry. This index captures the restrictiveness brought by regulations of an industry, which introduce barriers for new rivals to enter. In a similar manner, the policy in a customer's industry should not directly impact suppliers' internal information quality except through the supply chain. Also, the higher level of regulatory restriction for an industry will decrease the market competition and minimize the choice of suppliers, thereby enhancing the bargaining power of firms in the industry over their suppliers. Consistent with the baseline results, we find significant positive effects of customer bargaining power on suppliers' internal information quality in two stages least squares (2SLS) regressions using either of these two instrumental variables.

We then test the background mechanisms of why customer bargaining power can improve suppliers' internal information quality. We argue that the effect is driven by customers' monitoring incentives. As discussed above, suppliers' internal information quality is important for customers because it influences the quality of products provided and the information acquired (Cen et al. 2016; Bauer, Henderson, and Lynch 2018). In this sense, customer bargaining power should have a greater influence on suppliers' internal information quality if higher quality supplier internal information is more important for customers. Or, in other words, the effects should be more pronounced if customers have higher incentives to monitor suppliers. We perform several subsample tests to test this hypothesis.

Specifically, we use relationship-specific investment, special product producer, and aggregated customers' internal information quality to capture customers' monitoring incentives. The previous literature indicates that a higher level of relationship-specific investment means that the supplier is producing a more unique product for customers (Chu, Tian, and Wang 2019; Chen et al. 2022), which means that the relationship is more important for customers (as well as suppliers). This indicates that customers are more unwilling to see the failure of suppliers, so they are more incentivized to discipline them. Similarly, customers of special product producers also put a high valuation of the stability of the supply chain (Hui, Klasa, and Yeung 2012), so they have greater incentives to monitor suppliers. Our results indicate that only for those firms with higher level of relationship-specific investment and for those firms producing more unique products, will customer bargaining power significantly impact their internal information quality.

Finally, prior studies also find that customers are stricter to suppliers in the area where they themselves perform well. For instance, Dai, Liang, and Ng (2021) indicate that customers with better CSR performance are more willing to push suppliers to engage more in socially responsible investment. We therefore believe that customers with better internal information systems will also have higher incentives to monitor suppliers' internal information quality. Consistent with this hypothesis, we find that the influence of customer bargaining power only significantly impacts the internal information of firms with a high level of aggregated customer internal information quality. In sum, through all these tests, we find that customer bargaining power's influence on suppliers' internal information quality is more pronounced in firms whose customers care more about suppliers' internal information quality. These results are consistent with our prediction that our main effect is driven by customers' monitoring incentives.

Our results are also robust to a set of robustness checks. First, to mitigate the risk that the results are driven by the specific measurements used, we select several alternative bargaining power and information quality proxies. For the dependent variable, we use the disclosure of restatement results from unintentional error as an alternative internal information quality measurement. For the explanatory variable, we apply three alternative proxies to measure customer bargaining power, which are cost price margin, supplier industry HHI, and size weighted major customer sales. Second, to further mitigate the reverse causality problem, we lag all independent variables and control variables by one period. Third, we choose several alternative ways to select the sample. We check whether the results are robust by including other non-manufacturing firms. We also include government customers when estimating customer bargaining power. Lastly, we control for a set of additional control variables, such as customer characteristics, audit expertise, and corporate governance, to mitigate the possibility that our results are driven by specific confounding effects. To summarize, our results are robust to all the tests mentioned, which means that our findings are not likely to be driven by specific measurement, unique sample, or other confounding factors.

This chapter contributes to the existing literature in two ways. First, this chapter provides a new perspective on customers' influence on suppliers. To the best of our knowledge, this is the first research study to investigate how firms' customer bargaining power can affect their internal information quality. The existing literature mainly argues that powerful and concentrated customers will hurt suppliers' interests. Large customers can squeeze suppliers' margins (Fee and Thomas 2004), which may lead to a set of consequence for suppliers, such as higher cost of capital (Campello and Gao 2017), higher crash risk (Ma et al. 2020), or lower post-M&A premium (Dong, Li, and Li 2021). However, customers' power may also have some positive aspects. Some other researches suggests the customer bargaining power can also help to enhance suppliers' performance (Patatoukas 2012; Irvine, Park, and Yildizhan 2013). Consistent with these arguments, in this study, we highlight a positive aspect of customer bargaining power that it is helpful for firms to improve the efficiency of their internal information environment. These results provide a reasonable explanation of why suppliers can benefit from customer power. In our further analysis, we also find that the effect is driven by customers' monitoring incentives, which supports the view that customers have a disciplinary role in suppliers' operations (Chen et al. 2021).

In addition, as the number of research articles focusing on external determinants of firms' internal information quality and internal control quality is relatively small, this chapter also contributes to the literature by investigating a new external determinant of firms' internal information quality. [42] Existing studies focusing on internal control quality and internal information environment mainly investigate the internal determinants and consequence of internal control quality (Chalmers, Hay, and Khlif 2018). In this study, we extend the literature by finding a new external factor, which is customers' bargaining power, that will impact the firm's internal information environment.

[42] According to Chalmers, Hay, and Khlif (2018), there are 23 papers focusing on internal determinants of internal control quality, and 61 papers focusing on the consequence of internal control quality, while there are only 12 papers investigating external determinants.

The rest of the chapter proceeds as follows. Section 5.2 presents the sample selection, variable construction and measurements used in the study. Section 5.3 introduces the empirical methodology used, empirical results, and robustness checks. Section 5.4 describes the further analysis. Section 5.5 provides conclusions and implications.

5.2 Sample and measurements

5.2.1 Sample selection

Our sample is selected from all U.S. firms covered by Compustat Segment Database and the Audit Analytics database from 2004–2020. We start from 2004 because the internal control weakness data is only available since 2004, after the passage of SOX 404. The control variables data are drawn from CRSP/Compustat merged database. For additional controls and further analysis, the hostile takeover index is from Cain, McKeon, and Solomon (2017)'s paper.[43] Audit fee data is from the Audit Analytics database.

Consistent with prior studies (Campello and Gao 2017; Hui, Klasa, and Yeung 2012), we first test the effects for all manufacturing firms (SIC 2000–3999) at supplier level. We choose manufacturing firms for several reasons: (1) manufacturing firms are more dependent on the strong relationship with their major customers (Hui, Klasa, and Yeung 2012; Campello and Gao 2017), and major customers play a more important role in these industries. For instance, Hui, Klasa, and Yeung (2012) argue that firms in more labour-intensive sectors, such as service

[43] We thank Dr. Stephen McKeon for sharing the takeover index data on his website, which is available through https://pages.uoregon.edu/smckeon/.

sectors, care less about switching customers than manufacturing firms. (2) focusing on manufacturing firms can reduce the endogeneity problems brought by unobserved factors across industries (Campello and Gao 2017). (3) the majority of firms who report major customers are mainly found in manufacturing sectors.[44]

5.2.2 *Measures for customer bargaining power*

The customer information is collected from Compustat's Segment database. The Statement of Financial Accounting Standards (SFAS) (SFAS No. 14 before 1997, and SFAS No. 131 after 1997) requires firms to report all customers that account for more than 10% of their total revenues for the year.

One concern with this data is that some firms will voluntarily disclose customers representing less than 10% of their total sales. However, inclusion of those customers may cause bias, because not all suppliers voluntarily disclose those non-major customers. For example, two firms with same customer structure should have exact the same customer HH index. If one discloses those non-major customers, while the other do not, we will get different customer HH index for these two firms if we use all customer disclosed in calculating the customer concentration level. In addition, we cannot identify the background motivation of suppliers to disclose those customers, which also increase the possibility that the study impact by confounding factors. To be consistent with previous research (Campello and Gao 2017; Chen et al. 2022), we discard those customers representing less than 10% of

[44] Our results are stay robust if we also include other non-financial and non-utility industries.

sales. Consequently, the “major customers” in the following context only refers to those customers who account for more than 10% of suppliers’ total sales.

In addition, Compustat’s Segment database includes all kinds of customers, such as government and foreign countries. Following previous literature (Campello and Gao 2017; Dong, Li, and Li 2021; Chen et al. 2022), we first discard those non-corporate customers.[45] For those foreign customers, they only provide the name of country but no detailed information about the customer firms, while for those government customers, many of them are non-profit driven, which means they may not push suppliers as hard as corporate customers (Banerjee, Dasgupta, and Kim 2008; Cohen and Li 2020; Cohen et al. 2022).

The measure we used to capture customer bargaining power is the firms’ customer concentration base. A more concentrated customer base indicates that suppliers are more dependent on the commercial relationship with those major customers (Hui, Klasa, and Yeung 2012; Crawford et al. 2020; Chen et al. 2021), which suggests that the customers have higher bargaining power over those suppliers.[46] Following prior studies (Crawford et al. 2020; Hribar et al. 2020; Chen et al. 2022), we apply two measurements to proxy firms’ customer concentration. The first one is Major_Sales, which is the rate of sales assigned to all major customers. Specifically, for a unique supplier, Major_Sales is calculated as the sum of sales to all major customers scaled by total sales of this supplier. The detailed definition is following the equation below:

[45] We only keep those customers whose customer type in Compustat segment database is “COMPANY”. We also discard customers whose customer name is not reported, and customers whose sales from suppliers are not available.
[46] Customer concentration has been widely used as customer bargaining power proxies in prior literature, such as Hui, Klasa, and Yeung (2012), Fabbri and Klapper (2016), and Hribar et al. (2020).

$$Major\_Sales_{it} = \sum_{j=1}^{J} Sales_{ijt}/Sales_{it}$$

Where J stands for the total number of major customers for supplier i, and j is each specific major customer for supplier i. $Sales_{ijt}$ refers to the sales from supplier i to customer j in year t. $Sales_{it}$ refers to total sales of supplier i, during the year t. A higher value of Major_Sales indicates that the firm's customer base is more concentrated, and that customers have stronger bargaining power.

The second customer concentration measurement is Major_HHI. Patatoukas (2012) constructs this measure by calculating the HHI of all major customers. The specific definition is following the equation below:

$$Major\_HHI_{it} = \sum_{j=1}^{J} (Sales_{ijt}/Sales_{it})^2$$

Patatoukas (2012) suggests that the HHI captures the number of major customers the firm interacts with, and the importance of each customer to this supplier. He also argues that the higher value of Major_HHI indicates that customers have higher bargaining power.

5.2.3 Measures for internal information quality

We use two variables to measure a firm's internal information quality. The first one is earnings announcement speed (EAS), which is the number of days between the date of the fiscal year-end and the earnings announcement date, divided by 365. EAS is widely used as a proxy for a firm's internal information quality (Gallemore and Labro 2015; Heitzman and Huang 2019; Huang, Lao, and McPhee 2020). The longer is the period a firm needs to compile the information and prepare the financial statements, the less efficient is its internal information system. Gallemore and Labro (2015) argue that an accounting system that eliminates manual intervention, reducing redundancy, and streamlining reporting improves the efficiency of financial disclosure and accelerates the earnings announcement speed. Consequently, a higher value of EAS indicates that a firm takes more time processing and integrating information, which suggests a lower level of internal information quality.

The second internal information quality measurement is the disclosure of material internal control weakness (Weakness). It is a dummy variable that equals one if firms disclose a material internal control weakness in the current year and zero otherwise. Due to the extreme bad influence of several accounting frauds at the beginning of the 21st century, the U.S. Congress passed the Sarbanes–Oxley Act (SOX) to enhance firms' financial reporting quality. Specifically, section 404 of SOX requires firms to evaluate their internal controls on financial reporting and auditors will disclose whether there is a material weakness of the firm. According to Feng, Li, and McVay (2009) and Gallemore and Labro (2015), reporting a material weakness indicates a firm is suffering from untimely or even inaccurate internal financial information. In principle, firms which disclose a material weakness in the current year are more likely to face lower internal information quality.

5.2.4 Control variables

To alleviate the concern that the effect stems from some confounding factors, we control for a set of firm characteristics. First, we control for firm size (Size), measured by the natural logarithm of sales for the year, because size is vital for bargaining power and the efficiency of the internal information system. Also, we control for firm age in our tests. Second, a firm's profitability is also essential for its bargaining power and can be a reflection of its internal information quality. Consequently, we control for several performance measurements, including market-to-book ratio (MTB), return on assets (ROA), and sales growth rate (Gro). In addition, following previous studies (De Simone, Ege, and Stomberg 2015; Guo et al. 2016; Chen, Feng, and Li 2020), we also control for a set of variables which may impact the firm's internal control quality. Specifically, we include the loss indicator (Loss) to control for the impact of financial constraints. We also control for the number of segments (Seg) to exclude the influence brought by business complexity, and foreign exchange indicator (For) to exclude the influence brought by complexity of multinational operations. Lastly, we include a restructuring indicator (Rst) and acquisition indicator (Aqv) to control for the mismatch between a firm's internal control system and new organizational structure. For all the main variables and control variables, the detailed definitions can be found in Table 5.A.1.

5.2.5 Summary statistics

Table 5.1 reports the descriptive statistics for all variables used in this study. In detail, Table 5.1 displays the mean, standard deviation, and distribution of each variable. Because of the data availability, the sample size of EAS and Weakness is smaller than other variables. According to the summary statistics, nearly 8% of firm–year observations in our sample indicate the firm is suffering from material weakness. On average, major customers account for around 45% of sales of suppliers' total sales, these numbers are comparable with previous studies (Guo et al. 2016; Chen, Feng, and Li 2020; Chen et al. 2021; Chen et al. 2022).

5.3 Model and empirical results

5.3.1 Model specification

To examine whether customer bargaining power will impact firms' internal information quality at the supplier level, we apply the following regression model:

$$IIQ_{i,t} = \beta_0 + \beta_1 Cus\_Concentration_{i,t} + \beta_2 Controls_{i,t} + Industry\ FE + Year\ FE + \varepsilon_{i,t} \tag{5.1}$$

Where $IIQ_{i,t}$ is the internal information quality of supplier i in year t. $Cus\_Concentration_{i,t}$ is supplier i's customer concentration base in year t. $Controls_{i,t}$ includes all control variables introduced in section 5.2.4. Industry and year fixed effects are also included in the regression. Consistent with prior studies (Campello and Gao 2017; Chen et al. 2022), we do not include firm fixed effects due to little within firm variation of customer concentrations.[47]

5.3.2 Baseline regression results

We first investigate whether customer bargaining power will impact suppliers' internal information quality by running the regression of equation (5.1). Table 5.2 reports the baseline regression results. Specifically, columns (1)–(2) and (3)–(4)

[47] According to Chen et al. (2022), the within firm variation for customer concentration is only half of cross firm variation, which may not support including firm fixed effects. Also, Dhaliwal et al. (2016) and Chen et al. (2022) suggest using industry × year fixed effects to control for variables correlated with customer bargaining power and vary within the industry and year. We also perform a robustness checks using an industry × year fixed effects model and the robustness stays robust. The detailed regression results are reported in table 5.A.2.

show how customer bargaining power (measured by Major_Sales and Major_HHI) affects firms' earnings announcement speed and disclosure of material weakness, respectively. To better interpret the influence brought by customer bargaining power on the probability of material weakness disclosure, we use a logistic regression model in columns (3) and (4). The coefficients of all bargaining power measurements are negative and statistically significant. Considering that a lower value of EAS and Weakness indicates a higher level of internal information quality, these results are consistent with the hypothesis that higher levels of customer bargaining power will improve suppliers' internal information quality.

The coefficients of regression results also indicate a significant economic impact: a one standard deviation increase in the sum of major customers' sales (Major_Sales) will affect the time needed for suppliers to announce earnings (EAS) by 4.2%. Also, a one standard deviation increase in the major customer HHI (Major_HHI) will reduce the time needed for suppliers to announce earnings by 3%. To calculate the economic significance of customer bargaining power on suppliers' probability of disclosing material weakness, we first calculate the average marginal effects of the coefficients in a logistic model. The marginal effects of Major_Sales and Major_HHI are -0.071 and -0.110, respectively. Given that the standard deviation of Major_Sales and Major_HHI are 0.264 and 0.224, respectively, a one standard deviation increases in Major_Sales (Major_HHI) will decrease the probability of disclosure of material weakness by 1.87% (2.46%). Considering that the mean probability of material weakness disclosure for the full sample is 8%, a one standard deviation increase in Major_Sales (Major_HHI) will decrease the unconditional probability of material weakness disclosure by 23.4% (30.8%).

As for control variables, firm size and age show significantly negative influence on both EAS and Weakness, which is consistent with Guo et al. (2016) and Chen, Feng, and Li (2020)'s prediction that larger firms have better financial resources in implementing internal control functions. The market-to-book ratio and ROA are negatively related to EAS and Weakness, while Loss is positively related to these two internal information quality measurements. This indicates that more profitable firms are less likely to suffer from inefficient internal information systems. In addition, the transactions related to foreign currency will also decrease the speed of firms in announcing earnings.

5.3.3 Endogeneity

In section 5.3, we have found that suppliers with higher level of customers bargaining power are less likely to suffer from low quality internal information. However, the results cannot fully indicate the causal relationship between the two factors. First, because customers might also actively choose suppliers with better internal information quality, this positive association may suffer from reverse causality concerns. In addition, the results may also be affected by some unobserved confounding factors which may impact both customer bargaining power and suppliers' internal information quality simultaneously. To mitigate the endogeneity problem, we perform an instrumental variable approach by extracting an exogenous part of customer bargaining power and test how it will impact suppliers' internal information quality.

5.3.3.1 Instrumental variables

We apply two instrumental variables in this study. The first instrumental variable used is the aggregated customer industry-level merger wave (downstream M&A wave), which was initially developed by Campello and Gao (2017). The downstream M&A wave can be a good instrumental variable because it meets both inclusion and exclusion restrictions. For the inclusion restriction, the M&A activities in customer industries can increase the relative size of customers and lower the market competition in customer industries (Campello and Gao 2017). These activities, therefore, will increase the customer concentration and customer bargaining power (Fee and Thomas 2004; Bhattacharyya and Nain 2011). For the exclusion restrictions, the M&A activities in customer industries should not directly impact suppliers' internal information quality. It may only affect such internal information quality through its influence on the supply chain, by improving customers' bargaining power.

To construct the downstream merger wave variable, we follow the procedure applied by Campello and Gao (2017) and Chen et al. (2022). First, we collect the M&A expenditure of all customers from the Compustat database. We then calculate the customer industry-level M&A activities by taking the five-year mean value of M&A expenditure scaled by the total sales of the acquirer. To construct the aggregated customer industry M&A activities at the supplier level, we calculate the weighted sum of all customers' industry level M&A activities, weighted by the percentage of sales accounted for by each customer. The detailed model is formed below:

$$Cus\_MA\_Wave_{i,t} = \sum_{j=1}^{n} \%Sales_{i,j,t} \times 5\ year\ industry\ mean(\frac{M\&A\ expenditure_j}{Sales_j})$$

Where $Cus\_MA\_Wave_{i,t}$ is the supplier-level customer M&A activities. $\%Sales_{i,j,t}$ refers to the percentage of sales each customer j contributes to supplier i's total sales in year t. $M\&A\ expenditure_j$ is the M&A expenditure for customer j. To calculate the customer M&A activities, we need to select supplier–customer links with identifiable customers and suppliers. Following the procedure of Cohen and Frazzini (2008) and Cen et al. (2017), we match each of the customers with suppliers through a fuzzy name-matching algorithm and verify manually; we lose some supplier–year observations that cannot be accurately matched with an identifiable customer.

The second instrumental variable used in our study is aggregated customers' industry-level regulatory restrictions, which is also applied by Gutiérrez and Philippon (2017), Duan, Larkin, and Ng (2019), and Chen et al. (2022). As government regulations are published by many different agencies and covering many different industries, McLaughlin and Sherouse (2018) collected and analysis the strictness of each regulation and calculated an industry-year level regulatory restrictions index. The strictness of those regulations is measured based on textual analysis method which count the number of regulatory restrictions, denoted by the strings, "shall," "must," "may not," "required," and "prohibited," both individually and in total. Duan, Larkin, and Ng (2019) suggest that the higher level of regulatory stringency for an industry will increase fixed costs for new firms, and prohibit them from entering this industry. Consequently, the regulation in a customer's industry will decrease market competition and increase the relative size of these customer firms in the industry, thereby enhancing the bargaining power of customers. So, the instrumental variable meets the inclusion restriction. Also, the regulatory index in the customer industry should not directly impact suppliers' internal information quality except through its influence on customer industry competition. Hence, the exclusion restriction is also met.

Following Duan, Larkin, and Ng (2019) and Chen et al. (2022), we collect industry-level regulation data from McLaughlin and Sherouse (2018) and (McLaughlin 2020).[48] McLaughlin and Sherouse apply a custom-made text analysis and machine-learning algorithms to quantitively measure the characteristics of industry-level regulation, including volume, restrictiveness, and complexity. In this study, we only apply the index of restrictiveness brought by regulations provided by (McLaughlin 2020) for each 6-digit NAICS industry. To construct the customer regulation index for each supplier, we calculate the weighted sum of customer regulation index for each supplier, weighted by the percentage of supplier's sales each customer accounts for. The variable is defined as follows:

$$Cus\_Reg\_Index_{i,t} = \sum_{j=1}^{n} \%Sales_{i,j,t} \times Customer\ industry\ regulation\ index_{jt}$$

5.3.3.2 2SLS regression

We apply a 2SLS regression to extract the exogenous part of customer bargaining power and interpret the causal effect of such bargaining power on suppliers' internal information quality. In the first stage, we estimate the predicted value of customer bargaining power by regressing the Major_Sales and Major_HHI on instrumental variables as well as all control variables used in model (5.1). Then, in the second stage, we test the effect of customer bargaining power on suppliers' internal

[48] The data is available through: https://www.quantgov.org/bulk-download.

information quality using predicted customer bargaining power estimated from the first stage.

Panel A and panel C of Table 5.3 report the first stage of the 2SLS regression by adopting customer merger wave (Cus_MA_Wave) and customer regulation index (Cus_Reg_Index) as instrumental variable, respectively. As reported in Panel A, the coefficients of Cus_MA_Wave are highly positive and statistically significant, which indicates that the aggregated merger activities in customers' industries have a significant impact on customer concentration and bargaining power. In addition, the F-statistics are higher than the threshold of 10, which indicates that our instrument is not weak. The Kleibergen–Paap rk LM statistics is significant, which rejects the null hypothesis that our instrument is under identified. Similarly, Panel C of Table 5.3 indicates that Cus_Reg_Index also shows a significant positive effect on customer concentration, which suggests that regulatory restrictions will enhance customer bargaining power. The F-statistics and Kleibergen–Paap rk LM statistics also reject the null hypothesis that our instrumental variables are weak.

Panels B and D of Table 5.3 report the second stage regression results of the 2SLS regression by adopting Cus_MA_Wave and Cus_Reg_Index as instrumental variables, respectively. In panel B, the estimated customer bargaining power measurements, which are predicted by Cus_MA_Wave, have significantly negative effects on both EAS and Weakness, which are consistent with our baseline results. Similarly, panel D also indicates similar results by estimating customer bargaining power using Cus_Reg_Index. In sum, the results of the instrumental variable approach are consistent with our baseline regression results, which mitigates the concern that our findings result from endogeneity problems.

5.3.4 Robustness checks

The results of the 2SLS regression mitigate the concern that the baseline finding is influenced by endogeneity. In this section, we conduct a set of robustness checks to further strengthen our findings.

5.3.4.1 Alternative measurements and sample selection

In the baseline tests, we choose two widely used proxies to measure firms' internal information quality and customer bargaining power. This reduces the risk that the previous findings are driven by the specific measurements used or the inaccuracy of the measurements. In this subsection, several additional alternative measurements have been applied to further strengthen our findings. First, for firms' internal information quality, we choose disclosure of restatement because of unintentional error (Restat) as the alternative measurement. Specifically, Restat is an indicator variable that equals one if firms restate their financial statement because of unintentional errors and zero otherwise. Considering restating a financial statement is mainly driven by basic accounting errors; this behaviour indicates that the information reported is unreliable or inaccurate, which also suggests the inefficiency of firms' internal information systems (Gallemore and Labro 2015; Heitzman and Huang 2019). Panel A of Table 5.4 reports the baseline regression results by using Restat as the internal information quality proxy. The results are consistent with our baseline finding – the coefficients are all significantly negative, which indicates that a higher level of customer bargaining power will reduce the probability that the supplier restates the financial statement.

For customer bargaining power, we apply three alternative proxies, which are supplier price–cost margin (PCM), supplier industry level HHI (Industry_HHI), and size weighted sales of major customers (Major_Size). In detail, the price–cost margin is sales minus cost of goods sold and general and administrative expense, scaled by sales. Ahern (2012) argues that the price–cost margin captures the supplier's ability to price above marginal cost. He uses this variable to measure the substitutability of the firm's product, and the dependence of firms on their customers. The more a firm depends on its customers, the higher is the bargaining power its customers have. Consequently, we believe that a higher value of supplier PCM indicates a lower level of customer bargaining power.

Following Ahern (2012), we then calculate the supplier industry-level HHI to proxy for supplier industry-level competition. A more competitive supplier industry means the customers can easily switch suppliers within the industry, which will enhance the bargaining position of customers. Because the higher level of HHI indicates a lower level of market competition, we believe that the higher level of supplier HH index suggests a lower level of customer bargaining power.

Thirdly, following Campello and Gao (2017), we calculate the size weighted sales of major customers (Major_Size) as the alternative proxy for customer concentration. Major_Size is calculated as a percentage of sales each major customer accounts for, weighted by the size of those major customers:

$$Major\_HHI_{it} = \sum\nolimits_{j=1}^{J} (Sales_{ijt}/Sales_{it}) \times Size_{jt}$$

Panel B of Table 5.4 reports the regression results using alternative customer bargaining power proxies. As shown in columns (1)–(2), the coefficients of PCM are significantly positive. As noted previously, PCM captures suppliers' power to bargain for a higher price, so a higher value of PCM suggests a lower level of customer bargaining power. Thus, this effect is consistent with our main story that when customers are in a better bargaining position, suppliers should have better internal information quality. Similarly, a higher level of Industry_HHI indicates that the supplier industry is more concentrated, so that the customer has lower bargaining power. The positive coefficients in column (3)–(4) also support our baseline results. Lastly, as an alternative proxy for customer concentration, the coefficient of Major_Size is negatively significant, which is still consistent with our main story.

We then perform a robustness check by lagging all independent variables and control variables by one period. Although the customer concentration is a long-term effect with little time series variance, one may argue that using contemporaneous explanatory variables will increase the concern of reverse causality. Panel C of Table 5.4 reports the results by lagging all independent variables and control variables by one period. Our results are robust after performing this test.

Lastly, we test the robustness of our results by applying different samples. First, our baseline results test the effect only on manufacturing firms. In this section, we also check whether the effect exists when including non-manufacturing firms. To be consistent with the prior literature, we do not include financial and utility firms, because the fundamental characteristics of these firms are different from other firms. Panel D of Table 5.4 reports the results including both manufacturing industries and non-manufacturing industries. Consistent with our baseline results, customer concentration shows significantly positive effects on suppliers' internal information quality. Second, for our baseline regression, we only include company customers in our sample. In this section, we also check the robustness of our results by including government customers. Our results are still highly significant after using these alternative samples.

5.3.4.2 Control for corporate governance

Corporate governance is an important firm characteristic that will affect firms' monitoring and information environment. One may be concerned that it is a confounding factor which may be related to both customer bargaining power and suppliers' internal information quality. On the one hand, a firm's corporate governance characteristics, such as the expertise of the audit committee (Hoitash, Hoitash, and Bedard 2009), has a significant impact on the firm's probability of disclosure of internal control weakness over financial reporting. On the other hand, customers may be more willing to choose suppliers with stronger corporate governance. Consequently, in our study, it is also necessary to ensure that our results are not driven by suppliers' corporate governance level. To control for corporate governance, we include the takeover index constructed by Cain, McKeon, and Solomon (2017) in our test.

Panel A of Table 5.5 reports the results after controlling for the corporate governance level. Our findings stay robust after including the takeover index in our regression. In addition, we do not find that the takeover index has a significant impact on firms' internal information quality. To further strengthen this finding, we run another test without customer concentration variables.[49] According to the regression results in panel B of Table 5.5, the takeover index shows no significant influence on a firm's internal information quality if we control for several basic firm characteristics, such as size, age, ROA, and market-to-book ratio. These tests prove that our results are not driven by firms' corporate governance level.

5.3.4.3 Control for customer characteristics and auditor characteristics

Finally, we also control for several customer characteristics as well as auditor characteristics to avoid the possibility that our results are driven by traits of customers or the expertise of auditors. Specifically, we control for aggregated customer size, age, market-to-book ratio, and ROA. The aggregated value is calculated as the weighted average of all identifiable major customers, weighted by the percentage sales each customer accounts for in suppliers' total sales. In addition, we also control for a *Big4* variable, which is an indicator that equals one if the firm is audited by the four biggest auditors, to exclude the possibility that the effect is driven by the expertise of auditors.[50] Lastly, we also control for the audit fee spent by the firm during the year. As De Simone, Ege, and Stomberg (2015) suggested, the size of audit fee can also impact the firm's internal control quality. We include this variable to further mitigate the concern that the effect is driven by auditors' efforts.

Table 5.6 presents the results of controlling for customer characteristics (columns (1)–(4)), auditor characteristics (columns (5)–(8)), and both characteristics (columns

[49] We do not include customer bargaining power measurements because it will make us lose many observations.
[50] De Simone, Ege, and Stomberg (2015) and (Chen, Feng, and Li 2020) include the *BIG4* dummy to control for auditor quality.

(9)–(12)). Our results remain robust after controlling for these variables, which reject the null hypothesis that our results are driven by unique customer traits or auditor's expertise.

5.4 Further analysis

In section 5.3, we find that customers with higher bargaining power can enhance suppliers' internal information quality. This effect is unlikely to be driven by unobserved factors or reverse causality. In this section, we are going to investigate the background reason that drives this effect.

We argue that the positive effect of customer bargaining power on suppliers' internal information quality is driven by customers' monitoring incentives. On the one hand, suppliers are influential for customers' performance. The direct economic tie along the supply chain makes the customer attach great importance to suppliers' production and operations. On the other hand, the efficiency of the suppliers' internal information environment is influential for customers to acquire information about the stability of the supply chain and the quality of product bought (Cen et al. 2016; Bauer, Henderson, and Lynch 2018), which should also draw substantial attention from customers.[51] Consequently, we believe that the causal effect between customer bargaining power and suppliers' internal information quality should be more significant when customers have higher monitoring incentives to improve

[51] According to Baiman and Rajan (2002), reliable information sharing will impact the relationship between sellers and buyers. Bauer, Henderson, and Lynch (2018) also argue that powerful customers need accurate and reliable information about suppliers' ability to provide products and services with satisfactory quantity and quality.

supplier's information quality. We test this hypothesis through checking the two types of moderators which can reflect customers' monitoring incentives.

5.4.1 Strength of the relationship

We first test whether the strength of the customer–supplier relationship can moderate our effects. If the customers are more dependent on the commercial relationship, they should place more attention on the stability of this supply chain, which will also increase customers' monitoring incentives (Kang et al. 2015). In this subsection, we apply two proxies to measure the strength of the customer–supplier relationship.

5.4.1.1 Relationship-specific investment

The first measurement used to proxy the strength of customer–supplier relationship is suppliers' relationship-specific investment. The relationship-specific investment captures the uniqueness of production produced by suppliers to meet specific customers' requirements. These products may be customized by major customers such that they have little value to other potential buyers (Titman and Wessels 1988; Allen and Phillips 2000; Chen et al. 2022). Thus, the higher value of relationship-specific investment will strengthen the relationship, and it will increase the switching cost for both of them to choose a new partner (Dai, Liang, and Ng 2021; Chen et al. 2022). Consequently, we believe that the uniqueness of the product in a relationship will not significantly change the bargaining position of the customer but will increase the customer's incentives to monitor the supplier's operations.

Following prior studies (Raman and Shahrur 2008; Chen et al. 2022), we measure relationship-specific investment using suppliers' research and development (R&D) intensity which is the R&D investment scaled by total assets. Existing evidence suggests that customers of research-intensive firms are more likely to push suppliers to invest in relationship-specific projects (Allen and Phillips 2000; Chu, Tian, and Wang 2019). To test the hypothesis that customer bargaining power's impact on the firm's internal information quality is driven by customers' monitoring incentives, we split our sample into high and low subsamples based on the median value of firms' R&D intensity each year. We then run our baseline regression based on these subsamples.

Table 5.7 displays the results of subsample tests. The coefficients on EAS and weakness measures for high R&D intensity subsamples are statistically significant and consistent with our baseline results. However, the coefficients of low R&D intensity subsamples are statistically insignificant and generally smaller in magnitude. The results suggest that our main effect is more pronounced in suppliers whose customers put more importance on the relationship. The effect is consistent with our prediction that customers' impact on suppliers' internal information quality is driven by customers' monitoring incentives.

5.4.1.2 Special product producers

The second measurement used for the strength of relationship is the uniqueness of product produced for customers. Similar to the suppliers with a higher level of relationship-specific investment, the special product producers can fulfil some additional requirements, and will increase the switching cost for customers to choose a new supplier (Hui, Klasa, and Yeung 2012; Kang et al. 2015). According to Banerjee, Dasgupta, and Kim (2008) and Hui, Klasa, and Yeung (2012), firms with higher selling, general, and administrative (SG&A) expenditure are more likely to produce special products that require specialized servicing or spare parts. Thus, following Hui, Klasa, and Yeung (2012), we use firms' selling, general, and administrative cost, scaled by their total revenue, to proxy the uniqueness of the product supplied to our sample firms. Consistent with the last section, our sample is divided into subsamples based on the median value of SG&A/Sales. We then test our baseline regression based on these sub-samples.

Table 5.8 displays the results of subsample tests for firms with a high (low) level of SG&A/Sales. The coefficients are statistically significant for subsamples with high SG&A/Sales, while for the low SG&A/Sales sample, we do not find significant effects. Also, the magnitude of coefficients for the high SG&A/Sales sample is larger than that of the low SG&A/Sales sample. These results are consistent using both EAS and Weakness measurements. The results indicates that the uniqueness of products provided by suppliers can increase the effect of customer bargaining power on suppliers' internal information quality. Combined with the argument that more unique products increase customers' monitoring incentives, the results are consistent with our prediction that customer bargaining power can affect suppliers' information quality because of customers' monitoring incentives.

5.4.2 Customer internal information quality

In addition to suppliers' characteristics and the uniqueness of their products, we believe that customers' own internal information quality will also affect their incentives to monitor suppliers. Prior studies indicate that customers are more likely to push suppliers in the area where they themselves perform well. For instance, Dai, Liang, and Ng (2021) find that customers are more prone to affect suppliers' CSR if they have a high level of socially responsible investment themselves. Chu, Tian, and Wang (2019) also find that more innovative firms have positive effects on suppliers' innovation. Consequently, customers with a more efficient internal information environment are expected to be less tolerant of poor information quality in their suppliers.

To test this conjecture, we split our sample into subsamples with high (low) aggregated customer internal information quality. The aggregated customer internal information quality is calculated as the weighted sum of customer earnings announcement speed, weighted by the percentage of sales to each customer.[52] Table 5.9 displays the results of subsample tests for firms with good (low Cus_EAS) and bad (high Cus_EAS) aggregated customer internal information quality. For both EAS and Weakness measurements, the coefficients are only significant for subsamples with a high level of customer internal information quality. The results indicate that customers' own information quality can moderate the effects between bargaining power and suppliers' internal information quality. It is consistent with the prediction that customers with better internal information quality are less tolerant of bad information quality of suppliers, and also supports the hypothesis that the relationship between customer bargaining power and supplier internal information quality is driven by customers' monitor incentives.

[52] We do not use Weakness as customer internal information quality measurements because few firms have a record of disclosing material weakness, which will make a large difference in the size of two subsamples. Our results are stay robust if we choose Weakness as customer internal information quality measurements.

5.5 Conclusion

In this study, we investigate whether customer bargaining power will help suppliers to improve their internal information quality. By using data on all manufacturing firms with major company customers in U.S. markets, we find that customer bargaining power has a significantly positive effect on suppliers' internal information quality. In detail, a one standard deviation increases in the sum of major customers' sales (Major_Sales) and major customer HHI (Major_HHI) will reduce 4.2% and 3% of the time needed for suppliers to announce their earnings (EAS), respectively. For a firm's internal control quality over financial reporting, a one standard deviation increase in Major_Sales (Major_HHI) will decrease the probability of disclosure of material weakness by 1.87% (2.46%), respectively. These results are robust to various alternative measurements, alternative sample selection, additional control variables, and 2SLS regression. In our further analysis, we find these effects are more pronounced if the relationship is more important for customers and are more pronounced if customers put more importance on suppliers' information quality. Specifically, we find the effects are seen in supplier firms with higher levels of relationship-specific investment, higher levels of selling, general, and administrative expenditure, and higher levels of customer information quality. These results also support the hypothesis that the influence of customer bargaining power on suppliers' internal information quality is driven by customers' monitoring incentives.

This empirical chapter provide evidence that customers will push suppliers to improve their internal information environment. Previous studies are mainly focusing on the rent extraction effect brought by major customers. This chapter introduces a bright side of major corporate customers, that they are able to help suppliers to develop themselves.

6. Conclusion and implications

6.1 Summary of the thesis

This thesis explores the determinants of firms' information quality and the economic consequences brought by bad information quality. As for information's essential role in the efficiency of financial markets and corporate operations, the quality of information in the market is critical for economic development. Therefore, exploring the determinants and economic consequences of information quality is important. Although research on information quality has attracted much attention in the past few decades, some aspects still remain unexplored. In this thesis, we investigate the novel determinants of firms' information quality and the effects brought by low quality information.

The first empirical chapter (Chapter 3) investigates how firms' internal information quality moderates their capital structure peer effects. The results show that firms with lower internal information quality exhibit significantly higher levels of peer mimicking in financing decisions. Although firms with low quality internal information are more likely to mimic peers, we find this effect will hurt firms' value-mimickers achieve significantly lower future profitability than non-mimickers for firms with lower internal information quality. We argue that this effect (mimickers earn lower profit) exists because the impact of internal information quality on peer effects is driven by the firms' agency problem. The empirical results from our tests support this argument: the internal information quality's impact on the peer effects only exists in firms with weaker corporate governance.

The second and third empirical chapters (Chapter 4 and 5) investigate the determinants of firms' information quality. Chapter 4 explores the determinants of quality of information disclosed to the public, while Chapter 5 studies the determinants of firms' internal information quality. Specifically, Chapter 4 investigates how firms' dividend smoothing behaviour will influence the information asymmetry between insiders and outsiders, and how it affects firms' future stock price crash risk. By using data on dividend payers from 30 economies, we find that the higher levels of dividend smoothing are associated with higher stock price crash risk. By adopting difference-in-difference tests and an instrumental variable approach, we find that this association indicates a casual effect that dividend smoothing will increase crash risk. Also, we find that this effect exists because dividend smoothing will reduce the signalling effect of dividends, which will increase firms' information asymmetry level. Finally, we also find the effect only exists in economies with poor investor protection and weaker institutional quality.

Chapter 5 explores whether powerful customers will push suppliers to improve their internal information quality. By using all U.S. manufacturing firms with major customer information, we find that firms with more powerful customers, measured by customer concentration, have better internal information quality. Through 2SLS regressions with two different instrumental variables, we find that this effect is not driven by reverse causality or confounding factors. Finally, we also find that the effect is driven by customers' monitoring incentives.

6.2 Implications

The thesis has implications for today's accounting and corporate finance studies. First and foremost, the thesis contributes to the literature related to information quality. It is helpful for more deeply understanding the determinants and economic consequence of firms' information quality. The empirical studies in the thesis provide new evidence of how firms' information quality will affect firms' decision making, and whether firms' financial policy and stakeholders' attitudes will affect firms' information quality. Prior studies have investigated the determinants and economic consequence of firms' information quality in many aspects (Doyle, Ge, and McVay 2007; Feng, Li, and McVay 2009; Gallemore and Labro 2015; Heitzman and Huang 2019). However, the relationship of information quality with corporate peer effects, dividend policy, and customers' bargaining power, are rarely explored. This thesis provides evidence that firms' information quality will impact their financing decisions, and also proves that information quality will be affected by dividend policies and customer–supplier relationships.

The thesis also helps us to understand the background mechanism of corporate peer effects. Although peer influence is a hot topic in current corporate finance research, most of the related studies are focusing on investigating the existence of different kind of peer effects. These studies cover a wide range of corporate financial research areas, including capital structure (Leary and Roberts 2014), payout policy (Adhikari and Agrawal 2018; Grennan 2019), investment decisions (Bustamante and Frésard 2020), trade credit (Gyimah, Machokoto, and Sikochi 2020), and innovation (Machokoto, Gyimah, and Ntim 2021). However, the number of studies trying to find the background mechanism which drives the peer effect is small. This thesis contributes to the literature by exploring an explanation of why firms choose to mimic peers. The thesis discovers that bad internal information quality is a reason drives firms to engage more in capital structure peer mimicking. This explanation can also be extended to other future studies related to corporate peer effects. Actually, any peer mimicking behaviours which are incentivised by information acquiring can be influenced by firms' internal information quality, such as investment and trade credit. For instance, according to Bustamante and Frésard (2020) indicate that the peer mimicking on investment decision could be driven by a learning incentives from a mimicker. Gyimah, Machokoto, and Sikochi (2020) also indicate that peer effects on trade credit is more pronounced in firms with bad information environment. These kinds of peer influence are possibly be driven by managers' incentives to offset the shortage of internal information. The application of internal information quality as a potential channel for peer mimicking can be applied to other future related studies.

In addition, the thesis is also helpful for understanding the signalling role of dividend change. The traditional payout policy articles suggest that dividends play a signalling role in corporate discloses (Bhattacharya 1979; Miller and Rock 1985). Some subsequent studies indicate that the dividend change contains information about future earnings (Kasanen, Kinnunen, and Niskanen 1996; Ham, Kaplan, and Leary 2020). In addition to Guttman, Kadan, and Kandel (2010) and Wu (2018)'s study, we provide further evidence that dividend smoothing behaviour will also smooth out the useful information disclosed by dividend payments. This thesis further supports these arguments by showing that dividend smoothing conceals information from outsiders.

Finally, this thesis supplements the understanding of the role customers play in suppliers' operations. Prior studies have investigated customers' impact on suppliers in many different areas, such as tax avoidance (Cen et al. 2017), CSR (Dai, Liang, and Ng 2021), and corporate misconduct (Chen et al. 2021). This thesis enriches this strand of the literature by showing that customers will also drive suppliers to improve internal information quality.

6.3 Limitation and future studies

Although the thesis provides implications for corporate finance studies, it is still limited to relatively small areas. For instance, for the first research chapter (Chapter 3), the empirical study only focuses on capital structure peer effects. Firms' internal information quality may also be applied as an explanation for other types of corporate peer effects, such as investment or earnings management. It is meaningful to extend the studies to other types of peer effects which may be driven by firms' information quality. In addition, the background reason of peer mimicking for various corporate policies may be different. Not all kinds of peer effects can be explained by firms' information quality. For instance, it is hard to treat internal information quality as an explanation for competition driven peer mimicking such as dividend payments peer effects and innovation peer effects. In further studies, it will be worthwhile to further explore which types of peer effects are driven by firms' information quality and which types of peer effects are not.

Also, the research on the quality of information disclosed mainly focuses on how firms' behaviour will affect their future crash risk. However, crash risk is only one measure that can reflect firms' information quality. In future research, it will also be worthwhile to check whether firms' behaviour, such as dividend smoothing, will fundamentally impact the information transparency of the firm, not only from crash risk aspect.

In chapter three and five, we only concentrate on U.S market because of the data availability. The internal control data are only accessible for U.S. firms. However, different countries/ economies have various cultural background and institutional quality. It is meaningful to extend our research to international markets to see whether our effect can be generalised to different economies. We will try to extend the research to other countries when the data is available.

Lastly, because of the restrictions of available data, the measurements for firms' internal information quality in today's research are not fully satisfactory. This is mainly because the information on firms' internal operations is hard to access. Even so, some research articles are trying to find novel ways to capture firms' internal information environment. For instance, Huang, Li, and Markov (2019) assess firms' internal information asymmetry by comparing the top managers' earnings forecasts and employees' business outlook, which is a more direct way to capture firms' internal information sharing. In future research, it will be meaningful to further investigate the within the organization information transmission system, and to find more accurate and direct ways to get access to the quality of firms' internal information.

7. References

Abbott, Lawrence J, Brian Daugherty, Susan Parker, and Gary F Peters. 2016. 'Internal audit quality and financial reporting quality: The joint importance of independence and competence', *Journal of Accounting Research*, 54: 3-40.

Adhikari, Binay K, and Anup Agrawal. 2018. 'Peer influence on payout policies', *Journal of Corporate Finance*, 48: 615-37.

Ahern, Kenneth R. 2012. 'Bargaining power and industry dependence in mergers', *Journal of Financial Economics*, 103: 530-50.

Aivazian, Varouj A, Laurence Booth, and Sean Cleary. 2006. 'Dividend smoothing and debt ratings', *Journal of financial and quantitative analysis*, 41: 439-53.

Allen, Franklin, Antonio E Bernardo, and Ivo Welch. 2000. 'A theory of dividends based on tax clienteles', *Journal of Finance*, 55: 2499-536.

Allen, Jeffrey W, and Gordon M Phillips. 2000. 'Corporate equity ownership, strategic alliances, and product market relationships', *Journal of Finance*, 55: 2791-815.

Altamuro, Jennifer, and Anne Beatty. 2010. 'How does internal control regulation affect financial reporting?', *Journal of Accounting and Economics*, 49: 58-74.

Altman, Edward I. 1968. 'Financial ratios, discriminant analysis and the prediction of corporate bankruptcy', *Journal of Finance*, 23: 589-609.

An, Heng, and Ting Zhang. 2013. 'Stock price synchronicity, crash risk, and institutional investors', *Journal of Corporate Finance*, 21: 1-15.

An, Zhe, Chen Chen, Vic Naiker, and Jun Wang. 2020. 'Does media coverage deter firms from withholding bad news? Evidence from stock price crash risk', *Journal of Corporate Finance*, 64: 101664.

An, Zhe, Zhian Chen, Donghui Li, and Lu Xing. 2018. 'Individualism and stock price crash risk', *Journal of International Business Studies*, 49: 1208-36.

An, Zhe, Donghui Li, and Jin Yu. 2015. 'Firm crash risk, information environment, and speed of leverage adjustment', *Journal of Corporate Finance*, 31: 132-51.

Andreou, Panayiotis C, Constantinos Antoniou, Joanne Horton, and Christodoulos Louca. 2016. 'Corporate governance and firm-specific stock price crashes', *European Financial Management*, 22: 916-56.

Armstrong, Christopher S, John E Core, Daniel J Taylor, and Robert E Verrecchia. 2011. 'When does information asymmetry affect the cost of capital?', *Journal of Accounting Research*, 49: 1-40.

Atanassov, Julian, and Xiaoding Liu. 2020. 'Can corporate income tax cuts stimulate innovation?', *Journal of Financial and Quantitative Analysis*, 55: 1415-65.

Baginski, Stephen P, John L Campbell, Lisa A Hinson, and David S Koo. 2018. 'Do career concerns affect the delay of bad news disclosure?', *The Accounting Review*, 93: 61-95.

Baiman, Stanley, and Madhav V Rajan. 2002. 'The role of information and opportunism in the choice of buyer-supplier relationships', *Journal of Accounting Research*, 40: 247-78.

Banerjee, Abhijit V. 1992. 'A simple model of herd behavior', *Quarterly Journal of Economics*, 107: 797-817.

Banerjee, Shantanu, Sudipto Dasgupta, and Yungsan Kim. 2008. 'Buyer–supplier relationships and the stakeholder theory of capital structure', *Journal of Finance*, 63: 2507-52.

Barbier, Edward B, and Joanne C Burgess. 2021. 'Institutional quality, governance and progress towards the SDGs', *Sustainability*, 13: 11798.
Bauer, Andrew M. 2016. 'Tax avoidance and the implications of weak internal controls', *Contemporary Accounting Research*, 33: 449-86.
Bauer, Andrew M, Darren Henderson, and Daniel P Lynch. 2018. 'Supplier internal control quality and the duration of customer-supplier relationships', *The Accounting Review*, 93: 59-82.
Belsley, David A, Edwin Kuh, and Roy E Welsch. 2005. *Regression diagnostics: Identifying influential data and sources of collinearity* (John Wiley & Sons).
Ben-Nasr, Hamdi, and Hatem Ghouma. 2018. 'Employee welfare and stock price crash risk', *Journal of Corporate Finance*, 48: 700-25.
Bergstresser, Daniel, and Thomas Philippon. 2006. 'CEO incentives and earnings management', *Journal of Financial Economics*, 80: 511-29.
Bertrand, Marianne, and Sendhil Mullainathan. 2003. 'Enjoying the quiet life? Corporate governance and managerial preferences', *Journal of Political economy*, 111: 1043-75.
Bhattacharya, Sudipto. 1979. 'Imperfect information, dividend policy, and" the bird in the hand" fallacy', *The Bell Journal of Economics*: 259-70.
Bhattacharyya, Sugato, and Amrita Nain. 2011. 'Horizontal acquisitions and buying power: A product market analysis', *Journal of Financial Economics*, 99: 97-115.
Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch. 1992. 'A theory of fads, fashion, custom, and cultural change as informational cascades', *Journal of Political Economy*, 100: 992-1026.
———. 1998. 'Learning from the behavior of others: Conformity, fads, and informational cascades', *Journal of Economic Perspectives*, 12: 151-70.
Bird, Andrew, Alexander Edwards, and Thomas G Ruchti. 2018. 'Taxes and peer effects', *The Accounting Review*, 93: 97-117.
Bissessur, Sanjay W, and David Veenman. 2016. 'Analyst information precision and small earnings surprises', *Review of Accounting Studies*, 21: 1327-60.
Blouin, Jennifer L, Jana S Raedy, and Douglas A Shackelford. 2011. 'Dividends, share repurchases, and tax clienteles: Evidence from the 2003 reductions in shareholder taxes', *The Accounting Review*, 86: 887-914.
Bolton, Patrick, and David S Scharfstein. 1990. 'A theory of predation based on agency problems in financial contracting', *American Economic Review*: 93-106.
Boulton, Thomas J, and T Colin Campbell. 2016. 'Managerial confidence and initial public offerings', *Journal of Corporate Finance*, 37: 375-92.
Brav, Alon, John R Graham, Campbell R Harvey, and Roni Michaely. 2005. 'Payout policy in the 21st century', *Journal of financial economics*, 77: 483-527.
Burgstahler, David C, Luzi Hail, and Christian Leuz. 2006. 'The importance of reporting incentives: Earnings management in European private and public firms', *The Accounting Review*, 81: 983-1016.
Bustamante, M Cecilia, and Laurent Frésard. 2020. 'Does firm investment respond to peers' investment?', *Management Science*.
Byard, Donal, Ying Li, and Yong Yu. 2011. 'The effect of mandatory IFRS adoption on financial analysts' information environment', *Journal of Accounting Research*, 49: 69-96.
Cai, Kelly, and Hui Zhu. 2020. 'Customer-supplier relationships and the cost of debt', *Journal of Banking & Finance*, 110: 105686.

Cain, Matthew D, Stephen B McKeon, and Steven Davidoff Solomon. 2017. 'Do takeover laws matter? Evidence from five decades of hostile takeovers', *Journal of Financial Economics*, 124: 464-85.
Callen, Jeffrey L, and Xiaohua Fang. 2013. 'Institutional investor stability and crash risk: Monitoring versus short-termism?', *Journal of Banking & Finance*, 37: 3047-63.
———. 2015a. 'Religion and stock price crash risk', *Journal of financial and quantitative analysis*, 50: 169-95.
———. 2015b. 'Short interest and stock price crash risk', *Journal of Banking & Finance*, 60: 181-94.
Campello, Murillo, and Janet Gao. 2017. 'Customer concentration and loan contract terms', *Journal of Financial Economics*, 123: 108-36.
Cao, Jie, Hao Liang, and Xintong Zhan. 2019. 'Peer effects of corporate social responsibility', *Management Science*, 65: 5487-503.
Castillo, Augusto, and Keith Jakob. 2006. 'The Chilean ex-dividend day', *Global Finance Journal*, 17: 105-18.
Cen, Ling, Sudipto Dasgupta, Redouane Elkamhi, and Raunaq S Pungaliya. 2016. 'Reputation and loan contract terms: The role of principal customers', *Review of Finance*, 20: 501-33.
Cen, Ling, Edward L Maydew, Liandong Zhang, and Luo Zuo. 2017. 'Customer–supplier relationships and corporate tax avoidance', *Journal of Financial Economics*, 123: 377-94.
Chalmers, Keryn, David Hay, and Hichem Khlif. 2018. 'Internal control in accounting research: A review', *Journal of Accounting Literature*, 42: 80-103.
Chen, Chen, Xiumin Martin, Sugata Roychowdhury, Xin Wang, and Matthew T Billett. 2018. 'Clarity begins at home: Internal information asymmetry and external communication quality', *The Accounting Review*, 93: 71-101.
Chen, Hanwen, Daoguang Yang, Joseph H Zhang, and Haiyan Zhou. 2020. 'Internal controls, risk management, and cash holdings', *Journal of Corporate Finance*, 64: 101695.
Chen, Jie, Xunhua Su, Xuan Tian, and Bin Xu. 2022. 'Does customer-base structure influence managerial risk-taking incentives?', *Journal of Financial Economics*, 143: 462-83.
Chen, Jie, Xunhua Su, Xuan Tian, Bin Xu, and Luo Zuo. 2021. 'The Disciplinary Role of Major Corporate Customers', *Available at SSRN 3588351*.
Chen, Joseph, Harrison Hong, and Jeremy C Stein. 2001. 'Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices', *Journal of financial economics*, 61: 345-81.
Chen, Jun, Kam C Chan, Wang Dong, and Feida Zhang. 2017. 'Internal control and stock price crash risk: Evidence from China', *European Accounting Review*, 26: 125-52.
Chen, Xia, Mei Feng, and Chan Li. 2020. 'Family entrenchment and internal control: evidence from S&P 1500 firms', *Review of Accounting Studies*, 25: 246-78.
Cheng, CS Agnes, KC Kenneth Chu, and James Ohlson. 2020. 'Analyst forecasts: sales and profit margins', *Review of Accounting Studies*: 1-30.
Cheng, Mei, Dan Dhaliwal, and Yuan Zhang. 2013. 'Does investment efficiency improve after the disclosure of material weaknesses in internal control over financial reporting?', *Journal of Accounting and Economics*, 56: 1-18.
Cheng, Qiang, Young Jun Cho, and Holly Yang. 2018. 'Financial reporting changes and the internal information environment: Evidence from SFAS 142', *Review of Accounting Studies*, 23: 347-83.
Cheng, Qiang, Jimmy Lee, and Terry Shevlin. 2016. 'Internal governance and real earnings management', *The Accounting Review*, 91: 1051-85.

Chetty, Raj, and Emmanuel Saez. 2005. 'Dividend taxes and corporate behavior: Evidence from the 2003 dividend tax cut', *Quarterly Journal of Economics*, 120: 791-833.
Chu, Yongqiang, Xuan Tian, and Wenyu Wang. 2019. 'Corporate innovation along the supply chain', *Management Science*, 65: 2445-66.
Cohen, Daniel A, Aiyesha Dey, and Thomas Z Lys. 2008. 'Real and accrual‐based earnings management in the pre‐and post‐Sarbanes‐Oxley periods', *The Accounting Review*, 83: 757-87.
Cohen, Daniel A, and Bin Li. 2020. 'Customer-base concentration, investment, and profitability: The US government as a major customer', *The Accounting Review*, 95: 101-31.
Cohen, Daniel, Bin Li, Ningzhong Li, and Yun Lou. 2022. 'Major government customers and loan contract terms', *Review of Accounting Studies*, 27: 275-312.
Cohen, Lauren, and Andrea Frazzini. 2008. 'Economic links and predictable returns', *Journal of Finance*, 63: 1977-2011.
Coval, Joshua D, and Tobias J Moskowitz. 1999. 'Home bias at home: Local equity preference in domestic portfolios', *Journal of Finance*, 54: 2045-73.
Crawford, Steven, Ying Huang, Ningzhong Li, and Ziyun Yang. 2020. 'Customer concentration and public disclosure: Evidence from management earnings and sales forecasts', *Contemporary Accounting Research*, 37: 131-59.
Dai, Rui, Hao Liang, and Lilian Ng. 2021. 'Socially responsible corporate customers', *Journal of Financial Economics*, 142: 598-626.
Daniel, Naveen D, David J Denis, and Lalitha Naveen. 2008. 'Do firms manage earnings to meet dividend thresholds?', *Journal of Accounting and Economics*, 45: 2-26.
De Simone, Lisa, Matthew S Ege, and Bridget Stomberg. 2015. 'Internal control quality: The role of auditor-provided tax services', *The Accounting Review*, 90: 1469-96.
Dechow, Patricia M, Richard G Sloan, and Amy P Sweeney. 1995. 'Detecting earnings management', *The Accounting Review*: 193-225.
Devenow, Andrea, and Ivo Welch. 1996. 'Rational herding in financial economics', *European Economic Review*, 40: 603-15.
Dhaliwal, Dan, J Scott Judd, Matthew Serfling, and Sarah Shaikh. 2016. 'Customer concentration risk and the cost of equity capital', *Journal of Accounting and Economics*, 61: 23-48.
Dimson, Elroy. 1979. 'Risk measurement when shares are subject to infrequent trading', *Journal of financial economics*, 7: 197-226.
Dong, Yizhe, Chang Li, and Haoyu Li. 2021. 'Customer concentration and M&A performance', *Journal of Corporate Finance*, 69: 102021.
Dowdell Jr, Thomas D, David N Herda, and Matthew A Notbohm. 2014. 'Do management reports on internal control over financial reporting improve financial reporting?', *Research in Accounting Regulation*, 26: 104-09.
Doyle, Jeffrey, Weili Ge, and Sarah McVay. 2007. 'Determinants of weaknesses in internal control over financial reporting', *Journal of accounting and Economics*, 44: 193-223.
Duan, Rui, Yelena Larkin, and Lilian Ng. 2019. 'Short-term institutional investors and the diffusion of supply chain information', *Available at SSRN 3277201*.
Edmans, Alex, Sudarshan Jayaraman, and Jan Schneemeier. 2017. 'The source of information in prices and investment-price sensitivity', *Journal of Financial Economics*, 126: 74-96.
El-Khatib, Rwan, Kathy Fogel, and Tomas Jandik. 2015. 'CEO network centrality and merger performance', *Journal of Financial Economics*, 116: 349-82.

Ellahie, Atif, and Zachary Kaplan. 2021. 'Show Me the Money! Dividend Policy in Countries with Weak Institutions', *Journal of Accounting Research*, 59: 613-55.
Fabbri, Daniela, and Leora F Klapper. 2016. 'Bargaining power and trade credit', *Journal of Corporate Finance*, 41: 66-80.
Fairhurst, Douglas, and Yoonsoo Nam. 2020. 'Corporate Governance and Financial Peer Effects', *Financial Management*, 49: 235-63.
Fama, Eugene F, and Harvey Babiak. 1968. 'Dividend policy: An empirical analysis', *Journal of the American statistical Association*, 63: 1132-61.
Fee, C Edward, and Shawn Thomas. 2004. 'Sources of gains in horizontal mergers: evidence from customer, supplier, and rival firms', *Journal of Financial Economics*, 74: 423-60.
Feng, Mei, Chan Li, and Sarah McVay. 2009. 'Internal control and management guidance', *Journal of Accounting and Economics*, 48: 190-209.
Ferris, Stephen P, David Javakhadze, and Tijana Rajkovic. 2017. 'CEO social capital, risk-taking and corporate policies', *Journal of Corporate Finance*, 47: 46-71.
Foucault, Thierry, and Laurent Fresard. 2014. 'Learning from peers' stock prices and corporate investment', *Journal of Financial Economics*, 111: 554-77.
Foucault, Thierry, and Laurent Frésard. 2014. 'Learning from peers' stock prices and corporate investment', *Journal of Financial Economics*, 111: 554-77.
Francis, Bill B, Iftekhar Hasan, and Gergana L Kostova. 2016. 'When do peers matter?: A cross-country perspective', *Journal of International Money and Finance*, 69: 364-89.
Frank, Murray Z, and Vidhan K Goyal. 2009. 'Capital structure decisions: which factors are reliably important?', *Financial Management*, 38: 1-37.
Fudenberg, Drew, and Jean Tirole. 1995. 'A theory of income and dividend smoothing based on incumbency rents', *Journal of Political economy*, 103: 75-93.
Gallemore, John, and Eva Labro. 2015. 'The importance of the internal information environment for tax avoidance', *Journal of Accounting and Economics*, 60: 149-67.
Garrett, Jace, Rani Hoitash, and Douglas F Prawitt. 2014. 'Trust and financial reporting quality', *Journal of Accounting Research*, 52: 1087-125.
Goh, Beng Wee, and Dan Li. 2011. 'Internal controls and conditional conservatism', *The Accounting Review*, 86: 975-1005.
Gormley, Todd A, and David A Matsa. 2014. 'Common errors: How to (and not to) control for unobserved heterogeneity', *Review of Financial Studies*, 27: 617-61.
Graham, John R, and Campbell R Harvey. 2001. 'The theory and practice of corporate finance: Evidence from the field', *Journal of Financial Economics*, 60: 187-243.
Grennan, Jillian. 2019. 'Dividend payments as a response to peer influence', *Journal of Financial Economics*, 131: 549-70.
Guo, Jun, Pinghsun Huang, Yan Zhang, and Nan Zhou. 2016. 'The effect of employee treatment policies on internal control weaknesses and financial restatements', *The Accounting Review*, 91: 1167-94.
Gutiérrez, Germán, and Thomas Philippon. 2017. "Declining competition and investment in the US." In.: National Bureau of Economic Research.
Guttman, Ilan, Ohad Kadan, and Eugene Kandel. 2010. 'Dividend stickiness and strategic pooling', *Review of Financial Studies*, 23: 4455-95.
Gyimah, Daniel, Michael Machokoto, and Anywhere Siko Sikochi. 2020. 'Peer influence on trade credit', *Journal of Corporate Finance*, 64: 101685.
Hail, Luzi, Ahmed Tahoun, and Clare Wang. 2014. 'Dividend payouts and information shocks', *Journal of Accounting Research*, 52: 403-56.

Ham, Charles G, Zachary R Kaplan, and Mark T Leary. 2020. 'Do dividends convey information about future earnings?', *Journal of financial economics*, 136: 547-70.
Ham, Charles G, Zachary R Kaplan, and Steven Utke. 2021. 'Attention to dividends, inattention to earnings?', *Review of Accounting Studies*: 1-42.
Hanlon, Michelle, and Jeffrey L Hoopes. 2014. 'What do firms do when dividend tax rates change? An examination of alternative payout responses', *Journal of financial economics*, 114: 105-24.
Harp, Nancy L, and Beau Grant Barnes. 2018. 'Internal control weaknesses and acquisition performance', *The Accounting Review*, 93: 235-58.
He, Wen, Lilian Ng, Nataliya Zaiats, and Bohui Zhang. 2017. 'Dividend policy and earnings management across countries', *Journal of Corporate Finance*, 42: 267-86.
Healy, Paul M, and Krishna G Palepu. 2001. 'Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature', *Journal of Accounting and Economics*, 31: 405-40.
Heitzman, Shane, and Mengjie Huang. 2019. 'Internal information quality and the sensitivity of investment to market prices and accounting profits', *Contemporary Accounting Research*, 36: 1699-723.
Hoberg, Gerard, and Gordon Phillips. 2016. 'Text-based network industries and endogenous product differentiation', *Journal of Political Economy*, 124: 1423-65.
Hoitash, Udi, Rani Hoitash, and Jean C Bedard. 2009. 'Corporate governance and internal control over financial reporting: A comparison of regulatory regimes', *The Accounting Review*, 84: 839-67.
Hong, Harrison, and Jeremy C Stein. 2003. 'Differences of opinion, short-sales constraints, and market crashes', *Review of Financial Studies*, 16: 487-525.
Hribar, Paul, Sam Melessa, David Volant, and Jaron H Wilde. 2020. 'Customer Bargaining Power and Strategic Financial Reporting', *Available at SSRN 3696700*.
Hu, Jinshuai, Siqi Li, Alvaro G Taboada, and Feida Zhang. 2020. 'Corporate board reforms around the world and stock price crash risk', *Journal of Corporate Finance*, 62: 101557.
Huang, Kelly, Brent Lao, and Gregory McPhee. 2020. 'Internal information quality and patent‐related innovation', *Journal of Business Finance & Accounting*, 47: 489-518.
Huang, Kelly, Meng Li, and Stanimir Markov. 2019. "The information asymmetry between management and rank-and-file employees: Determinants and consequences." In.: AAA.
Hui, Kai Wai, Sandy Klasa, and P Eric Yeung. 2012. 'Corporate suppliers and customers and accounting conservatism', *Journal of Accounting and Economics*, 53: 115-35.
Hung, Mingyi, Xi Li, and Shiheng Wang. 2015. 'Post-earnings-announcement drift in global markets: Evidence from an information shock', *Review of Financial Studies*, 28: 1242-83.
Hutton, Amy P, Alan J Marcus, and Hassan Tehranian. 2009. 'Opaque financial reports, R2, and crash risk', *Journal of financial economics*, 94: 67-86.
Im, Hyun Joong, Jia Liu, and Young Joon Park. 2021. 'Policy uncertainty and peer effects: Evidence from corporate investment in China', *International Review of Financial Analysis*, 77: 101834.
Irvine, Paul, Shawn Saeyeul Park, and Celim Yildizhan. 2013. 'Customer-base concentration, profitability and distress across the corporate life cycle'.
Javakhadze, David, Stephen P Ferris, and Nilanjan Sen. 2014. 'An international analysis of dividend smoothing', *Journal of Corporate Finance*, 29: 200-20.
Jayaraman, Sudarshan, and Joanna Shuang Wu. 2019. 'Is silence golden? Real effects of mandatory disclosure', *Review of Financial Studies*, 32: 2225-59.

Jennings, Jared N, Hojun Seo, and Lloyd Tanlu. 2013. "The effect of organizational complexity on earnings forecasting behavior." In.: AAA.

Jin, Li, and Stewart C Myers. 2006. 'R2 around the world: New theory and new tests', *Journal of financial economics*, 79: 257-92.

John, Kose, Anzhela Knyazeva, and Diana Knyazeva. 2015. 'Governance and payout precommitment', *Journal of Corporate Finance*, 33: 101-17.

Kalda, Ankit. 2020. 'Peer financial distress and individual leverage', *Review of Financial Studies*, 33: 3348-90.

Kalwani, Manohar U, and Narakesari Narayandas. 1995. 'Long-term manufacturer-supplier relationships: do they pay off for supplier firms?', *Journal of Marketing*, 59: 1-16.

Kang, Jun-Koo, Wei-Lin Liu, Sangho Yi, and Le Zhang. 2015. 'Monitoring role of customer firms in suppliers and its effect on supplier value: Evidence from block acquisitions of suppliers by customer firms', *Journal of Financial Intermediation*, 24: 537-63.

Kasanen, Eero, Juha Kinnunen, and Jyrki Niskanen. 1996. 'Dividend-based earnings management: Empirical evidence from Finland', *Journal of Accounting and Economics*, 22: 283-312.

Kaustia, M., and V. Rantala. 2015. 'Social learning and corporate peer effects', *Journal of Financial Economics*, 117: 653-69.

Khurana, Inder K, Raynolde Pereira, and Eliza Zhang. 2018. 'Is real earnings smoothing harmful? Evidence from firm‐specific stock price crash risk', *Contemporary Accounting Research*, 35: 558-87.

Kim, Jaehyeon, Yongtae Kim, and Jian Zhou. 2017. 'Languages and earnings management', *Journal of Accounting and Economics*, 63: 288-306.

Kim, Jeong-Bon, Yinghua Li, and Liandong Zhang. 2011a. 'CFOs versus CEOs: Equity incentives and crashes', *Journal of financial economics*, 101: 713-30.

———. 2011b. 'Corporate tax avoidance and stock price crash risk: Firm-level analysis', *Journal of financial economics*, 100: 639-62.

Kim, Yongtae, Haidan Li, and Siqi Li. 2014. 'Corporate social responsibility and stock price crash risk', *Journal of Banking & Finance*, 43: 1-13.

Klein, April. 2002. 'Audit committee, board of director characteristics, and earnings management', *Journal of Accounting and Economics*, 33: 375-400.

Krishnan, Jayanthi. 2005. 'Audit committee quality and internal control: An empirical analysis', *The Accounting Review*, 80: 649-75.

Krishnan, Jayanthi, Yuan Wen, and Wanli Zhao. 2011. 'Legal expertise on corporate audit committees and financial reporting quality', *The Accounting Review*, 86: 2099-130.

Kumar, Praveen. 1988. 'Shareholder-manager conflict and the information content of dividends', *Review of Financial Studies*, 1: 111-36.

Kumar, Praveen, and Bong-Soo Lee. 2001. 'Discrete dividend policy with permanent earnings', *Financial Management*: 55-76.

La Porta, Rafael , Florencio Lopez-de-Silanes, Andrei Shleifer, and Robert W Vishny. 1998. 'Law and finance', *Journal of Political economy*, 106: 1113-55.

La Porta, Rafael, Florencio Lopez‐de‐Silanes, and Andrei Shleifer. 2006. 'What works in securities laws?', *Journal of Finance*, 61: 1-32.

Lai, Shu-Miao, Chih-Liang Liu, and Sheng-Syan Chen. 2020. 'Internal control quality and investment efficiency', *Accounting Horizons*, 34: 125-45.

Lambrecht, Bart M, and Stewart C Myers. 2012. 'A Lintner model of payout and managerial rents', *Journal of Finance*, 67: 1761-810.

Landsman, Wayne R, Edward L Maydew, and Jacob R Thornock. 2012. 'The information content of annual earnings announcements and mandatory adoption of IFRS', *Journal of Accounting and Economics*, 53: 34-54.

Larcker, David F, Eric C So, and Charles CY Wang. 2013. 'Boardroom centrality and firm performance', *Journal of Accounting and Economics*, 55: 225-50.
Larkin, Yelena, Mark T Leary, and Roni Michaely. 2017. 'Do investors value dividend-smoothing stocks differently?', *Management Science*, 63: 4114-36.
Laux, Christian, Gyöngyi Lóránth, and Alan D Morrison. 2018. 'The adverse effect of information on governance and leverage', *Management Science*, 64: 1510-27.
Leary, Mark T, and Roni Michaely. 2011. 'Determinants of dividend smoothing: Empirical evidence', *Review of Financial Studies*, 24: 3197-249.
Leary, Mark T, and Michael R Roberts. 2014. 'Do peer firms affect corporate financial policy?', *Journal of Finance*, 69: 139-78.
Lee, King Fuei. 2020. 'Peer Effects on Firm Dividend Policies in Taiwan', *Journal of Financial Studies*, 28: 113-44.
Li, Si, and Xintong Zhan. 2019. 'Product market threats and stock crash risk', *Management Science*, 65: 4011-31.
Li, Xiaorong, Steven Shuye Wang, and Xue Wang. 2017. 'Trust and stock price crash risk: Evidence from China', *Journal of Banking & Finance*, 76: 74-91.
Li, Yiwei, and Yeqin Zeng. 2019. 'The impact of top executive gender on asset prices: Evidence from stock price crash risk', *Journal of Corporate Finance*, 58: 528-50.
Lin, Yupeng, Ying Mao, and Zheng Wang. 2018. 'Institutional ownership, peer pressure, and voluntary disclosures', *The Accounting Review*, 93: 283-308.
Lintner, John. 1956. 'Distribution of incomes of corporations among dividends, retained earnings, and taxes', *American Economic Review*, 46: 97-113.
Liu, Nan, and Reza Espahbodi. 2014. 'Does dividend policy drive earnings smoothing?', *Accounting Horizons*, 28: 501-28.
Loughran, Tim, and Jay R Ritter. 1995. 'The new issues puzzle', *Journal of Finance*, 50: 23-51.
Lustgarten, Steven H. 1975. 'The impact of buyer concentration in manufacturing industries', *Review of Economics and Statistics*: 125-32.
Ma, Xiaofang, Wenming Wang, Jiangang Wu, and Wenlan Zhang. 2020. 'Corporate customer concentration and stock price crash risk', *Journal of Banking & Finance*, 119: 105903.
Machokoto, Michael, Daniel Gyimah, and Collins G Ntim. 2021. 'Do peer firms influence innovation?', *British Accounting Review*: 100988.
Malkiel, Burton G. 2003. 'The efficient market hypothesis and its critics', *Journal of Economic Perspectives*, 17: 59-82.
Manski, Charles F. 1993. 'Identification of endogenous social effects: The reflection problem', *Review of Economic Studies*, 60: 531-42.
Marsh, Paul. 1982. 'The choice between equity and debt: An empirical study', *Journal of Finance*, 37: 121-44.
McGuire, Sean T, Scott G Rane, and Connie D Weaver. 2018. 'Internal information quality and tax-motivated income shifting', *Journal of the American Taxation Association*, 40: 25-44.
McLaughlin, Patrick A. 2020. '3.2 Annual (dataset)', *QuantGov, Mercatus Center at George Mason University, Arlington, VA*.
McLaughlin, Patrick A, and Oliver Sherouse. 2018. 'Regdata us 3.1 annual (dataset)', *QuantGov, Mercatus Center at George Mason University, Arlington, VA*.
Miller, Merton H, and Kevin Rock. 1985. 'Dividend policy under asymmetric information', *Journal of Finance*, 40: 1031-51.
Morellec, Erwan, Boris Nikolov, and Norman Schürhoff. 2018. 'Agency conflicts around the world', *Review of Financial Studies*, 31: 4232-87.

Murfin, Justin, and Ken Njoroge. 2015. 'The implicit costs of trade credit borrowing by large firms', *Review of Financial Studies*, 28: 112-45.
Myllymäki, Emma-Riikka. 2014. 'The persistence in the association between Section 404 material weaknesses and financial reporting quality', *Auditing: A Journal of Practice & Theory*, 33: 93-116.
Naiker, Vic, and Divesh S Sharma. 2009. 'Former audit partners on the audit committee and internal control deficiencies', *The Accounting Review*, 84: 559-87.
Nissim, Doron, and Amir Ziv. 2001. 'Dividend changes and future profitability', *Journal of Finance*, 56: 2111-33.
Patatoukas, Panos N. 2012. 'Customer-base concentration: Implications for firm performance and capital markets', *The Accounting Review*, 87: 363-92.
Pattenden, Kerry, and Garry Twite. 2008. 'Taxes and dividend policy under alternative tax regimes', *Journal of Corporate Finance*, 14: 1-16.
PBS. 2004. "Is Wal-Mart Good For America?" In, https://www.pbs.org/wgbh/pages/frontline/shows/walmart/. PBS Frontline.
Porter, Michael E. 1974. 'Consumer behavior, retailer power and market performance in consumer goods industries', *Review of Economics and Statistics*: 419-36.
Raman, Kartik, and Husayn Shahrur. 2008. 'Relationship-specific investments and earnings management: Evidence on corporate suppliers and customers', *The Accounting Review*, 83: 1041-81.
Ravenscraft, David J. 1983. 'Structure-profit relationship at the line of business and industry level', *Review of Economics and Statistics*: 22-31.
Rechner, Paula L, and Dan R Dalton. 1991. 'CEO duality and organizational performance: A longitudinal analysis', *Strategic Management Journal*, 12: 155-60.
Roychowdhury, Sugata. 2006. 'Earnings management through real activities manipulation', *Journal of Accounting and Economics*, 42: 335-70.
Scharfstein, David S, and Jeremy C Stein. 1990. 'Herd behavior and investment', *American Economic Review*: 465-79.
Shroff, Nemit. 2017. 'Corporate investment and changes in GAAP', *Review of Accounting Studies*, 22: 1-63.
Sialm, Clemens, Zheng Sun, and Lu Zheng. 2020. 'Home bias and local contagion: Evidence from funds of hedge funds', *Review of Financial Studies*, 33: 4771-810.
Sterin, Mikhail. 2020. 'The influence of audit committee expertise on firms' internal controls: Evidence from mergers and acquisitions', *Accounting Horizons*, 34: 193-211.
Sun, Yan. 2016. 'Internal control weakness disclosure and firm investment', *Journal of Accounting, Auditing & Finance*, 31: 277-307.
Titman, Sheridan, and Roberto Wessels. 1988. 'The determinants of capital structure choice', *Journal of Finance*, 43: 1-19.
Wang, Jin. 2012. 'Do firms' relationships with principal customers/suppliers affect shareholders' income?', *Journal of Corporate Finance*, 18: 860-78.
Wu, Kai, and Seiwai Lai. 2020. 'Intangible intensity and stock price crash risk', *Journal of Corporate Finance*, 64: 101682.
Wu, Yufeng. 2018. 'What's behind smooth dividends? Evidence from structural estimation', *Review of Financial Studies*, 31: 3979-4016.
Xie, Biao, Wallace N Davidson III, and Peter J DaDalt. 2003. 'Earnings management and corporate governance: the role of the board and the audit committee', *Journal of Corporate Finance*, 9: 295-316.
Xu, Lin, Yulei Rao, Yingmei Cheng, and Jianxin Wang. 2020. 'Internal coalition and stock price crash risk', *Journal of Corporate Finance*, 64: 101640.

Xu, Nianhang, Xiaorong Li, Qingbo Yuan, and Kam C Chan. 2014. 'Excess perks and stock price crash risk: Evidence from China', *Journal of Corporate Finance*, 25: 419-34.
Xu, Yongxin, Yuhao Xuan, and Gaoping Zheng. 2021. 'Internet searching and stock price crash risk: Evidence from a quasi-natural experiment', *Journal of financial economics*, 141: 255-75.
Zaman, Rashid, Nader Atawnah, Muhammad Haseeb, Muhammad Nadeem, and Saadia Irfan. 2021. 'Does corporate eco-innovation affect stock price crash risk?', *The British Accounting Review*, 53: 101031.

8. Tables and Figure

8.1 Tables for chapter 3

Table 3. 1 Summary statistics

The sample includes all nonfinancial, nonutility firms from the CRSP-Compustat Merged database from 1965-2017 with non-missing data for all firm characteristics. All variables are winsorized at 1st and 99th level and defined in Appendix (Table 3.A.1). Peer firm average variables are calculated as the mean value of all firms within the industry-year excluding firm *i*'s observation. Industries are defined by the three-digit SIC code. Firm specific variables denote firm *i*'s variable in year *t*. For the main independent variables, EAS stands for earnings announcement speed. Dret is the difference in insider trading profitability between divisional managers and top managers in last three years. Restatement is an indicator variable which equals one if firm discloses an unintentional restatement in the current year and zero otherwise. Weakness is an indicator variable equal to one if a firm reports a material weakness in the current year and zero otherwise.

	Nobs	Mean	SD	P1	P25	P50	P75	P99
Dependent variables								
Market Leverage	100745	0.268	0.246	0	0.051	0.209	0.429	0.915
Book Leverage	100745	0.236	0.197	0	0.069	0.214	0.352	0.878
Main independent variables								
EAS	91984	0.146	0.062	0.047	0.099	0.137	0.184	0.332
Dret	25223	-0.006	0.226	-0.854	-0.091	-0.003	0.083	0.725
Peer market leverage	100745	0.268	0.141	0.038	0.153	0.251	0.359	0.684
Peer book leverage	100745	0.236	0.098	0.047	0.166	0.226	0.289	0.540
Control variables								
Size (Log(sales))	100745	5.342	2.191	-0.122	3.832	5.266	6.826	10.601
MTB	100745	1.360	1.166	0.286	0.690	0.982	1.556	7.295
Prof	100745	0.107	0.148	-0.588	0.068	0.126	0.182	0.389
Tang	100745	0.311	0.224	0.009	0.135	0.260	0.441	0.893
Equity shock	100745	-0.008	0.531	-0.842	-0.327	-0.093	0.173	2.362
Peer size	100745	5.339	1.295	2.699	4.352	5.166	6.212	8.825
Peer MTB	100745	1.356	0.605	0.511	0.908	1.220	1.662	3.312
Peer Prof	100745	0.107	0.066	-0.110	0.071	0.116	0.152	0.245
Peer Tang	100745	0.311	0.178	0.062	0.182	0.262	0.397	0.770
Peer equity shock	100745	-0.010	0.152	-0.408	-0.090	-0.024	0.055	0.576
Other variables								
ROA	100745	0.005	0.166	-0.917	-0.004	0.042	0.080	0.248
ROE	100357	-0.008	0.515	-3.055	-0.005	0.053	0.100	2.360
Takeover	66049	0.170	0.086	0.045	0.102	0.152	0.224	0.416
Entrenched	23599	0.467	0.499	0	0	0	1	1
Restatement	26372	0.103	0.304	0	0	0	0	1
Weakness	25592	0.067	0.251	0	0	0	0	1
Size_rel	100745	1.008	0.385	-0.028	0.768	0.995	1.231	2.159
Z-score	97946	1.621	2.516	-12.465	1.064	2.055	2.895	5.738

Table 3. 2 Baseline regression-OLS results

The sample includes all nonfinancial, nonutility firms from the CRSP-Compustat Merged database from 1965-2017 with non-missing data for all firm characteristics. All variables are defined in Appendix (Table 3.A.1). The table displays OLS estimated coefficients and t-statistics, clustered at firm level, in parentheses. The peer firm average variables are calculated as the mean value of all firms within the industry excluding firm *i*'s observation. Industries are defined by the three-digit SIC code. All control variables are lagged by one period to be consistent with related studies. Column (1) displays how peers' leverage influence firm's leverage, while columns (2) and (3) show the moderating effect of IIQ on peer effects. Columns (2) and (3) measure firms' internal information quality using earnings announcement speed (EAS) and the difference in insider trading profitability between divisional managers and top managers (Dret), respectively. ***, ** and* indicate statistical significance level at 1%, 5% and 10 % level, respectively.

VARIABLES	(1) Market leverage	(2) Market leverage	(3) Market leverage
EAS × Peer leverage		1.066***	
		(6.713)	
Dret × Peer leverage			0.162***
			(2.737)
EAS		0.683***	
		(14.519)	
Dret			0.001
			(0.040)
Peer leverage	0.164***	-0.008	0.133***
	(8.791)	(-0.296)	(4.492)
Peer Size	-0.005*	-0.003	0.001
	(-1.784)	(-1.180)	(0.339)
Peer MTB	0.008**	0.006*	-0.004
	(2.549)	(1.853)	(-0.801)
Peer Prof	0.102***	0.033	0.088**
	(3.525)	(1.132)	(2.029)
Peer Tang	0.019	-0.004	-0.024
	(0.761)	(-0.141)	(-0.573)
Equity shock	-0.022***	-0.017***	-0.017***
	(-18.907)	(-15.305)	(-8.256)
Firm Size	0.012***	0.028***	0.014***
	(12.779)	(25.682)	(9.132)
Firm MTB	-0.058***	-0.049***	-0.044***
	(-47.650)	(-40.926)	(-28.759)
Firm Prof	-0.297***	-0.268***	-0.195***
	(-30.343)	(-27.259)	(-13.241)
Firm Tang	0.188***	0.204***	0.158***
	(14.875)	(15.645)	(8.157)
Constant	0.222***	0.044**	0.099**
	(13.606)	(2.418)	(2.530)
Industry/ Year fixed effects	Yes	Yes	Yes
Observations	100,745	91,984	25,223
Adjusted R^2	0.339	0.393	0.386

Table 3. 3 Baseline regression-2SLS results

The sample includes all nonfinancial, nonutility firms from the CRSP-Compustat Merged database from 1965-2017 with non-missing data for all firm characteristics. All variables are defined in Appendix (Table 3.A.1). The table displays two stage least squares (2SLS) estimated coefficients and t-statistics, clustered at firm level, in parentheses. The peer firm average variables are calculated as the mean value of all firms within the industry excluding firm *i*'s observation. Industries are defined by the three-digit SIC code. All control variables are lagged by one period to be consistent with related studies. Columns (1) and (2) display how peers' leverage influence firm's leverage, while columns (3)- (6) show the moderating effects of IIQ on peer effects. In columns (3) and (4), firm's internal information quality is measured by earnings announcement speed (EAS). Columns (5) and (6) measure firms' internal information quality using Dret variable, which indicates the difference in insider trading profitability between divisional managers and top managers. ***, ** and* indicate statistical significance level at 1%, 5% and 10 % level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	First stage	Second stage	First stage	Second stage	First stage	Second stage
VARIABLES	Peer leverage	Market leverage	Peer leverage	Market leverage	Peer leverage	Market leverage
EAS × Peer leverage				2.035***		
				(8.042)		
Dret × Peer leverage						0.295***
						(3.082)
EAS			0.036***	0.416***		
			(4.915)	(6.151)		
Dret					0.005**	-0.029
					(2.273)	(-1.473)
Peer leverage		0.348***		0.002		0.149
		(3.804)		(0.019)		(0.709)
Peer equity shock	-0.043***		-0.038***		-0.033***	
	(-19.639)		(-6.664)		(-8.186)	
Peer equity shock × EAS			-0.022			
			(-0.630)			
Peer equity shock × Dret					-0.002	
					(-0.110)	
Peer Size	0.012***	-0.007**	0.012***	-0.005	0.015***	0.001
	(8.455)	(-2.439)	(8.386)	(-1.605)	(5.321)	(0.209)
Peer MTB	-0.078***	0.023***	-0.078***	0.019**	-0.072***	-0.003
	(-46.698)	(2.837)	(-45.582)	(2.166)	(-28.695)	(-0.178)
Peer Prof	-0.392***	0.176***	-0.387***	0.094*	-0.289***	0.093
	(-28.599)	(3.729)	(-27.718)	(1.917)	(-12.639)	(1.234)
Peer Tang	0.197***	-0.017	0.203***	-0.032	0.226***	-0.026
	(12.777)	(-0.557)	(12.601)	(-0.981)	(8.694)	(-0.401)

Equity shock	-0.001***	-0.021***	-0.001***	-0.017***	-0.001	-0.017***
	(-3.166)	(-18.562)	(-3.051)	(-14.900)	(-1.028)	(-8.224)
Firm Size	-0.000	0.012***	0.000	0.028***	0.000	0.014***
	(-0.824)	(12.875)	(1.364)	(25.685)	(0.796)	(9.143)
Firm MTB	0.000	-0.058***	0.001*	-0.049***	-0.000	-0.044***
	(1.481)	(-47.754)	(1.955)	(-41.129)	(-0.554)	(-28.761)
Firm Prof	0.007***	-0.298***	0.008***	-0.272***	-0.000	-0.194***
	(2.664)	(-30.435)	(3.305)	(-27.534)	(-0.051)	(-13.214)
Firm Tang	0.007**	0.187***	0.005*	0.205***	0.008	0.158***
	(2.206)	(14.822)	(1.668)	(15.825)	(1.501)	(8.141)
Constant	0.312***	0.165***	0.300***	0.034	0.270***	0.097
	(36.958)	(5.048)	(34.184)	(0.945)	(14.724)	(1.425)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	100,745	100,745	91,984	91,984	25,223	25,223
Adjusted R^2	0.734	0.337	0.739	0.391	0.768	0.385

Table 3. 4 Difference-in-difference tests

This table displays the impact of SOX 404 adoption on firms' financial policy peer effects. The application of SOX 404 is treated as an exogenous shock for firm's internal information quality. Post is an indicator variable equal to one for post-event years (2005, 2006 and 2007), and zero for pre-event years (2001, 2002 and 2003). Treated is an indicator variable equal to one if a firm reports material weakness in 2004 which was revised in the following year, and zero otherwise. The sample includes all nonfinancial, nonutility firms with material weakness data from Audit Analytics. Panel A displays the difference-in-difference tests results with peer leverage estimated by instrumental variable. Panels B and C display results employing propensity score matching (PSM). All treated firms are matched with three control firms with similar characteristics in the year before the event (2003). Panel B presents the statistics of firm specific characteristics after PSM. Panel C displays the two stage least squares (2SLS) regression results after the propensity score matching. Panels A and C display two stage least squares (2SLS) estimated coefficients and t-statistics, clustered at firm level in parentheses. Industries are defined by the three-digit SIC code. All the variables are defined in Appendix (Table 3.A.1). ***, ** and* indicate statistical level at 1%, 5% and 10 % level, respectively.

Panel A. Difference in difference tests

	(1)	(2)
VARIABLES	Market leverage	Market leverage
Post × Treated × Peer leverage	-0.594**	-0.471**
	(-2.220)	(-2.179)
Post × Treated	0.068	0.091*
	(1.117)	(1.851)
Post × Peer leverage	-0.407***	-0.486***
	(-7.098)	(-8.132)
Treated × Peer leverage	-0.003	0.275
	(-0.009)	(0.899)
Peer leverage	0.407*	0.385*
	(1.674)	(1.787)
Treated	-0.010	
	(-0.148)	
Constant	0.013	-0.070
	(0.159)	(-0.863)
First stage instrument	-0.039***	-0.040***
	(-6.818)	(-10.07)
Control variables	Yes	Yes
Industry fixed effects	Yes	No
Firm fixed effects	No	Yes
Year fixed effects	Yes	Yes
Observations	10,856	10,856
Adjusted R^2	0.400	0.773

Panel B. Summary statistics after PSM				
Variable	Average Treated	Average Controls	Difference	T-statistics
Size	5.774	5.927	-0.153	-0.54
MTB	1.232	1.155	0.077	0.53
Prof	0.066	0.09	-0.025	-1.14
Tang	0.297	0.329	-0.033	-0.85
Equity shock	0.026	0.12	-0.094	0.9

Panel C. Difference in difference tests after PSM		
	(1)	(2)
VARIABLES	Market leverage	Market leverage
Post × Treated × Peer leverage	-0.795**	-0.519*
	(-2.492)	(-1.832)
Post × Treated	0.094	0.076
	(1.260)	(1.263)
Post × Peer leverage	-0.241	-0.166
	(-1.225)	(-0.871)
Treated × Peer leverage	-0.125	0.187
	(-0.303)	(0.523)
Peer leverage	2.186**	1.492**
	(2.448)	(2.118)
Treated	0.006	
	(0.068)	
Constant	-0.466*	-0.308
	(-1.675)	(-1.060)
First stage instrument	-0.029*	-0.034***
	(-1.802)	(-2.901)
Control variables	Yes	Yes
Industry fixed effects	Yes	No
Firm fixed effects	No	Yes
Year fixed effects	Yes	Yes
Observations	1,123	1,123
Adjusted R^2	0.555	0.755

Table 3. 5 Robustness checks

The sample includes all nonfinancial, nonutility firms from the CRSP-Compustat Merged database from 1965-2017 with non-missing data for all firm characteristics. The variables are defined in Appendix (Table 3.A.1). The table displays two-stage least squares (2SLS) estimated coefficients and t-statistics, clustered at firm level in parentheses. The peer firm average variables are calculated as the mean value of all firms within the industry excluding firm *i*'s observation. Industries are defined by the three-digit SIC code. All control variables are lagged by one period to be consistent with related studies. Panel A lagged all main independent variables by one period. Panel B displays the results including firm fixed effects. ***, ** and* indicate statistical significance level at 1%, 5% and 10 % level, respectively.

Panel A. Lagged independent variables

	(1)	(2)
VARIABLES	Market leverage	Market leverage
EAS_{t-1} × Peer $leverage_{t-1}$	2.075***	
	(7.569)	
$Dret_{t-1}$ × Peer $leverage_{t-1}$		0.199**
		(2.073)
EAS_{t-1}	0.243***	
	(3.253)	
$Dret_{t-1}$		-0.017
		(-0.871)
Peer $leverage_{t-1}$	-0.387***	0.071
	(-8.300)	(1.544)
Constant	0.298***	-0.006
	(13.384)	(-0.130)
First stage instrument	-0.038***	-0.033***
	(-6.665)	(-8.187)
Control variables	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	80,824	21,716
Adjusted R^2	0.375	0.387

Panel B. Firm fixed effect		
	(1)	(2)
VARIABLES	Market leverage	Market leverage
EAS × Peer leverage	1.517***	
	(6.966)	
Dret × Peer leverage		0.176**
		(2.065)
EAS	0.349***	
	(5.765)	
Dret		-0.010
		(-0.596)
Peer leverage	-0.004	0.077
	(-0.049)	(0.422)
Constant	-0.025	0.060
	(-0.839)	(1.159)
First stage instrument	-0.033***	-0.029***
	(-6.141)	(-7.251)
Control variables	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	91,984	25,223
Adjusted R^2	0.709	0.739

Table 3. 6 Internal information quality, mimicking and future profitability

The sample includes all nonfinancial, nonutility firms from CRSP-Compustat Merged database from 1965-2017 with non-missing data for all firm characteristics. All variables are defined in Appendix (Table 3.A.1). The table displays OLS regression estimated coefficients and t-statistics clustered at firm level in parentheses. The table displays the heterogeneity of firm mimicking behaviour's influence on their future profitability for firms with different levels of internal information quality. The dependent variables are firm's ROE and ROA in year t+1. The *Mimicker* variable is an indicator variable equal to one if firms are treated as mimickers in the current year and zero otherwise. Columns (1)- (4) indicate mimicking behaviour's influence on future profitability for low internal information quality firms, while columns (5)- (8) indicate the influence for high internal information quality firms. ***, ** and* indicate statistical significance level at 1%, 5% and 10 % level, respectively.

	High EAS		High Dret		Low EAS		Low Dret	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	ROE_{t+1}	ROA_{t+1}	ROE_{t+1}	ROA_{t+1}	ROE_{t+1}	ROA_{t+1}	ROE_{t+1}	ROA_{t+1}
Mimicker	-0.013**	-0.004**	-0.022**	-0.006**	-0.005	-0.000	-0.004	-0.001
	(-2.280)	(-2.130)	(-2.475)	(-2.009)	(-1.588)	(-0.189)	(-0.467)	(-0.422)
Leverage	-0.262***	-0.037***	-0.334***	-0.027***	-0.133***	-0.026***	-0.269***	-0.023***
	(-14.788)	(-9.527)	(-8.374)	(-3.182)	(-9.766)	(-9.091)	(-7.384)	(-2.927)
Size	0.041***	0.014***	0.031***	0.015***	0.016***	0.007***	0.018***	0.012***
	(17.845)	(21.866)	(11.489)	(14.224)	(15.196)	(17.594)	(7.910)	(12.437)
MTB	0.011***	-0.003**	0.009***	0.007***	0.007***	0.008***	0.010***	0.009***
	(4.352)	(-2.075)	(2.803)	(4.166)	(3.900)	(7.770)	(3.781)	(5.868)
Current ROE/ROA	0.436***	0.573***	0.313***	0.580***	0.523***	0.614***	0.374***	0.584***
	(25.828)	(48.956)	(7.205)	(28.544)	(17.290)	(37.433)	(9.039)	(27.824)
Constant	-0.017	-0.022***	-0.128***	-0.070	0.039***	-0.017***	-0.106***	-0.061***
	(-0.898)	(-4.859)	(-3.289)	(-1.502)	(3.455)	(-5.753)	(-5.300)	(-7.395)
Industry/ Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,412	36,596	9,801	9,829	44,131	44,228	11,854	11,887
Adjusted R^2	0.261	0.412	0.175	0.446	0.265	0.427	0.180	0.436

Table 3. 7 Internal information quality, agency costs and peer effects

The sample includes all nonfinancial, nonutility firms in US market with non-missing data of CEO duality in Execucomp database or non-missing data with takeover index from Stephen McKeon's personal webpage. All variables are defined in Appendix (Table 3.A.1). The table displays two-stage least squares (2SLS) estimated coefficients and t-statistics clustered at firm level in parentheses. The peer firm average variables are calculated as the mean value of all firms within the industry excluding firm *i*'s observation. Industries are defined by the three-digit SIC code. All control variables are lagged by one period to be consistent with related studies. The table displays the heterogeneity in firm's internal information quality's influence on financial policy peer effects for firms with different level of corporate governance. Column (1)- (2) and (5)- (6) present the influence of corporate governance for firms with bad internal information quality. Column (3)- (4) and (7)- (8) present the influence of corporate governance for firms with good internal information quality. A CEO is defined as entrenched if he/she is also the chair of the board. A firm is defined as high (low) takeover index firm if its takeover index value is above (below) the median level within the industry-year. ***, ** and* indicate statistical significance level at 1%, 5% and 10 % level, respectively.

	High EAS		Low EAS		High EAS		Low EAS	
	Entrenched CEO	Not entrenched CEO	Entrenched CEO	Not entrenched CEO	Low takeover index	High takeover index	Low takeover index	High takeover index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Market leverage	Market leverage	Market leverage	Market leverage	Market leverage	Market leverage	Market leverage	Market leverage
Peer leverage	1.178*	0.366	0.331	0.056	0.536**	0.347	0.221	0.347
	(1.867)	(0.770)	(1.388)	(0.129)	(2.204)	(1.364)	(1.131)	(1.603)
Constant	-0.162	-0.032	0.040	0.118	0.025	0.175**	0.148**	0.263***
	(-0.895)	(-0.312)	(0.552)	(1.423)	(0.315)	(2.042)	(2.258)	(3.528)
First stage instrument	-0.023***	-0.039***	-0.039***	-0.026***	-0.045***	-0.045***	-0.039***	-0.044***
	(-3.078)	(-4.195)	(-5.629)	(-3.118)	(-9.407)	(-8.806)	(-7.569)	(-8.694)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry/ Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,003	5,105	7,543	5,877	18,015	14,541	18,489	15,004
Adjusted R^2	0.465	0.465	0.513	0.474	0.353	0.365	0.410	0.418

Table 3. 8 Further robustness checks

The sample includes all nonfinancial, nonutility firms from the CRSP-Compustat Merged database from 1965-2017 with non-missing data for all firm characteristics. The table displays two stage least squares (2SLS) estimated coefficients and t-statistics clustered at firm level in parentheses. The peer firm average variables are calculated as the mean value of all firms within the industry excluding firm *i*'s observation. Industries are defined by three-digit SIC codes, except panel in C. All control variables are lagged by one period to be consistent with related studies. Panel A displays results using *Restatement* and *Weakness* as IIQ proxies. *Restatement* and *Weakness* are two indicator variables equal to one if a firm reports an unintentional restatement (weakness) and zero otherwise. Panel B shows baseline tests using book leverage as leverage measurement. Panel C shows baseline tests using the TNIC classification as the peer group definition. Panel D displays baseline tests using high dimensional fixed effects model. Panel E displays baseline tests by adding additional control variables. ***, ** and* indicate statistical significance level at 1%, 5% and 10 % level, respectively.

Panel A. Alternative IIQ measurements		
	(1)	(2)
VARIABLES	Market leverage	Market leverage
Restatement × Peer leverage	0.149***	
	(2.899)	
Weakness × Peer leverage		0.221***
		(2.699)
Restatement	0.009	
	(0.846)	
Weakness		0.019
		(1.271)
Peer leverage	0.052	-0.016
	(0.206)	(-0.064)
Constant	0.175*	0.025
	(1.725)	(0.648)
First stage instrument	-0.028***	-0.027***
	(-7.141)	(-7.018)
Control variables	Yes	Yes
Industry/ Year fixed effects	Yes	Yes
Observations	26,372	25,592
Adjusted R^2	0.389	0.396

Panel B. Alternative leverage measurements

VARIABLES	(1) Book leverage	(2) Book leverage
EAS × Peer leverage	1.910***	
	(3.847)	
Dret × Peer leverage		0.295*
		(1.736)
Peer leverage	0.086	0.403
	(0.362)	(0.837)
EAS	0.249**	
	(2.124)	
Dret		-0.052
		(-1.403)
Constant	0.017	0.075
	(0.379)	(0.992)
First stage instrument	-0.014***	-0.013***
	(-3.078)	(-3.800)
Control variables	Yes	Yes
Industry/ Year fixed effects	Yes	Yes
Observations	91,984	25,223
Adjusted R^2	0.251	0.297

Panel C. Alternative industry classification (TNIC)

VARIABLES	(1) Market leverage	(2) Market leverage
EAS × Peer leverage	2.766***	
	(11.706)	
Dret × Peer leverage		0.315***
		(3.970)
Peer leverage	0.009	0.427*
	(0.044)	(1.746)
EAS	0.284***	
	(2.632)	
Dret		-0.033**
		(-2.171)
Constant	0.001	0.299***
	(0.018)	(5.001)
First stage instrument	-0.018***	-0.020***
	(-3.314)	(-5.438)
Control variables	Yes	Yes
Industry/ Year fixed effects	Yes	Yes
Observations	58,236	24,903
Adjusted R^2	0.375	0.374

Panel D. High dimensional fixed effects		
	(1)	(2)
VARIABLES	Market leverage	Market leverage
EAS × Peer leverage	0.609*	
	(1.870)	
Dret × Peer leverage		0.172*
		(1.778)
Peer leverage	-0.013	-0.012
	(-0.114)	(-0.057)
EAS	0.585***	
	(6.810)	
Dret		-0.013
		(-0.676)
Constant	-0.070*	-0.015
	(-1.921)	(-0.297)
First stage instrument	-0.033***	-0.034***
	(-6.138)	(-7.017)
Control Variables	Yes	Yes
Firm fixed effects	Yes	Yes
Industry× Year fixed effects	Yes	Yes
Observations	91,984	25,223
Adjusted R^2	0.722	0.758

Panel E. Additional controls

VARIABLES	(1) Market	(2) Market	(3) Market	(4) Market	(5) Market	(6) Market	(7) Market	(8) Market
EAS × Peer leverage	1.863***		1.203***		2.340***		4.775***	
	(6.735)		(4.712)		(7.958)		(7.816)	
Dret × Peer leverage		0.294***		0.328***		0.289***		0.153*
		(3.074)		(3.482)		(3.014)		(1.828)
Peer leverage	0.091	0.404*	0.471***	0.346*	0.032	0.576***	-0.196	0.289
	(0.735)	(1.800)	(4.466)	(1.674)	(0.246)	(2.752)	(-1.021)	(1.232)
Size_rel	0.072***	0.136***						
	(3.517)	(5.323)						
Size_rel × Peer leverage	-0.053	-0.513***						
	(-1.196)	(-5.711)						
Z-score			0.012***	0.007**				
			(6.262)	(2.388)				
Z-score × Peer leverage			-0.151***	-0.148***				
			(-15.224)	(-8.671)				
Takeover					-0.010	0.136*		
					(-0.158)	(1.830)		
Takeover × Peer leverage					-0.724***	-1.350***		
					(-3.178)	(-4.049)		
Entrenched							-0.004	0.004
							(-0.404)	(0.527)
Entrenched × Peer							-0.011	-0.049
							(-0.234)	(-1.224)
EAS/ Dret	0.463***	-0.029	0.524***	-0.037*	0.497***	-0.028	-0.238*	0.008
	(6.459)	(-1.467)	(7.836)	(-1.888)	(6.672)	(-1.466)	(-1.796)	(0.434)
First stage instrument	-0.046***	-0.054***	-0.026***	-0.033***	-0.035***	-0.035***	-0.024*	-0.027***

	(-3.749)	(-3.509)	(-3.898)	(-6.025)	(-3.689)	(-3.745)	(-1.886)	(-3.523)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry/ Year fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91,984	25,223	89,474	24,464	66,049	19,581	23,528	15,363
Adjusted R^2	0.392	0.386	0.415	0.409	0.394	0.391	0.452	0.448

8.2 Tables for chapter 4

Table 4. 1 Summary statistics

The sample includes firms with dividend payment data from 30 economies from 1987 to 2018. All financial and utility and ADR firms are excluded from the sample. Panel A presents the descriptive statistics of firm- and country-level variables used in the empirical analysis in this chapter. Panel B displays the crash risk sample distribution by economy, of all firm-year observations with SOA data. Panel C presents the crash risk sample distribution by economy, of all firm-year observation with Adjfreq data. All variables are defined in Appendix (Table 4.A.1).

Panel A. Descriptive statistics								
	Nobs	Mean	SD	P1	P25	P50	P75	P99
Dependent Variables								
$Ncskew_t$	83788	-0.140	0.715	-2.073	-0.517	-0.132	0.234	1.855
$Duvol_t$	83788	-0.079	0.344	-0.886	-0.303	-0.082	0.140	0.778
Independent Variables								
SOA_{t-1}	54463	0.292	0.321	-0.188	0.055	0.188	0.443	1.268
$Adjfreq_{t-1}$	83788	3.168	1.654	0	2	4	5	5
Control Variables								
$Size_{t-1}$	83788	12.975	1.821	9.221	11.641	12.875	14.195	17.231
Lev_{t-1}	83788	0.198	0.158	0	0.055	0.181	0.310	0.624
ROA_{t-1}	83788	0.053	0.053	-0.079	0.020	0.043	0.076	0.247
MTB_{t-1}	83788	2.207	2.465	0.282	0.858	1.473	2.561	16.356
$Ncskew_{t-1}$	83788	-0.148	0.701	-2.023	-0.522	-0.140	0.220	1.833
$Sigma_{t-1}$	83788	0.037	0.017	0.012	0.026	0.034	0.046	0.091
Ret_{t-1}	83788	-0.082	0.081	-0.403	-0.103	-0.057	-0.032	-0.007
$Accm_{t-1}$	83788	0.237	0.182	0.028	0.113	0.186	0.304	0.918
$Dturn_{t-1}$	83788	0.002	0.057	-0.221	-0.008	0.000	0.010	0.251
$SD(EPS)_{t-1}$	83788	0.561	1.239	0.002	0.055	0.191	0.521	7.892
Dps_{t-1}	83788	0.404	0.826	0	0.047	0.146	0.400	5.129
GDP_grow_{t-1}	83788	0.027	0.029	-0.054	0.012	0.022	0.042	0.111
$GDP/Capita_{t-1}$	83788	10.216	0.937	7.642	10.389	10.650	10.742	11.163
$Mcap/GDP_{t-1}$	83788	1.123	1.468	0.190	0.605	0.881	1.240	10.783
Other Variables								
$Fore\ Error_{t-1}$	54884	0.688	1.697	0.004	0.093	0.237	0.629	9.806
$Fore\ Disper_{t-1}$	45748	0.118	0.238	0	0.025	0.056	0.116	1.385
$DisAccruals_{t-1}$	79503	0.077	0.086	0	0.022	0.050	0.100	0.458
$AbnProd_{t-1}$	79092	0.128	0.129	0.001	0.040	0.088	0.170	0.679
$AbnDisExp_{t-1}$	67222	0.103	0.109	0.001	0.030	0.068	0.137	0.588

Panel B. Distribution of SOA sample					
	Nobs	N of Firms	*Mean of SOA*	Mean of *Ncskew*	Mean of *Duvol*
AUSTRALIA	1004	150	0.459	-0.026	-0.027
AUSTRIA	119	17	0.378	-0.129	-0.101
BELGIUM	290	32	0.347	-0.152	-0.086
CANADA	1358	186	0.187	-0.046	-0.029
CHILE	163	22	0.696	-0.125	-0.070
CHINA	2462	433	0.661	-0.024	0.000
FRANCE	1777	185	0.414	-0.181	-0.099
GERMANY	1632	218	0.425	-0.074	-0.043
GREECE	251	50	0.513	-0.204	-0.125
HONG KONG	1324	196	0.513	-0.272	-0.139
INDIA	2999	581	0.443	-0.350	-0.194
INDONESIA	174	33	0.845	-0.311	-0.152
IRELAND	169	19	0.218	0.061	0.025
ISRAEL	113	28	0.800	-0.071	-0.045
ITALY	175	32	0.327	-0.295	-0.162
JAPAN	20434	1967	0.188	-0.152	-0.081
MALAYSIA	2086	262	0.478	-0.261	-0.138
NETHERLANDS	468	56	0.557	-0.147	-0.096
NEW ZEALAND	247	28	0.565	-0.154	-0.077
NORWAY	165	17	0.425	-0.175	-0.101
PAKISTAN	202	37	0.543	-0.335	-0.189
POLAND	107	24	0.631	-0.106	-0.071
SINGAPORE	984	135	0.454	-0.202	-0.111
SOUTH AFRICA	425	55	0.499	-0.144	-0.079
SPAIN	383	39	0.522	-0.180	-0.108
SWITZERLAND	711	64	0.440	-0.149	-0.090
THAILAND	817	143	0.694	-0.240	-0.120
TURKEY	262	30	0.780	-0.372	-0.192
UNITED KINGDOM	2559	423	0.186	-0.172	-0.103
UNITED STATES	10603	971	0.124	0.019	-0.003
TOTAL	54463	6433			

Panel C. Distribution of Adjfreq sample					
	Nobs	N of Firms	*Mean of Adjfreq*	Mean of *Ncskew*	Mean of *Duvol*
AUSTRALIA	1749	160	4.180	-0.045	-0.039
AUSTRIA	183	18	3.464	-0.160	-0.107
BELGIUM	400	32	3.993	-0.162	-0.092
CANADA	2265	201	3.296	-0.077	-0.047
CHILE	265	23	3.717	-0.159	-0.092
CHINA	4626	451	3.960	0.007	0.010
FRANCE	2622	196	3.714	-0.199	-0.111
GERMANY	2422	223	3.634	-0.076	-0.048
GREECE	376	54	4.138	-0.199	-0.115
HONG KONG	2185	198	4.019	-0.255	-0.134
INDIA	5723	615	3.312	-0.361	-0.200
INDONESIA	296	35	3.733	-0.356	-0.171
IRELAND	213	19	4.596	0.019	0.008
ISRAEL	268	35	4.511	-0.086	-0.053
ITALY	280	49	3.525	-0.243	-0.134
JAPAN	29648	2100	2.248	-0.151	-0.082
MALAYSIA	3326	276	3.720	-0.267	-0.139
NETHERLANDS	747	58	4.149	-0.150	-0.102
NEW ZEALAND	379	30	3.939	-0.122	-0.063
NORWAY	234	17	3.530	-0.173	-0.100
PAKISTAN	399	47	4.138	-0.301	-0.178
POLAND	203	24	4.020	-0.108	-0.067
SINGAPORE	1617	143	3.533	-0.211	-0.114
SOUTH AFRICA	670	58	4.430	-0.152	-0.081
SPAIN	577	40	4.081	-0.214	-0.117
SWITZERLAND	1024	70	3.548	-0.171	-0.100
THAILAND	1423	145	4.185	-0.268	-0.137
TURKEY	406	31	4.690	-0.399	-0.210
UNITED KINGDOM	3806	479	4.023	-0.188	-0.111
UNITED STATES	15456	1007	3.384	-0.003	-0.015
TOTAL	83788	6834			

Table 4. 2 The impact of dividend smoothing on crash risk

The table displays the OLS results for the impact of dividend smoothing on a firm's future crash risk. The dependent variables are the firm's negative skewness (Ncskew) and down-to-up volatility (Duvol). Dividend smoothing is measured by the speed of adjustment (SOA) and adjustment frequency (Adjfreq). All independent variables and control variables are lagged by one period relative to the dependent variables. Specifically, firm-level controls include *Size*, *Lev*, *ROA*, *MTB*, *Ncskew*$_{(t-1)}$, *Sigma*, *Ret*, *Accm (earnings management)*, *Dturn (difference in turnover)*, *SD (eps)*, and *DPS*. Country-level controls include *GDP_growth*, *GDP/Capita*, and *Mcap/GDP*. All models include country, industry, and year fixed effects, as well as the intercept. The t-statistics, based on robust standard errors clustered by firm, are reported in parentheses. All variables are defined in Appendix (Table 4.A.1). ***, ** and* indicate statistical significance level at 1%, 5%, and 10 % level, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$
SOA_{t-1}	-0.034***	-0.017***		
	(-2.772)	(-2.967)		
$Adjfreq_{t-1}$			-0.006***	-0.003***
			(-3.111)	(-3.481)
$Size_{t-1}$	0.044***	0.020***	0.041***	0.019***
	(18.403)	(17.933)	(20.835)	(20.442)
Lev_{t-1}	0.037	0.012	0.058***	0.024**
	(1.504)	(1.002)	(2.942)	(2.537)
ROA_{t-1}	0.334***	0.149***	0.305***	0.139***
	(3.909)	(3.761)	(4.584)	(4.380)
MTB_{t-1}	0.006***	0.003***	0.007***	0.003***
	(3.347)	(3.477)	(4.509)	(4.128)
$Ncskew_{t-1}$	0.025***	0.012***	0.030***	0.015***
	(4.682)	(5.035)	(7.252)	(7.697)
$Sigma_{t-1}$	1.391	0.274	0.546	-0.132
	(1.640)	(0.701)	(0.873)	(-0.447)
Ret_{t-1}	0.034	-0.020	0.008	-0.040
	(0.200)	(-0.254)	(0.069)	(-0.731)
$Accm_{t-1}$	-0.021	-0.009	-0.024	-0.012
	(-1.026)	(-0.980)	(-1.599)	(-1.635)
$Dturn_{t-1}$	-0.022	-0.034	0.004	-0.013
	(-0.384)	(-1.254)	(0.087)	(-0.642)
$SD(EPS)_{t-1}$	-0.006*	-0.003*	-0.006**	-0.003**
	(-1.875)	(-1.728)	(-2.272)	(-2.163)
DPS_{t-1}	0.014***	0.007***	0.013***	0.007***
	(2.624)	(2.611)	(2.770)	(2.965)
GDP_grow_{t-1}	0.237	0.076	0.356**	0.168**
	(0.967)	(0.650)	(2.238)	(2.141)
$GDP/Capita_{t-1}$	-0.074	-0.046*	-0.217***	-0.105***
	(-1.525)	(-1.912)	(-7.796)	(-7.607)
$Mcap/GDP_{t-1}$	0.024***	0.012***	0.015***	0.008***
	(3.152)	(3.336)	(3.220)	(3.844)
Constant	-0.052	0.099	1.479***	0.720***

	(-0.104)	(0.396)	(5.224)	(5.154)
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	54,463	54,463	83,788	83,788
Adjusted R^2	0.0492	0.0572	0.0495	0.0571

Table 4. 3 Difference-in-difference tests

The table displays difference-in-difference (DiD) estimation of how an exogenous shock to dividend smoothing, the Jobs and Growth Tax Relief Reconciliation Act (JGTRRA), impacts the firm's stock price crash risk. The regression covers the sample period from 1999-–2006. ***Treat*** is a dummy variable equal to one if the firm is domiciled in the U.S. and zero if the firm is domiciled in a country that does not have a tax treaty with the U.S. ***Post*** is a dummy variable equal to one for years after 2003 and zero otherwise. Panel A presents the multivariate DiD estimation results. Panel B reports the dynamic effect of JGTRRA implementation on crash risk. Panel C displays results applying the PSM procedure. All independent variables and control variables are lagged by one period relative to the dependent variables. Specifically, firm-level controls include *Size*, *Lev*, *ROA*, *MTB*, *Ncskew*$_{(t-1)}$, *Sigma*, *Ret*, *Accm (earnings management)*, *Dturn (difference in turnover)*, *SD (eps)*, and *DPS*. Country-level controls include *GDP_growth*, *GDP per capita*, and *Mcap/GDP*. The t-statistics, based on robust standard errors clustered by firm, are reported in parentheses. All variables are defined in Appendix (Table 4.A.1). ***, ** and* indicate statistical significance level at 1%, 5%, and 10 % level, respectively.

Panel A. Difference-in-difference estimation

	(1)	(2)	(3)	(4)
VARIABLES	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$
Treat × Post	-0.259***	-0.138***	-0.291***	-0.159***
	(-2.724)	(-3.129)	(-2.861)	(-3.392)
$Size_{t-1}$	0.064***	0.030***	0.282***	0.143***
	(7.931)	(7.802)	(6.415)	(7.025)
Lev_{t-1}	0.055	0.023	0.190	0.114
	(0.613)	(0.584)	(1.091)	(1.447)
ROA_{t-1}	0.718***	0.333***	0.220	0.109
	(2.904)	(2.921)	(0.657)	(0.712)
MTB_{t-1}	-0.000	0.001	-0.002	0.000
	(-0.008)	(0.532)	(-0.298)	(0.168)
$Ncskew_{t-1}$	-0.008	-0.010	-0.138***	-0.067***
	(-0.416)	(-1.252)	(-7.142)	(-7.758)
$Sigma_{t-1}$	9.122***	4.327***	7.578**	4.014**
	(3.523)	(3.490)	(2.326)	(2.577)
Ret_{t-1}	0.946**	0.431*	0.782	0.417
	(1.972)	(1.912)	(1.369)	(1.541)
$Accm_{t-1}$	0.004	0.001	-0.027	-0.013
	(0.162)	(0.125)	(-0.914)	(-1.046)
$Dturn_{t-1}$	0.086**	0.043*	0.071	0.034
	(2.031)	(1.959)	(1.626)	(1.559)
$SD(EPS)_{t-1}$	0.027	0.008	0.024	0.009
	(1.359)	(0.871)	(0.856)	(0.760)
DPS_{t-1}	0.063**	0.034***	0.145*	0.051
	(2.152)	(2.593)	(1.869)	(1.594)
GDP_grow_{t-1}	1.290**	0.691**	0.657	0.434
	(2.053)	(2.232)	(1.008)	(1.368)
$GDP/Capita_{t-1}$	-3.003**	-1.616***	-2.218*	-1.383**
	(-2.418)	(-2.825)	(-1.743)	(-2.396)
$Mcap/GDP_{t-1}$	-0.010	-0.007	-0.073	-0.037
	(-0.207)	(-0.294)	(-1.239)	(-1.348)

Constant	29.751**	16.081***	18.859	12.215**
	(2.319)	(2.724)	(1.437)	(2.048)
Country FE	Yes	Yes	No	No
Industry FE	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,150	4,150	4,150	4,150
Adjusted R^2	0.0820	0.0872	0.115	0.117

Panel B. Dynamic difference-in-difference estimation				
	(1)	(2)	(3)	(4)
VARIABLES	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$
$Before_{-3} \times Treat$	-0.352	-0.213	-0.346	-0.203
	(-1.227)	(-1.543)	(-1.248)	(-1.553)
$Before_{-2} \times Treat$	-0.210	-0.151	-0.207	-0.150
	(-0.502)	(-0.763)	(-0.537)	(-0.829)
$Before_{-1} \times Treat$	-0.037	-0.035	-0.050	-0.043
	(-0.137)	(-0.271)	(-0.201)	(-0.367)
$After_{+1} \times Treat$	-0.414*	-0.223*	-0.479**	-0.260**
	(-1.689)	(-1.946)	(-2.035)	(-2.408)
$After_{+2} \times Treat$	-0.510*	-0.284**	-0.607**	-0.343***
	(-1.809)	(-2.114)	(-2.227)	(-2.672)
$After_{+3} \times Treat$	-0.323	-0.196	-0.411	-0.258*
	(-1.009)	(-1.302)	(-1.332)	(-1.802)
Constant	11.588	6.297	5.517	6.506
	(0.565)	(0.655)	(0.235)	(0.619)
Firm-level controls	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	No	No
Industry FE	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,150	4,150	4,150	4,150
Adjusted R^2	0.0828	0.0892	0.115	0.119

Panel C. Test with PSM				
	(1)	(2)	(3)	(4)
VARIABLES	Ncskew	Duvol	Ncskew	Duvol
Treat × Post	-0.205*	-0.110**	-0.246**	-0.137**
	(-1.769)	(-2.027)	(-2.029)	(-2.440)
$Size_{t-1}$	0.090***	0.037***	0.231***	0.121***
	(6.826)	(6.045)	(3.940)	(4.509)
Lev_{t-1}	0.010	-0.001	0.200	0.111
	(0.080)	(-0.014)	(0.903)	(1.084)
ROA_{t-1}	0.309	0.156	0.015	-0.004
	(0.946)	(1.039)	(0.036)	(-0.019)
MTB_{t-1}	-0.003	-0.001	-0.003	-0.002
	(-0.475)	(-0.194)	(-0.402)	(-0.363)
$Ncskew_{t-1}$	-0.012	-0.013	-0.122***	-0.061***
	(-0.494)	(-1.188)	(-4.465)	(-4.880)
$Sigma_{t-1}$	8.646***	4.009**	7.223*	3.658*
	(2.683)	(2.536)	(1.781)	(1.832)
Ret_{t-1}	0.805	0.327	0.777	0.349
	(1.403)	(1.193)	(1.156)	(1.065)
$Accm_{t-1}$	0.013	0.009	-0.033	-0.012
	(0.463)	(0.659)	(-1.112)	(-0.806)
$Dturn_{t-1}$	0.042**	0.021**	0.029	0.014
	(2.183)	(2.035)	(1.487)	(1.384)
$SD(EPS)_{t-1}$	-0.009	-0.006	-0.009	-0.000
	(-0.409)	(-0.448)	(-0.276)	(-0.001)
DPS_{t-1}	0.116***	0.060***	0.325*	0.118
	(3.087)	(3.451)	(1.814)	(1.490)
GDP_grow_{t-1}	2.437***	1.271***	1.844**	1.020***
	(3.238)	(3.436)	(2.434)	(2.739)
$GDP/Capita_{t-1}$	-3.900**	-2.132***	-3.629**	-2.044***
	(-2.514)	(-2.983)	(-2.329)	(-2.877)
$Mcap/GDP_{t-1}$	-0.050	-0.019	-0.086	-0.039
	(-0.894)	(-0.734)	(-1.379)	(-1.360)
Constant	37.900**	20.866***	33.463**	18.982***
	(2.414)	(2.888)	(2.128)	(2.640)
Country FE	Yes	Yes	No	No
Industry FE	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,194	2,194	2,194	2,194
Adjusted R^2	0.0666	0.0625	0.0901	0.0794

Table 4. 4 Two-stage least squares (2SLS) regression

The table displays the two-stage least squares (2SLS) results for the impact of dividend smoothing on a firm's future crash risk. Column (1) and (4) report the first-stage regression results by adopting the country-industry average dividend smoothing level as the instrumental variable. Column (2)–(3) and (5)–6) present the second-stage results. All independent variables and control variables are lagged by one period relative to the dependent variables. Specifically, firm-level controls include *Size*, *Lev*, *ROA*, *MTB*, *Ncskew*$_{(t-1)}$, *Sigma*, *Ret*, *Accm (earnings management)*, *Dturn (difference in turnover)*, *SD (eps)*, and *DPS*. Country-level controls include *GDP_growth*, *GDPper capita*, and *Mcap/GDP*. The t-statistics, based on robust standard errors clustered by firm, are reported in parentheses. All variables are defined in Appendix (Table 4.A.1). ***, ** and* indicate statistical significance level at 1%, 5%, and 10 % level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	SOA $_{t-1}$	Ncskew$_t$	Duvol$_t$	Adjfreq $_{t-1}$	Ncskew$_t$	Duvol$_t$
Estimated SOA $_{t-1}$		-0.511**	-0.239**			
		(-2.485)	(-2.492)			
Estimated Adjfreq $_{t-1}$					-0.052***	-0.026***
					(-2.993)	(-3.084)
Peer SOA $_{t-1}$	0.165***					
	(6.006)					
Peer Adjfreq $_{t-1}$				0.236***		
				(12.333)		
Size$_{t-1}$	-0.006***	0.042***	0.019***	0.164***	0.048***	0.023***
	(-2.919)	(14.699)	(14.419)	(17.076)	(13.803)	(13.660)
Lev$_{t-1}$	-0.017	0.021	0.004	0.022	0.054***	0.021**
	(-0.838)	(0.810)	(0.291)	(0.232)	(2.620)	(2.133)
ROA$_{t-1}$	0.662***	0.628***	0.282***	5.396***	0.544***	0.255***
	(11.525)	(3.766)	(3.649)	(23.124)	(4.644)	(4.528)
MTB$_{t-1}$	0.006***	0.009***	0.004***	0.001	0.006***	0.003***
	(4.713)	(3.856)	(4.065)	(0.151)	(4.150)	(3.863)
Ncskew$_{t-1}$	-0.002	0.021***	0.010***	0.008	0.030***	0.014***
	(-0.907)	(3.783)	(4.186)	(0.989)	(6.831)	(7.360)
Sigma$_{t-1}$	2.886***	2.692**	0.855*	8.051***	0.779	-0.032
	(6.949)	(2.531)	(1.729)	(4.260)	(1.164)	(-0.101)
Ret$_{t-1}$	0.372***	0.210	0.063	1.192***	0.059	-0.017
	(4.798)	(1.101)	(0.711)	(3.536)	(0.485)	(-0.298)
Accm$_{t-1}$	-0.023*	-0.025	-0.010	0.072	-0.016	-0.008
	(-1.760)	(-1.124)	(-0.985)	(1.296)	(-0.993)	(-1.014)
Dturn$_{t-1}$	-0.046**	-0.045	-0.045	-0.382***	-0.013	-0.022
	(-2.419)	(-0.763)	(-1.629)	(-5.336)	(-0.302)	(-1.024)
SD(EPS)$_{t-1}$	-0.015***	-0.013***	-0.006***	-0.053***	-0.009***	-0.004***
	(-6.322)	(-2.836)	(-2.634)	(-4.084)	(-3.167)	(-2.997)
DPS$_{t-1}$	0.008	0.018***	0.009***	0.009	0.015***	0.008***
	(1.260)	(2.933)	(3.014)	(0.387)	(3.041)	(3.321)
GDP_grow$_{t-1}$	0.240*	0.441	0.174	-0.604	0.380**	0.194**
	(1.833)	(1.545)	(1.257)	(-1.557)	(2.226)	(2.290)
GDP/Capita$_{t-1}$	-0.132***	-0.160**	-0.075**	-0.781***	-0.272***	-0.126***
	(-2.777)	(-2.517)	(-2.454)	(-7.427)	(-8.041)	(-7.644)

Mcap/GDP$_{t-1}$	0.005	0.026**	0.013***	0.020	0.018***	0.010***
	(0.690)	(2.480)	(2.728)	(1.306)	(3.117)	(3.689)
Constant	1.563***	0.953	0.455	7.766***	2.078***	0.961***
	(3.159)	(1.393)	(1.382)	(7.225)	(5.948)	(5.637)
Country/ Industry/	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,470	49,470	49,470	77,646	77,646	77,646
Adjusted R^2	0.351	0.0500	0.0584	0.288	0.0505	0.0583
F	36.070			152.109		

Table 4. 5 The impact of dividend smoothing on crash risk: alternative fixed effect model

The table displays the impact of dividend smoothing on the firm's future crash risk by adopting an alternative fixed effects model. The dependent variables are firm's negative skewness (Ncskew) and down-to-up volatility (Duvol). Dividend smoothing is measured by the speed of adjustment (SOA) and adjustment frequency (Adjfreq). Column (1)–(4) present the OLS regression results with *firm* and *year* fixed effects, while column (5)–(8) present the OLS regression results with *firm*, *industry × year* and *country × year* fixed effects. All independent variables and control variables are lagged by one period relative to the dependent variables. Specifically, firm-level controls include *Size*, *Lev*, *ROA*, *MTB*, *Ncskew*$_{(t-1)}$, *Sigma*, *Ret*, *Accm (earnings management)*, *Dturn (difference in turnover)*, *SD (eps)*, and *DPS*. Country-level controls include *GDP_growth*, *GDP per capita*, and *Mcap/GDP*. All models include country, industry, and year fixed effects, as well as the intercept. The t-statistics, based on robust standard errors clustered by firm, are reported in parentheses. All variables are defined in Appendix (Table 4.A.1). ***, ** and* indicate statistical significance level at 1%, 5%, and 10 % level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$
SOA_{t-1}	-0.039*	-0.018*			-0.046**	-0.020**		
	(-1.947)	(-1.848)			(-2.254)	(-2.083)		
$Adjfreq_{t-1}$			-0.005*	-0.003**			-0.006**	-0.003**
			(-1.687)	(-2.198)			(-2.040)	(-2.445)
Constant	-0.306	-0.182	1.961***	0.888***	-2.877***	-1.442***	-2.386***	-1.195***
	(-0.423)	(-0.510)	(5.429)	(5.060)	(-20.744)	(-22.139)	(-25.626)	(-27.015)
Firm-level controls	Yes	Yes	Yes	Yes	No	No	No	No
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Country × Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No	No	No	No
Observations	54,463	54,463	83,788	83,788	54,463	54,463	83,788	83,788
Adjusted R^2	0.0948	0.0973	0.0838	0.0899	0.109	0.116	0.102	0.112

Table 4. 6 Robustness checks: Alternative dividend smoothing measurements

The table displays the baseline regression analysis using an alternative dividend smoothing estimation model. Panel A presents results using an alternative SOA model. Columns (1)–(2) estimate SOA using the last ten-years' median payout ratio as the firm's target payout ratio. Columns (3)–(4) set SOA equal to one (zero) if the firm-year observation exceeds one (below zero). Column (5)–(6) estimate SOA with the firm's total payout (cash dividend plus share repurchases). Panel B displays robustness checks for the adjustment frequency measurements. Columns (1)–(6) estimate the adjustment frequency using a different threshold for significant dividend change, while columns (7)–(10) estimate the adjustment frequency using a different rolling window for variable estimation. All independent variables and control variables are lagged by one period relative to the dependent variables. Specifically, firm-level controls include *Size*, *Lev*, *ROA*, *MTB*, *Ncskew*$_{(t-1)}$, *Sigma*, *Ret*, *Accm (earnings management)*, *Dturn (difference in turnover)*, *SD (eps)*, and *DPS*. Country-level controls include *GDP_growth*, *GDP per capita*, and *Mcap/GDP*. The t-statistics, based on robust standard errors clustered by firm, are reported in parentheses. All variables are defined in Appendix (Table 4.A.1). ***, ** and* indicate statistical significance level at 1%, 5%, and 10 % level, respectively.

Panel A. Alternative SOA model

	TPR: 10-year median		0≤ SOA≤ 1		Total Payout	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Ncskew$_t$	Duvol$_t$	Ncskew$_t$	Duvol$_t$	Ncskew$_t$	Duvol$_t$
SOA$_{t-1}$	-0.024**	-0.012**	-0.033**	-0.017***	-0.019*	-0.011**
	(-2.208)	(-2.273)	(-2.490)	(-2.707)	(-1.651)	(-1.992)
Size$_{t-1}$	0.044***	0.020***	0.044***	0.020***	0.044***	0.020***
	(18.430)	(17.949)	(18.451)	(17.957)	(18.457)	(17.973)
Lev$_{t-1}$	0.036	0.011	0.037	0.012	0.037	0.012
	(1.457)	(0.955)	(1.518)	(1.017)	(1.525)	(1.015)
ROA$_{t-1}$	0.328***	0.146***	0.338***	0.152***	0.325***	0.146***
	(3.850)	(3.697)	(3.962)	(3.838)	(3.798)	(3.672)
MTB$_{t-1}$	0.006***	0.003***	0.006***	0.003***	0.006***	0.003***
	(3.301)	(3.414)	(3.293)	(3.407)	(3.261)	(3.377)
Ncskew$_{t-1}$	0.025***	0.012***	0.025***	0.012***	0.025***	0.012***
	(4.707)	(5.064)	(4.690)	(5.047)	(4.710)	(5.066)
Sigma$_{t-1}$	1.325	0.238	1.361	0.259	1.308	0.234
	(1.565)	(0.608)	(1.605)	(0.663)	(1.546)	(0.598)
Ret$_{t-1}$	0.024	-0.025	0.025	-0.024	0.019	-0.027
	(0.145)	(-0.321)	(0.150)	(-0.305)	(0.112)	(-0.350)
Accm$_{t-1}$	-0.020	-0.009	-0.020	-0.009	-0.020	-0.009
	(-1.005)	(-0.954)	(-1.006)	(-0.953)	(-0.979)	(-0.921)
Dturn$_{t-1}$	-0.021	-0.033	-0.030	-0.037	-0.023	-0.034
	(-0.370)	(-1.236)	(-0.540)	(-1.381)	(-0.411)	(-1.277)
SD(EPS)$_{t-1}$	-0.006*	-0.003*	-0.006*	-0.003*	-0.006*	-0.003*
	(-1.949)	(-1.766)	(-1.873)	(-1.673)	(-1.877)	(-1.708)
DPS$_{t-1}$	0.015***	0.007***	0.015***	0.007***	0.014***	0.007**
	(2.685)	(2.655)	(2.748)	(2.731)	(2.594)	(2.548)
GDP_grow$_{t-1}$	0.233	0.075	0.236	0.077	0.236	0.076

	(0.949)	(0.642)	(0.961)	(0.656)	(0.963)	(0.652)
GDP per capita$_{t-1}$	-0.070	-0.044*	-0.072	-0.045*	-0.071	-0.044*
	(-1.437)	(-1.810)	(-1.472)	(-1.845)	(-1.462)	(-1.835)
Mcap/GDP$_{t-1}$	0.023***	0.012***	0.023***	0.012***	0.023***	0.012***
	(3.110)	(3.287)	(3.123)	(3.302)	(3.095)	(3.284)
Constant	-0.099	0.073	-0.080	0.082	-0.087	0.079
	(-0.196)	(0.290)	(-0.160)	(0.328)	(-0.174)	(0.315)
Country/ Industry/ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	54,463	54,463	54,463	54,463	54,463	54,463
Adjusted R^2	0.0491	0.0571	0.0492	0.0572	0.0491	0.0571

Panel B. Alternative Adjfreq measurements										
	significant change: △>0%		significant change: △>2%		significant change: △>5%		rolling window: 6 years		rolling window: 7 years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$
$Adjfreq_{t-1}$	-0.005***	-0.003***	-0.006***	-0.003***	-0.006***	-0.003***	-0.005***	-0.003***	-0.004***	-0.002***
	(-2.967)	(-3.328)	(-3.318)	(-3.763)	(-3.193)	(-3.604)	(-3.004)	(-3.281)	(-2.921)	(-3.160)
Constant	1.476***	0.718***	1.481***	0.721***	1.476***	0.718***	1.293***	0.638***	0.574	0.306*
	(5.213)	(5.142)	(5.231)	(5.164)	(5.214)	(5.143)	(4.021)	(4.034)	(1.627)	(1.761)
Firm level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83,788	83,788	83,788	83,788	83,788	83,788	78,244	78,244	72,504	72,504
Adjusted R^2	0.0495	0.0571	0.0495	0.0571	0.0495	0.0571	0.0494	0.0574	0.0495	0.0576

Table 4. 7 Dividend smoothing and information asymmetry

The table displays the impact of dividend smoothing on the firm's information transparency level. A firm's information asymmetry level is measured by analyst forecast dispersion *(Fore Disper*) and analyst forecast error (*Fore Error*). Dividend smoothing is measured by speed of adjustment (SOA) and adjustment frequency (Adjfreq). All independent variables and control variables are lagged by one period relative to the dependent variables. Specifically, firm-level controls include *Size*, *Lev*, *ROA*, *MTB*, $Ncskew_{(t-1)}$, *Sigma*, *Ret*, *Accm (earnings management)*, *Dturn (difference in turnover)*, *SD (eps)*, and *DPS*. Country-level controls include *GDP_growth*, *GDP per capita*, and *Mcap/GDP*. The t-statistics, based on robust standard errors clustered by firm, are reported in parentheses. All variables are defined in Appendix (Table 4.A.1). ***, ** and* indicate statistical significance level at 1%, 5%, and 10 % level, respectively.

VARIABLES	(1) Fore $Disper_t$	(2) Fore $Error_t$	(3) Fore $Disper_t$	(4) Fore $Error_t$
SOA_t	-0.013***	-0.196***		
	(-2.698)	(-4.671)		
$Adjfreq_t$			-0.004***	-0.018**
			(-3.685)	(-2.451)
Constant	11.889	2.024	2.390	1.681
	(0.362)	(0.956)	(0.127)	(1.228)
Firm-level controls	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	30,524	36,185	45,748	54,884
Adjusted R^2	0.144	0.174	0.135	0.149

Table 4. 8 Dividend smoothing and earnings management

The table displays the impact of dividend smoothing on earnings management. A firm's earnings management is measured by discretionary accruals (*DisAccrual*), abnormal production cost (*AbnProd*, and abnormal discretionary expense (*AbnDisExp*). Dividend smoothing is measured by speed of adjustment (SOA) and adjustment frequency (Adjfreq). All independent variables and control variables are lagged by one period relative to the dependent variables. Specifically, firm-level controls include *Size*, *Lev*, *ROA*, *MTB*, $Ncskew_{(t-1)}$, *Sigma*, *Ret*, *Accm (earnings management)*, *Dturn (difference in turnover)*, *SD (eps)*, and *DPS*. Country-level controls include *GDP_growth*, *GDP per capita*, and *Mcap/GDP*. The t-statistics, based on robust standard errors clustered by firm, are reported in parentheses. All variables are defined in Appendix (Table 4.A.1). ***, ** and* indicate statistical significance level at 1%, 5%, and 10 % level, respectively.

VARIABLES	(1) $DisAccrual_t$	(2) $AbnProd_t$	(3) $AbnDisExp_t$	(4) $DisAccrual_t$	(5) $AbnProd_t$	(6) $AbnDisExp_t$
SOA_t	-0.003	0.000	-0.000			
	(-1.513)	(0.068)	(-0.109)			
$Adjfreq_t$				0.000	-0.000	-0.001
				(1.503)	(-0.132)	(-1.239)
Constant	0.149*	0.208	0.154	0.091*	0.201***	0.197***
	(1.784)	(1.576)	(1.305)	(1.865)	(2.592)	(3.090)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,129	49,947	43,894	79,503	79,092	67,222
Adjusted R^2	0.0936	0.205	0.224	0.0961	0.198	0.223

Table 4. 9 The impact of dividend smoothing on crash risk: Cross-country analysis

The table displays the impact of dividend smoothing on a firm's future crash risk across different economies. The sample is split into above (high) and below (low) median groups according to the economies' disclosure index (La Porta, Lopez-de-Silanes, and Shleifer 2006) (Panel A), liability index (La Porta, Lopez-de-Silanes, and Shleifer 2006) (Panel B), and institutional quality (Ellahie and Kaplan 2021) (Panel C). The dependent variables are the firm's negative skewness (Ncskew) and down-to-up volatility (Duvol). Dividend smoothing is measured by the speed of adjustment (SOA) and adjustment frequency (Adjfreq). All independent variables and control variables are lagged by one period relative to the dependent variables. Specifically, firm-level controls include *Size*, *Lev*, *ROA*, *MTB*, *Ncskew*$_{(t-1)}$, *Sigma*, *Ret*, *Accm (earnings management)*, *Dturn (difference in turnover)*, *SD (eps)*, and *DPS*. Country level-controls includes *GDP_growth*, *GDP per capita*, and *Mcap/GDP*. The t-statistics, based on robust standard errors clustered by firm, are reported in parentheses. All variables are defined in Appendix (Table 4.A.1). ***,** and* indicate statistical significance level at 1%, 5%, and 10 % level, respectively.

Panel A. Disclosure index

	Low				High			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$
SOA_{t-1}	-0.062***	-0.029***			0.008	0.003		
	(-3.781)	(-3.699)			(0.386)	(0.377)		
$Adjfreq_{t-1}$			-0.005**	-0.003**			-0.004	-0.002
			(-1.985)	(-2.209)			(-1.261)	(-1.606)
Constant	-1.178	-0.693*	2.057***	0.864***	-0.008	0.241	0.707	0.648*
	(-1.576)	(-1.806)	(5.581)	(4.732)	(-0.009)	(0.523)	(1.008)	(1.955)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,733	30,733	46,765	46,765	21,831	21,831	34,284	34,284
Adjusted R^2	0.0498	0.0546	0.0490	0.0537	0.0593	0.0734	0.0612	0.0735

Panel B. Liability index								
	Low				High			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$
SOA_{t-1}	-0.034**	-0.017***			-0.047	-0.020		
	(-2.453)	(-2.599)			(-1.567)	(-1.416)		
$Adjfreq_{t-1}$			-0.004*	-0.003**			-0.005	-0.002
			(-1.892)	(-2.531)			(-1.349)	(-1.209)
Constant	-0.263	0.006	1.566***	0.765***	-3.350	-2.329	-4.606	-2.777
	(-0.491)	(0.023)	(5.354)	(5.319)	(-0.667)	(-0.921)	(-1.321)	(-1.590)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,892	39,892	61,600	61,600	12,672	12,672	19,449	19,449
Adjusted R^2	0.0506	0.0586	0.0508	0.0591	0.0259	0.0342	0.0298	0.0378

Panel C. Institution quality

	Low				High			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$	$Ncskew_t$	$Duvol_t$
SOA_{t-1}	-0.040**	-0.020***			-0.034	-0.014		
	(-2.532)	(-2.665)			(-1.556)	(-1.519)		
$Adjfreq_{t-1}$			-0.004*	-0.002**			-0.004	-0.002
			(-1.752)	(-2.129)			(-1.276)	(-1.405)
Constant	-0.212	0.059	1.777***	0.870***	-1.981	-0.720	-0.671	-0.195
	(-0.364)	(0.201)	(5.818)	(5.743)	(-1.125)	(-0.909)	(-0.569)	(-0.340)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,049	30,049	47,689	47,689	22,856	22,856	35,048	35,048
Adjusted R^2	0.0591	0.0664	0.0600	0.0678	0.0417	0.0523	0.0426	0.0513

Table 4. 10 Further robustness checks

The table displays further robustness tests for the baseline results. Columns (1)–(4) report the results excluding Japanese firms from the sample. Columns (5)–(8) report the results excluding U.S. firms from the sample. Columns (5)–(8) report the results excluding 2008 and 2009 observations. The dependent variables are the firm's negative skewness (Ncskew) and down-to-up volatility (Duvol). Dividend smoothing is measured by the speed of adjustment (SOA) and adjustment frequency (Adjfreq). All independent variables and control variables are lagged by one period relative to the dependent variables. Specifically, firm-level controls include *Size*, *Lev*, *ROA*, *MTB*, $Ncskew_{(t-1)}$, *Sigma*, *Ret*, *Accm (earnings management)*, *Dturn (difference in turnover)*, *SD (eps)*, and *DPS*. Country-level controls include *GDP_growth*, *GDP per capita*, and *Mcap/GDP*. The t-statistics, based on robust standard errors clustered by firm are reported in parentheses. All variables are defined in Appendix (Table 4.A.1). ***, ** and* indicate statistical significance level at 1%, 5%, and 10 % level, respectively.

	Exclude JAPAN				Exclude U.S.				Exclude 2008-2009			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Ncskew	Duvol	Ncskew	Duvol	Ncskew	Duvol	Ncskew	Duvol	Ncskew	Duvol	Ncskew	Duvol
SOA_{t-1}	-0.027**	-0.014**			-0.036***	-0.019***			-0.034***	-0.018***		
	(-1.988)	(-2.143)			(-2.810)	(-3.106)			(-2.642)	(-3.047)		
$Adjfreq_{t-1}$			-0.006**	-0.003***			-0.004**	-0.003***			-0.006***	-0.003***
			(-2.428)	(-2.764)			(-2.171)	(-2.706)			(-3.181)	(-3.586)
Constant	-0.061	0.071	1.780***	0.834***	0.171	0.210	1.666***	0.814***	-0.829	-0.309	1.503***	0.716***
	(-0.106)	(0.253)	(5.382)	(5.185)	(0.339)	(0.841)	(5.834)	(5.778)	(-1.513)	(-1.144)	(5.090)	(4.935)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,029	34,029	54,140	54,140	43,860	43,860	68,332	68,332	49,432	49,432	75,839	75,839
Adjusted R^2	0.0562	0.0683	0.0591	0.0705	0.0502	0.0580	0.0502	0.0582	0.0488	0.0568	0.0479	0.0551

8.3 Tables for chapter 5

Table 5. 1 Summary statistics

This table displays the summary statistics of variables used in this study. Panel A displays the mean, median, 25th and 75th value of variables. The sample covers all manufacturing firms (SIC code 2000–3999) from 2004–2020 with non-missing data for all independent variables and control variables. Detailed variable definitions are displayed in Appendix (Table 5. A.1) and section 2.1.

	Nobs	Mean	SD	P25	P50	P75
Dependent variables						
EAS	8705	0.149	0.060	0.101	0.142	0.186
Weakness	8383	0.080	0.271	0	0	0
Independent variables						
Major_Sales	9504	0.450	0.264	0.230	0.397	0.622
Major_HHI	9504	0.176	0.224	0.040	0.091	0.202
Control variables						
Size	9504	5.647	2.270	4.105	5.733	7.301
Age	9504	2.496	1.012	1.946	2.708	3.258
MTB	9504	1.848	1.626	0.882	1.346	2.188
ROA	9504	-0.079	0.313	-0.113	0.023	0.074
Gro	9504	0.178	0.730	-0.058	0.059	0.206
Loss	9504	0.412	0.492	0	0	1
Seg	9504	2.462	0.766	1.946	2.565	3.045
For	9504	0.430	0.495	0	0	1
Rst	9504	0.399	0.490	0	0	1
Aqv	9504	0.418	0.493	0	0	1
Other variables						
Restat	8460	0.084	0.277	0	0	0
PCM	18060	-0.210	1.819	0.033	0.109	0.180
HHI	19975	0.303	0.227	0.145	0.224	0.405
Major_Size	6288	3.273	2.879	1.233	2.418	4.707
Hostile_Index	5551	0.145	0.084	0.086	0.126	0.180
Cus_Size	6288	7.409	3.755	4.071	7.890	10.697
Cus_Age	6288	2.028	1.101	1.079	2.003	2.944
Cus_ROA	6288	0.034	0.148	0.011	0.035	0.074
Cus_Mtb	6288	1.374	1.107	0.601	1.197	1.807
Big4	9552	0.574	0.494	0	1	1
Audit_Fee	9054	13.692	1.265	12.848	13.728	14.523

Table 5. 2 Customer bargaining power and supplier internal information quality

This table displays the regression results of how customer bargaining power impacts suppliers' internal information quality (IIQ). The regression covers manufacturing firms (SIC code 2000-3999) with non-missing data for all variables. The dependent variable (suppliers IIQ) is measured by suppliers' earnings announcement speed (EAS) and the indicator of disclosure of material weakness (Weakness). Customer bargaining power is measured by sum of major customers' sales (Major_Sales) and the Herfindahl–Hirschman index of major customers (Major_HHI). Firm level variables, including Size, Age, MTB, ROA, Loss, Gro, Seg, For, Rst, and Aqv, as well as industry and year fixed effects are included in each regression. All variables are defined in Appendix (Table 5.A.1). Columns (1)– (2) reports the results of OLS regression, while columns (3)- (4) indicates the results of logit regression. Standard errors are robust to heteroskedasticity. ***, **, or * indicates statistical significance level at the 1%, 5%, or 10% levels, respectively

	OLS		Logistic	
	(1)	(2)	(3)	(4)
VARIABLES	EAS	EAS	Weakness	Weakness
Major_Sales	-0.024***		-1.019***	
	(-5.450)		(-3.826)	
Major_HHI		-0.026***		-1.588***
		(-5.330)		(-4.454)
Size	-0.013***	-0.013***	-0.212***	-0.230***
	(-18.826)	(-18.871)	(-5.180)	(-5.504)
Age	-0.003***	-0.003***	-0.237***	-0.241***
	(-3.117)	(-3.022)	(-4.177)	(-4.296)
MTB	-0.007***	-0.007***	-0.243***	-0.249***
	(-11.420)	(-11.477)	(-3.780)	(-3.824)
ROA	-0.008**	-0.008**	-0.122	-0.176
	(-2.137)	(-2.276)	(-0.546)	(-0.801)
Loss	0.007***	0.007***	0.447***	0.420***
	(3.779)	(3.643)	(3.531)	(3.329)
Gro	0.001	0.001	-0.073	-0.055
	(0.639)	(1.166)	(-1.092)	(-0.783)
Seg	-0.001	-0.001	0.024	0.022
	(-0.671)	(-0.555)	(0.248)	(0.233)
For	0.005**	0.005**	0.157	0.160
	(2.218)	(2.355)	(1.292)	(1.323)
Rst	-0.014***	-0.014***	-0.185	-0.173
	(-7.438)	(-7.529)	(-1.641)	(-1.535)
Aqv	-0.006***	-0.006***	-0.091	-0.077
	(-4.031)	(-3.791)	(-0.822)	(-0.691)
Constant	0.258***	0.251***	1.167**	1.088**
	(43.375)	(44.393)	(2.255)	(2.175)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	8,705	8,705	8,383	8,383
Adjusted/ Pseudo R^2	0.342	0.340	0.0926	0.0948

Table 5. 3 Two stage least squares regression

This table displays the two stages least squares (2SLS) regression results of how customer bargaining power impacts suppliers' internal information quality (IIQ). The instrumental variable (IV) used for panels A and B is the value of merger wave in customer industries (*Cus_MA_Wave*), and the IV used in panel C and D is the aggregate regulatory restrictions index for customers' industries (*Cus_Reg_Index*). Specifically, Panels A and C report the first stage regressions using *Cus_MA_Wave* and *Cus_Reg_Index* as instrumental variable, respectively. Panels B and D report the second stage regressions using *Cus_MA_Wave* and *Cus_Reg_Index* as instrumental variable, respectively. The regressions cover manufacturing firms (SIC code 2000-3999) with non-missing data for all variables. Suppliers' internal information quality is measured by suppliers' earnings announcement speed (EAS) and the indicator of disclosure of material weakness (Weakness). Customer bargaining power is measured by sum of major customers' sales (Major_Sales), and the Herfindahl–Hirschman index of major customers (Major_HHI). Firm level variables, including Size, Age, MTB, ROA, Loss, Gro, Seg, For, Rst, and Aqv, as well as industry and year fixed effects are included in each regression. All variables are defined in Appendix (Table 5.A.1). Standard errors are robust to heteroskedasticity. ***, **, or * indicates statistical significance level at the 1%, 5%, or 10% levels, respectively

Panel A. Instrumental variable: Customer merger wave (First stage)				
	EAS Sample		Weakness Sample	
	(1)	(2)	(3)	(4)
VARIABLES	Major_Sales	Major_HHI	Major_Sales	Major_HHI
Cus_MA_Wave	1.472***	1.705***	1.354***	1.649***
	(16.115)	(18.253)	(15.358)	(18.553)
Constant	0.625***	0.265***	0.652***	0.282***
	(15.650)	(11.878)	(15.007)	(11.001)
Control Variables	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	4,783	4,783	4,583	4,583
Under identification test				
Kleibergen-Paap rk LM statistic:	160.778	137.608	144.844	130.112
Weak identification test				
Cragg-Donald Wald F statistic:	669.1	2057.52	628.572	2135.46
Kleibergen–Paap Wald F statistic:	259.705	333.164	235.871	344.225

Panel B. Instrumental variable: Customer merger wave (Second stage)				
	(1)	(2)	(3)	(4)
VARIABLES	EAS	EAS	Weakness	Weakness
Eestimated Major_Sales	-0.050***		-0.145***	
	(-3.886)		(-2.790)	
Eestimated Major_HHI		-0.043***		-0.119***
		(-3.823)		(-2.799)
Constant	0.279***	0.259***	0.320***	0.259***
	(22.515)	(29.729)	(5.459)	(5.823)
Control Variables	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	4,783	4,783	4,583	4,583
Adjusted R^2	0.327	0.335	0.0185	0.0276

Panel C. Instrumental variable: Customer regulatory restrictions index (First stage)				
	EAS Sample		Weakness Sample	
	(1)	(2)	(3)	(4)
VARIABLES	Major_Sales	Major_HHI	Major_Sales	Major_HHI
Reg_index	0.050***	0.048***	0.050***	0.049***
	(17.530)	(17.582)	(16.763)	(17.212)
Constant	0.539***	0.220***	0.542***	0.215***
	(8.338)	(6.717)	(8.021)	(5.776)
Control variables	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,823	2,823	2,761	2,761
Under identification test				
Kleibergen–Paap LM statistic:	144.25	144.392	131.907	133.737
Weak identification test				
Cragg-Donald Wald F statistic:	1059.216	1672.113	1053.321	1682.9
Kleibergen–Paap Wald F statistic:	307.29	309.139	280.994	296.242

Panel D. Instrumental variable: Customer regulatory restrictions index (Second stage)				
	(1)	(2)	(3)	(4)
VARIABLES	EAS	EAS	Weakness	Weakness
Eestimated Major_Sales	-0.030***		-0.102**	
	(-2.835)		(-2.491)	
Eestimated Major_HHI		-0.031***		-0.105**
		(-2.788)		(-2.541)
Constant	0.276***	0.266***	0.343***	0.310***
	(18.139)	(19.225)	(3.802)	(3.630)
Control variables	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,823	2,823	2,761	2,761
Adjusted R^2	0.364	0.363	0.0181	0.0222

Table 5. 4 Robustness checks

This table contains several robustness tests of how customer bargaining power impacts suppliers' internal information quality (IIQ). Panel A re-examines the baseline results by using unintentional error restatement (*Restat*) as IIQ measurement. Panel B re-estimates the baseline regression by adopting price-cost margin (*PCM*), industry level HHI index of supplier (*Industry_HHI*), and weighted sum of major customer size (*Major_Size*) as alternative measurements for customer bargaining power. Panel C displays the results of tests which lag all independent variables and control variables by one period. Panel D displays the results of baseline model which include all other non-financial and non-utility industries. Panel E re-estimates customer bargaining power by including government customers. Firm level variables, including Size, Age, MTB, ROA, Loss, Gro, Seg, For, Rst, and Aqv, as well as industry and year fixed effects are included in each regression. All variables are defined in Appendix (Table 5.A.1). Standard errors are robust to heteroskedasticity. ***, **, or * indicates statistical significance level at the 1%, 5%, or 10% levels, respectively

Panel A. Alternative IIQ measurement

	(1)	(2)	(3)	(4)
VARIABLES	Restat (OLS)	Restat (OLS)	Restat (Logit)	Restat (Logit)
Major_Sales	-0.033**		-0.443**	
	(-2.382)		(-2.301)	
Major_HHI		-0.028*		-0.444*
		(-1.701)		(-1.656)
Constant	0.120***	0.108***	-0.889**	-1.022***
	(5.694)	(5.484)	(-2.380)	(-2.831)
Control variables	Yes	Yes	Yes	Yes
Industry/Year fixed effects	Yes	Yes	Yes	Yes
Observations	8,460	8,460	8,433	8,433
Adjusted/ Pseudo R^2	0.0189	0.0185	0.0403	0.0398

Panel B. Alternative customer bargaining power measurements

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	EAS	Weakness	EAS	Weakness	EAS	Weakness
PCM	0.005***	0.114***				
	(12.129)	(4.969)				
Industry_HHI			0.024***	0.304**		
			(4.719)	(2.399)		
Major_Size					-0.001*	-0.059**
					(-1.835)	(-2.297)
Constant	0.257***	0.774**	0.231***	-0.270	0.225***	0.064
	(62.675)	(2.294)	(62.159)	(-0.562)	(36.907)	(0.133)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry/Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,503	15,845	18,190	17,442	6,493	6,269
Adjusted/ Pseudo R^2	0.380	0.0941	0.357	0.0736	0.317	0.0828

Panel C. Lagged independent variables				
	(1)	(2)	(3)	(4)
VARIABLES	EAS $_t$	EAS $_t$	Weakness $_t$	Weakness $_t$
Major_Sales$_{t-1}$	-0.017***		-0.633**	
	(-3.611)		(-2.126)	
Major_HHI $_{t-1}$		-0.018***		-1.067***
		(-3.424)		(-2.759)
Constant	0.257***	0.225***	0.813	0.787
	(62.675)	(11.684)	(1.367)	(1.386)
Control variables	Yes	Yes	Yes	Yes
Industry/Year fixed effects	Yes	Yes	Yes	Yes
Observations	7,939	7,939	7,843	7,843
Adjusted/ Pseudo R^2	0.323	0.321	0.0811	0.0827

Panel D. Including non-manufacturing industries				
	(1)	(2)	(3)	(4)
VARIABLES	EAS	EAS	Weakness	Weakness
Major_Sales	-0.015***		-0.692***	
	(-4.676)		(-3.542)	
Major_HHI		-0.014***		-0.952***
		(-3.574)		(-3.593)
Constant	0.255***	0.250***	-0.261	-0.371
	(56.600)	(56.757)	(-0.383)	(-0.557)
Control variables	Yes	Yes	Yes	Yes
Industry/Year fixed effects	Yes	Yes	Yes	Yes
Observations	14,255	14,255	13,525	13,525
Adjusted/ Pseudo R^2	0.330	0.328	0.0977	0.0980

Panel E. Including Government customers

VARIABLES	(1) EAS	(2) EAS	(3) Weakness	(4) Weakness
Major_Sales	-0.018***		-0.764***	
	(-4.452)		(-3.074)	
Major_HHI		-0.017***		-1.265***
		(-3.829)		(-3.868)
Constant	0.257***	0.250***	0.946*	0.919*
	(44.847)	(46.294)	(1.928)	(1.937)
Control variables	Yes	Yes	Yes	Yes
Industry/Year fixed effects	Yes	Yes	Yes	Yes
Observations	9,354	9,354	8,935	8,935
Adjusted/ Pseudo R^2	0.349	0.347	0.0848	0.0870

Table 5. 5 Control for corporate governance

This table re-examines the baseline tests by controlling for corporate governance. Panel A displays the results including corporate governance level (*Hostile_Index)* as control variable. Panel B examines whether corporate governance level will impact firms' internal information quality (IIQ). The regressions cover manufacturing firms (SIC code 2000-3999) with non-missing data for all variables. Firm level variables, including Size, Age, MTB, ROA, Loss, Gro, Seg, For, Rst, and Aqv, as well as industry and year fixed effects are included in each regression. All variables are defined in Appendix (Table 5.A.1). Standard errors are robust to heteroskedasticity. ***, **, or * indicates statistical significance level at the 1%, 5%, or 10% levels, respectively

Panel A. Control for hostile takeover index

	(1)	(2)	(3)	(4)
VARIABLES	EAS	EAS	Weakness	Weakness
Major_Sales	-0.022***		-0.264*	
	(-4.623)		(-1.657)	
Major_HHI		-0.017***		-0.474**
		(-2.859)		(-2.154)
Hostile_Index	0.011	0.014	0.222	0.236
	(0.483)	(0.620)	(0.326)	(0.350)
Size	-0.014***	-0.014***	-0.146***	-0.151***
	(-17.877)	(-17.567)	(-5.076)	(-5.176)
Age	0.001	0.001	0.020	0.019
	(0.627)	(0.677)	(0.295)	(0.284)
MTB	-0.006***	-0.006***	-0.058*	-0.057*
	(-7.886)	(-7.790)	(-1.822)	(-1.794)
ROA	-0.012***	-0.012***	-0.069	-0.080
	(-2.623)	(-2.601)	(-0.454)	(-0.527)
Loss	0.001	0.001	-0.003	0.003
	(0.572)	(0.661)	(-0.074)	(0.077)
Gro	0.006***	0.006***	0.235***	0.231***
	(2.788)	(2.756)	(2.651)	(2.609)
Seg	-0.004*	-0.003*	0.013	0.013
	(-1.896)	(-1.691)	(0.203)	(0.203)
For	0.004*	0.005**	0.111	0.111
	(1.907)	(2.035)	(1.413)	(1.418)
Rst	-0.009***	-0.009***	0.000	0.004
	(-4.607)	(-4.693)	(0.005)	(0.049)
Aqv	-0.004**	-0.004**	-0.069	-0.067
	(-2.463)	(-2.139)	(-0.927)	(-0.903)
Constant	0.245***	0.236***	0.096	0.085
	(37.479)	(37.839)	(0.276)	(0.252)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	5,519	5,519	4,593	4,593
Adjusted/ Pseudo R^2	0.341	0.336	0.0902	0.0912

Panel B. The impact of corporate governance on IIQ				
	(1)	(2)	(3)	(4)
VARIABLES	EAS	Weakness	EAS	Weakness
Hostile_Index	-0.002	-0.117	-0.001	-0.007
	(-0.150)	(-0.249)	(-0.034)	(-0.120)
Size	-0.015***	-0.101***	-0.014***	-0.013***
	(-33.523)	(-6.946)	(-26.397)	(-5.524)
Age	0.002*	0.008	0.002*	0.004
	(1.825)	(0.197)	(1.646)	(0.626)
MTB	-0.005***	-0.080***	-0.006***	-0.009***
	(-11.506)	(-4.215)	(-12.334)	(-3.930)
ROA	-0.010***	-0.209**	-0.005*	0.001
			(-1.739)	(0.074)
Loss			0.002**	0.006
			(2.159)	(1.337)
Gro			0.010***	0.044***
			(5.653)	(4.564)
Seg			0.000	0.013**
			(0.140)	(2.243)
For			0.003*	0.011*
			(1.854)	(1.676)
Rst			-0.009***	-0.007
			(-6.425)	(-1.146)
Aqv			-0.003**	-0.001
			(-2.282)	(-0.232)
Constant	0.230***	-0.038	0.227***	0.098***
	(70.782)	(-0.202)	(55.491)	(5.223)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	17,779	13,482	11,294	9,546
Adjusted R^2	0.357	0.0677	0.382	0.0353

Table 5. 6 Control for customer characteristics and auditor characteristics

This table re-examines the baseline tests by controlling for customer characteristics and auditor characteristics. Columns (1)– (2) display the results including aggregate customer size, age, market to book ratio and ROA as additional control variables. Columns (3)– (4) include indicator of four biggest auditor (*BIG4*) and natural logarithm of audit fees (Audit_Fee) as additional control variables. Columns (5)– (6) add all additional controls in the regression model. All the regressions cover manufacturing firms (SIC code 2000-3999) with non-missing data for all variables. Firm level variables, including Size, Age, MTB, ROA, Loss, Gro, Seg, For, Rst, and Aqv, as well as industry and year fixed effects are included in each regression. All variables are defined in Appendix (Table 5.A.1). Standard errors are robust to heteroskedasticity. ***, **, or * indicates statistical significance level at the 1%, 5%, or 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	EAS	EAS	Weakness	Weakness	EAS	EAS	Weakness	Weakness	EAS	EAS	Weakness	Weakness
Major_Sales	-0.017***		-0.259*		-0.020***		-0.925***		-0.015***		-0.270*	
	(-3.327)		(-1.712)		(-4.685)		(-3.475)		(-2.823)		(-1.713)	
Major_HHI		-0.019***		-0.441**		-0.020***		-1.455***		-0.013**		-0.486**
		(-3.147)		(-2.376)		(-4.097)		(-4.038)		(-2.112)		(-2.406)
Cus_Size	0.000	0.000	0.007	0.006					0.000	0.000	0.003	0.002
	(0.395)	(0.392)	(0.458)	(0.422)					(0.246)	(0.274)	(0.177)	(0.121)
Cus_Age	-0.000	0.000	0.043	0.051					0.001	0.001	0.048	0.057
	(-0.130)	(0.242)	(0.952)	(1.110)					(0.357)	(0.669)	(1.054)	(1.234)
Cus_MTB	-0.001	-0.001	-0.093**	-0.088*					-0.002	-0.002	-0.078*	-0.072
	(-1.492)	(-1.344)	(-1.980)	(-1.871)					(-1.629)	(-1.569)	(-1.696)	(-1.578)
Cus_ROA	0.000	0.000	-0.000	-0.000					0.000	0.000	-0.000	-0.000
	(0.447)	(0.560)	(-0.835)	(-0.837)					(0.347)	(0.456)	(-0.739)	(-0.739)
Audit_Fee					-0.005***	-0.005***	0.161	0.189*	-0.003*	-0.003	0.210***	0.221***
					(-2.963)	(-2.843)	(1.548)	(1.730)	(-1.675)	(-1.560)	(3.336)	(3.407)
BIG4					-0.017***	-0.017***	-0.590***	-0.578***	-0.014***	-0.014***	-0.257***	-0.253***
					(-7.423)	(-7.394)	(-5.399)	(-5.295)	(-5.451)	(-5.433)	(-3.867)	(-3.812)
Constant	0.237***	0.231***	-0.086	-0.110	0.303***	0.294***	-0.719	-1.066	0.271***	0.262***	-2.222***	-2.348***

	(32.073)	(34.835)	(-0.299)	(-0.399)	(17.522)	(16.871)	(-0.577)	(-0.838)	(12.683)	(12.251)	(-2.952)	(-3.070)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry/Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,799	5,799	5,516	5,516	8,305	8,305	8,214	8,214	5,484	5,484	5,420	5,420
Adjusted/ Pseudo R^2	0.329	0.327	0.0841	0.0852	0.357	0.354	0.0976	0.0995	0.345	0.343	0.0961	0.0975

Table 5. 7 Monitor incentives: Relationship-specific investment

This table displays the results of how relationship-specific investment (RSI) between suppliers and customer impacts major customers' disciplinary behaviour. The RSI is measured by suppliers' research and development expenditure scaled by total asset (R&D). The table re-examines the baseline tests by splitting the sample into subsamples with high and low R&D investment based on the median value of the year. The regressions cover manufacturing firms (SIC code 2000-3999) with non-missing data for all variables. Suppliers' internal information quality is measured by suppliers' earnings announcement speed (EAS) and the indicator of disclosure of material weakness (Weakness). Customer bargaining power is measured by sum of major customers' sales (Major_Sales) and the Herfindahl–Hirschman index of major customers (Major_HHI). Firm level variables, including Size, Age, MTB, ROA, Loss, Gro, Seg, For, Rst, and Aqv, as well as industry and year fixed effects are included in each regression. All variables are defined in Appendix (Table 5.A.1). Standard errors are robust to heteroskedasticity. ***, **, or * indicates statistical significance level at the 1%, 5%, or 10% levels, respectively

	High R&D		Low R&D		High R&D		Low R&D	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	EAS	EAS	EAS	EAS	Weakness	Weakness	Weakness	Weakness
Major_Sales	-0.021***		-0.007		-1.219***		0.024	
	(-4.289)		(-0.955)		(-3.507)		(0.057)	
Major_HHI		-0.011**		-0.014		-1.187***		-0.447
		(-2.059)		(-1.310)		(-2.835)		(-0.664)
Constant	0.213***	0.202***	0.284***	0.283***	1.960	1.525	1.129	1.268*
	(28.493)	(28.733)	(31.776)	(32.444)	(1.332)	(0.995)	(1.446)	(1.687)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,745	3,745	3,453	3,453	3,616	3,616	3,296	3,296
Adjusted/ Pseudo R^2	0.389	0.383	0.451	0.452	0.0849	0.0816	0.137	0.138

Table 5. 8 Monitor incentives: Durable/ special product producer

This table displays the results of how unique product producers impact customers' disciplinary behaviour. The unique product producer is measured by suppliers' selling, general and administrative expenses scaled by sales (SG&A). The table re-examines the tests of baseline model by splitting the sample into subsamples with high and low SG&A based on the median value of the year. The regression covers manufacturing firms (SIC code 2000-3999) with non-missing data for all variables. Suppliers' internal information quality is measured by suppliers' earnings announcement speed (EAS) and the indicator of disclosure of material weakness (Weakness). Customer bargaining power is measured by sum of major customers' sales (Major_Sales) and the Herfindahl–Hirschman index of major customers (Major_HHI). Firm level variables, including Size, Age, MTB, ROA, Loss, Gro, Seg, For, Rst, and Aqv, as well as industry and year fixed effects are included in each regression. All variables are defined in Appendix (Table 5.A.1). Standard errors are robust to heteroskedasticity. ***, **, or * indicates statistical significance level at the 1%, 5%, or 10% levels, respectively

	High SG&A		Low SG&A		High SG&A		Low SG&A	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	EAS	EAS	EAS	EAS	Weakness	Weakness	Weakness	Weakness
Major_Sales	-0.031***		-0.010		-1.579***		-0.156	
	(-6.202)		(-1.639)		(-4.678)		(-0.428)	
Major_HHI		-0.024***		-0.015		-1.863***		-0.388
		(-4.458)		(-1.606)		(-4.190)		(-0.743)
Constant	0.251***	0.239***	0.281***	0.278***	0.457	0.207	2.581***	2.579***
	(33.865)	(34.191)	(34.623)	(35.754)	(0.695)	(0.324)	(3.635)	(3.755)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,692	4,692	4,013	4,013	4,433	4,433	3,903	3,903
Adjusted/ Pseudo R^2	0.357	0.349	0.380	0.379	0.0895	0.0884	0.127	0.127

Table 5. 9 Disciplinary incentives: Customers' internal information quality

This table displays the results of how customer IIQ level impacts customers' disciplinary behaviour. The customer IIQ level is measured by aggregated customer earning announcement speed (Cus_EAS). The table re-examines the tests of baseline model by splitting the sample into subsamples with high and low Cus_EAS based on the median value of the year. The regression covers manufacturing firms (SIC code 2000-3999) with non-missing data for all variables. Suppliers' internal information quality is measured by suppliers' earnings announcement speed (EAS) and the indicator of disclosure of material weakness (Weakness). Customers bargaining power is measured by sum of major customers' sales (Major_Sales) and the Herfindahl–Hirschman index of major customers (Major_HHI). Firm level variables, including Size, Age, MTB, ROA, Loss, Gro, Seg, For, Rst, and Aqv, as well as industry and year fixed effects are included in each regression. All variables are defined in Appendix (Table 5.A.1). Standard errors are robust to heteroskedasticity. ***, **, or * indicates statistical significance level at the 1%, 5%, or 10% levels, respectively

	Low Cus_EAS		High Cus_EAS		Low Cus_EAS		High Cus_EAS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	EAS	EAS	EAS	EAS	Weakness	Weakness	Weakness	Weakness
Major_Sales	-0.026***		-0.005		-0.856**		0.120	
	(-4.077)		(-0.617)		(-2.102)		(0.233)	
Major_HHI		-0.023***		-0.012		-0.989**		-0.720
		(-2.651)		(-1.426)		(-2.221)		(-0.808)
Constant	0.254***	0.243***	0.220***	0.222***	0.085	-0.152	1.444**	1.890***
	(27.685)	(28.237)	(20.651)	(23.216)	(0.096)	(-0.200)	(2.422)	(3.664)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,476	2,476	2,521	2,521	2,153	2,153	2,121	2,121
Adjusted/ Pseudo R^2	0.382	0.375	0.310	0.311	0.118	0.117	0.120	0.121

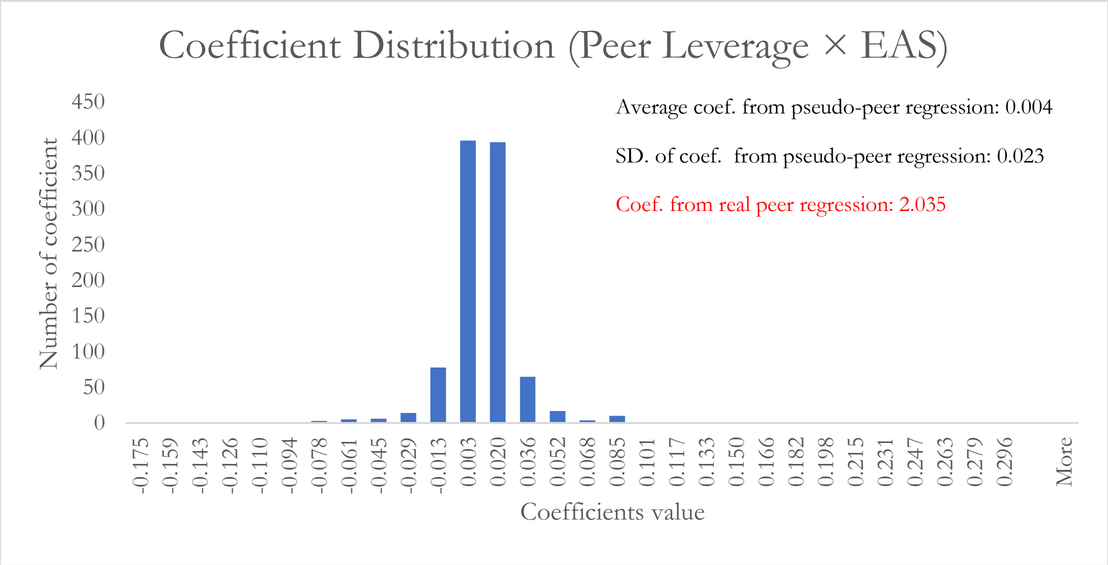

Figure 3.1.A. Peer Leverage × EAS

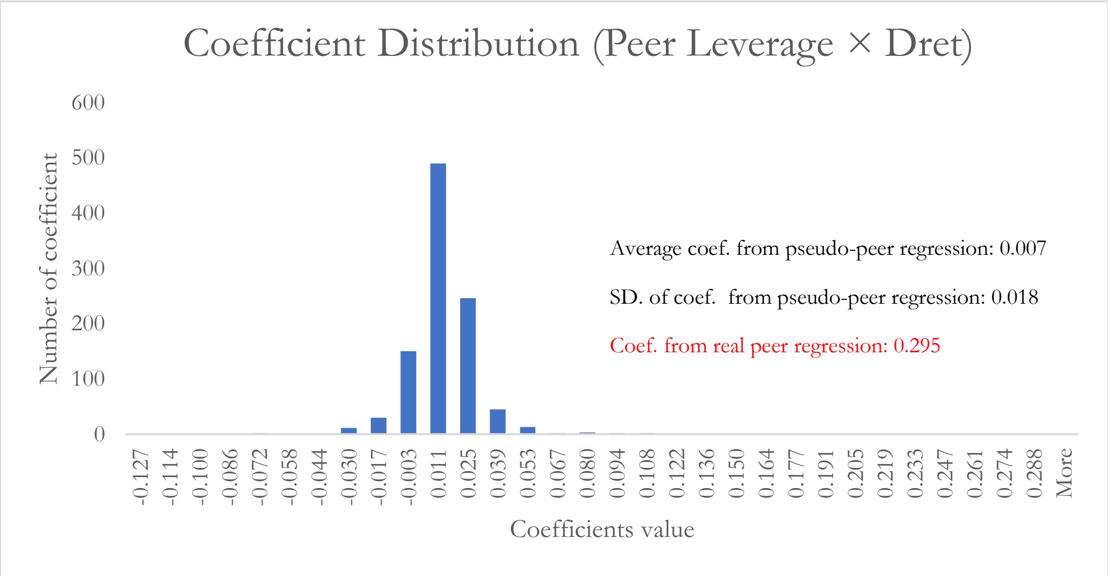

Figure 3.1.B. Peer Leverage × Dret

Figure 3. 1 Placebo tests: coefficient distribution

The figure presents the distrbution of coefficients from the placebo tests (section 3.4.3). For each firm with n peers, we randomly selected n firms from entire market as its pseudo-peer firms and use the average leverage of pseudo-peers to conduct our baseline regression- equation (2). We repeated this process 1000 times and reported the distribution of the coeffients (β_1 in equation (2)) in the figures.The horizental-asix in the figure is the coefficient value and the vertical-asix refers to the number of coefficients in this value range.

9. Appendix

Table 3.A.1 Variable Definitions

We draw firms' monthly stock return data from the Center for Research in Security Prices (CRSP) database, and accounting data from the Compustat database available on the Wharton Research Data Services server. Earnings announcement data comes from Compustat and I/B/E/S database. Insider trading data comes from Thomson Financial. Firm's restatement and material weakness data come from Audit Analytics. CEO duality data is drawn from the ExecuComp database. Firms' takeover index data comes from Dr Stephen McKeon's personal webpage. Following Leary and Roberts (2014)'s paper, we start our sample from 1965 and extend it to 2017. All financial firms (SIC code 6000–6999), utility (SIC code 4900–4999) and government entities (SIC code greater than or equal to 9000) are excluded from the sample.

Variable Name	References	Variable Definition
Total Book Assets	Leary and Roberts (2014)	Total Book Assets: **at**
Total Debt		Short-Term Debt (**dltt**)+Long-Term Debt(**dlc**)
Book Leverage		Total Debt/Total Book Assets
Market Value of Assets (MVA)		Stock Price (**prcc_f**) ×Common Share (**cshpri**)+Long-TermDebt (**dlc**)+Short-Term Debt (**dltt**)+Preferred Stock left(**pstkl**)-Liquidating Value (**txditc**)
Market Leverage		Total Debt/MVA
Size		Log (Sales) = Log(**sale**)

Tang		Asset tangibility. Net PPE (**ppent**)/ Total Book Assets (**at**)
Prof		Profitability. EBITDA (**oibdp**) / Total Book Assets (**at**)
MTB		Market-to-book ratio. MVA/Total Book Assets (**at**)
EAS		Number of days between the fiscal year end and earnings announcement date, scaled by 365.
Restatement	Gallemore and Labro (2015)	Dummy variable: equal to one if the firm reported restatements caused by unintentional errors in the fiscal year, and zero otherwise.
Weakness		Dummy variable: equal to one if the firm reported a SOX Section 404 material weakness in the fiscal year, and zero otherwise
Dret	Chen et al. (2018)	Difference between the profitability of insider trading for divisional managers and top managers during the last three years. Trading profit is measured by the average cumulative size-adjusted abnormal return following opportunistic trade over the six-month period for firm *i* in year *t*, over the prior three fiscal years. Routine trades are excluded (trades will be defined as routine trade if a manager trade in the similar month for at least three years). CEO, CFO and COO are defined as top managers. Divisional managers are managers with role code = AV, EVP, O, OP, OT, S, SVP, VP, GP, LP, M, MD, OE, TR, GM, C, CP in Thomson Financial database.
ROE		Return on equity: net income (**ni**)/ (Price× Number of shares outstanding)
ROA		Return on Asset: net income (**ni**)/ Total assets (**at**)
Entrenched	Baginski et al. (2018)	Entrenched CEO. A dummy variable equal to one if a CEO is defined as entrenched and zero otherwise. A CEO is defined as entrenched if he/ she is also the chair of the board.

Takeover	Cain, McKeon, and Solomon (2017)	Takeover index from Cain, McKeon, and Solomon (2017). A higher index indicates a higher level of corporate governance for the firm.
Size_rel		Relative size. Firm size compared with peer firms' average size.
Z-score	Leary and Roberts (2014)	Altman's Z-score (Altman 1968). Z-score= (3.3 × pretax income **(pi)** +sales (**sale)** + 1.4 × retained earnings (**re)** + 1.2 × (current asset (**act)** −current liabilities (**lct)**))/ total asset (**at)**.

Table 3.A.2. Stock Return Factor Regression Results

The sample includes monthly return for all non-financial, non-utility firms in the monthly CRSP database from 1965–2017. The sample excludes firms which are not available in the annual Compustat database. The table displays the average value of factor loadings and adjusted R^2 values from regression:

$$R_{ijt} = \alpha_{ijt} + \beta_{ijt}^{M}(RM_t - RF_t) + \beta_{ijt}^{IND}(\bar{R}_{-ijt} - RF_t) + \eta_{ijt}$$

Where R_{ijt} is the return to firm *i* in industry *j* during month *t*. $(RM_t - RF_t)$ is the market excess return. $(\bar{R}_{-ijt} - RF_t)$ is the industry excess return for all the firms average return excluding firm *i*'s return. The industries are defined by 3-digit SIC codes. The regression is estimated for each firm on a rolling annual basis using historical monthly returns data from the CRSP database. Each regression requires at least 24 months of historical data and uses up to 60 months of data in the estimation. Expected returns are computed using the estimated factor loadings and realized factor returns one year. Idiosyncratic returns are computed as the difference between realized and expected returns.

	Mean	Median	SD
α_{it}	0.007	0.006	0.020
β_{it}^{M}	0.407	0.444	0.992
β_{it}^{IND}	0.640	0.537	0.689
Obs. Per Regression	54	60	11
Adjusted R^2	0.233	0.213	0.176
Average Monthly Return	0.014	0.000	0.176
Expected Monthly Return	0.016	0.014	0.087
Idiosyncratic Monthly Return	-0.002	-0.010	0.167

Table 4.A.1 Chapter 4 variable defination

Variable	Description	Source
Ncskew	The negative coefficient skewness, calculated by taking the negative of the third moment of firm-specific weekly returns for each sample year and dividing it by the standard deviation of firm-specific weekly returns raised to the third power. A higher value of Ncskew indicates higher level of crash risk.	Datastream
Duvol	The down-to-up volatility. For any stock in each year, the weekly stock returns are divided into groups that are above the annual mean (up group) and below the annual mean (down group). The *Duvol* is calculated as the logarithm of the standard deviation of the up group to the standard deviation of the down group. A higher value of *Duvol* indicates a higher level of crash risk.	Datastream
SOA	Speed of adjustment. According to Leary and Michealy (2011), SOA is the speed by which the firm's payout ratio converges to its target payout ratio (TPR). The TPR is calculated as the firm's median level of dividend per share (DPS) to earnings per share during the sample period. The previous year's deviation of the firm's dividend level to its target dividend level is calculated as the product of TPR and earnings per share minus last year's dividend per share. Finally, we regress the firm's deviation of last year's dividend level to its target level on the firm's true dividend change this year, which is calculated as this year's DPS minus last year's dividend	Worldscope

	change, based on the last ten years' observations. The coefficient of the regressor is the speed of adjustment of the firm's dividend level. A higher level of SOA indicates a lower level of dividend smoothing.	
Adjfreq	The adjustment frequency is the number of times the firm significantly changes its dividend policy during the last five years. A significant change is defined as more than one percent change in absolute value. A higher level of Adjfreq indicates a lower level of dividend smoothing.	Worldscope
Size	The natural logarithm of the firm's market capitalization.	Worldscope
Lev	The ratio of the firm's total debt to its total assets.	Worldscope
ROA	The ratio of the firm's net income to its total assets.	Worldscope
MTB	The ratio of market value to book value of equity.	Worldscope
Sigma	The standard deviation of the firm-specific weekly return within a given year.	Datastream
Ret	The mean of the firm-specific weekly return within a given year, multiplied by 100.	Datastream
Accm	The three-years rolling sum of the firm's absolute value of discretionary accruals. The discretionary accruals are calculated based on the modified Jones model. (Dechow, Sloan, and Sweeney 1995).	Worldscope

Dturn	The difference between the average monthly stock turnover over the current year and that over the previous year. The monthly stock turnover is calculated as the monthly trading volume divided by the number of shares outstanding during the month.	Worldscope
SD (EPS)	The standard deviation of earnings per share over the last five years.	Worldscope
DPS	Dividend per share.	Worldscope
GDP_grow	The countries' annual GDP growth rate.	World Development Indicators
GDP/Captia	The natural logarithm of countries' annual GDP per capita.	World Development Indicators
Mcap/GDP	The countries' stock market capitalization scaled by its GDP.	World Development Indicators
Fore Error	Analyst forecast errors. The absolute difference between actual annual earnings per share and the median level of earnings forecast, standardized by the absolute value of the median earnings per share forecast.	I/B/E/S
Fore Disper	Analysts' forecast dispersion. The standard deviation of analysts' earnings per share forecast, standardized by the absolute value of the median earnings per share forecast.	I/B/E/S
DisAccruals	The discretionary accruals. The discretionary accruals are calculated based on the modified Jones model. (Dechow, Sloan, and Sweeney	Worldscope

	1995). See section 4.1.2.	
AbnProd	Abnormal production cost. The absolute value of residuals for Roychowdhury's (2006) production cost model. See section 4.1.2.	Worldscope
AbnDisexp	Abnormal discretionary expenses. The absolute value of residuals for Roychowdhury's (2006) discretionary expenses model. See section 4.1.2.	Worldscope

Table 4.A.2: Chapter 4 Country-level variable definitions

Variable	Description	Source
Disclosure index	An index which is constructed as the arithmetic mean of six disclosure requirement laws index: (1) prospectus; (2) compensation; (3) shareholders; (4) inside ownership; (5) irregular contracts; and (6) transactions. The disclosure index is a variable ranging from zero to one, and a higher value indicates a higher level of investor protection about information disclosure.	La Porta, Lopez-de-Silanes, and Shleifer (2006)
Liability index	An index which is constructed as the arithmetic mean of three measurements concerning the difficulty of investors recovering their loss due to misleading information: (1) a liability standard for the issuer and its directors; (2) a liability standard for distributors; and (3) a liability standard for accountants. The liability index is a variable ranging from zero to one, and a higher value indicates a higher level of issuer liability.	La Porta, Lopez-de-Silanes, and Shleifer (2006)
Institutional quality	An index constructed as the sum of the following four variables from World Bank's Worldwide Governance Indicator dataset: control of corruption, regulatory quality, rule of law, and government effectiveness. The institutional quality is normalized between zero and one and a higher value indicates stronger institutional quality.	Ellahie and Kaplan (2021)

Table 5.A.1 Chapter 5 Variable definition

Variable	Description	Source
Dependent Variables		
EAS	Number of days between the fiscal year end and earnings announcement date, scaled by 365.	Compustat and I/B/E/S
Weakness	Dummy variable: equals one if the firm reported a SOX Section 404 material weakness in the fiscal year, and zero otherwise	Audit Analytics
Independent Variables		
Major_Sales	Sum of sales to all major customers scales by the total sales for each supplier. The major customer is defined as any customer which account for more than 10% of total sales of the year.	Compustat Segment
Major_HHI	Herfindahl–Hirschman Index (HHI) of all major customers for each supplier, which is the sum of square of sales to each major customers scaled by its total sales in the fiscal year. The major customer is defined as any customer which account for more than 10% of total sales of the year.	Compustat Segment
Control Variables		
Size	The natural logarithm of the firm's sales (**sale**).	Compustat
Age	The natural logarithm of the firms' age. The firms' age is calculated as the difference between first year it is recorded by Compustat database and the current year, plus one.	Compustat
MTB	Market-to-book ratio, which is the market value of asset to the book value of asset (Leary and Roberts, 2014). Market value of asset is calculated as: stock price (**prcc_f**) × common share (**csho**) + total asset (**at**)	Compustat

	– book value of equity (**ceq**).	
ROA	The ratio of the firm’s net income (**ni**) to its total assets (**at**).	Compustat
Gro	Sales growth. Current year’s sales (**sale**) minus previous year’s sales ($\mathbf{sale}_{t-1}$), scaled by previous year’s sales ($\mathbf{sale}_{t-1}$).	Compustat
Loss	Loss indicator. Dummy variable that is assigned a value of one if the income before extraordinary items (**ib**) for the current fiscal year is negative, and zero otherwise	Compustat
Seg	Number of segments. Natural logarithm of the number of business and geographic segments for the fiscal year (log (number of “BUSSEG” and number of “GEOSEG”))	Compustat Segment
For	Foreign currency transaction indicator. Dummy variable that is assigned a value of one if firm have non-zero foreign currency adjustment (**fca**) during the fiscal year, and zero otherwise.	Compustat
Rst	Restructuring indicator. Dummy variable equals one if the firm reports a non-zero value in any of the four restructuring items during the fiscal year, and zero otherwise (**rca**, **rcd**, **rceps**, or **rcp**)	Compustat
Aqv	Merger and acquisition indicator. Dummy variable equals one if the firm engages in acquisitions in the given fiscal year, and zero otherwise (**aqa**, **aqc**, **aqi**, **aqp**, or **aqs**)	Compustat
Additional Control Variables		
Hostile Index	Takeover index from Cain, McKeon, and Solomon (2017). A higher index indicates a higher level of corporate governance for the firm.	Cain, McKeon, and Solomon (2017)

Cus_Size	Aggregated customer size. For a specific supplier, Cus_Size is calculated as sum of all major customers' *Size* weighted by the percentage of sales to each major customer. This number is scaled by the rate of total major customer sales to total sales.	Compustat
Cus_Age	Aggregated customer age. For a specific supplier, Cus_Age is calculated as sum of all major customers' *Age* weighted by the percentage of sales to each major customer. This number is scaled by the rate of this supplier's total major customer sales to its total sales.	Compustat
Cus_MTB	Aggregated customer market-to-book ratio. For a specific supplier, Cus_MTB is calculated as sum of all major customers' *MTB* weighted by the percentage of sales to each major customer. This number is scaled by the rate of this supplier's total major customer sales to its total sales.	Compustat
Cus_ROA	Aggregated customer ROA. For a specific supplier, Cus_ ROA is calculated as sum of all major customers' *ROA* weighted by the percentage of sales to each major customer. This number is scaled by the rate of this supplier's total major customer sales to its total sales.	Compustat
BIG4	Auditor indicator. Dummy variable equals one if the firm is audited by one of the four biggest audit firms, and zero otherwise (**au**=2, 4, 5, or 7)	Compustat
Audit_Fee	Natural logarithm of audit fee of the fiscal year.	Audit Analystics
Other Variables		
PCM	Price cost margin. Supplier sales (**sale**) deduct cost of goods sold (**cogs**) and general and administrative expense (**xsga**), scaled by sales (**sale**).	Compustat
Industry_HHI	Industry level Herfindahl–Hirschman index for each supplier.	Compustat

Major_Size	Size weighted sales of major customers. The Major_Size is calculated as sum of all size-weighted percentage of sales each major customer accounts for, weighted by the size of those major customers. The major customer is defined as any customer which account for more than 10% of total sales of the year.	Compustat
Relationship-specific investment	The research and development (**xrd**) expenditure of suppliers scaled by total sales (**sale**).	Compustat
Unique product producer	Selling, general and administrative expenditure (**xsga**), of each supplier, scaled by its total assets (**at**).	Compustat

Table 5.A.2 Baseline results: Industry-year fixed effects

This table displays the regression results of how customer bargaining power impacts suppliers' internal information quality (IIQ) by including industry × year fixed effects. The regression covers manufacturing firms (SIC code 2000-3999) with non-missing data for all variables. The dependent variable (suppliers IIQ) is measured by suppliers' earnings announcement speed (EAS) and the indicator of disclosure of material weakness (Weakness). Customer bargaining power is measured by sum of major customers' sales (Major_Sales) and the Herfindahl–Hirschman index of major customers (Major_HHI). Firm level variables, including Size, Age, MTB, ROA, Loss, Gro, Seg, For, Rst, and Aqv are included in each regression. All variables are defined in Appendix (Table 5.A.1). Columns (1)- (2) reports the results of OLS regression, while columns (3)- (4) indicates the results of logit regression. Standard errors are robust to heteroskedasticity. ***, **, or * indicates statistical significance level at the 1%, 5%, or 10% levels, respectively

	OLS		Logistic	
	(1)	(2)	(3)	(4)
VARIABLES	EAS	EAS	Weakness	Weakness
Major_Sales	-0.024***		-0.980***	
	(-5.350)		(-3.581)	
Major_HHI		-0.025***		-1.518***
		(-5.184)		(-4.203)
Size	-0.012***	-0.013***	-0.194***	-0.211***
	(-18.067)	(-18.097)	(-4.610)	(-4.964)
Age	-0.003***	-0.003***	-0.237***	-0.239***
	(-2.798)	(-2.690)	(-4.128)	(-4.222)
MTB	-0.007***	-0.007***	-0.203***	-0.207***
	(-10.444)	(-10.494)	(-3.373)	(-3.403)
ROA	-0.010***	-0.011***	-0.226	-0.267
	(-2.693)	(-2.827)	(-1.005)	(-1.200)
Loss	0.007***	0.007***	0.473***	0.450***
	(3.704)	(3.567)	(3.567)	(3.426)
Gro	0.000	0.001	-0.056	-0.036
	(0.515)	(1.002)	(-0.823)	(-0.513)
Seg	-0.001	-0.001	0.032	0.031
	(-0.624)	(-0.506)	(0.326)	(0.316)
For	0.005**	0.005**	0.162	0.167
	(2.359)	(2.486)	(1.299)	(1.339)
Rst	-0.013***	-0.013***	-0.185	-0.171
	(-7.044)	(-7.119)	(-1.592)	(-1.471)
Aqv	-0.007***	-0.006***	-0.151	-0.137
	(-4.147)	(-3.889)	(-1.309)	(-1.194)
Constant	0.256***	0.249***	1.192	1.135
	(42.003)	(42.968)	(1.030)	(1.002)
Industry × Year fixed effects	Yes	Yes	Yes	Yes
Observations	8,705	8,705	7,629	7,629
Adjusted/ Pseudo	0.329	0.327	0.112	0.114