Stock Price Crash Risk:

Evidence from China

PhD Thesis

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ABSTRACT

Stock Price Crash Risk: Evidence from China

This thesis presents three closely related empirical studies which examine, in separate working paper format, important yet understudied determinants of stock price crash risk: trade credit provision, debt and financial assets investment. Drawing from agency theory, particularly, the role of information transparency and "bad news hoarding" under the Chinese emerging markets setting, we document some distinctive patterns from a large sample of Chinese firms which strongly support our predictions. First, we find that trade credit provision significantly increases stock-price crash risk which consistent with our hypotheses that customer-supplier economic links through trade credit facilitate bad news hoarding. Second, we find that debt financing decreases stock price crash risk. This finding supports our prediction that creditors play an effective monitoring role in China's weak informational environment consequently constraint bad news hoarding. Last but not least, we show that firms investing less in capital assets hold more financial assets. Stock price crash risk decreases with financial assets investment and increases with capital investment. These findings support the view that for firms with severer agency problems, capital investment increases agency costs and facilitate bad news hoarding, whereas financial assets investment reduces firm information asymmetry due to better information transparency.

CHAPTER 1

Prologue

Finance literature has largely focused on the importance of information transparency in safeguarding shareholder values. In this thesis, I continue the ongoing discussions among finance scholars on the role of information quality by investigating individual stock price crash risk. Typically, crash risk is defined as large negative return outliers, which is measured by “negative coefficient of skewness” and “down-to-up volatility” of market adjusted individual stock returns (Chen et al., 2001). Among several pioneering studies, Jin and Myer (2006) investigate the role of synchronicity between managers and outside investors in impacting probability of stock price crashes. They propose that lack of information transparency allows managers to extract part of firm’s operating cash flows that is not perceived by outside investors. Hence, mangers are incentivized to reduce downside risk by hoarding bad news. However, they may only do this up to certain limit and eventually are forced to release bad news to market at once, leading to stock price crashes.

A large body of recent literature builds on these early works and investigates the determinants of crash risk particularly focusing on various aspects of firm that are associated with information transparency. One stream of literature has paid attention to the impacts of quality and nature of financial reporting on crash risk, such as accounting regime (Bleck and Liu, 2007), opaque financial information (Hutton et al., 2009), corporate tax avoidance (Kim et al., 2011), IFRS adoption (Defond et al., 2014), financial statement comparability (Kim et al., 2016), conditional accounting conservatism (Kim and Zhang, 2016), financial derivatives and opacity (Dewally et al., 2013), as well as fair value accounting of investment property (Hsu et al., 2019). The other stream of literature focuses on managerial risk taking through risky practices, incentivizing of risk, or cultural and behavioral risk predilections (Callen and Fang, 2015a; Hong et al., 2018; Kim et al., 2011a; 2011b; Li et al., 2017; Xu et al., 2013; Yuan et al., 2016).

While the majority of these earlier studies are conducted on the Western, especially the US market, a notable stream has paid attention to the Chinese stock markets where individual stock price crashes are more prevalent. These papers identify several factors rather distinctive under the Chinese context that are related to crash risk such as: political connection (Chen et al., 2018; Li and Chan, 2016; Luo et al., 2016; Piotroski et al., 2015), institutions-related explanations, legal voids and analyst coverage (Zhang et al., 2017; Chen et al., 2018; Xu et al., 2013; Xu et al., 2014; Yuan et al., 2016), as well as lack of social trust (Li et al., 2017; Cao et al., 2016).

Overall, the Chinese stock markets are characterized with sever information asymmetry, weak corporate governance, and frequent price crashes (Xu et al., 2014; Chauhan et al., 2015; Luo et al., 2016). Although the Chinese economy is the second largest in the world, its financial markets are less developed compare to Western developed countries. The Chinese banking system is dominated by the “Big-5” state-controlled banks. A number of studies such as Ge and Qiu (2007), Cull el al. (2009), Wu et al. (2012), and Wu et al. (2014) consistently document that Chinese firms, especially those in private sector, rely heavily on trade credit as a form of informal debt financing as a result of state banks’ discriminations against firms without political connections. However, discourse of trade credit provision is limited despite the fact of the substantial amount of loans through trade credit supply-chain. Unlike private firm, listed state-owned enterprises (SOEs) enjoy preferential access to bank loans. Due to regulatory compliance requirements and relationship lending, listed firms have stronger incentives to disclose information to banks. Consequently, the agency role of creditors in reducing information asymmetry between shareholders and managers is particularly relevant under the Chinese institutional setting. Furthermore, sever information asymmetry make firm face high costs of external financing costs (Froot et al. 1993). Firm may choose to invest in a variety of financial assets as substituted assets to generate sufficient internal funds therefore optimal investment decision. Therefore, whether substituted assets improve information quality needs timely investigate.

While the above features of the Chinese setting have been widely referred to in the fast-emerging literature on crash risk in China, systematic empirical investigations are scant. Even when relevant predictions are reasonably clear when drawing from agency theory, likely channels through which trade credit, debt-holders and financial assets influence financial information transparency, i.e., bad news hoarding, and in turn stock price crash risk are untested. This thesis presented as three related but self-contained chapters aim to fill these gaps.

In Chapter 2, we investigate the influence of trade-credit provision on stock-price crash risk. Using a sample of Chinese listed firms from 2001-2019, we find that trade credit provision significantly increases stock-price crash risk. Overall, evidence supports that trade credit provision impacts crash risk through an information channel that customer-supplier economic links through trade credit facilitate bad news hoarding. We further evidence that, in China, an emerging market with less developed credit environment, this link being heightened when firm information asymmetry is more severe. We further illustrate that this positive relationship between trade credit provision and crash risk is exacerbated by high levels of financial distress, and by industrial diversification, while also being mitigated by internal control quality.

In Chapter 3, we examine the effects of debt financing on stock-price crash risk. Using a large sample of non-financial firm in China from 2002-2016, we find that debt financing decreases stock price crash risk. We use both fixed-effects model and system-GMM model. We find consistent results for both the market value financial leverage and the book value debt-to-assets ratio as debt measures. This finding supports our prediction that creditor serve as monitoring role in China's weakly informational environment which constraint managerial bad news hoarding. We further find that this negative and significant relationship is not affected by state ownership. Also, debt maturity structure appears to have insignificant influence on crash risk itself as well as the relationship between debt and crash risk. This result indicates that the negative leverage-crash relation is unlikely to be due to the rollover pressure of short-term debt.

In Chapter 4, we examine the impacts of financial assets investment on stock price crash risk in China. Firms in developing countries are more likely to substitute more liquid and reversible financial assets for capital assets due to incomplete financial markets while still earning higher returns than holding cash. Analyzing a sample of Chinese firms from 2007-2019, we show that firms investing less in capital assets hold more financial assets. Concomitantly, stock price crash risk decreases with financial assets investment and increases with capital assets investment. These findings support the view that for firms with agency problems, capital investment increase agency costs and facilitate bad news hoarding, while financial assets investment reduce firm information asymmetry due to more stringent accounting disclosure requirements and consequently better information transparency. In our further analysis, we find that financial assets measured at fair value, long-term financial assets and investment property are particularly effective in mitigating crash risk. Consistently, we find the negative link between financial assets investment and crash risk is heightened among firms with lower financial reporting quality, higher financial distress risk, or poorer performance.

This thesis contributes to the relatively little research on how extension of credit by firms impacts their financial stability, as well as the debt and crash risk relationship in general. Our findings suggest that trade credit provision, rather than usage, needs to be focused on in order to assess the impact of trade credit on societies' financial vulnerability. This thesis also contributes to the research on the role of financial assets disclosures by non-financial sector firms in improving their transparency which is built on the growing literature focusing on the motivation of financial assets holdings (Duchin, 2017; Tang and Zhang, 2019; Huang et al., 2019). Findings of this thesis should be of great interest to scholars interested in the role of information disclosure in emerging financial markets; as well as to investors and regulators concerned about stock price crash risk.

CHAPTER 2

Trade Credit Provision and Stock Price Crash Risk

2.1. Introduction

There continues to be considerable interest in the field of finance in the role of information transparency in equity pricing and equity returns. In this chapter, we continue the ongoing interest of finance scholarship in the role of information quality by investigating stock price crash risk. Crash risk measures negative distribution of returns on individual stock, which is caused by firm-specific information (Chen et. al., 2001; Jin and Myers, 2006). By building a theoretical model, Jin and Myer (2006) investigate the role of synchronicity between managers and outside investors in impacting probability of stock price crashes. They find that investors' perception is imperfect in capturing firm-specific information. Inside managers capture more firm-specific risk when fail investors' expectation. Along with increasing opaqueness, managers continue to capture more information than investors, which leads to higher idiosyncratic risk to investors. Hutton et al. (2009) extend this investigation by looking more specifically at the role of information quality aspect of property rights protection on crash risk. They find that a lack of financial transparency leads to both higher synchronicity and, at the firm level, higher firm-specific crash risk. The clear link here is that the obfuscation of information makes resolving asymmetric information costlier, with consequently less pricing of idiosyncratic risk.

A large body of recent literature investigating the determinants of crash risk identifies many factors related to information obfuscation, financial reporting quality, or hidden underreported risks (bad-news hoarding). These papers include the quality and nature of financial reporting

(DeFond et al., 2014; Hutton et al., 2009; Kim and Zhang, 2016; Kim et al., 2016), managerial risk taking through risky practices, incentivizing of risk, or cultural and behavioral risk predilections (Callen and Fang, 2015a; Hong et al., 2018; Kim et al., 2011a; 2011b; Li et al., 2017; Xu et al., 2013; Yuan et al., 2016); as well as short interest that can lead to sudden unveiling of hoarded bad news (Callen and Fang, 2015b).

However, the provision of trade credit has so far received little attention with regard to identifying factors that increase crash risk. Trade credit is generated when goods and services are delivered to customers without cash payments (Mian and Smith Jr., 1992; Choi and Kim, 2005; Ng, Smith, and Smith, 1999). It is generally considered that firms use trade credit as an important short-term financing resource especially when access to formal financing institutions is limited (Brennan, Maksimovics, and Zechner, 1988; Ferris, 1981; Petersen and Rajan, 1997).

In this chapter, we argue that trade credit provision facilitates information asymmetry for following three reasons: First, trade credit provision provides a vehicle for managers to manipulate information on bad debts arising from credit sales. Managers can strategically approve credit sales to less credit worthy customers causing high bad debts risk (Petersen and Rajan, 1997). This activity is associated with high bad debts risk resulting in bad news hoarding consequently causing future stock price crashes. Second, previous studies conclude that firm generates significant costs and reduces liquidity with an increase in trade receivables (Barrot, 2016; Murfin and Njoroge, 2015). Due to significant customer substitution costs, managers continue to issue trade credit to customer when they are aware of the default risk (Titman and Wessels, 1988; Petersen and Rajan, 1997). Hence, suppliers of trade credit have strong incentives to withhold information on their liquidity risk exposures resulting in higher crash risk. Finally, to increase capacity, supplier firms are more likely to suffer from overinvestment causing sever information asymmetry, which is widely considered as a consequence of “managerial empire building” and “entrenchment”, (Aggarwal and Samwick, 2006). Suggested by empirical studies, firms have incentives to use trade credit to manage short-term growth (Fisman and Love, 2003; Ferrando and Mulier, 2013), with managerial myopia (Schwartz, 1974). Meanwhile, making sales and getting payments separately provide managers with opportunities to manipulate the disclosures of financial information associated with the timing of business transactions. Given possible channels through which trade credit provision increases information asymmetry, we hypothesize that managers have incentive to manipulate financial information when extending trade credit, and it facilitates bad news hoardings for investors. When accumulated bad news reaches the upper limit, it releases to the market at once and results in stock price crash.

We consider that China is an ideal country to focus on this chapter. First, the resolving of asymmetric information inherent creates transaction costs (Grossman and Stiglitz, 1980; Hart, 2001; Williamson, 1979). In emerging markets, institutional voids (Khanna and Palepu, 2010) lead to lower information quality and greater crash risk. As the second large stock market in terms of capitalization, China is very representative of emerging economies. Furthermore, the Chinese stock market experiences frequent crashes that makes this an important issue. Second, ownership structure differences of Chinese firms enable us to evidence more reliable results with regard to the determinants of crash risk. For example, a number of studies document that state affiliation is an important mediating factor for stock price crash risk in China (Chen et al., 2018; Li and Chan, 2016; Luo et al., 2016; Piotroski et al., 2015; Xu et al., 2014). Third, the Chinese banking system is dominated by the “Big-5” state-controlled banks. A number of studies such as Ge and Qiu (2007), Cull el al., (2009), and Wu et al., (2012), Wu et al., (2014) consistently document that Chinese firms, especially those in the private sector, rely heavily on trade credit as a form of informal debt financing as a result of state banks' discrimination against firms without political connections. Particularly, despite substantial borrowing through supply chains, disclosures of trade credit usages and provisions by Chinese listed firms remain low. The requirement on details of trade credit usage and provisions has been limited.[1] Finally, the provision of trade credit among Chinese listed firms has received much less scholarly attention than trade credit financing despite that fact that the former is economically more significant than the latter.[2] The size of the Chinese stock markets and the significance of trade credit usage/provision ensure sufficient variations in the data which in turn facilitate empirical analysis.

Using a large sample of Chinese firms from 2001-2019, we empirically test our hypotheses on the relationship between trade credit provision and crash risk. Following recent studies (Chen et. al., 2001; Jin and Myers, 2006; Hutton et al., 2009), we use two measures of stock price crash risk: negative skewness (NCSKEW) and down-to-up volatility (DUVOL). By adopting both fixed-effects regression and system-GMM estimators we find that trade credit provision is significantly and positively associated with future stock price crash risk. The results are robust after controlling for firm level factors as well as firm and year fixed-effects. We also get consistent results by using alternative measures of trade credit. This finding indicates that extending trade credit does increase stock price crash risk.

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[1] In 2007, the China Securities Regulatory Commission (CSRC) issued Publicly Traded Corporations Information Disclosure Content and Format Principals (particularly, No. 2 - Content and Format of Annual Report). According to this principal, listed firms are required to disclose the major (top 5) customers in their annual reports along with their respective percentages of sales in total sales. However, similar disaggregated values of trade credit usage and provisions are not disclosed.

[2] Our statistics suggest that the average trade credit provision is 31% higher than the trade credit financing among publicly traded corporations in China during the sample period. This difference accounts for 5.6% of sales values on average.

We further investigate possible channels through which trade credit provision lead to great crash risk. We examine three measures of information asymmetry, which trade credit provision may facilitate. It is well documented in the literature that financially distressed firms are often associated with greater moral hazard problems while diversified firms are more likely to have agency problems. We find that this positive relationship is more pronounced among financially distressed firms and industrially diversified firms. In contrast, we find this positive relationship being mitigated by internal control quality, which is consistent with the view that internal control quality increase information quality (Chen et al., 2018).

In additional robustness tests, we further find that firms cash holdings can partially mitigate the effects of trade credit on stock price crash risk by moderating possible unexpected cash flow shocks. Our findings should be of great interest to scholars interested in the role of information disclosure in financial markets; as well as to investors and regulators concerned about equity market crash risk.

At last, we explore whether this positive relationship varies with ownership structure in China. Compare to SOEs, the cost advantage of trade credit in non-state-owned enterprises (Non-SOEs) is heightened because institutional voids create greater credit rationing which is caused by more asymmetric information (Fisman and Love, 2003; Stiglitz and Weiss, 1981). Therefore, the positive relationship between trade credit provision and crash risk tends to be more pronounced in private firms. Our results to support our prediction.

The reminder of this chapter is structured as follows. Section 2.2 is literature review and hypotheses development. Section 2.3 describes sample selection and methodology used. Section 2.4 presents empirical results. Section 2.5 discusses further robustness testing and findings. Section 2.6 is the conclusion.

2.2 Background hypotheses development

2.2.1 Cause of Crash risk

Chen, Hong, and Stein (2001) proposed the concept of individual stock price crash risk. Compared to prior work that focuses on crashes caused by financial market mechanisms (e.g., Campbell and Hentschel, 1992), Chen, Hong, and Stein (2001) emphasize how absence of firm-specific information engenders vulnerability to individual stock price crashes. Related to lack of uniform information quality leading to crash risk, Hong and Stein (2003) propose that different opinions among investors and short-sales constraints encourage a propensity for large market level crashes.

In light of Chen, Hong, and Stein (2001), a growing literature has emerged on the causes of individual stock price crash risk. For example, Jin and Myers (2006) regard crashes as large and negative return outliers. They propose that managers may choose to hide negative information and accelerate positive information release in order to maximize their own rents (bad-news hoarding). However, managers can only withhold bad news up to a limit. Inevitably there will be a large amount of bad news released, causing a market reaction that likely leads to a large-scale stock-price crash.

A number of studies have paid attention to the association between financial reporting quality and crash risk. For instance, a number of scholars document that firms can reduce crash risk by adopting such practices as International Financial Reporting Standards (IFRS), better financial statement comparability, and conservative accounting policy (DeFond et al., 2014; Kim et al., 2016; Kim and Zhang, 2016). Related to this, Kim et al., (2014) find evidence from the US that socially responsible firms generally observe a high principal of transparency, which prevent bad news hoarding and consequently lead lower crash risk.

Naturally, therefore, managerial practices that mislead investors through such practices as earnings management, creating complicated tax shelters, or receiving option-based compensation consequently engender higher stock price crash risk (Kim, et al., 2011a; Kim, et al., 2011b). Another stream of the literature investigates the influence of firm ownership and control on stock crash risk in US market. Consistent with agency theory, Callen and Fang (2015b) find that institutional investors provide extra monitoring therefore decrease crash risk. On the other hand, Hong, Kim, and Welker (2017) find excess control rights of firm controlling shareholders increases crash risk.

In consistency with the above evidence from the US market, an important strand of literature has paid particular attention to the Chinese market where individual stock price crashes are more prevalent because that the firms ownership structure and institutional environment differs from the US. For instance, around half of the listed firms in China are under government control. Piotroski et al., (2015) document that politically connected managers tend to hide bad news around politically sensitive events such as national congress meetings and provincial governors' turnovers. Results show that closely held firms decrease crash risk during political events and increase crash risk afterwards. A competing view is that because political connected managers or party-controlled directors represent interest of state shareholders, they are more likely to release bad news to safeguard the careers of connected politicians (Chen et al., 2018; Li and Chan, 2016; Luo et al., 2016).

Other recent studies, focusing on institutions-related explanations, analyze legal voids (Zhang, Wang, and Jiang, 2017; Chen et al., 2018); as well as lack of social trust (Li, Wang, and Wang, 2017; Cao, Xia, and Chan, 2016). Further, in line with the agency theory, Xu et al., (2013) find analyst coverage reduces crash risk, while Xu et al. (2014) find that excess managerial perks consumption is associated with higher crash risk. Yuan, Sun, and Cao (2016) find firms purchasing directors' and officers' liability insurances exhibit lower crash risk, while Chen et al. (2017) document that high quality of internal control system alleviates stock price crash risk.

2.2.2 Trade credit

Extensive empirical studies have examined how the use of trade credit, particularly accounts payables, affects firms from several aspects, such as cash holdings policy, investment quality, sales growth, and stock returns (Wu, et al.,, 2012; Aktas et al., 2012; Goto, et al., 2015). Traditionally, suppliers have a monitoring advantage over banks, because suppliers obtain additional information on borrowers through normal business relations, with no further costs (e.g., Emery, 1984). Studies also look at trade credit provisions and firm performance provide mixed evidence. One view is that trade-credit usage and provision mitigates information asymmetry between buyers and suppliers regarding product quality, for example through regular visits of sales representatives to customers (Mian and Smith Jr., 1992; Biais and Gollier, 1997). Therefore, it may cultivate a mutually beneficial relationships and improve suppliers' operating performance (Cuñat, 2006; Box et al., 2018). Another view is that trade credit provisions entail significant costs to suppliers **(**Schwartz, 1974; Barrot, 2016). Since no existing studies investigate the effect of trade credit provision on crash risk, this chapter tries to fill this gap.

2.2.3 Hypotheses

2.2.3.1 Trade credit provision and stock price crash risk

Several mechanisms associated with trade credit provision may facilitate bad news hoarding and consequently lead to stock price crashes. First, trade credit provision provides a vehicle for managers to manipulate information on bad debts arising from credit sales. Managers who pursue short-term high growth can strategically approve credit sales to customers regardless of their creditworthiness causing high bad debts risk (Petersen and Rajan, 1997). In fact, Berger and Udell (1998) find that managers of trade credit suppliers tend to issue more trade credit to smaller, younger and more opaque firms that have difficulties to get access to formal finance. Supplier firms take such trade credit as an implicit equity stake in customers. Because managers of supplier firms do not only want to meet customers demand in short term. Rather, managers may hope to generate future profits from customers. However, the favored risky customers may expose supplier firms to significant default risk and potential bad debt losses. In order to boost sales and market shares, managers may also strategically offer better trade credit terms (i.e., lower interest rate, more discount amounts, longer payment dates) (Porter, 1974; Niskanen and Niskanen, 2006). In order to mask these activities, managers may deliberately relay the recognition of bad debt beyond one financial reporting period resulting in bad news hoarding consequently causing future stock price crashes.

Second, suppliers of trade credit have incentives to withhold information on their liquidity risk exposures. Typically, suppliers of trade credit act as liquidity providers when customers face short-term liquidity shocks. For instance, Berger and Udell (1998) find that managers of trade credit suppliers tend to issue more trade credit to smaller, younger and more opaque firms that have difficulties to get access to formal finance. Supplier firms take such trade credit as an implicit equity stake in customers because managers of supplier firms may hope to generate long-term profits from their customers. However, the favored risky customers may expose supplier firms to significant default risk. Furthermore, due to significant customer substitution costs, when customer firms experience liquidity shocks and default on payments, supplier firms' managers have strong incentives to issue more trade credit to maintain their sales causing moral hazard problem (Titman and Wessels, 1988; Petersen and Rajan, 1997). Managers who are aware of these risks hence have an incentive to hide bad news from investors in order to avoid adverse selection. Consequently, crash risk of suppliers' stocks may increase.

Third, trade credit provision provides opportunity for managers to engage in "managerial empire building" (Aggarwal and Samwick (2006). Empirical studies suggest that managers have incentives to use trade credit to manage short-term growth (Fisman and Love, 2003; Ferrando and Mulier, 2013), with managerial myopia (Schwartz, 1974). Meanwhile, the mechanism that making sales and getting payments separately provides managers with opportunities to manipulate the disclosures of financial information associated with the timing of business transactions. Also, Zhu and Jiang, (2009) suggest that extension of trade credit allows for self-dealing opportunities for unrecognized tunneling of resources to firms receiving the credit. Taking together, trade credit provision may engender stock price crash risk. Based on the above discussions, we give our first hypothesis:

H1: Stock price crash risk is positively associated with trade credit provision.

2.2.3.2 Trade credit provision and stock price crash risk: the role of information asymmetry

As discussed above, trade credit provision can positively impact stock-price crash risk through providing opportunities for managers to hide bad news. We consider that a predilection to hoard bad news will be conditioned by firm-level information asymmetry. In such firms, where there is already substantial bad news hidden from investors, bad-news hoarding via trade credit provision will be heightened. Managers of less-transparent firms will be more likely to hide bad news. Hence, we expect a stronger (weaker) relationship between trade credit provision and stock-price crash risk in less (more) transparent firms. We consider several situations that are associated with different levels of information asymmetry to test our hypothesis. By using three proxies of firm specific information asymmetry, we formally test our predictions regarding the conditioning role of information asymmetry.

Managers of distressed firms are often associated with severe moral hazard problems while their firms are facing liquidity problems and losing market shares (Altman, 1984; Opler and Titman, 1994). Trade credit provisions potentially expose suppliers to credit risk along the customer-supplier chain. For instance, Cohen and Frazzini (2008) find that stock returns are predictable across "economically linked" firms in the US. More recently Lian (2017) find that supplier's financial distress is influenced by their major customer's financial conditions. Consistent with this view, managers' opportunistic behavior are likely to be exacerbated among distressed firm particularly in terms of using/manipulating trade credit to boost sales and earnings performance. Consequently, they tend to suppress bad news from investors leading to higher stock price crash risk. Therefore, we propose the second hypothesis:

H2a: The positive association between trade credit provision and stock price crash risk is more pronounced for financially distressed firms.

Due to agency cost, managers of diversified firm may derive private benefits over their private costs (Jensen, 1986). Denis et al., (1997) find consistent evidence that managers gain greater benefits because of the power from managing industrially diversified firm than single-industry firms, consequently, reduce firm value. Furthermore, managers may gain greater private benefit at lower costs through more liquid assets such as trade receivables (Myers and Rajan, 1998). In this vein, industrial diversification may also facilitate bad news hoarding and increase stock crash risk. Based on the argument above, we give our third hypothesis:

H2b: The positive association between trade credit provision and stock price crash risk is more pronounced for industrially diversified *firms.*

A number of recent studies show that strong firm internal control system ensures the quality of information discourse (Beneish et al.,2008; Hammersley et al., 2008). Consequently, firms disclosing internal control weaknesses have high cost of capital (Ashbaugh-Skaife et al., 2009). Consistent with this view, Chen et al., (2017) find that higher internal control quality is associated with lower stock price crash risk in China. As discussed above, we lead to our last hypothesis:

H2c: The internal control quality mitigates the positive relationship between trade credit provision and stock price crash risk.

2.3. Sample and methodology

2.3.1 Sample selection

We collect weekly individual and market stock returns, corporate governance, and annual report data from China Stock Market Accounting Research (CSMAR) database and data on financial distress and firm industrial diversification from WIND. The initial sample includes all A-share listed firms in Shanghai and Shenzhen stock exchanges from 2001 to 2019. Following extant literature, we exclude financial sector firms and firms with stock return less than 30 trading weeks in a fiscal year. Our final sample contains 24,701 firm-year observations.

2.3.2 Measures of stock price crash risk

Following Chen et al., (2001), Hutton et al., (2009), we adopt two measures of stock price crash risk: *negative skewness* (NCSKEW) and *down-to-up volatility* (DUVOL). We first apply the following expanded index model regression to estimate firm-specific weekly returns:

$$r_{i,t} = \alpha_i + \beta_{1,i}\, r_{m,t-2} + \beta_{2,i}\, r_{m,t-1} + \beta_{3,i}\, r_{m,t} + \beta_{4,i}\, r_{m,t+1} + \beta_{5,i}\, r_{m,t+2} + \varepsilon_{i,t} \qquad (2.1),$$

where $r_{i,t}$ is return on stock i in week t. $r_{m,t}$ is value-weighted return on A share market index in week t. We control for the two lead and two lag terms of the market index to allow for non-synchronous trading (Dimson, 1979). The firm-specific weekly returns are denoted as $W_{i,t}$, which is computed as the nature log of one plus regression residual estimated from Eq. (2.1), that is $W_{i,t}$ = ln (1 + $\varepsilon_{i,t}$).

Negative skewness (NCSKEW) is computed by taking the third moment of firm specific weekly return for each year over the standard deviation of firm specific weekly return raised to third power, then multiplying -1 as follows:

$$NCSKEW_{i,t} = -\frac{n(n-1)^{3/2}\sum W_{i,t}^3}{(n-1)(n-2)(\sum W_{i,t}^2)^{3/2}} \quad (2.2),$$

where $W_{i,t}$ is firm-specific weekly return for firm i in year t, and n is the number of weeks in year t. A higher value of NCSKEW represents a more negatively skewed return distribution and higher crash risk.

To calculate down-to-up volatility (DUVOL) for each firm i over year t, we separate all weeks in each fiscal year into two groups: “down” weeks where the specific weekly returns are less than the annual mean, and “up” weeks where the specific weekly returns are higher than the annual mean. The DUVOL is computed as the nature log of the standard deviation of “down” weeks over the standard deviation of “up” weeks as follows:

$$DUVOL_{i,t} = \log\left\{(n_u - 1)\sum_{Down} W_{i,t}^2 \Big/ (n_d - 1)\sum_{Up} W_{i,t}^2\right\} \quad (2.3),$$

where $W_{i,t}$ is firm-specific weekly return for firm i in year t, n_u is the number of “up” weeks and n_d is the number of “down” weeks. A higher value of DUVOL represents a higher crash risk.

2.3.3 Measures of trade credit provision

Accounts receivable is the major account that represents the volume of trade credit extended by sample firms (as suppliers to customers) in their balance sheets. For robustness, we construct two measures of trade credit provision: 1) the value of accounts receivable scaled by total assets (AccRev); 2) the value of total trade receivables scaled by total assets (TotalRev). Total trade receivables are calculated as accounts receivable plus notes receivable, not including the "other receivables" account.

2.3.4 Proxies for information asymmetry

2.3.4.1 Financial distress (Z-score)

Financial distress of a firm is estimated using the Altman Z-score model (1968). A higher Z-score indicates better financial health.

2.3.4.2 Industrial diversification (H-index)

Firm industrial diversification is measured by the Herfindahl concentration index (H-index) calculated from firm/year top 5 sales by industries. A lower value of H-index indicates a higher degree of firm diversification.

2.3.4.3 Internal control quality (ICQ)

We use the internal control index for Chinese listed firms obtained from the DIB internal control and risk management database[3]. A higher value of internal control index represents a higher quality of internal control system.

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[3] The DIB internal control quality index is published annually by Dibo ltd. (Shenzhen) since 2000 (Wang

2.3.5 Empirical models

To examine our prediction on the relationship between trade credit provision and stock price crash risk, we first apply the following fixed-effects regression model:

$$Crash_{i,t} = \alpha_i + \beta_1\, TradeCredit_{i,t-1} + \gamma\, Controls_{i,t-1} + \varepsilon_{i,t} \qquad (2.4),$$

where the dependent variable $Crash_{i,t}$ refers to the two measures of stock price crash risk, namely NCSKEW or DUVOL. $TradeCredit_{it-1}$ signifies two trade credit proxies: AccRev and TotalRev. We impose a year lag on the independent variables to investigate whether trade credit, reported in year *t-1* financial statements, can predict stock price crash risk in year *t*. Firm fixed effects α_i is included in the model to control for unobserved heterogeneity among firms.

Following prior literature on crash risk, we select a group of control variables in the regression model, denoted as $Controls_{it-1}$. As a number of studies document state affiliation is an important mediating factor for stock price crash risk in China (Chen et al., 2018; Li and Chan, 2016; Luo et al., 2016; Piotroski, Wong, and Zhang, 2015; Xu et al., 2014), we include a state-owned enterprise dummy (SOE) (assigned "1" for firms under control of the Chinese government and "0" if not). Considering crash-risk persistence (Chen, Hong, and Stein, 2001), we control for NCSKEW/DUVOL in the current fiscal year t. As more volatile stocks are deemed to be more crash prone and past stock performance can predict future stock price crash risk (Chen, Hong, and Stein, 2001), we control for stock volatility (SIGMA) and past return (RETURN). We further

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et al. (2018). It is designed to keep tracking of the quality of firm level internal control information reflected in financial reports, CSRC filings, and public announcements. The ratings (ICQ) range from 0 to 999 are computed as the sum of 5 component ratings in accordance with the CSRC guideline on listed firms' internal control system, namely the control environment, risk assessment, control activity, information and communication, and monitoring. A higher rating indicates better internal control quality. For estimation, we scale the ratings by 1000.

control for detrended share turnover (DTURN), estimated as average monthly share turnover over the current fiscal year minus the average monthly share turnover over the previous fiscal year. We also include firm size (SIZE), market to book ratio (MTB), financial leverage (LEV) and return on assets (ROA). Following Chen, Hong, and Stein (2001); and Hutton, Marcus, and Tehranian (2009), we also control for the absolute value of discretionary accruals (DACC), estimated by the Modified Jones Model (Dechow, Sloan, and Sweeney, 1995).

In addition, we use the following random-effects GLS estimation to address endogeneity concerns:

$$Crash_{i,t} = \alpha_i + \beta_1\, TradeCredit_{i,t-1} + \gamma\, Controls_{i,t-1} + \tau_t\, Year_{t-1} + \varepsilon_{i,t} \qquad (2.5),$$

where the dependent variable $Crash_{i,t}$ refers to the two measures of stock price crash risk, namely NCSKEW or DUVOL. $TradeCredit_{it-1}$ signifies two trade credit proxies: AccRev and TotalRev. We impose a year lag on the independent variables to investigate whether trade credit, reported in year *t-1* financial statements, can predict stock price crash risk in year *t*. Firm fixed effects α_i and year fixed effects $Year_t$ are included in the model to control for unobserved heterogeneity among firms and years respectively.

To further address endogeneity concern, we then adopt the two-step system-GMM estimator based on Kim, Li, and Li (2014). Specifically, we estimate the following dynamic model using two-step system-GMM estimator (Arellano and Boverm, 1995; Blundell and Bond, 1998) with bias-corrected robust standard errors (Windmeijer, 2005):

$$Crash_{i,t} = \alpha_i + \beta_1 Crash_{i,t-1} + \beta_2 Crash_{i,t-2} + \beta_3 TradeCredit_{i,t} + \gamma\, Controls_{i,t} + \varepsilon_{i,t} \qquad (2.6),$$

where the dependent variable $Crash_{i,t}$ refers to the two measures of stock price crash risk, namely NCSKEW or DUVOL. The independent variable $TradeCredit_{it}$ represents two trade credit proxies: AccRev and TotalRev. This dynamic model controls for two lags of the dependent variables. This allows us to observe the impact of trade credit provision on crash risk conditional on historical crash risk information, i.e, a short-run effect (Arellano and Bover, 1995). All independent variables are considered as endogenous variables in this system-GMM estimation. For estimation, we take first difference of Equation (6) to control for unobserved heterogeneity and eliminate potential omitted-variable bias. We use up to the maximum of five lagged values of the endogenous variables as instruments. For diagnostics, we report the Arellano-Bond second-order serial correlation AR(2) tests, and Hansen J tests of over-identifying restrictions. The first order serial correlation is expected due to first-differencing.[4]

Finally, to examine H2, the role of different information asymmetry proxies on the relationship between trade credit and crash risk, we adopt a revised fixed-effects regression model in Equation (2.7) as follows:

$$Crash_{i,t} = \alpha_i + \beta_1 TradeCredit_{i,t-1} + \beta_2 TradeCredit_{it-1} * InfAsy_{i,t-1} + \beta_3 InfAsy_{i,t-1} + \gamma\ Controls_{i,t-1} + \varepsilon_{i,t-1} \quad (2.7)$$

Specifically, we include the three proxies for firm level information asymmetry (denoted as $InfAsy_{it}$) along with their interactions with $TradeCredit_{i,t-1}$. The remaining variables are defined as the same as those in Equation (2.4).

Detailed descriptions of these variables are provided in Appendix 2.A. Table 2.1 reports the summary statistics of the variables used in this chapter. We winsorize these variables at 1% level in both tails to mitigate the effects of extreme values. The mean values of both crash risk measures, NCSKEW and DUVOL, are –0.173 and –0.116, respectively. These statistics are generally

[4] We note the continued use of the GMM method in the literature to account for endogeneity (e.g., Hoechle et al., 2012). Our variables are well suited to the use of lagged variables. Addressing possible endogeneity with a GMM approach avoids concerns for heteroskedasticity and the appropriateness of instruments inherent in an instrumental variable approach (Baum, Schaffer, and Stillman, 2003).

comparable to those reported in prior studies (Chen et al., 2018; Li, Wang, and Wang, 2017a). On average, trade credit provision, measured by the balance of accounts receivable (AccRev), among sample firm/years accounts for 11% of asset values. Appendix 2.B shows the pairwise correlation coefficients of the variables.

(Insert Table 2.1 here)

2.4. Empirical results

2.4.1 Baseline results

Table 2.2 reports a set of fixed-effects regressions investigating the effect of trade credit provision (account receivable scaled by total assets) on crash risk. The dependent variables are $NCSKEW_t$ and $DUVOL_t$, in Panels A and B respectively. The coefficients on the trade credit provision measure, $AccRev_{t-1}$, in both Models 1 and 4 are positive and significant, suggesting, consistent with our prediction, that firms extending more trade credit have higher crash risk. We also find negative and significant coefficients for stock return volatility (SIGMA), which suggests that firms have more volatile stock returns experiencing less stock price crashes. The results are consistent with Ben-Nasr and Ghouma (2018) and Deng et al., (2018). In addition, we find insignificant coefficients of DACC, the absolute value of discretionary accruals, probably because as we discussed above that trade credit provision provides a vain for managerial earnings manipulation therefore cancel out the effects of accruals. Several control variables, including detrended share turnover (DTURN), stock return volatility (SIGMA), past stock return (RETURN), firm size (SIZE), market to book ratio (MTB), financial leverage (LEV) and return on assets (ROA) also have significant influence on crash risk.

A number of studies suggest state affiliation is an important mediating factor with regard to stock-price crash risk in China (Chen et al., 2018; Li and Chan, 2016; Luo et al., 2016; Piotroski, Wong, and Zhang, 2015; Xu et al., 2014). Specifically, managers of SOEs are more likely to engage in timely release of bad news timely in order to safeguard the careers of connected politicians (Chen et al., 2018; Li and Chan, 2016; Luo et al., 2016); thereby improving information transparency of SOEs. Therefore, we expect that for SOEs the link between trade credit and crash risk will be less strong due to less hidden bad news. In table 2.2, we further repeat the analysis using subsamples of SOEs (Models 2 and 5) and Non-SOEs (Models 3 and 6). We find that $AccRev_t$ consistently has a positive and significant influence on crash risk in all models. Notably, the coefficients on $AccRev_t$ are larger for Non-SOEs in Models 3 and 6 than those for SOEs in Models 2 and 5. Consistent with previous evidence (Chen et al., 2018; Li and Chan, 2016; Luo et al., 2016; Piotroski, Wong, and Zhang, 2015; Xu et al., 2014), these subsample results indicate that provisions of trade credit are less consequential to stock crash risk among SOEs than non-SOEs.

(Insert Table 2.2 here)

In Table 2.3, we report results of robustness checks using total trade receivables scaled by total assets as an alternative measure of trade credit provisions. The total trade receivables are calculated as accounts receivable plus notes receivables. We continue to find positive and significant coefficients on the trade credit provision measure regarding $TotaRev_{t-1}$ in both Models 1 and 4. Next, similar to Table 2.2, we repeat the analysis using subsamples of SOEs (Models 3 and 6) and Non-SOEs (Models 2 and 5). We continue to find that coefficients on $TotaRev_{t-1}$ are significant. Besides, coefficients on $TotaRev_{t-1}$ in Models 3 and 6 are larger than those in Models 2 and 5. These results are consistent with our prediction that the positive relationship between trade credit provision and crash risk is more pronounced in Non-SOEs. In summary, results reported in Table 3, using, alternatively, total trade receivables scaled by total assets, are highly consistently with those reported in Table 2.2.

(Insert Table 2.3 here)

Table 2.4 reports a series of test results to address endogeneity concern, including fixed-effects regression, random-effects regressions and two-step system-GMM estimator. In these regressions, the independent variables are AccRev. Models 1 and 2 use fixed-effects regression. Models 3 and 4 use the random-effects regression. We use same control variables as those in table 2.2&2.3. In addition, we further include year fixed effects to control for unobserved heterogeneity among firms and years respectively. In particular, in order to further control for endogeneity, we use the 1-period lagged independent variables and the current period dependent variables crash risk, measured as $NCSKEW_t$ and $DUVOL_t$. Models 6 and 7 report regressions using the two-step dynamic panel-data system estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) with bias-corrected robust standard errors (Windmeijer, 2005). We continue to find that the coefficients on trade credit provision are positive and statistically significant in all models, which further consistent with our hypothesis.

(Insert Table 2.4 here)

In contrast to trade credit provision, trade credit financing lead to lower crash risk (Cao, Ye, Zhang and Li, 2018). To address the influence of trade credit financing on crash risk, we further control for trade credit financing measured by AccPay, the value of accounts payables scaled by total assets. We report our results in table 2.5. Consistent with Cao, Ye, Zhang and Li, (2018), we find crash risk is significantly and negatively related to trade credit financing. More importantly, the coefficients of trade credit provision are still positive and significant across different model specifications, suggesting trade credit provision increase stock price crash risk with or without considering the effects of trade credit financing.

(Insert Table 2.5 here)

2.4.2 Information asymmetry, trade credit provision and crash risk

In this section, we report a battery of further tests controlling for a number of alternative proxies for information asymmetry. We adopt a number of proxies for firm-specific information asymmetry. Considering that trade credit provision influences stock price crash risk through an information channel, particularly bad news hoarding, we expect the positive connection between trade credit provision and crash risk to be stronger among firms associated with higher information asymmetry.

We include three firm-specific information asymmetry measures. Potential interconnections among trade credit provision, information asymmetry, crash risk, and the set of control variables introduce considerable simultaneity in our models (Chen, Hong, and Stein, 2001; Hong and Stein, 2003; Smith, 1987). We now discuss the results associated with the different proxies for information asymmetry in the order of their appearance in our analysis.

First, as discussed in Section 2.3.4, trade credit provisions potentially expose suppliers to credit risk along the customer-supplier chain, in turn increasing stock-return uncertainty (Cohen and Frazzini, 2008; Lian, 2017). Consequently, in Equation (7), we include Altman's Z-score (Altman, 1968) as a proxy for supplier credit risk. In Table 2.6 we report results controlling for supplier credit risk. The coefficients on the interaction TradeCredit*Z-score are negative and significant across the four models. This suggests that financial distress, shown by lower Z-scores, exacerbates the impact of trade credit provision on crash risk.

Notably, the relationship between trade credit provision and crash risk is still positive and significant after controlling for the interaction TradeCredit*Z-score. According to Opler and Titman (1994) and Lian (2017), financially distressed firms are associated with severer moral hazard problems and information asymmetry. Therefore, trade credit provision of financially distressed firms particularly facilitates bad news hoarding, leading to even higher crash risk.

(Insert Table 2.6 here)

Second, as a further test, we consider that diversification at the firm level may increase information asymmetry associated with credit sales. In Table 2.7, we report results using the industrial concentration H-index as a proxy for information asymmetry. We find negative coefficients on TradeCredit*H-index in all models. These are statistically significant. According to agency theory, diversified (lower H-index) firms are associated with weaker governance and severer information asymmetry (Myers and Rajan, 1998). Results reported in Table 2.7 suggest that the relation between trade credit provision and crash risk is exacerbated by industrial diversification. Taken together, results suggest that firm industrial diversification (lower H-index) facilitates the bad news hoarding associated with trade credit provision; hence concomitantly increasing stock price crash risk.

(Insert Table 2.7 here)

As a third consideration, we note that the presence of internal control systems may mitigate operational and credit risks associated with accounts receivables, facilitating the flow of internal information. In Table 2.8, we report results controlling for an internal control quality index ICQ.

We report consistent negative coefficients on TradeCredit*ICQ in all models. They are all statistically significant. These results, consistent with Chen et al. (2017), suggest that better internal control quality (higher ICQ) enhances corporate governance and alleviates information asymmetry; and thus constrains managers' ability to withhold bad news. Importantly, the coefficients on the trade-credit measures are again positive and significant. Overall, the results of Table 2.8 suggest that strong internal control quality mitigates the impact of trade credit provision on crash risk.

(Insert Table 2.8 here)

Overall, the results of this section suggest that the association between levels of trade-credit provision and stock-price crash risk is robust to controlling for differing levels of information asymmetry. Additionally, the relation is strengthened for firms with severe information asymmetry.

2.5. Further robustness testing: controlling for cash holdings, and other factors

Although it has been documented that cash holdings may be associated with higher agency costs (Harford, Mansi, and Maxwell, 2008; Jensen, 1986), cash reserves may also alleviate liquidity difficulties and buffer against unexpected cash-flow shocks. We consider that cash holdings are beneficial to firms who supply trade credit, especially when they are exposed to the risk of customer default (Opler et al. (1999); Wu, Rui, and Wu (2012). Hence, we predict that more cash holdings will mitigate the positive relationship between trade credit provision and crash risk. Reported in Table 2.9, we include in the set of independent variables the value of cash and cash equivalents scaled by total assets; as well as the interactions of these measures with trade credit provision. We find, first, that the coefficients on the trade credit measures, AccRev and TotalRev, remain positive and highly significant. Second, the coefficients on the interaction Trade credit*Cash are negative and significant in model 2&4, consistent with a mitigating influence of cash holdings on the link of trade credit provision and stock crash risk. This evidence supports that firms are exposed to high liquidity risk from extending trade credit, and that cash holdings, relieving companies' liquidity risk, mitigate the crash risk induced by trade credit provision.

(Insert Table 2.9 here)

As a further robustness check, we adjust our trade credit measure by including the allowance for uncollectible accounts within accounts receivable, scaled by total assets. According to Chinese accounting rules, the expected value of bad debt losses from accounts receivable are recorded as "allowance for uncollectible accounts." Our previous analysis does not consider this item. Appendix 2.C reports these results of further robustness testing. Results are highly consistent with those reported in Table 2.2.

Lastly, as reported in Appendix 2.D, we report results of similar testing with trade-credit provision scaled by operating costs. These results are substantially in agreement with earlier tests. We find positive and significant coefficients on the trade credit provision measures $AccRev/OCs_t$ and $TotalRev/ OCs_t$ across the models. As with the scaling by total assets in earlier testing, our results are robust to the scaling of trade credit provision by operating costs.

2.6. Conclusions

Recently, empirical studies have investigated the role of trade credit usage on market stability, finding that trade credit usage makes firms less susceptible to equity market crash risk because of increased monitoring from respective providers of trade credit. In contrast, we investigate the influence of trade-credit *provision* on stock-price crash risk in an emerging-market setting. In this chapter, by examining the role of trade credit provision, we provide addition empirical evidence on the role of information quality on equity returns, particularly on firm specific crash risk. We suggest that the provision of trade credit positively impacts crash risk through an information channel: managers have more incentive to withhold bad news when firms extend trade credit provision.

By investigating a large sample of Chinese listed firms, and controlling for a host of previously identified determinants, our empirical results consistently support our predictions. We find significant positive relation between trade credit provision and crash risk, with results robust to different measures of stock-price crash risk, alternative calculations of trade credit provisions, and various model specifications. In addition, our results support our hypothesis that the link between trade credit provision and crash risk is stronger when information asymmetry between managers and investors is more severe. Controlling for state ownership and three measures of information asymmetry, we find that with higher information asymmetry, the positive relation between trade credit provision and crash risk is heightened. Our findings contribute to the literature on the sources of firm-specific crash risk and should be of particular interest to scholars interested in the role of information disclosure. Results have important implications for emerging markets with less developed credit environments. Our findings suggest that trade credit provision, rather than usage, needs to be focused on in order to assess the impact of trade credit on societies' financial vulnerability.

Tables

Table 2.1: Summary statistics of variables.

This table presents the summary statistics of all variables for the sample period 2001–2019. See Appendix A for variable definitions.

Variable	Obs.	Mean	Std. Dev	Min	Max
NCSKEW	24,701	-0.173	0.914	-2.546	2.140
DUVOL	24,701	-0.116	0.775	-1.880	1.930
AccRev	24,701	0.110	0.103	0	0.475
TotalRev	24,701	0.136	0.115	0	0.514
Accpay	24,701	0.085	0.072	0	0.344
DTURN	24,701	-0.074	0.403	-1.663	0.883
SIGMA	24,701	0.049	0.018	0.018	0.105
RETURN	24,701	-0.001	0.007	-0.019	0.018
SIZE	24,701	22.208	1.079	19.952	25.264
MTB	24,701	3.553	3.643	-1.373	26.310
LEV	24,701	0.481	0.213	0.069	1.128
ROA	24,701	0.034	0.067	-0.282	0.212
DACC	24,701	0.075	0.103	0	5.344
SOE	24,701	0.528	0.499	0	1.000
Z-score	24,701	5.352	7.140	-1.220	47.190
H-index	24,701	0.777	0.204	0.333	1.000
ICQ	24,701	0.651	0.145	0	1.000
Cash	24,701	0.164	0.117	0.006	0.573
TotalAccRev	24,701	0.125	0.117	0	0.563
AccRev/OCs	24,701	0.343	0.448	0	2.827
TotalRev/ OCs	24,701	0.407	0.485	0.001	3.051

Table 2.2: The effects of trade credit provision scaled by total assets on crash risk

This table reports fixed-effects regressions testing the effects of trade credit provision on crash risk . The dependent variable is NCSKEW and is DUVOL. The key independent variables of interest are current period trade-credit measures AccRev. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1. All regressions include firm-level control variables, the crash-risk measures in year t-1 and firm fixed-effects.The t-statistics in parentheses are based on robust standard errors clustered on firms. See Appendix A for variable definitions. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels respectively.

	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	All	SOE	Non-SOE	All	SOE	Non-SOE
Dep. Var	$NCSKEW_t$	$NCSKEW_t$	$NCSKEW_t$	$DUVOL_t$	$DUVOL_t$	$DUVOL_t$
$AccRev_{t-1}$	1.380***	1.379***	1.383***	1.368***	1.319***	1.435***
	(12.02)	(8.79)	(7.63)	(13.99)	(9.72)	(9.22)
$NCSKEW_{t-1}$	-0.067***	-0.036***	-0.133***			
	(-7.70)	(-3.12)	(-10.22)			
$DUVOL_{t-1}$				-0.091***	-0.060***	-0.159***
				(-9.20)	(-4.61)	(-10.35)
$DETURN_{t-1}$	-0.062***	-0.045*	-0.099***	-0.100***	-0.107***	-0.117***
	(-3.91)	(-1.88)	(-4.54)	(-7.43)	(-5.44)	(-6.21)
$SIGMA_{t-1}$	-4.588***	-3.679***	-5.768***	-4.570***	-3.871***	-5.402***
	(-11.19)	(-6.89)	(-8.57)	(-13.15)	(-8.44)	(-9.54)
$RETURN_{t-1}$	7.810***	9.169***	5.187***	6.137***	7.091***	3.562**
	(7.20)	(6.05)	(3.28)	(5.76)	(4.73)	(2.29)
$SIZE_{t-1}$	0.099***	0.096***	0.138***	0.096***	0.097***	0.127***
	(10.99)	(7.46)	(9.68)	(12.40)	(8.84)	(10.39)
MTB_{t-1}	0.017***	0.022***	0.011***	0.012***	0.015***	0.008***
	(6.78)	(6.02)	(3.20)	(5.67)	(4.85)	(2.65)
LEV_{t-1}	-0.166***	-0.379***	0.065	-0.193***	-0.343***	-0.023
	(-2.83)	(-4.49)	(0.72)	(-3.93)	(-4.97)	(-0.30)
ROA_{t-1}	-0.286**	0.180	-0.561***	-0.397***	0.025	-0.625***
	(-2.16)	(0.96)	(-2.95)	(-3.48)	(0.16)	(-3.69)
$DACC_{t-1}$	0.049	0.041	0.034	0.012	-0.026	0.035
	(0.81)	(0.45)	(0.38)	(0.22)	(-0.33)	(0.42)
SOE_{t-1}	0.021			0.029		
	(0.58)			(0.93)		
Constant	-2.305***	-2.206***	-3.155***	-2.150***	-2.124***	-2.855***
	(-11.28)	(-7.73)	(-9.80)	(-12.25)	(-8.74)	(-10.31)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	24,701	13,605	11,096	24,701	13,605	11,096
R-squared	0.031	0.028	0.048	0.041	0.036	0.060
# firm	2,558	1,270	1,639	2,558	1,270	1,639

Table 2.3: Alternative measure of trade credit provision

This table reports fixed-effects regressions testing the effects of trade credit provision on crash risk. The dependent variable is NCSKEW and is DUVOL. The key independent variables of interest are current period trade-credit measures TotalRev. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1. All regressions include firm-level control variables, the crash-risk measures in year t-1 and firm fixed-effects.The t-statistics in parentheses are based on robust standard errors clustered on firms. See Appendix A for variable definitions. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels respectively.

	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	All	SOE	Non-SOE	All	SOE	Non-SOE
Dep. Var	$NCSKEW_t$	$NCSKEW_t$	$NCSKEW_t$	$DUVOL_t$	$DUVOL_t$	$DUVOL_t$
$TotalRev_{t-1}$	1.004***	0.960***	1.018***	1.026***	0.954***	1.097***
	(9.81)	(6.64)	(6.24)	(11.72)	(7.83)	(7.71)
$NCSKEW_{t-1}$	-0.065***	-0.035***	-0.131***			
	(-7.52)	(-3.00)	(-10.11)			
$DUVOL_{t-1}$				-0.090***	-0.059***	-0.158***
				(-9.02)	(-4.51)	(-10.24)
$DETURN_{t-1}$	-0.056***	-0.038	-0.094***	-0.094***	-0.101***	-0.113***
	(-3.53)	(-1.58)	(-4.32)	(-7.03)	(-5.12)	(-5.97)
$SIGMA_{t-1}$	-4.585***	-3.704***	-5.750***	-4.557***	-3.881***	-5.373***
	(-11.15)	(-6.92)	(-8.52)	(-13.07)	(-8.46)	(-9.46)
$RETURN_{t-1}$	7.819***	9.239***	5.119***	6.174***	7.166***	3.518**
	(7.22)	(6.11)	(3.24)	(5.80)	(4.79)	(2.27)
$SIZE_{t-1}$	0.089***	0.085***	0.130***	0.087***	0.087***	0.121***
	(10.10)	(6.76)	(9.18)	(11.41)	(8.15)	(9.79)
MTB_{t-1}	0.017***	0.021***	0.011***	0.012***	0.014***	0.008***
	(6.78)	(5.94)	(3.25)	(5.67)	(4.78)	(2.69)
LEV_{t-1}	-0.154***	-0.362***	0.075	-0.181***	-0.327***	-0.014
	(-2.61)	(-4.27)	(0.83)	(-3.68)	(-4.72)	(-0.18)
ROA_{t-1}	-0.326**	0.137	-0.580***	-0.436***	-0.017	-0.645***
	(-2.44)	(0.72)	(-3.05)	(-3.81)	(-0.11)	(-3.81)
$DACC_{t-1}$	0.048	0.036	0.034	0.010	-0.030	0.034
	(0.79)	(0.40)	(0.38)	(0.18)	(-0.38)	(0.41)
SOE_{t-1}	0.025			0.033		
	(0.70)			(1.04)		
Constant	-2.082***	-1.946***	-2.983***	-1.943***	-1.887***	-2.694***
	(-10.40)	(-7.03)	(-9.29)	(-11.27)	(-8.06)	(-9.70)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	24,701	13,605	11,096	24,701	13,605	11,096
R-squared	0.028	0.026	0.045	0.038	0.034	0.057
# firm	2,558	1,270	1,639	2,558	1,270	1,639

Table 2.4: Endogeneity correction: Firm and year fixed effects model, random-effects model and system GMM
In these regressions, the independent variables are AccRev. Models 1 and 2 use the firm and year fixed-effects regression. Models 3 and 4 use the random-effects regression controlling for firm effects. To reduce endogeneity concerns, we regress crash risk measures computed for year t+1 on independent variables at the end of year t. Models 6 and 7 report regressions using the two-step system GMM estimator with bias-corrected robust standard. We control for the first two lags of the dependent variable in the models. The instruments use up to the maximum of five lagged values of the endogenous variables. AR (2) test for second order serial correlations and Hansen J test for overidentifying restrictions are reported (p-values). Detailed variable description are listed in Appendix A. *, **, *** are for significant levels at the 0.10, 0.05, and 0.01, respectively.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Method	Fixed-effects	Fixed-effects	Random-effects	Random-effects	SYS-GMM	SYS-GMM
Dep. Var	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t}$	$DUVOL_{t}$
$AccRev_t$	0.321***	0.346***	0.208***	0.199***	1.618***	1.274***
	(2.79)	(3.49)	(3.66)	(4.24)	(8.50)	(9.09)
$NCSKEW_t$	-0.041***		0.076***			
	(-4.82)		(9.29)			
$DUVOL_t$		-0.044***		0.069***		
		(-4.69)		(7.57)		
$DETURN_t$	-0.074***	-0.062***	-0.067***	-0.053***	-0.231***	-0.163***
	(-3.75)	(-3.82)	(-3.81)	(-3.66)	(-8.76)	(-8.14)
$SIGMA_t$	0.915*	0.693	2.212***	1.833***	3.231***	1.258**
	(1.79)	(1.60)	(5.02)	(4.96)	(4.89)	(2.37)
$RETURN_t$	4.305***	2.821**	15.697***	13.560***	-65.423***	-69.713***
	(3.57)	(2.47)	(13.90)	(12.65)	(-40.39)	(-52.49)
$SIZE_t$	0.398***	0.368***	0.053***	0.045***	-0.048***	-0.047***
	(22.56)	(23.95)	(7.28)	(7.41)	(-4.10)	(-5.16)
MTB_t	0.014***	0.012***	0.016***	0.013***	0.004	-0.000
	(5.67)	(5.51)	(8.84)	(8.27)	(0.89)	(-0.02)
LEV_t	-0.011	-0.043	-0.146***	-0.156***	-0.282***	-0.283***
	(-0.18)	(-0.83)	(-4.80)	(-6.25)	(-2.83)	(-3.61)
ROA_t	-0.930***	-0.893***	-0.604***	-0.682***	0.880***	0.486**
	(-7.07)	(-7.98)	(-5.78)	(-7.64)	(3.06)	(2.08)
$DACC_t$	-0.071	-0.094*	0.085	0.058	-0.274	-0.437**
	(-1.19)	(-1.75)	(1.47)	(1.15)	(-1.11)	(-2.27)
SOE_t	-0.051	-0.028	-0.057***	-0.026***	0.093**	0.049
	(-1.43)	(-0.92)	(-4.66)	(-2.62)	(2.21)	(1.49)
$NCSKEW_{t-1}$					-0.018*	
					(-1.91)	
$NCSKEW_{t-2}$					-0.061***	
					(-7.15)	
$DUVOL_{t-1}$						-0.023***
						(-2.74)
$DUVOL_{t-2}$						-0.067***
						(-8.84)
Constant	-8.106***	-7.350***	-0.691***	-0.420***	0.518*	0.756***
	(-20.23)	(-21.15)	(-3.59)	(-2.63)	(1.88)	(3.53)
Obs.	24,701	24,701	24,701	24,701	23,750	23,750
R-squared	0.147	0.195	0.115	0.159		
AR(2)					0.951	0.639
Hansen's J					0.578	0.579
# firm	2,558	2,558	2,558	2,558	2,352	2,352

Table 2.5: Robustness test: controlling trade credit financing

In these regressions, the independent variables are AccRev. We use same control variables as table 3&4. In addition, we control for trade credit financing measured as AccPay. Models 1 and 2 use the firm and year fixed-effects regression. Models 3 and 4 use the random-effects regression controlling for firm effects. To reduce endogeneity concerns, we regress crash risk measures computed for year t+1 on independent variables at the end of year t. Models 3 and 4; 7 and 8 report regressions using the two-step system GMM estimator with bias-corrected robust standard. We control for the first two lags of the dependent variable in the models. The instruments use up to the maximum of five lagged values of the endogenous variables. AR (2) test for second order serial correlations and Hansen J test for overidentifying restrictions are reported (p-values). Detailed variable description are listed in Appendix A. *, **, *** are for significant levels at the 0.10, 0.05, and 0.01, respectively.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Method	Fixed-effects	Fixed-effects	Random-effects	Random-effects	SYS-GMM	SYS-GMM
Dep. Var	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t}$	$DUVOL_{t}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
$AccRev_{t}$	1.413***	1.418***	0.562***	0.574***	1.512***	1.126***
	(12.26)	(14.51)	(8.67)	(10.50)	(17.16)	(17.94)
$AccPay_{t}$	-0.248	-0.378***	-0.233**	-0.309***	-0.411***	0.300***
	(-1.51)	(-2.77)	(-2.40)	(-3.84)	(-3.31)	(3.19)
$NCSKEW_{t-1}$					-0.021***	
					(-4.42)	
$NCSKEW_{t-2}$					-0.062***	
					(-15.03)	
$DUVOL_{t-1}$						-0.023***
						(-5.44)
$DUVOL_{t-2}$						-0.069***
						(-18.60)
Constant	-2.320***	-2.175***	-0.214*	-0.110	0.588***	0.828***
	(-11.35)	(-12.39)	(-1.74)	(-1.06)	(4.56)	(8.43)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	24,701	24,701	24,701	24,701	23,750	23,750
R-square	0.031	0.041	0.016	0.025		
AR(2)					0.923	0.637
Hansen's J					0.962	0.971
# Firm	2,558	2,558	2,558	2,558	2,352	2,352

Table 2.6: The effects of financial distress (Z-score) on trade credit provision and crash risk relationship

This table reports firm fixed-effects regressions. The dependent variable is NCSKEW and DUVOL. The key independent variables of interest are trade-credit measures AccRev and TotalRev. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1.The t-statistics in parentheses are based on robust standard errors clustered on firms. See Appendix A for variable definitions. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels respectively.

Model	(1)	(2)	(3)	(4)
Dep. Var	$NCSKEW_t$	$NCSKEW_t$	$DUVOL_t$	$DUVOL_t$
$AccRev_t$*$Z\text{-}score_{t-1}$	-0.041***		-0.039***	
	(-2.84)		(-3.10)	
$AccRev_{t-1}$	1.607***		1.609***	
	(12.89)		(14.99)	
$TotalRev_t$*$Z\text{-}score_{t-1}$		-0.036***		-0.033***
		(-2.87)		(-3.09)
$TotalRev_{t-1}$		1.229***		1.256***
		(10.85)		(12.87)
$Z\text{-}score_{t-1}$	0.005**	0.006**	0.005***	0.005***
	(2.49)	(2.55)	(2.92)	(2.95)
$NCSKEW_{t-1}$	-0.073***	-0.072***		
	(-8.31)	(-8.15)		
DUVOLt-1			-0.097***	-0.096***
			(-9.47)	(-9.30)
$DETURN_{t-1}$	-0.057***	-0.051***	-0.094***	-0.088***
	(-3.33)	(-2.98)	(-6.35)	(-5.97)
$SIGMA_{t-1}$	-4.733***	-4.697***	-4.793***	-4.748***
	(-10.81)	(-10.70)	(-12.68)	(-12.53)
$RETURN_{t-1}$	7.422***	7.417***	5.660***	5.682***
	(6.46)	(6.45)	(5.01)	(5.02)
$SIZE_{t-1}$	0.097***	0.087***	0.096***	0.086***
	(10.66)	(9.60)	(12.26)	(11.07)
MTB_{t-1}	0.014***	0.014***	0.010***	0.010***
	(5.64)	(5.64)	(4.62)	(4.62)
LEV_{t-1}	-0.166***	-0.156**	-0.187***	-0.177***
	(-2.63)	(-2.46)	(-3.43)	(-3.24)
ROA_{t-1}	-0.103	-0.143	-0.238**	-0.278**
	(-0.78)	(-1.08)	(-2.09)	(-2.43)
$DACC_{t-1}$	0.006	0.003	-0.018	-0.021
	(0.09)	(0.04)	(-0.32)	(-0.38)
SOE_{t-1}	0.030	0.034	0.037	0.041
	(0.89)	(1.01)	(1.27)	(1.40)
Constant	-2.281***	-2.047***	-2.175***	-1.951***
	(-11.18)	(-10.14)	(-12.37)	(-11.21)
Firm fixed effects	Yes	Yes	Yes	Yes
Obs.	22,454	22,454	22,454	22,454
R-squared	0.032	0.029	0.042	0.039
# firm	2,302	2,302	2,302	2,302

Table 2.7: The effects of firm diversification on trade credit provision and crash risk relationship

This table reports firm fixed-effects regressions. The dependent variable is NCSKEW and DUVOL. The key independent variables of interest are trade-credit measures AccRev and TotalRev. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1.The t-statistics in parentheses are based on robust standard errors clustered on firms. See Appendix A for variable definitions. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels respectively.

Model	(1)	(2)	(3)	(4)
Dep. Var	$NCSKEW_t$	$NCSKEW_t$	$DUVOL_t$	$DUVOL_t$
$AccRev_t$*$H\text{-}index_{t-1}$	-1.985***		-1.978***	
	(-4.32)		(-5.02)	
$AccRev_{t-1}$	2.966***		2.975***	
	(7.92)		(9.23)	
$TotalRev_t$*$H\text{-}index_{t-1}$		-1.711***		-1.688***
		(-4.10)		(-4.75)
$TotalRev_{t-1}$		2.467***		2.468***
		(7.14)		(8.31)
$H\text{-}index_{t-1}$	0.129*	0.124*	0.104*	0.096
	(1.81)	(1.67)	(1.73)	(1.55)
$NCSKEW_{t-1}$	-0.086***	-0.085***		
	(-8.71)	(-8.58)		
$DUVOL_{t-1}$			-0.107***	-0.105***
			(-9.19)	(-9.06)
$DETURN_{t-1}$	-0.083***	-0.078***	-0.118***	-0.113***
	(-4.77)	(-4.49)	(-7.99)	(-7.66)
$SIGMA_{t-1}$	-4.756***	-4.705***	-4.954***	-4.899***
	(-10.16)	(-10.03)	(-12.32)	(-12.17)
$RETURN_{t-1}$	5.955***	5.991***	4.734***	4.806***
	(4.86)	(4.90)	(3.87)	(3.93)
$SIZE_{t-1}$	0.113***	0.104***	0.116***	0.106***
	(10.60)	(9.84)	(12.16)	(11.32)
MTB_{t-1}	0.013***	0.014***	0.010***	0.010***
	(4.70)	(4.75)	(3.83)	(3.89)
LEV_{t-1}	-0.189***	-0.183***	-0.223***	-0.217***
	(-2.84)	(-2.74)	(-3.90)	(-3.78)
ROA_{t-1}	-0.068	-0.103	-0.227*	-0.262**
	(-0.45)	(-0.67)	(-1.72)	(-1.98)
$DACC_{t-1}$	-0.071	-0.077	-0.092	-0.097*
	(-1.11)	(-1.18)	(-1.61)	(-1.69)
SOE_{t-1}	-0.005	-0.001	0.010	0.015
	(-0.14)	(-0.02)	(0.30)	(0.43)
Constant	-2.688***	-2.473***	-2.627***	-2.411***
	(-10.59)	(-9.87)	(-11.71)	(-10.90)
Firm fixed effects	Yes	Yes	Yes	Yes
Obs.	19,124	19,124	19,124	19,124
R-squared	0.035	0.033	0.048	0.045
# firm	2,187	2,187	2,187	2,187

Table 2.8: The effects of internal control on trade credit provision and crash risk relationship

This table reports firm fixed-effects regressions. The dependent variable is NCSKEW and DUVOL. The key independent variables of interest are trade-credit measures AccRev and TotalRev. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1.The t-statistics in parentheses are based on robust standard errors clustered on firms. See Appendix A for variable definitions. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels respectively.

Model	(1)	(2)	(3)	(4)
Dep. Var	$NCSKEW_t$	$NCSKEW_t$	$DUVOL_t$	$DUVOL_t$
$AccRev_t$*ICQ_{t-1}	-1.670***		-1.500***	
	(-3.57)		(-3.74)	
$AccRev_{t-1}$	2.427***		2.331***	
	(8.14)		(9.12)	
$TotalRev_t$*ICQ_{t-1}		-1.313***		-1.209***
		(-3.14)		(-3.36)
$TotalRev_{t-1}$		1.845***		1.815***
		(6.83)		(7.83)
ICQ_{t-1}	0.128*	0.135*	0.153***	0.164***
	(1.85)	(1.85)	(2.58)	(2.61)
$NCSKEW_{t-1}$	-0.074***	-0.073***		
	(-8.61)	(-8.44)		
$DUVOL_{t-1}$			-0.100***	-0.099***
			(-10.05)	(-9.88)
$DETURN_{t-1}$	-0.056***	-0.050***	-0.095***	-0.090***
	(-3.34)	(-3.00)	(-6.62)	(-6.26)
$SIGMA_{t-1}$	-4.775***	-4.757***	-4.703***	-4.677***
	(-11.24)	(-11.17)	(-12.87)	(-12.77)
$RETURN_{t-1}$	7.736***	7.731***	5.750***	5.775***
	(6.90)	(6.89)	(5.23)	(5.24)
$SIZE_{t-1}$	0.099***	0.090***	0.097***	0.088***
	(11.42)	(10.40)	(12.98)	(11.82)
MTB_{t-1}	0.015***	0.015***	0.011***	0.011***
	(6.83)	(6.77)	(5.79)	(5.74)
LEV_{t-1}	-0.168***	-0.153***	-0.194***	-0.181***
	(-3.14)	(-2.88)	(-4.24)	(-3.95)
ROA_{t-1}	-0.166	-0.220	-0.314***	-0.367***
	(-1.21)	(-1.61)	(-2.68)	(-3.12)
$DACC_{t-1}$	0.027	0.026	-0.004	-0.005
	(0.44)	(0.42)	(-0.07)	(-0.10)
SOE_{t-1}	0.015	0.019	0.028	0.031
	(0.46)	(0.58)	(0.97)	(1.10)
Constant	-2.370***	-2.154***	-2.253***	-2.049***
	(-11.68)	(-10.67)	(-12.93)	(-11.82)
Firm fixed effects	Yes	Yes	Yes	Yes
Obs.	23,665	23,665	23,665	23,665
R-squared	0.033	0.030	0.043	0.040
# firm	2,420	2,420	2,420	2,420

Table 2.9: The effects of cash holdings on trade credit provision and crash risk relationship

This table reports firm fixed-effects regressions. The dependent variable is NCSKEW and DUVOL. The key independent variables of interest are trade-credit measures AccRev and TotalRev. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1.The t-statistics in parentheses are based on robust standard errors clustered on firms. See Appendix A for variable definitions. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels respectively.

Model	(1)	(2)	(3)	(4)
Dep. Var	$NCSKEW_t$	$NCSKEW_t$	$DUVOL_t$	$DUVOL_t$
$AccRev_t$*$Cash_{t-1}$	-0.999		-1.165*	
	(-1.26)		(-1.68)	
$AccRev_{t-1}$	1.524***		1.518***	
	(10.00)		(11.62)	
$TotalRev_t$*$Cash_{t-1}$		-0.956		-1.065*
		(-1.40)		(-1.80)
$TotalRev_{t-1}$		1.142***		1.166***
		(8.44)		(10.05)
$Cash_{t-1}$	0.198*	0.201*	0.153*	0.157*
	(1.91)	(1.87)	(1.77)	(1.73)
$NCSKEW_{t-1}$	-0.067***	-0.065***		
	(-7.73)	(-7.54)		
$DUVOL_{t-1}$			-0.092***	-0.090***
			(-9.22)	(-9.04)
$DETURN_{t-1}$	-0.061***	-0.055***	-0.099***	-0.094***
	(-3.78)	(-3.43)	(-7.34)	(-6.97)
$SIGMA_{t-1}$	-4.589***	-4.581***	-4.574***	-4.557***
	(-11.20)	(-11.15)	(-13.16)	(-13.08)
$RETURN_{t-1}$	7.770***	7.788***	6.117***	6.158***
	(7.16)	(7.18)	(5.73)	(5.78)
$SIZE_{t-1}$	0.099***	0.090***	0.096***	0.087***
	(11.06)	(10.18)	(12.44)	(11.48)
MTB_{t-1}	0.017***	0.017***	0.012***	0.012***
	(6.72)	(6.72)	(5.65)	(5.64)
LEV_{t-1}	-0.151**	-0.140**	-0.187***	-0.176***
	(-2.55)	(-2.36)	(-3.76)	(-3.54)
ROA_{t-1}	-0.303**	-0.340**	-0.400***	-0.438***
	(-2.27)	(-2.53)	(-3.49)	(-3.80)
$DACC_{t-1}$	0.047	0.046	0.010	0.009
	(0.77)	(0.75)	(0.19)	(0.16)
SOE_{t-1}	0.021	0.025	0.028	0.032
	(0.57)	(0.68)	(0.90)	(1.02)
Constant	-2.351***	-2.129***	-2.175***	-1.971***
	(-11.51)	(-10.66)	(-12.42)	(-11.49)
Firm fixed effects	Yes	Yes	Yes	Yes
Obs.	24,701	24,701	24,701	24,701
R-squared	0.031	0.028	0.041	0.038
# firm	2,558	2,558	2,558	2,558

Appendix 2.A: Description of variables.

NCSKEW	The negative skewness of firm specific weekly return over the fiscal year.
DUVOL	The down to up volatility. The log of the ratio of standard deviations of down-weeks to standard deviations of up-week firm specific weekly returns.
AccRev	The value of accounts receivable scaled by total assets. According to Chinese accounting rules, accounts receivable records the balance of amounts should be received by an enterprise from other enterprises for sales of goods, products, materials, and services rendered, or for project settlement. The balance of accounts receivable does not include provisions for bad debts from accounts receivable.
TotalRev	The value of total trade receivables scaled by total assets. The total trade receivables are calculated as accounts receivable plus notes receivables and not including the "other receivables" account. Notes Receivable is notes that are neither due nor discounted by banks yet, including trade acceptance notes and bank acceptance notes but excluding the endorsed notes receivable. The balance of notes receivable does not include provisions for bad debts from notes receivables.
AccPay	The value of accounts payables scaled by total assets.
DTURN	The average monthly share turnover over the current fiscal year minus the average monthly share turnover over the previous fiscal year. Monthly share turnover is percentage of the monthly trading volume over the total number of shares outstanding during the month.
SIGMA	The standard deviation of firm-specific weekly returns over the fiscal year.
RETURN	The mean of firm-specific weekly returns over the fiscal year.
SIZE	The nature logarithm of the market value of equity.
MTB	The percentage of the market value of equity on the book value of equity.
LEV	The percentage of total liabilities over total assets.
ROA	The percentage of return on assets.
DACC	The absolute value of discretionary accruals estimated by Modified Jones Model (Dechow et al., 1995).
SOE	A dummy variable, which equals to 1 if the firm's controlling shareholder is the Chinese government or its agency, and 0 if it is a private investor or firm.
Z-score	The degree of financial distress of the firm as in Altman Z-Score model (Altman, 1968).
H-index	The Herfindahl index of industrial diversifications computed firm/year top three sales by industries.
ICQ	Internal control index for Chinese listed firms is obtained from the DIB internal control and risk management database.
Cash	The value of cash holdings scaled by total assets. The value of cash holdings is the amounts of Cash and Cash Equivalents in the balance sheet.
TotalAccRev	The value of accounts receivable plus allowance for uncollectible accounts scaled by total assets.
AccRev/OCs	The value of accounts receivable scaled by operating costs.
TotalRev/OCs	The value of total receivables scaled by operating costs.

Appendix 2.B: The correlations matrix

Variables	NCSKEW	DUVOL	AccRev	TotalRev	Accpay	DTURN	SIGMA	RETURN	SIZE	MTB	LEV	ROA	DACC	SOEs	Z-score	H-index	ICQ
DUVOL	0.921***																
AccRev	0.075***	0.079***															
TotalRev	0.062***	0.064***	0.922***														
Accpay	-0.011*	-0.009	0.346***	0.368***													
DTURN	-0.118***	-0.130***	-0.029***	-0.032***	0.035***												
SIGMA	-0.215***	-0.250***	0.039***	0.029***	0.056***	0.290***											
RET	-0.588***	-0.717***	-0.056***	-0.042***	0.013**	0.093***	0.252***										
SIZE	-0.179***	-0.211***	-0.175***	-0.116***	0.035***	0.033***	0.048***	0.194***									
MTB	-0.066***	-0.108***	0.058***	0.041***	0.039***	0.052***	0.315***	0.200***	0.064***								
LEV	-0.003	-0.002	0.066***	0.032***	0.322***	0.110***	0.053***	-0.046***	-0.060***	0.060***							
ROA	-0.111***	-0.138***	-0.101***	-0.044***	-0.068***	-0.086***	-0.072***	0.201***	0.338***	0.000	-0.420***						
DACC	0.004	-0.006	0.020***	0.012*	0.003	0.000	0.101***	0.022***	-0.029***	0.107***	0.095***	-0.050***					
SOE	-0.039***	-0.028***	-0.135***	-0.112***	0.092***	0.120***	-0.111***	-0.018***	0.049***	-0.129***	0.178***	-0.069***	-0.062***				
Z-score	-0.049***	-0.073***	-0.037***	-0.020***	-0.203***	-0.055***	0.170***	0.152***	0.145***	0.341***	-0.608***	0.311***	0.014**	-0.204***			
H-index	-0.009	-0.010	0.015**	0.071***	0.108***	-0.064***	0.003	0.018***	0.055***	-0.002	-0.056***	0.082***	-0.004	-0.073***	0.089***		
ICQ	-0.104***	-0.118***	-0.067***	-0.028***	-0.007	0.002	-0.122***	0.119***	0.264***	-0.161***	-0.196***	0.485***	-0.084***	0.086***	0.029***	0.034***	
Cash	-0.019***	-0.030***	-0.055***	-0.059***	-0.007	-0.106***	0.008	0.070***	0.064***	0.062***	-0.321***	0.267***	0.003	-0.075***	0.352***	0.073***	0.113***

This table presents the Pearson correlation matrix among variables. The variables definitions are provided in Appendix 2.A.
***,**, and * indicates significance at 1%, 5%, and 10% respectively.

Appendix 2.C: Robustness test using the sum of account receivables and allowance for uncollectible accounts as the measure of trade credit provision.

This table reports fixed-effects regressions testing the effects of trade credit provision on crash risk. The dependent variable is NCSKEW and is DUVOL. The key independent variable TotalAccRev is the sum of account receivables and allowance for uncollectible accounts scaled by total assets. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1. All regressions include firm-level control variables, the crash-risk measures in year t-1 and firm fixed-effects.The t-statistics in parentheses are based on robust standard errors clustered on firms. See Appendix A for variable definitions. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels respectively.

Model	(1)	(2)
Dep. Var	$NCSKEW_t$	$DUVOL_t$
$TotalAccRevt_{t-1}$	1.200***	1.166***
	(11.62)	(13.11)
$NCSKEW_{t-1}$	-0.072***	
	(-8.37)	
$DUVOL_{t-1}$		-0.098***
		(-9.77)
$DETURN_{t-1}$	-0.061***	-0.099***
	(-3.82)	(-7.30)
$SIGMA_{t-1}$	-4.654***	-4.620***
	(-11.22)	(-13.13)
$RETURN_{t-1}$	7.391***	5.590***
	(6.71)	(5.16)
$SIZE_{t-1}$	0.101***	0.098***
	(11.06)	(12.46)
MTB_{t-1}	0.015***	0.011***
	(6.19)	(5.07)
LEV_{t-1}	-0.156***	-0.190***
	(-2.63)	(-3.82)
ROA_{t-1}	-0.200	-0.309***
	(-1.50)	(-2.71)
$DACC_{t-1}$	0.036	0.000
	(0.59)	(0.00)
SOE_{t-1}	0.011	0.024
	(0.30)	(0.75)
Constant	-2.340***	-2.183***
	(-11.30)	(-12.28)
Fixed effects	Yes	Yes
Obs.	24,158	24,158
R-squared	0.030	0.040
# firm	2,550	2,550

Appendix 2.D: Robustness test using trade credit provision scaled by COGS as the measure of trade credit provision.

This table reports fixed-effects regressions testing the effects of trade credit provision on crash risk. The dependent variable is NCSKEW and is DUVOL. The independent variables are AccRev/OCs and TotalRev/OCs. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1. All regressions include firm-level control variables, the crash-risk measures in year t-1 and firm fixed-effects. The t-statistics in parentheses are based on robust standard errors clustered on firms. See Appendix A for variable definitions. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels respectively.

Model	(1)	(2)	(3)	(4)
Dep. Var	$NCSKEW_t$	$DUVOL_t$	$NCSKEW_t$	$DUVOL_t$
$AccRev/OCs_t$	0.243***	0.234***		
	(11.02)	(12.08)		
$TotalRev/OCs_t$			0.200***	0.196***
			(9.92)	(11.04)
$NCSKEW_{t-1}$	-0.065***		-0.065***	
	(-7.56)		(-7.48)	
DUVOLt-1		-0.090***		-0.090***
		(-9.07)		(-8.98)
$DETURN_{t-1}$	-0.056***	-0.093***	-0.053***	-0.091***
	(-3.53)	(-6.96)	(-3.37)	(-6.80)
$SIGMA_{t-1}$	-4.672***	-4.663***	-4.662***	-4.649***
	(-11.45)	(-13.47)	(-11.42)	(-13.43)
$RETURN_{t-1}$	7.841***	6.138***	7.852***	6.172***
	(7.23)	(5.75)	(7.25)	(5.78)
$SIZE_{t-1}$	0.087***	0.084***	0.082***	0.079***
	(9.80)	(11.04)	(9.28)	(10.46)
MTB_{t-1}	0.018***	0.013***	0.018***	0.013***
	(7.08)	(6.00)	(7.07)	(5.99)
LEV_{t-1}	-0.133**	-0.160***	-0.126**	-0.154***
	(-2.28)	(-3.28)	(-2.16)	(-3.14)
ROA_{t-1}	-0.200	-0.313***	-0.223*	-0.333***
	(-1.48)	(-2.71)	(-1.66)	(-2.88)
$DACC_{t-1}$	0.046	0.009	0.047	0.010
	(0.76)	(0.16)	(0.78)	(0.17)
SOE_{t-1}	0.031	0.039	0.033	0.041
	(0.87)	(1.26)	(0.92)	(1.31)
Constant	-1.988***	-1.827***	-1.880***	-1.727***
	(-9.96)	(-10.73)	(-9.47)	(-10.19)
Fixed effects	Yes	Yes	Yes	Yes
Obs.	24,695	24,695	24,695	24,695
R-squared	0.030	0.039	0.028	0.037
# firm	2,558	2,558	2,558	2,558

CHAPTER 3

Debt and Stock Price Crash Risk in Weak Information Environment

3.1. Introduction

Modigliani and Miller (1958) reveal that, in frictionless capital markets without agency costs, capital structure is irrelevant to firm value and the cost of equity increases with the level of debt. Hence, the leveraging effect of debt suggests that stock risk increases with the level of debt. In contrast, the agency theory of Jensen and Meckling (1976) shows that shareholders have the incentives to expropriate creditors by investing in high risk and high expected returns projects especially among highly leveraged firms. If the level of debt is high, most of the benefits are cashed by shareholders while the potential losses in highly risky projects are shifted to creditors. Anticipating such incentives, creditors engage in corporate governance to protect their interests. Typically, creditor protection is facilitated by debt covenants. Alternatively, lenders may take advantage of regulatory monitoring as a substitute for covenants (Black et al., 2004; Chauhan et al., 2015). Creditor rights protection through these channels can mitigate information asymmetry between shareholders and managers as well as between firm controlling shareholders and minority shareholders (Jensen and Meckling, 1976; Barclay and Smith, 1995). Consequently, the specific risk of stocks associated with the quality of firm level corporate governance may be reduced under creditors' influences.

This chapter contributes to the literature by empirically testing the above views of debt and stock specific risk in light of Modigliani and Miller (1958) and Jensen and

Meckling (1976). More specifically, we use a large sample of listed firms from China and focus on an important form of specific risk: stock price crash risk. The concept of individual stock price crash risk was first introduced by Chen et al. (2001). Typically, crash risk is measured by “negative coefficient of skewness” and “down-to-up volatility” of market adjusted individual stock returns. Under agency theory framework, self-interested managers have incentives to withhold negative information from investors, but they can only do so up to a limit. Eventually when “hoarded” bad news are released/revealed stock price will crash (Chen et al., 2001; Jin and Myers, 2006).

We believe the Chinese setting and crash risk are ideally suited for further research in this area. First, the Chinese stock market is characterized with sever information asymmetry, weak corporate governance, and frequent price crashes (Xu et al., 2014; Chauhan et al., 2015; Luo et al., 2016). Examining the Chinese setting, for instance, Xu et al. (2014) show excess perk consumption increases crash risk in state-owned enterprises, Luo et al. (2016) find that political connection lowers crash risk, and Yuan et al. (2016) illustrate that firms purchase directors' and officers' insurance have lower crash risk. Similarly, Chauhan et al. (2015) examine a regulatory setup in India and find that bank nominated directors reduce borrowing firms’ crash-risk.

Second, while extant international studies focus on aspects of internal corporate governance that influence “bad news hoarding” arguably the main cause of stock price crash risk, (Chen et al., 2001; Jin and Myers, 2006), creditors’ influence as external governance mechanism has been left largely unexplored. Hence, the present studies adds important evidence to this international literature.

Third, whether creditors, especially banks, reduce bad news hoarding by managers in in borrowing firms and concomitantly mitigate stock price crash risk has important and direct policy implications for investors and regulators in emerging markets. The Chinese financial system resembles most typical features of the emerging markets world hence this chapter has wider implications.

Fourth, China's commercial banking sector is dominated by the "Big-5" state-owned banks and heavily regulated by the Chinese government. Listed state-owned enterprises (SOEs) enjoy preferential access to bank loans. Private sector firms' accesses to formal financing, particularly long-term bank loans, often rely on their political connections (Allen et al., 2005). Moreover, to alleviate bank discrimination, non-state-owned firms have a greater propensity to hold significant ownership in commercial banks than SOEs (Lu et al., 2012; Pan and Tian, 2015). Due to regulatory compliance requirements and relationship lending, listed firms have stronger incentives to disclose information to banks. Consequently, the agency role of creditors in reducing information asymmetry between shareholders and managers is particularly relevant under the Chinese institutional setting.

In this chapter, we conduct a number of tests and document consistent evidence of a negative and significant relationship between the level of debt and stock price crash risk among Chinese firms. Our finding suggests that shareholders may substitute bank monitoring for quality public disclosure of news by listed firms when information environment is poor.

The remainder of the chapter is structured as follows: section 3.2 outlines our data and methods, section 3.3 discusses our results, and section 3.4 concludes.

3.2. Data and methods

We collect our data from China Stock Market & Accounting Research database. Our sample includes all Chinese A-share listed firms during the period of 2002-2016 excluding those from the financial sector, or cross-listed outside of mainland China, or with negative book value of equity, or with fewer than 30 weeks stock returns data. We follow Chen et al. (2001), Xu et al. (2014), Chauhan et al. (2015), Luo et al. (2016), and Yuan et al. (2016) to measure stock price crash risk using both the "negative coefficient of skewness (NCSKEW)" and "down-to-up volatility (DUVOL)" of firm-specific returns. Specifically, we first obtain the regression errors $\varepsilon_{i,t}$ from the following expanded market model:

$$R_{i,t} = \alpha_i + \beta_1 R_{M,t-2} + \beta_2 R_{M,t-1} + \beta_4 R_{M,t} + \beta_1 R_{M,t+1} + \beta_1 R_{M,t-2} + \varepsilon_{i,t} \quad (3.1),$$

where the return on stock i in week t ($R_{i,t}$) is estimated using is the lead and lag terms of the return on the value-weighted market index ($R_{M,t}$). We calculate the firm-specific weekly return on stock i in week t ($W_{i,t}$) as the natural logarithm of 1 plus the regression error, that is $W_{i,t} = \ln(1+ \varepsilon_{i,t})$. We then compute, based on the numbers of weeks n, up weeks n_u, and down weeks n_d, two measures of crash risk as follows:

$$\text{NCSKEW}_{i,t} = -[n(n-1)^{3/2}\Sigma W_{i,t}^3]/[(n-1)(n-2)\,(\Sigma W_{i,t}^2)^{3/2}] \qquad (3.2);$$

$$\text{DUVOL}_{i,t} = \log\{[(n_u-1)\textstyle\sum_{Down} W_{i,t}^2]/[(n_d-1)\sum_{Up} W_{i,t}^2]\} \qquad (3.3).$$

Higher values of NCSKEW or DUVOL indicates greater crash risk.

To investigate the debt-crash risk relationship, we estimate the following model controlling for firm fixed-effects and year fixed-effects, with robust standard errors clustering by firm and year:

$$\text{CrashRisk}_{i,t} = \alpha_i + \beta_1\text{DEBT}_{i,t-1} + \beta_2\text{Control}_{i,t-1} + \beta_3\text{YEAR} + \nu_{i,t} \qquad (3.4),$$

where DEBT is measured using both the market value financial leverage ratio and the book value Debt/Assets ratio for robustness.[5] To further address the endogeneity of capital structure decision, we use the two-step Arellano and Bover (1995)/Blundell and Bond (1998) dynamic panel-data system estimator with Windmeijer (2005) bias-corrected robust standard errors to estimate a revised model:

$$\text{CrashRisk}_{i,t} = \alpha_i + \beta_1\text{CrashRisk}_{i,t-1} + \beta_2\text{CrashRisk}_{i,t-2} + \beta_3\text{DEBT}_{i,t} + \beta_4\text{Control}_{i,t} + \nu_{i,t}$$

(3.5).

All independent variables are considered as endogenous. We first-difference equation (3.5) to eliminate unobserved heterogeneity α_i and to reduce potential omitted variable bias and then use lagged values of the endogenous variables as instruments for estimation. The maximum of four lags of dependent/endogenous variable are used as GMM instruments. We control for the first two lags of the dependent variable in the

[5] Debt among Chinese listed firms mainly consist of bank loans and trade credit. Hence, we use the book value of debt and the market value of equity to calculate the market-value-based financial leverage ratio.

model to mitigate second order serial correlations (the first order autocorrelation is expected due to first-differencing). We report the test of second order autocorrelation AR(2) and Hansen's J test of overidentifying restrictions. The null hypotheses are there is no second order autocorrelation and overidentifying restrictions are valid. Hence, rejecting the null hypotheses indicates the GMM model is invalid. Due to dynamic specification, the interpretation of equation (3.5) differs from that of equation (3.4). The coefficient β_3 in equation (3.5) represents the short-run effect of debt on concurrent crash risk conditional on all past information controlled by the lagged crash risk measures.

In equations (3.4) and (3.5), $Control_{i,t}$ denotes a number of control variables in line with the extant crash risk literature (Chen et al., 2001; Xu et al., 2014; Chauhan et al., 2015; Luo et al., 2016; Yuan et al., 2016), including: the change of average monthly stock trading volume compared to the previous year (DTurn), the standard deviation of firm-specific weekly returns (Sigma), the mean of firm-specific weekly returns (Return), the log of market capitalization (Size), the price-to-book ratio (P/B), the return on assets (ROA), and earnings management measured as the absolute value of discretionary accruals (EM). Table 3.1 reports summary statistics of the variables after winsorizing them at 1th and 99th percentiles to control for outliers. On average, the market value financial leverage is 16%, the book value debt-to-assets ratio is 48%, and long-term debt accounts for 74% of total debt (LT-Debt %). Within our sample, 52% of firm-year observations are under control of the Chinese government. We classify these firms as state-owned enterprises (SOEs) and the remainder firms as non-SOEs (private-owned enterprises).

(Insert Table 3.1 here)

3.3. Results

Table 3.2 shows regression results for the impacts of debt on stock price crash risk using fixed effects model. We regress the current period independent variables Debt measured as Leverage and Debt/Assets against the forward 1-period crash risk variables F.NCSKEW and F.DUVOL to reduce reverse causality concern. Firm fixed-effects and year fixed-effects are included in the model to control for unobservable heterogeneity across firms and years. We further control for the current period crash risk NCSKEW and DUVOL to address missing variables concern. We find that the market value financial leverage is negatively and significantly associated with the both forward 1-period crash risk measures, NCSKEW and DUVOL in model 1 and 2. Consistently, the coefficients of Debt/Assets, measure of book value debt-to-assets ratio, are negative and significant in model 3 and 4. Our results reveal that creditors mitigate stock crash risk. Both banks and the less developed corporate bond market in China are heavily regulated by the Chinese government. In addition, corporate debt in China is primarily short-term (Jiang et al., 2017). Hence, to secure short-term debt refinancing, firms have stronger incentives to disclose information to creditors who are under stringent regulatory monitoring. Therefore, the extent of “bad new hoarding” may be reduced due to creditors' monitoring. As our results indicate, stock price crash risk is contained.

(Insert Table 3.2 here)

To address the endogeneity of capital structure decision, we further use the system-GMM estimators to test the relationship between debt and stock price crash risk and list results in Table 3.3. We continue to find negative and significant coefficients on both debt measures, Leverage and Debt/Assets across four models, which is consistent with results in table 3.2 using fixed-effects models. The AR(2) and Hansen tests fail to reject the null hypotheses suggesting the GMM models used are valid. Again, the results support our prediction that creditors serve as extra monitoring, which increases information quality of debt borrowers, constraint bad news hoarding and consequently reduce crash risk.

(Insert Table 3.3 here)

A number of studies suggest state affiliation is an important mediating factor with regard to stock-price crash risk in China (Chen et al., 2018; Li and Chan, 2016; Luo et al., 2016; Piotroski, Wong, and Zhang, 2015; Xu et al., 2014). The evidence about the effects of state ownership on stock price crash risk is mixed. One stream of literature states that managers of SOEs are more likely to engage in timely release of bad news timely in order to safeguard the careers of connected politicians (Chen et al., 2018; Li and Chan, 2016; Luo et al., 2016); thereby improving information transparency of SOEs. While the other stream of literature find that due to the political concerns, State-Owned Enterprises (SOEs) are more likely to hide bad news (Piotroski et al., 2015; Li et al., 2017), leading to higher crash risk.

In Table 3.4, we conduct a robustness test use the subsamples analysis between state-owned enterprises (SOEs) and Non-SOEs. Model 1 and 2 are results for subsample of SOEs and model 3 and 4 are results for subsample of non-SOEs. We find, first, the influence of leverage on stock crash risk remains negative and significant across all 4 regressions. Second, where model specifications are the same but subsamples are different (for instance, models 1 and 3), the coefficients on leverage are mostly comparable. All and all, we conclude that the mitigating effects of creditors on borrowing firms' stock price crash risk are homogeneous among SOEs and non-SOEs.[6]

(Insert Table 3.4 here)

In Table 3.5, we repeat our subsamples analysis using system-GMM estimators. Consistent with results in Table 3.4, both NCSKEW and DUVOL are negatively and significantly related to Leverage across four models for both SOEs and Non-SOEs, which support our prediction that debt reduce stock price crash risk through an information channel: by constraint managerial bad news hoarding. Furthermore, this negative and significant relationship between debt and crash risk is effective for both SOEs and Non-SOEs

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[6] Regressions using the debt-to-assets ratio find similar results. In addition, we include a SOE dummy and its interactions with the debt measures in Table 3.3 regressions and find that while the coefficients on the debt measures remain negative and significant, the interactions are insignificant across 3 of the 4 models. These additional tests are not reported to conserve space.

(Insert Table 3.5 here)

In Table 3.6, we conduct a further robustness test considering possible influences of debt maturity structure on the relationship between debt and crash risk using fixed-effects model. The prior literature proposes two competing views on debt maturity choices. On one hand, Barclay and Smith (1995), for instance, argue that long-term debt is associated with stronger creditor monitoring over borrowing firms. On the other hand, Diamond (1991, 1993) and Rajan (1992) suggest that with the presence of information asymmetry, lenders would prefer the use of short-term debt than long-term debt to monitor firms better due to rollover pressure of short-term debt on borrowing firms' managers. To this end, table 3.6 regressions further incorporate the percentage of debt that is long-term, denoted as LT-debt %, as a measure of debt maturity structure and its interaction with leverage as independent variables. We find that the results on leverage and crash risk remain consistent with those in Tables 3.2. In particular, debt maturity structure appears to have insignificant influence on crash risk itself as well as the relationship between debt and crash risk. This result indicates that the negative leverage-crash relation is unlikely to be due to the rollover pressure of short-term debt.

(Insert Table 3.6 here)

To be robustness, we repeat our analysis of influences of debt maturity structure on the relationship between debt and crash risk using system-GMM model and list results in Table 3.7. Not surprisingly, we further find consistent results as results in Table 3.6. Specifically, we neither find significant effects of debt maturity structures on crash risk nor the relationship between debt and crash risk. More importantly, the coefficients of leverage remain negative and significant as our previous results, which prove our prediction that crash risk is reduced by creditors monitoring.

(Insert Table 3.7 here)

3.4. Conclusion

In this chapter, we follow first chapter and continue to analysis the credit environment in China and its impacts of information transparency. Specifically, we investigate a primary financing resource in China, debt, and its influence on stock price crash risk. According to regulation of Chinese government, bank loan and corporate debt is strictly regulated. Suggested by Jiang et al., (2017), corporate debt in China is primarily short-term. In order to obtain debt refinancing, Chinese firms have stronger incentives to disclose information to creditors. Therefore, creditors serve as an extra monitoring mechanism, in which the extent of managerial "bad new hoarding" can be reduced.

Using sample of Chinese firms from 2002-2016, We find that crash risk is negatively and significantly related to debt financing. For robustness, we adopt the fixed effects model and two-step GMM model. We also use two measures of financial leverage, the market value financial leverage ratio and the book value Debt/Assets ratio. We find consistent results. Our results support our view that creditors play an important role of monitoring in reducing bad news hoarding by managers. In further analysis, we find consistent results for the different of firm ownerships and debt maturity structures. Specifically, we conclude that the mitigating effects of creditors on borrowing firms' stock price crash risk are homogeneous among SOEs and non-SOEs. Debt maturity structure appears to have insignificant influence on crash risk itself as well as the debt-crash relationship. This result indicates that the negative leverage-crash relation is unlikely to be due to the rollover pressure of short-term debt. Our paper contributes to the stream of literature in light of Modigliani and Miller (1958) and Jensen and Meckling (1976). Findings should be of great interest to scholars interested in the role of information transparency in emerging financial markets; as well as to investors and regulators concerned about stock price crash risk.

Tables:

Table 3.1: Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
NCSKEW	23,809	-0.17	0.90	-2.55	2.08
DUVOL	23,809	-0.14	0.67	-2.25	2.04
Leverage	23,809	0.16	0.11	0.01	0.52
Debt/Assets	23,809	0.48	0.20	0.06	1.05
DTurn	23,809	-0.05	0.40	-1.54	0.89
Sigma	23,809	0.65	0.25	0.26	1.54
Return	23,809	0.42	1.19	-2.01	4.06
Size	23,809	22.91	1.16	20.63	26.19
P/B	23,809	3.75	3.77	0.23	27.61
ROA	23,809	0.05	0.06	-0.23	0.26
EM	23,809	0.08	0.09	0.00	0.50
LT-Debt %	23,809	9.79	14.70	0.00	64.89

Table 3.2: Debt and stock price crash risk using fixed-effects model

Model	1	2	3	4
Method	Fixed-effects	Fixed-effects	Fixed-effects	Fixed-effects
Dep. Var.	F.NCSKEW	F.NCSKEW	F.DUVOL	F.DUVOL
Leverage	-1.925***		-0.456***	
	(-15.39)		(-4.34)	
Debt/Assets		-0.997***		-0.106**
		(-13.75)		(-1.97)
DTurn	-0.028	-0.033	0.017	0.014
	(-1.25)	(-1.47)	(0.93)	(0.72)
Sigma	0.000	0.048	-0.055	-0.041
	(0.01)	(0.98)	(-1.29)	(-0.97)
Return	-0.013	-0.000	-0.004	0.002
	(-1.04)	(-0.02)	(-0.43)	(0.20)
Size	0.311***	0.410***	0.051***	0.061***
	(17.99)	(20.97)	(4.21)	(4.51)
P/B	-0.006*	0.015***	-0.004	0.000
	(-1.95)	(4.95)	(-1.59)	(0.19)
ROA	-0.350***	-0.618***	0.042	0.064
	(-2.62)	(-4.45)	(0.40)	(0.57)
EM	-0.074	-0.063	-0.032	-0.028
	(-0.96)	(-0.82)	(-0.54)	(-0.48)
NCSKEW	-0.057***	-0.059***		
	(-7.01)	(-7.18)		
DUVOL			-0.073***	-0.073***
			(-9.67)	(-9.65)
Constant	-6.340***	-8.414***	-1.029***	-1.265***
	(-16.43)	(-19.98)	(-3.85)	(-4.44)
Obs.	21,230	21,230	21,230	21,230
R-squared	0.149	0.147	0.025	0.024
# of firms	2,170	2,170	2,170	2,170

Robust t-statistics in brackets. ***1% significance, **5% significance, * 10% significance.

Table 3.3: Debt and stock price crash risk using system-GMM model

Model	1	2	3	4
Method	GMM	GMM	GMM	GMM
Dep. Var.	NCSKEW	NCSKEW	DUVOL	DUVOL
Leverage	-1.390***		-0.421***	
	(-7.41)		(-3.76)	
Debt/Assets		-0.524***		-0.193**
		(-4.00)		(-2.39)
DTurn	0.310***	0.318***	0.089**	0.094***
	(5.83)	(5.88)	(2.52)	(2.66)
Sigma	-0.421***	-0.417***	-0.159***	-0.159***
	(-10.07)	(-9.95)	(-5.03)	(-5.09)
Return	-0.110***	-0.101***	-0.043***	-0.043***
	(-7.45)	(-6.79)	(-4.05)	(-4.12)
Size	-0.104***	-0.089***	-0.058***	-0.054***
	(-7.63)	(-6.23)	(-6.67)	(-5.83)
P/B	-0.005	0.021***	-0.001	0.008**
	(-0.87)	(3.92)	(-0.26)	(2.23)
ROA	-0.020	0.480	0.680***	0.843***
	(-0.05)	(1.31)	(2.99)	(3.69)
EM	0.405	0.568	-0.046	0.002
	(0.97)	(1.31)	(-0.18)	(0.01)
L.NCSKEW	-0.047***	-0.049***		
	(-3.71)	(-3.82)		
L2.NCSKEW	-0.046***	-0.045***		
	(-3.82)	(-3.79)		
L.DUVOL			0.015	0.015
			(1.29)	(1.34)
L2.DUVOL			0.003	0.001
			(0.30)	(0.10)
Constant	2.738***	2.276***	1.351***	1.236***
	(8.79)	(7.17)	(7.11)	(6.18)
Obs.	20,189	20,189	20,189	20,189
# of firms	2,127	2,127	2,127	2,127
AR(2) p-value	0.71	0.62	0.39	0.47
Hansen p-value	0.37	0.39	0.33	0.31

Robust t-statistics in brackets. ***1% significance, **5% significance, * 10% significance.

Table 3.4: Robustness test using the subsample of SOEs and non-SOEs and fixed effects model

Sub-sample	SOE		Non-SOE	
Model	1	2	3	4
Method	Fixed-effects	Fixed-effects	Fixed-effects	Fixed-effects
Dep. Var.	F.NCSKEW	F.DUVOL	F. NCSKEW	F.DUVOL
Leverage	-2.150***	-0.438***	-2.027***	-0.519**
	(-13.24)	(-3.04)	(-8.41)	(-2.42)
Constant	-7.819***	-1.834***	-5.404***	-0.333
	(-12.42)	(-3.93)	(-7.83)	(-0.69)
Controls	Yes	Yes	Yes	Yes
Observations	10,588	10,588	8,737	8,737
R-squared	0.141	0.022	0.189	0.035
Number of firms	1,130	1,130	1,342	1,342

Robust t-statistics in brackets. ***1% significance, **5% significance, * 10% significance.

Table 3.5: Robustness test using the subsample of SOEs and non-SOEs and system-GMM model

Sub-sample	SOE		Non-SOE	
Model	1	2	3	4
Method	GMM	GMM	GMM	GMM
Dep. Var.	NCSKEW	DUVOL	NCSKEW	DUVOL
Leverage	-0.926***	-0.347**	-1.445***	-0.281**
	(-4.18)	(-2.29)	(-5.23)	(-1.98)
L.NCSKEW	-0.027*		-0.094***	
	(-1.83)		(-5.35)	
L2.NCSKEW	-0.039***		-0.083***	
	(-2.70)		(-5.01)	
L.DUVOL		0.003		0.023
		(0.23)		(1.41)
L2.DUVOL		-0.010		-0.018
		(-0.71)		(-1.16)
Constant	2.571***	1.298***	2.493***	1.470***
	(7.16)	(5.34)	(5.31)	(4.98)
Controls	Yes	Yes	Yes	Yes
Observations	10,834	10,834	8,459	8,459
Number of firms	1,120	1,120	1,302	1,302
AR(2) p-value	0.76	0.89	0.82	0.78
Hansen p-value	0.36	0.37	0.37	0.39

Robust t-statistics in brackets. ***1% significance, **5% significance, * 10% significance.

Table 3.6: Robustness test further controlling for the maturity structure of debt and using fixed-effects model

Model	1	2	3	4
Method	Fixed-effects	Fixed-effects	Fixed-effects	Fixed-effects
Dep. Var.	F.NCSKEW	F.DUVOL	F.NCSKEW	F.DUVOL
Leverage	-1.875***	-0.463***	-1.920***	-0.474***
	(-14.98)	(-4.36)	(-12.92)	(-3.82)
LT-Debt %	-0.002***	0.000	-0.002**	0.000
	(-2.84)	(0.45)	(-2.26)	(0.13)
Leverage*LT-Debt %			0.003	0.001
			(0.54)	(0.17)
Constant	-6.498***	-1.009***	-6.494***	-1.008***
	(-16.54)	(-3.71)	(-16.55)	(-3.71)
Controls	Yes	Yes	Yes	Yes
Observations	21,230	21,230	21,230	21,230
R-squared	0.149	0.025	0.149	0.025
Number of firms	2,170	2,170	2,170	2,170

Robust t-statistics in brackets. ***1% significance, **5% significance, * 10% significance.

Table 3.7: Robustness test further controlling for the maturity structure of debt and using system-GMM model

Model	1	2	3	4
Method	GMM	GMM	GMM	GMM
Dep. Var.	NCSKEW	DUVOL	NCSKEW	DUVOL
Leverage	-1.312***	-0.390***	-1.577***	-0.365***
	(-6.60)	(-3.24)	(-13.50)	(-4.08)
LT-Debt %	-0.002	0.000	-0.002	0.001
	(-0.93)	(0.39)	(-1.46)	(1.55)
Leverage*LT-Debt %			0.013***	-0.004
			(2.87)	(-1.03)
L.NCSKEW	-0.047***		-0.047***	
	(-3.82)		(-7.72)	
L2.NCSKEW	-0.046***		-0.043***	
	(-3.83)		(-7.43)	
L.DUVOL		0.012		0.013*
		(1.03)		(1.92)
L2.DUVOL		-0.001		-0.002
		(-0.08)		(-0.32)
Constant	2.617***	1.368***	2.759***	1.376***
	(8.13)	(7.02)	(17.76)	(11.87)
Controls	Yes	Yes	Yes	Yes
Observations	20,189	20,189	20,189	20,189
R-squared				
Number of firms	2,127	2,127	2,127	2,127
AR(2) p-value	0.69	0.54	0.67	0.51
Hansen p-value	0.35	0.36	0.32	0.39

Robust t-statistics in brackets. ***1% significance, **5% significance, * 10% significance.

CHAPTER 4

Financial Assets Investment and Stock Price Crash Risk

4.1. Introduction

Extensive studies examine capital investment based on the neoclassical theory of investment developed more than 30 years ago (Myers, 1977; Myers and Majluf, 1984; McConnell and Muscarella, 1985; Jensen, 1986). Notably, this literature has largely ignored the fact that when monetary assets with competitive interest rates are available, investors could alternatively invest in monetary assets (Tobin, 1965). For instance, Duchin et al. (2017) reveal that U.S. industrial firms invest heavily in a wide range of financial assets such as corporate debt, equity, and mortgage-backed securities. This shift in asset allocation from capital assets towards financial assets may have important implications on firm governance, liquidity and performance which warrant further scholarly research.

In prior literature, several studies have documented “transparency and easier to value” as a distinctive advantage of holding alternative assets. For instance, Muller and Riedl (2002) find that in the UK, the disclosure requirement of investment property increases external monitoring therefore reduces information asymmetry across traders, which results in lower equity market price differences. Extending these findings, Muller et al. (2011) show that due to the disclosure requirement of investment property, European real-estate sector firms exhibit high financial reporting quality, and concomitantly, information asymmetry across market participants is reduced. In a similar vein, Fontes et al. (2018) examine financial sector firms in the European Union and reveal that their disclosures of information on financial assets mitigates information asymmetry between managers and investors, hence, facilitates equity valuations. An important question arising from this is whether financial assets can enhance the transparency of non-financial sector firms. Indeed, from a more general perspective, the development of financial sector should reduce information asymmetry between fund providers and users, thereby mitigating funding constraints and improving investment efficiency of firms (Love, 2003).

To our knowledge, no prior work has systematically examined the interconnections among financial assets, capital assets, information asymmetry, and shareholder values. Never the less, a number of studies focusing on the use of financial derivatives by firms has shed some light on these issues. For instance, Chen and King (2015) find that firms using financial derivatives can mitigate agency costs associated with under-investment problems. Since derivatives generate sufficient funds at low cost, managers are more likely to pursue optimal investment policy (Froot et al., 1993; Bessembinder,1991; Campbell and Kracaw, 1990). Against this backdrop, this paper aims to conduct a more systematic analysis examining both the broadly defined financial assets and capital assets held by corporations, and their impacts on information asymmetry and shareholder values through the lens of stock price crash risk.

Crash risk is defined as large negative return outliers (Chen et al., 2001; Jin and Myers, 2006). Jin and Myer (2006) propose that the lack of information transparency allows managers to extract part of firm's operating cash flows that is not perceived by outside investors. Hence, mangers are incentivized to conceal downside risk by "*hoarding bad news*". However, they may only do this up to certain limit and eventually are forced to release bad news to market at once, leading to stock price crashes. An extensive literature have since investigated the determinants of crash risk particularly focusing on various drivers of information transparency, such as accounting regime (Bleck and Liu, 2007), opaque financial information (Hutton et al., 2009), corporate tax avoidance (Kim et al., 2011), IFRS adoption (Defond, et al., 2014), financial statement comparability (Kim et al., 2016), conditional accounting conservatism (Kim and Zhang, 2016), financial derivatives and opacity (Dewally et al., 2013), and fair value accounting of investment property (Hsu, et al., 2019).

Notably, this literature has not paid attention to financial assets holdings by corporations from non-financial sector despite their significance. According to Duchin et al., (2017), the largest financial holding in a non-financial firm in US is about 70% of its book assets. Compared to capital assets, financial assets are subject to more stringent accounting disclosures and are easier to value, hence, may deter managers from bad news hoarding and consequently lower crash risk.

We use data from China to conduct an empirical analysis. We consider China is an ideal country to perform this study for the following reasons. First, financial assets have become increasingly important investments by Chinese listed firm in recent years (Allen et al., 2019; Huang et al., 2019, Tang and Zhang, 2019). This type of investments gives rise to a large amount of financial gains accounting for about 26% of firm's total profit on average among Chinese non-financial firms[7]. The economic significance of financial assets investment warrants both regulatory and scholarly attention. Second, despite extensive evidence from developed countries (Aivazian et al., 2005; Denis and Sibilkov, 2010; Duchin et al, 2017; Tobin, 1965; Tornell, 1990), the influence of financial investments by non-financial sector firms in emerging markets has receive far less attention. Froot et al. (1993) theorize that financial assets like derivatives curtail the underinvestment problem in the case that a firm faces a high cost of external financing. By investing in financial assets, managers can generate sufficient internal funds therefore leading to optimal investment decision. Although the Chinese economy is the second largest in the world, its financial markets are less developed and firm external financing costs are high. This speaks to a need for more investigation on the role of financial assets investments by firms in emerging markets like China.

While there is a growing literature on financial assets investment for non-financial firms in the US and China which considers financial assets as important components of corporate cash holdings and mostly focused on the motivation of financial assets holdings (Duchin, 2017; Tang and Zhang, 2019; Huang et al., 2019). We significantly extend this literature by examining the impacts of assets substitution on the quality of

[7] Detailed data and statistics on financial gains are available upon request.

firm's information environment through stock price crash risk (Jin and Myer, 2006; Hutton, 2009). To the best of our knowledge, it is the first study on the role of assets substitution in improving the quality of firm's information environment. Hence, our work has important implications to both regulators and practitioners in both developed and emerging markets around the world.

Using a large sample of Chinese listed firms from 2007-2019, we show that firms investing less in capital assets hold more financial assets. Stock price crash risk decreases with financial assets holdings and increases with capital assets investment. The result is robustness to alternative measures of financial assets and different estimation methods. Our findings support the conjecture that financial assets reduce firm information asymmetry due to better information transparency. We conduct further analysis of financial assets classes and illustrate that fair value measures of financial assets, long-term financial assets and investment property are more informationally transparent and hence are associated with lower crash risk. Consistently, we find that the negative link between financial assets investment and crash risk is stronger among firms with lower financial reporting quality, higher financial distress risk, and poorer performance.

The remainder of this chapter is structured as follows: Section 4.2 reviews literature and develops our hypotheses; Section 4.3 describes sample selection and methodology; Section 4.4 presents empirical results; and Section 4.5 presents conclusions.

4.2. Research background and hypotheses development

4.2.1 Accounting disclosures requirements on capital assets and financial assets

Chinese Ministry of Finance published new Chinese accounting standards (CAS) in 2006. It became effectively to all Chinese publicly traded corporation on January 1, 2007. In order to ensure transparent and comparable information, the new CAS substantially adopted the International Financial Reporting Standards (IFRS) with a few exceptions and modifications to reflect the unique conditions of Chinese market. One of fundamental changes in the new CAS with regard of financial instruments, or publicly known as financial assets and liabilities (Deloitte Touche Tohmastu, 2006). According to Europe Communities 2002: Art.1, the purpose of such changes is to increase information transparency and financial reporting quality, therefore create an efficient and functional capital market.

The disclosure requirements of fixed assets are mostly consistent with the old CAS. According to CAS (2006) 4- Fixed assets, firms are required to report capital assets in fixed assets account on balance sheets. The detailed information of capital assets such as classification and depreciation method should be disclosed in the notes to financial statements. The fixed assets are measured at historical costs which remains the same as old CAS.

Compare to capital assets, financial assets are more comprehensively disclosed under the new CAS. In addition, fair value measures are largely adopted for financial assets. According to CAS (2006) 22-Financial instrument recognition and measurement, before presentation of financial assets, financial assets should be classified according to their contractual cash flow characteristics and the business model under which they are held. Such requirements can limit opportunistic earnings management by limiting accounting choices and reducing the amount of reporting discretion. Specifically, financial assets are classified into three categories: if financial assets are held to collect contractual cash flows (principal and interest), they are measured at amortized cost. If financial asserts are held for sale in near term or given evidence of short-term profit taking, they are measured at fair value with any value changes recognized through profit and loss (FVTPL). If financial assets are held with a business model whose objective is achieved by both collecting contractual cash flows and selling financial assets, they are measured at fair value and any value changes are included in other comprehensive income (FVOCI). Consequently, the financial assets are presented in following accounts on firms' balance sheets: cash, trading financial assets, derivatives financial assets, net loans and receivables, available-for-sale financial assets, held-to-maturity investment, net investment property. Addition to this, CAS (2006) 37- Presentation of Financial Instruments gives explicit and comprehensive presentation and disclosures rules of financial assets, which require firms to disclose information such as accounting policies, measuring basis, information of hedge accounting, nature, and extent of exposure to risks arising from financial assets and so on.

More importantly, CAS (2006) is considered more prudential and restrictive regarding the fair value estimations which China's criteria make sure that estimate methods reflect the real value of financial assets (Hsu and Wu, 2019). Those conservative requirements decrease information asymmetry by constraint earning manipulation opportunities from fair value estimation (Bagna et al., 2014).

4.2.2 The substitution relationship between capital assets and financial assets

Typically, a non-financial sector firm faces a portfolio choice in investment decisions between two categories of assets: capital assets and financial assets.[8] According to Tobin (1965), the respective rates of returns determine firm portfolio allocations between capital assets and financial assets. Consistent with this view, Tornell (1990) finds that compared to investing in irreversible fixed assets, non-financial firms in developing countries are more likely to invest in liquid and reversible assets in financial market which also yield higher rates of return. Similarly, Crotty (2005) shows that non-financial firms choose to increase financial investments in response to high costs of external finance and low real investment profits. Demir (2009) further documents that in emerging markets, real sector firms prefer to invest in reversible short-term financial assets than in fixed assets especially under higher economy uncertainty. Contrary to this, Huang et al. (2019) find in China that when economic policy uncertainty increases, managers are less motivated to speculate on financial assets since it is difficult to forecast future return. Also paying attention to China, Tang and Zhang (2019) construct a portfolio choice model and find that both

[8] This chapter also differs from those examine substitution between capital assets and intangible assets such as R&D and innovation (Gugler, 2003; Kumar and Li, 2016).

risk and the rates of return gap between financial and capital assets affect investment decision. Furthermore, firm tend to invest more in financial assets if capital investment involves higher risk. Zhang and Zheng (2020) extend this argument and highlight that instead of return, relative risk is the key determination of the financial investment decision of Chinese firms who tend to invest in risk-bearing instruments such as stocks and mutual fund to offset risk in the real sector.

4.2.3 Crash risk

A large body of literature has documented that asymmetrical volatility attributes to large negative market return distributions or "stock price crashes" using various theories and approaches, such as stochastic bubble models (Blanchard and Watson, 1982), leverage effects (Black, 1976; Christie, 1982), volatility feedback mechanism (French et al., 1987; Campbell and Hentschel, 1992), as well as heterogeneous opinions among investors (Hong and Stein, 2003). Chen et al. (2001) find that investor heterogeneity along with short-selling constraint facilitate more positive information over negative information, leading to more negatively skewed return distribution which they define as price crashes of individual stocks.

Following Chen et al. (2001), Jin and Myer (2006) and Hutton et al., (2009) reveal that crash risk is driven by firm "bad news hoarding", especially in more opaque information environment. Among the extant literature on crash risk, a number of scholars have shed some light on the influences of accounting rules on crash risk.

Financial statement comparability enables investors to understand information from comparable firms at lower costs. Furthermore, accounting conservatism may restrict managers' ability to overstate performance, therefore constrain bad news hoarding, leading to a lower crash risk (Kim et al., 2016; Kim and Zhang, 2016). For instance, Bleck and Liu, (2007) show that historical cost accounting provides managers opportunities to mask firm's financial performance. In contrast, marking to market offers investor timely information and early warnings. Therefore, historical cost accounting leads to more opacity, resulting more frequent crashes in financial market. Defond et al., (2015) provide cross country evidence that mandatory IFRS adoption reduces crash risk of non-financial firms within severer information environment whereas enhances crash risk of financial firms in countries with weaker legal protection. Focusing on US banks, Dewally et al., (2013) find that financial derivatives reduce bank information transparency and engender higher stock price crash risk. Moreover, Hsu et al. (2018) provide direct evidence that fair value disclosures reduce crash risk among U.S. banks by increasing information transparency. Deng et al. (2018) studing mutual fund herding behavior and show that poor accounting disclosure leads to future stock price crashes.

4.2.4 Hypotheses development

As discussed earlier, managers' financial assets investment decisions should depend on the interest rate of returns. However, agency theory suggests that managers may use their information advantage for their own benefits at the expense of marginal investors. So far, it remains unclear that what impact on information asymmetry could engender from investment portfolio choice between financial assets and capital assets. We consider that stock price crash risk is an ideal channel to perform this investigation.

Conventionally, firms invest in capital assets to increase their market values (McConnell and Muscarella, 1985). It is rational for managers to pursue as many positive Net Present Value (NPV) projects as available in a perfect market world without financial frictions (Miller and Modigliani, 1958). However, agency theory implies that asymmetrical information between managers and investors leads to both under-investments and over-investments (Jensen, 1986; Myers, 1977; Myers and Majluf, 1984). Jenson (1986) illustrates that managers may accept negative net present value projects due to private benefits from controlling more assets, leading to firm overinvestment problem. This problem is commonly associated with managerial "empire-building" or "entrenchment" (Jensen, 1986; Bebchuk & Stole, 1993; Malmendier & Tate, 2005; Aggarwal and Samwick, 2006). Titman et al. (2004) suggest that investors underreact to the empire building implications of increased investment expenditures, hence, firms increasing capital investments may subsequently achieve negative abnormal return. On the other hand, managers may forgo some positive net present value projects due to private costs of investment such as their work time and efforts. Consequently, underinvestment occurs due to "managerial slack" (Myers, 1977). Both overinvestment and underinvestment problems are exacerbated by managers' private rent seeking activities, hence, may provide strong incentives for them to hide bad news associated with inefficient capital assets investment decisions. We therefore propose the following hypothesis:

H1: Capital assets investment increases stock price crash risk.

Contrary to capital assets, as aforementioned, financial assets decrease information asymmetry between managers and investors and consequently restrain managerial bad news hoardings. In China, with less developed financial system, external financing is heightened and often resulting in higher cost (Allen et al., 2005). Under this type of environment, non-financial firms may prefer to invest in more liquid and reversible financial assets which generate higher returns at lower costs (Tobin,1965; Tornell,1990; Crotty, 2005; Demir, 2009; Duchin et al., 2019). Firm may use financial assets to generate sufficient fund and mitigate agency costs associated with under-investment problems especially when access to external financing is limited. If managers are more likely to pursue optimal investment policy when funding constrains are lifted due to gains from financial assets investments, lower principal-agent costs arising from capital investment decisions should consequently decrease information asymmetry (Froot et al., 1993; Bessembinder,1991; Campbell and Kracaw, 1990).

Furthermore, disclosure requirements of financial assets investment may also enhance information transparency. As previously discussed, a fundamental difference between fixed assets and financial assets accounting disclosures under CAS (2006) is their valuation methods. Scholarly work has shown that fair value measures of financial assets provide more relevant information and greater explanatory power than historical value estimates (Barth, 1994, 2006; Landsman, 2007; Hodder, 2006; Koonce et al, 2011). Specifically, Barth (1994, 2006) uses samples of banks and shows that fair value measures of investment securities provide more relevant information and greater explanatory power than historical value estimates. Similarly, Landsman (2007) shows that compared to historical values, fair values of bank's securities are incrementally informative to investors. Hodder (2006) suggests that compare to historical value income, full-fair-value income volatility are more informative and more related to capital pricing. Koonce et al. (2011) instead investigate information advantage on fair value of financial assets to individual investors. Otto and Volpin (2018) further suggest that fair value estimation of financial assets can help mitigate agency problem since it provides investors more information. Therefore, financial assets are expected to increase information transparency. Taken together, financial assets investment should constrain bad news hoarding, consequently, reduce crash risk. We propose our second hypothesis based on above argument:

H2: Financial assets investment decreases stock price crash risk.

4.3. Sample and research design

We collected weekly stock returns and financial reports data from China Stock Market Accounting Research (CSMAR) database for years 2007-2019. Our sample starts from 2007 since that is the first year that data on financial assets became available under the new CAS (2006). Our initial sample includes all the A-share publicly traded firms on Shanghai and Shenzhen stock exchanges. Following literature on crash risk (Hutton et al., 2009; Kim et al., 2016), we exclude financial sector firms, firms with stock return less than 30 trading weeks in a fiscal year and sample with missing values. Our final sample contains 21,518 firm-year observations.

4.3.1 Measures of stock price crash risk

Following Chen et al., (2001), Hutton et al., (2009), we adopt two measures of stock price crash risk: *negative skewness* (NCSKEW) and *down-to-up volatility* (DUVOL). We first apply the following expanded index model regression to estimate firm-specific weekly returns:

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

where $r_{i,t}$ is return on stock *i* in week *t*. $r_{m,t}$ is value-weighted return on A share market index in week *t*. We control for the two lead and two lag terms of the market index to allow for non-synchronous trading (Dimson, 1979). The firm-specific weekly returns are denoted as $W_{i,t}$, which is computed as the nature log of one plus regression residual estimated from Eq. (4.1), that is $W_{i,t} = \ln (1 + \varepsilon_{i,t})$.

Negative skewness (NCSKEW) is computed by taking the third moment of firm specific weekly return for each year over the standard deviation of firm specific weekly return raised to third power, then multiplying -1 as follows:

$$NCSKEW_{i,t} = -\frac{n(n-1)^{3/2}\sum W_{i,t}^{3}}{(n-1)(n-2)(\sum W_{i,t}^{2})^{3/2}} \qquad (4.2),$$

where $W_{i,t}$ is firm-specific weekly return for firm *i* in year *t*, and n is the number of weeks in year t. A higher value of NCSKEW represents a more negatively skewed return distribution and higher crash risk.

To calculate down-to-up volatility (DUVOL) for each firm *i* over year *t*, we separate all weeks in each fiscal year into two groups: "down" weeks where the specific weekly returns are less than the annual mean, and "up" weeks where the specific weekly returns are higher than the annual mean. The DUVOL is computed as the nature log of the standard deviation of "down" weeks over the standard deviation of "up" weeks as follows:

$$DUVOL_{i,t} = \log\left\{(n_u - 1)\sum_{Down} W_{i,t}^2 \Big/ (n_d - 1)\sum_{Up} W_{i,t}^2\right\} \quad (4.3),$$

where $W_{i,t}$ is firm-specific weekly return for firm *i* in year *t*, n_u is the number of "up" weeks and n_d is the number of "down" weeks. A higher value of DUVOL represents a higher crash risk.

4.3.2 Measures of capital assets and financial assets

When investigating capital assets, we follow Chen et al. (2011) and measure Chinese firms' investments as cash payments for fixed assets, intangible assets, and other long-term assets from the cash flow statements minus cash receipts from selling these assets. This is scaled by total assets for empirical tests, denoted as CAP_INV. The financial assets holding are calculated using the sum of following values on firms' balance sheets: trading financial assets, derivatives financial assets, net loans and receivables, available-for-sale financial assets,

held-to-maturity investment, net investment property. We use the total value of financial assets scaled by total assets (FA_INV) as the measure of financial assets when conducting empirical tests. We recognize while this holding measure does not directly reflect changes in financial assets balance in comparison to the capital assets investment measure. From portfolio perspective, however, holding of financial assets indeed may still been seen as "investment", hence, we label it accordingly to facilitate our discussions. For robustness, we use a dummy variable (FA_Dummy) as alternative measure of financial assets, which is assigned "1" if financial assets holding of a firm is above sample median for a fiscal year and "0" if otherwise. We also report further tests using categories of financial assets.

4.3.3 Empirical models

We conduct several baseline tests on the influences of capital assets and financial assets investments on stock price crash risk, respectively, using the following random-effects GLS estimations[9]:

$$Crash_{i,t} = \alpha_i + \beta_1\, CAP\_INV_{i,t-1} + \gamma\, Controls_{i,t-1} + \rho Year_{t-1} + \varepsilon_{i,t-1} \qquad (4.4),$$

$$Crash_{i,t} = \alpha_i + \beta_1\, FA\_INV_{i,t-1} + \gamma\, Controls_{i,t-1} + \rho Year_{t-1} + \varepsilon_{i,t-1} \qquad (4.5),$$

[9] We find similar results using fixed-effects regressions and they are available upon request from authors.

where the dependent variable $Crash_{i,t}$ refers to the two measures of stock price crash risk, namely *NCSKEW* or *DUVOL*. We impose a year lag on the independent variables to investigate whether financial assets holdings in year *t-1* financial statements can predict stock price crash risk in year t. We also include year fixed-effects, denoted as $Year_{t-1}$, in the models to control for unobserved heterogeneity across firms that are fixed for each year.

Following Chen et al. (2001), we select a group of control variables in the regression models, denoted as $Controls_{i,t-1}$. In particular, crash risk is persistent, we control for NCSKEW/DUVOL in the current fiscal year t-1. Since high volatility stocks are more prone to crash and past stock performance can predict future crash risk, we control for stock volatility (SIGMA), past return (RETURN) and detrended share turnover (DTURN). We also include a set of firm level controls, firm size (SIZE), market to book ratio (MTB), financial leverage (LEV) and return on assets (ROA), as well as the absolute value of discretionary accruals (DACC) estimated by the Modified Jones Model (Dechow et al., 1995) in the models.

While the random-effects GLS estimations are less informative in dealing with the issue of simultaneity in making investment in both capital assets and financial assets leading to considerable endogenous concerns, we further analyze the joint-effects of capital assets and financial assets on crash risk by using three-stage-least squares (3SLS) simultaneous equations system estimation as follows:

$$FA\_INV_{i,t} = \alpha_i + \beta_1\, CAP\_INV_{i,t} + \gamma\, Controls_{i,t} + \rho Year_t + \varepsilon_{i,t} \qquad (4.6a),$$

$$Crash_{i,t+1} = \alpha_i + \beta_1\, CAP\_INV_{i,t} + \gamma\, Controls_{i,t} + \rho Year_t + \varepsilon_{i,t} \qquad (4.6b),$$

$$Crash_{i,t+1} = \alpha_i + \beta_1\, FA\_INV_{i,t} + \gamma\, Controls_{i,t} + \rho Year_t + \varepsilon_{i,t} \qquad (4.6c).$$

Detailed descriptions of the variables are provided in Appendix 4.A. Table 4.1 reports the summary statistics of the variables used in this chapter. We drop firm-years whose FA_INV ratio is greater than 74.3% (top 99.9% cutoff) from our sample since in they are virtually "financial firms". Then we winsorize all other continuous variables at 1% level in both tails to mitigate the effects of extreme values. The mean values of NCSKEW and DUVOL are -0.240 and -0.168, respectively, whereas the standard deviations of NCSKEW and DUVOL are 0.899 and 0.756, respectively, which are generally comparable to prior studies (Xu et al., 2013; Li et al., 2017). On average financial assets holdings account for 3.8% of total assets among all sample firm-years. Appendix 4.B shows the correlation matrix of variables used in this chapter[10].

(Insert Table 4.1 here)

4.4. Empirical results

4.4.1 Baseline results

Table 4.2 reports our baseline results. Panel A regressions suggest that crash risk is significantly and positively associated with capital asset investments CAP_INV in both models supporting Hypothesis H1. In panel B, we find the coefficients on financial asset investments FA_INV are negative and significant supporting Hypothesis H2. In

[10] All correlations are above 5* significant.

panel C, we find consistent coefficients for both CAP_INV and FA_INV as panel A and B. Consistent with Chen et al. (2001) and Hutton et al. (2009), several control variables include detrended share turnover (DTURN), stock return volatility (SIGMA), past stock return (RETURN), firm size (SIZE), market to book ratio (MTB), financial leverage (LEV), return on assets (ROA) as well as the absolute value of discretionary accruals (DACC) also have significant influences on crash risk.

(Insert Table 4.2 here)

Next, to mitigate the endogeneity concern due to simultaneity, we adopt three-stage-least squares (3SLS) regression estimation as in equations 4.6 a, b & c. Results are reported in Table 4.3. As discussed in section 4.1, firms face portfolio choices between capital assets and financial assets (Tobin, 1965). Models (1) and (4) show that FA_INV is significantly and negatively associated with CAP_INV, supporting with our prediction that capital investment and financial assets investment are substitutional in firm's investment decision. Consistent with baseline results in Table 4.2, when the dependent variables are crash risk measures, we notice that the coefficients on capital investments measure, CAP_INV_t, are positive and statistically significant in model (2) and (5), while the coefficients on financial assets investments measure, FA_INV_t, are negative and statistically significant in model (3) and (6). These results seem to further indicate that capital investment and financial assets investment are substitutional. More importantly, they further support our hypotheses that firm invest more in capital assets are subject to higher crash risk whereas financial assets investment decreases crash risk.

(Insert Table 4.3 here)

To ensure the robustness of our findings, in Table 4.4, we adopt industry-year-median adjusted capital investment and financial assets investment measures and rerun the three-stage-least squares (3SLS) regressions in Table 4.4. Industry-year-median adjusted measures are calculated by subtracting the industry-year-median from the original measures of capital investment and financial assets investment for each firm/year. By doing so, we mitigate the potential economic and industry impacts on capital investment and financial assets investment. Results in Table 4.4 are highly similar to those in Table 4.3.

(Insert Table 4.4 here)

In Table 4.5, we conduct our second robustness check on the link between financial assets investment and crash risk by using the FA_Dummy which is assigned 1 if the firm has financial assets above the sample median in a fiscal year, or 0 if otherwise. We continue to see that both crash risk measures NSCKEW and DUVOL are negatively and significantly associated with FA_Dummy across four models with different model specifications further confirming our prediction that firms invest more in financial assets are subject to lower future crash risk. Our baseline tests complete here with findings strongly support both Hypotheses H1 and H2.

(Insert Table 4.5 here)

4.4.2 Additional tests: categories of financial assets

Next, we distinguish different categories of financial assets and examine if they influence crash risk differently. In line with CAS (2006), we classify firm’s financial assets classes along three demission: valuation method, liquidity and characteristics.

According to various studies that pay attention to equity value differences between fair values and historical values in financial assets, fair value accounting measures of financial assets compared to their historical values provide more relevant information to stock valuation (Barth, 1994, 2006; Landsman, 2007; Hodder, 2006; Koonce et al, 2011). Otto and Volpin (2018), for instance, argue that fair value estimation of financial assets can help mitigate agency problem since it provides investors with better information. Therefore, we expect that compare to historical cost measure, fair value measure of financial assets requires managers to release bad news more timely and hence may lead to lower crash risk. We classify financial assets as measured either at historical value or fair value according to their contractual cash flow characteristics and the business model as defined in CAS (2006). Financial assets measured at historical value include net loan receivables and financial assets held beyond maturity. Financial assets measured at fair value include trading financial assets, derivatives, available-for-sale financial assets and investment properties. Table 4.6 reports the relationships between these two categories of financial assets with crash risk, respectively. Model (1) and (2) show that the coefficients on financial assets measured at fair value, denoted as FA_Fair, are negative and significant, which is consistent with our discussions above and support hypothesis H2. In contrast, we find the coefficients on financial assets measured at historical value, denoted as FA_Historical, are not significant in both model (3) and (4), which further confirming the role of accounting rules on the financial assets and crash risk relationship.

(Insert Table 4.6 here)

Under CAS (2006), financial assets in listed firms are either recorded in short-term or long-term financial assets. Short-term financial assets include trading financial assets and derivatives. Long-term financial assets include net loan receivables, available-for-sale financial assets, financial assets held beyond maturity and investment property. In Table 4.7, we repeat the analysis using these categories of financial assets. We find negative and significant coefficients on Long-term FA in both model (3) and (4), whereas the coefficients on Short-term FA are insignificant. These additional results are also in line with our explanation that the negative association between financial assets investment and crash risk is driven by enhanced transparency on asset values. In particular, Dewally et al. (2013) find that financial derivatives reduce bank information transparency and engender higher stock price crash risk. Consequently, as derivatives are a significant component of short-term financial assets under CAS (2006) rules, the relationship between short-term financial assets and crash risk becomes statistically insignificant due to mixed effects from both derivatives and trading financial assets.

(Insert Table 4.7 here)

Due to booming property markets in the recent decade, many manufacturing sector firms in China have been diversifying into the real-estate sector (Fang et al., 2016; Wall street journal, 2019). Investment properties are recorded as financial assets under CAS (2006) but compared to other types of financial assets they are less liquid and traded less frequently due to features such as location and condition. According to Liang and Riedl (2014), investment properties provide more relevant and transparent information during periods of increasing property prices than during a downward trend. In addition, fair value measure of investment property releases more private information timely. The booming property markets in China attract considerable investor attention and consequently shareholders and auditors tend to pay more attention to the value of investment properties held by listed firms. Therefore, we expect investment properties would discourage managerial bad news hoarding and reduce future crash risk.

In line with the above arguments, we further examine investment properties and other financial assets separately in Table 4.8. We continued find crash risk is negatively related to financial assets. More importantly, the coefficients on investment property are more significant than those on non-property financial assets suggesting that our findings so far may be driven by investment properties.

(Insert Table 4.8 here)

To shed more lights on this, we conduct a set of subsample tests on SOEs (state-owned enterprises) and Non-SOEs. Previous studies document that state affiliation is an important mediating factor for stock price crash risk in China (Chen et al., 2018; Li and Chan, 2016; Luo et al., 2016). For example, due to the political concerns, SOEs are more likely to hide bad news when political concerns are more important (Piotroski et al., 2015; Li et al., 2017), leading to higher crash risk. Therefore, we expect the relationship between investment property and crash risk is more pronounced in SOEs than Non-SOEs. In line with this prediction, in Table 4.9 we repeat the analysis using subsamples of SOEs (Models 2 and 5) and Non-SOEs (Models 3 and 6) and show that investment properties have negative and significant influence on crash risk among SOEs but not among non-SOEs.

(Insert Table 4.9 here)

In contrast, Table 4.10 regressions focusing on non-property financial assets suggest that the negative connection between financial assets and crash risk is still significant for the Non-SOE subsample. All in all, our results in Tables 4.8-4.10 have strong implications to both stock market investors and real-estate sector regulators in China and in general reconfirms the role of financial assets in enhancing corporate transparency with differing levels of effectiveness associated with firm ownership types. Our additional tests using categories of financial assets under CAS (2006) complete here.

(Insert Table 4.10 here)

4.4.3 The moderating roles of financial reporting quality, distress and performance

In order to shed further light on the mechanisms behind the financial assets and crash risk relationship reported so far, we consider three firm level proxies of information asymmetry that may moderate the negative impact of financial assets investment on crash risk: financial reporting quality, financial distress risk and performance. In Tables 4.11 to 4.13, we present these tests and discuss our findings in more details here.

A number of studies suggest that opaque environment is a prominent determinant of crash risk (Jin and Myer, 2006; Hutton et al., 2009). Since we argue that financial assets investment improves information transparent, the negative impacts of financial assets investment on crash risk should be more pronounced in firm with more opaque financial information. Following Hutton et al., (2009), we include the absolute value of discretionary accruals scaled by total assets, denoted as DACC, and its interaction with financial assets investment FA*DACC to capture the moderating effect of financial reporting quality in our model. Table 4.11 models (1) and (2) show that the coefficients on FA_INV remain negative and significant as in Table 4.2. More importantly, the coefficients on FA_INV*DACC are both positive and significant, which support our prediction, and hence also the transparency enhancement explanation of financial assets investment in mitigating crash risk.

(Insert Table 4.11 here)

Opler and Titman (1994) suggests that financially distressed firm are associated with severer moral hazard problems and information asymmetry. Kim et al. (2011), also studying crash risk, suggest that firm with higher distress risk has incentive to hide managers' abnormal behaviors from investor. Therefore, in line with our information channel argument, we expect that the negative effect of financial assets investment on crash risk is more prominent in firm with higher distress risk. We use Altman Z-score as a proxy for firm distress risk (Altman, 1968). A lower Z-score indicates higher distress risk. We classify firm-years into high- or low-distress risk observations by comparing Z-scores with the sample median value. In Table 4.12, we report regressions using these subsamples. The results show that FA_INV is significant for high-distress risk subsample but insignificant for the low-distress risk subsample. Hence, our argument for the underlining information channel is supported.

(Insert Table 4.12 here)

Poorly performing firms are associated with high agency costs, particularly associated with capital investments (Jensen, 1986: Lang et al., 1989). Therefore, one can expect that the negative relationship between financial assets investment and crash risk to be stronger in poorly performing firms. Using Tobin's Q as a proxy of firm performance, we classify firm-years into low Tobin's Q or high Tobin's Q observation by comparing against sample median Tobin's Q ratio. In Table 4.13, we conduct a final subsample test and find that crash risk is significantly and negatively associated with financial assets investment in the low Tobin's Q subsample but not the high Tobin's Q subsample, which is again consistent with our explanation [11].

[11] Alternatively, we also examine the interactions Z-score*FA_INV Tobin's Q*FA_INV but find they are insignificant suggesting threshold effects of Z-score and Tobin's Q in moderating the relationship between FA_INV and crash risk.

(Insert Table 4.13 here)

4.5. Conclusions

Firm in emerging markets such as China are more likely to substitute more liquid and reversible financial assets for capital assets due to incomplete financial markets while still earning higher returns. Compare to capital assets, disclosures on financial assets are more transparent due to requirements on accounting standards, which mitigate the manager's bad news hoarding behavior. This chapter explores the understudied relationships between capital assets, financial assets and stock price crash risk.

Using a large sample of Chinese firms from 2007-2019, we find that firms investing less in capital assets hold more financial assets. Moreover, we stock price crash risk decreases with financial assets investment and increases with capital investment. The empirical results support our arguments that for firms with severe agency problems, capital investment increases agency costs and hence also stock price crash risk, whereas financial assets investment decrease crash risk through enhancing information transparency under financial reporting rules emphasizing fair value accounting for financial assets.

Tables:

Table 4.**1: Summary statistics of variables.**

This table presents the summary statistics of all variables for the sample period 2007-2019. See Appendix A for variable definitions.

Variable	Obs.	Mean	Std. Dev	Mean	Max
NCSKEW	21,518	-0.240	0.899	-2.661	1.987
DUVOL	21,518	-0.168	0.756	-1.904	1.865
FA_INV	21,518	0.038	0.082	0.000	0.743
CAP_INV	21,518	0.051	0.049	0.000	0.237
FA_Dummy	21,518	0.500	0.500	0.000	1.000
DTURN	21,518	-0.092	0.492	-5.916	4.100
SIGMA	21,518	0.051	0.019	0.012	0.179
RETURN	21,518	-0.001	0.007	-0.051	0.046
SIZE	21,518	22.478	1.019	19.434	28.437
MTB	21,518	3.718	3.860	0.222	28.187
LEV	21,518	0.473	0.211	0.064	1.000
ROA	21,518	0.037	0.066	-0.262	0.222
DACC	21,518	0.075	0.106	0.000	5.344
Z-score	21,518	5.862	7.808	-0.310	51.360
Tobin's Q	21,518	2.222	1.582	0.908	10.777

Table 4.2: Capital assets, Financial assets and stock price crash risk

This table presents the results using random-effects GLS estimator. The key independent variable CAP_INV is capital investment scaled by total assets in year t. The key independent variable FA_INV is financial assets scaled by total assets in year t-1. The dependent variables are measured as NCSKEW and DUVOL in year t, respectively. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1. The t-statistics in parentheses are based on robust standard errors clustered on firms. Detailed variable descriptions are listed in Appendix A. *, **, *** are for significant levels at the 0.10, 0.05, and 0.01, respectively.

	Panel A		Panel B		Panel C	
Model	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	$NCSKEW_t$	$DUVOL_t$	$NCSKEW_t$	$DUVOL_t$	$NCSKEW_t$	$DUVOL_t$
CAP_INV_{t-1}	0.570***	0.424***			0.513***	0.395***
	(4.84)	(4.34)			(4.33)	(4.00)
FA_INV_{t-1}			-0.272***	-0.144**	-0.242***	-0.122*
			(-3.14)	(-2.16)	(-2.81)	(-1.86)
$NCSKEW_{t-1}$	0.089***		0.089***		0.088***	
	(9.91)		(9.95)		(9.85)	
$DUVOL_{t-1}$		0.075***		0.076***		0.074***
		(7.64)		(7.75)		(7.61)
$DETURN_{t-1}$	-0.054***	-0.047***	-0.058***	-0.050***	-0.052***	-0.046***
	(-3.62)	(-3.80)	(-3.91)	(-4.11)	(-3.49)	(-3.72)
$SIGMA_{t-1}$	2.240***	1.743***	2.219***	1.741***	2.194***	1.721***
	(4.96)	(4.76)	(4.93)	(4.76)	(4.87)	(4.70)
$RETURN_{t-1}$	18.449***	15.752***	18.480***	15.824***	18.435***	15.744***
	(15.90)	(14.84)	(15.92)	(14.93)	(15.90)	(14.84)
$SIZE_{t-1}$	0.041***	0.038***	0.044***	0.040***	0.041***	0.038***
	(5.82)	(6.56)	(6.16)	(6.93)	(5.75)	(6.52)
MTB_{t-1}	0.017***	0.012***	0.017***	0.012***	0.017***	0.012***
	(9.00)	(7.76)	(9.05)	(7.79)	(9.10)	(7.82)
LEV_{t-1}	-0.156***	-0.150***	-0.173***	-0.161***	-0.163***	-0.153***
	(-4.71)	(-5.63)	(-5.20)	(-6.04)	(-4.91)	(-5.75)
ROA_{t-1}	-0.489***	-0.592***	-0.475***	-0.580***	-0.497***	-0.596***
	(-4.29)	(-6.35)	(-4.16)	(-6.20)	(-4.37)	(-6.40)
$DACC_{t-1}$	0.152**	0.125**	0.143**	0.116**	0.157**	0.127**
	(2.48)	(2.34)	(2.34)	(2.18)	(2.55)	(2.38)
Constant	-1.377***	-1.225***	-1.372***	-1.232***	-1.348***	-1.211***
	(-8.27)	(-8.98)	(-8.22)	(-8.98)	(-8.08)	(-8.84)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.107	0.154	0.107	0.153	0.108	0.154
Obs.	21,508	21,508	21,518	21,518	21,518	21,518
# firms	2,692	2,692	2,692	2,692	2,692	2,692

Table 4.3: Endogeneity correction: 3SLS estimation

This table presents the results using 3SLS estimation for exploring the effects of financial assets investment and capital investment on crash risk. The dependent variables are measured as NCSKEW and DUVOL in year t+1, respectively. The key independent variable FA_INV is financial assets scaled by total assets in year t. To reduce endogeneity concerns, we regress crash risk measures computed for year t+1 on independent variables at the end of year t. The t-statistics in parentheses are based on robust standard errors clustered on firms. Detailed variable descriptions are listed in Appendix A. *, **, *** are for significant levels at the 0.10, 0.05, and 0.01, respectively.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	FA_INV_t	$NCSKEW_{t+1}$	$NCSKEW_{t+1}$	FA_INV_t	$DUVOL_{t+1}$	$DUVOL_{t+1}$
CAP_INV_t	-0.239***	0.571***		-0.239***	0.424***	
	(-21.61)	(4.64)		(-21.61)	(4.21)	
FA_INV_t			-2.387***			-1.776***
			(-4.53)			(-4.13)
$NCSKEW_t$		0.088***	0.088***			
		(10.38)	(10.13)			
$DUVOL_t$					0.074***	0.074***
					(7.78)	(7.67)
$DETURN_t$	0.008***	-0.054***	-0.035**	0.008***	-0.047***	-0.032**
	(6.12)	(-3.72)	(-2.22)	(6.12)	(-3.90)	(-2.50)
$SIGMA_t$	-0.167***	2.235***	1.837***	-0.167***	1.741***	1.445***
	(-4.21)	(5.04)	(3.96)	(-4.21)	(4.79)	(3.81)
$RETURN_t$	0.165*	18.395***	18.791***	0.165*	15.724***	16.018***
	(1.79)	(15.60)	(15.71)	(1.79)	(14.60)	(14.72)
$SIZE_t$	-0.002**	0.041***	0.038***	-0.002**	0.038***	0.035***
	(-2.51)	(5.85)	(5.11)	(-2.51)	(6.57)	(5.86)
MTB_t	0.000	0.017***	0.018***	0.000	0.012***	0.012***
	(1.45)	(9.69)	(9.76)	(1.45)	(8.26)	(8.36)
LEV_t	-0.029***	-0.156***	-0.224***	-0.029***	-0.150***	-0.201***
	(-10.01)	(-4.92)	(-6.40)	(-10.01)	(-5.76)	(-7.00)
ROA_t	-0.035***	-0.489***	-0.573***	-0.035***	-0.591***	-0.654***
	(-3.42)	(-4.30)	(-4.83)	(-3.42)	(-6.34)	(-6.74)
$DACC_t$	0.022***	0.152***	0.206***	0.022***	0.125***	0.165***
	(4.23)	(2.58)	(3.32)	(4.23)	(2.58)	(3.25)
Constant	0.116***	-1.376***	-1.099***	0.116***	-1.225***	-1.019***
	(7.85)	(-8.35)	(-6.03)	(7.85)	(-9.04)	(-6.82)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	21,508	21,508	21,508	21,508	21,508	21,508
R^2	0.038	0.105	0.072	0.038	0.141	0.113

Table 4.4: Robustness check: industry-year-median adjusted financial assets investment and capital investment

This table presents the results using 3SLS estimation for exploring the effects of financial investment and capital investment on crash risk. The dependent variables are measured as NCSKEW and DUVOL in year t+1, respectively. The key independent variable Adj_ FA_INV is industry-year-median adjusted financial assets investment in year t. To reduce endogeneity concerns, we regress crash risk measures computed for year t+1 on independent variables at the end of year t. The t-statistics in parentheses are based on robust standard errors clustered on firms. Detailed variable descriptions are listed in Appendix A. *, **, *** are for significant levels at the 0.10, 0.05, and 0.01, respectively.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Adj_ FA_INV_t	$NCSKEW_{t+1}$	$NCSKEW_{t+1}$	Adj_ FA_INV_t	$DUVOL_{t+1}$	$DUVOL_{t+1}$
Adj_ CAP_INV_t	-0.138***	0.472***		-0.138***	0.333***	
	(-12.35)	(3.67)		(-12.35)	(3.16)	
Adj_ FA_INV_t			-3.416***			-2.413***
			(-3.50)			(-3.05)
$NCSKEW_t$		0.088***	0.089***			
		(10.41)	(9.68)			
$DUVOL_t$					0.075***	0.075***
					(7.80)	(7.48)
$DETURN_t$	0.009***	-0.056***	-0.026	0.009***	-0.048***	-0.027*
	(6.80)	(-3.80)	(-1.44)	(6.80)	(-3.99)	(-1.84)
$SIGMA_t$	-0.180***	2.211***	1.598***	-0.180***	1.726***	1.293***
	(-4.69)	(4.98)	(3.15)	(-4.69)	(4.74)	(3.14)
$RETURN_t$	0.214**	18.390***	19.128***	0.214**	15.724***	16.244***
	(2.41)	(15.60)	(15.78)	(2.41)	(14.60)	(14.82)
$SIZE_t$	-0.002***	0.043***	0.034***	-0.002***	0.039***	0.033***
	(-3.99)	(6.03)	(4.31)	(-3.99)	(6.75)	(5.13)
MTB_t	0.000***	0.017***	0.019***	0.000***	0.012***	0.013***
	(2.61)	(9.72)	(9.71)	(2.61)	(8.27)	(8.37)
LEV_t	-0.036***	-0.164***	-0.287***	-0.036***	-0.156***	-0.243***
	(-13.13)	(-5.18)	(-5.90)	(-13.13)	(-6.00)	(-6.16)
ROA_t	-0.048***	-0.486***	-0.650***	-0.048***	-0.588***	-0.704***
	(-4.85)	(-4.26)	(-4.99)	(-4.85)	(-6.30)	(-6.64)
$DACC_t$	0.010*	0.141**	0.175***	0.010*	0.117**	0.140***
	(1.92)	(2.40)	(2.82)	(1.92)	(2.42)	(2.78)
Constant	0.120***	-1.371***	-0.961***	0.120***	-1.222***	-0.933***
	(8.40)	(-8.31)	(-4.43)	(8.40)	(-9.01)	(-5.29)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	21,508	21,508	21,508	21,508	21,508	21,508
R^2	0.022	0.104	0.038	0.022	0.140	0.091

Table 4.5: Robustness check: alternative measure of financial assets

This table presents the results using random-effects GLS estimator for the relation between financial assets and stock price crash risk. The dependent variables are measured as NCSKEW and DUVOL in year t, respectively. The key independent variable is FA_Dummy in year t-1. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1. The t-statistics in parentheses are based on robust standard errors clustered on firms. Detailed variable descriptions are listed in Appendix A. *, **, *** are for significant levels at the 0.10, 0.05, and 0.01, respectively.

Model	(1)	(2)	(3)	(4)
Dep. Var	$NCSKEW_t$	$NCSKEW_t$	$DUVOL_t$	$DUVOL_t$
FA_Dummy_{t-1}	-0.067***	-0.074***	-0.050***	-0.057***
	(-5.37)	(-5.77)	(-5.00)	(-5.60)
$NCSKEW_{t-1}$	0.089***	0.080***		
	(9.88)	(8.88)		
$DUVOL_{t-1}$			0.075***	0.068***
			(7.68)	(6.99)
$DETURN_{t-1}$	-0.055***	-0.056***	-0.047***	-0.048***
	(-3.69)	(-3.73)	(-3.86)	(-3.89)
$SIGMA_{t-1}$	2.156***	2.231***	1.682***	1.808***
	(4.78)	(4.94)	(4.59)	(4.91)
$RETURN_{t-1}$	18.525***	17.749***	15.842***	15.289***
	(15.94)	(15.24)	(14.92)	(14.40)
$SIZE_{t-1}$	0.046***	0.059***	0.042***	0.050***
	(6.43)	(8.26)	(7.16)	(8.44)
MTB_{t-1}	0.017***	0.016***	0.012***	0.011***
	(8.78)	(8.37)	(7.55)	(7.28)
LEV_{t-1}	-0.164***	-0.162***	-0.156***	-0.164***
	(-4.95)	(-4.73)	(-5.86)	(-5.94)
ROA_{t-1}	-0.466***	-0.540***	-0.577***	-0.631***
	(-4.08)	(-4.75)	(-6.15)	(-6.72)
$DACC_{t-1}$	0.140**	0.123**	0.116**	0.097*
	(2.32)	(2.02)	(2.19)	(1.80)
Constant	-1.395***	-1.642***	-1.241***	-1.395***
	(-8.36)	(-9.52)	(-9.08)	(-9.75)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Industry fixed	No	Yes	No	Yes
R^2	0.108	0.111	0.154	0.156
Obs.	21,518	21,518	21,518	21,518
# firms	2,692	2,692	2,692	2,692

Table 4.6: Fair value measure of financial assets, historical value measure of financial assets and crash risk

This table presents the results using random-effects GLS estimator for the effects of financial assets on stock price crash risk. The dependent variables are measured as NCSKEW and DUVOL in year t, respectively. In model 1 and 2 the key independent variable FA_Fair is sum of financial assets measured by fair value scaled by total assets in year t. In model 3 and 4, the key independent variable FA_Historical is sum of financial assets measured at historical value scaled by total assets in year t. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1. The t-statistics in parentheses are based on robust standard errors clustered on firms. Detailed variable descriptions are listed in Appendix A. *, **, *** are for significant levels at the 0.10, 0.05, and 0.01, respectively.

Model	(1)	(2)	(3)	(4)
Dep. Var	$NCSKEW_t$	$DUVOL_t$	$NCSKEW_t$	$DUVOL_t$
FA_Fair_{t-1}	-0.274***	-0.141**		
	(-3.02)	(-2.02)		
$FA\_Historical_{t-1}$			-0.510	-0.432
			(-1.23)	(-1.20)
$NCSKEW_{t-1}$	0.089***		0.090***	
	(9.94)		(10.03)	
$DUVOL_{t-1}$		0.076***		0.076***
		(7.75)		(7.79)
$DETURN_{t-1}$	-0.058***	-0.050***	-0.061***	-0.052***
	(-3.92)	(-4.12)	(-4.09)	(-4.22)
$SIGMA_{t-1}$	2.222***	1.743***	2.271***	1.765***
	(4.94)	(4.77)	(5.03)	(4.82)
$RETURN_{t-1}$	18.475***	15.822***	18.518***	15.846***
	(15.92)	(14.93)	(15.94)	(14.94)
$SIZE_{t-1}$	0.044***	0.040***	0.045***	0.041***
	(6.16)	(6.93)	(6.31)	(7.04)
MTB_{t-1}	0.017***	0.012***	0.017***	0.012***
	(9.06)	(7.79)	(8.91)	(7.68)
LEV_{t-1}	-0.172***	-0.161***	-0.167***	-0.158***
	(-5.18)	(-6.02)	(-5.02)	(-5.92)
ROA_{t-1}	-0.474***	-0.580***	-0.462***	-0.574***
	(-4.16)	(-6.19)	(-4.05)	(-6.12)
$DACC_{t-1}$	0.143**	0.116**	0.136**	0.112**
	(2.33)	(2.18)	(2.23)	(2.12)
Constant	-1.372***	-1.233***	-1.409***	-1.251***
	(-8.21)	(-8.98)	(-8.47)	(-9.17)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
R^2	0.107	0.153	0.107	0.153
Obs.	21,518	21,518	21,518	21,518
# firms	2,692	2,692	2,692	2,692

Table 4.7: Short-term financial assets, long-term financial assets and crash risk

This table presents the results using random-effects GLS estimator for the effects of financial assets on stock price crash risk. The dependent variables are measured as NCSKEW and DUVOL in year t, respectively. In model 1 and 2 the key independent variable Short-term FA is sum of short-term financial assets scaled by total assets in year t-1. In model 3 and 4, the key independent variable Long-term FA is sum of long-term financial assets scaled by total assets in year t-1. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1. The t-statistics in parentheses are based on robust standard errors clustered on firms. Detailed variable descriptions are listed in Appendix A. *, **, *** are for significant levels at the 0.10, 0.05, and 0.01, respectively.

Model	(1)	(2)	(3)	(4)
Dep. Var	$NCSKEW_t$	$DUVOL_t$	$NCSKEW_t$	$DUVOL_t$
Short-term FA_{t-1}	-0.073	-0.330		
	(-0.16)	(-0.88)		
Long-term FA_{t-1}			-0.284***	-0.140**
			(-3.20)	(-2.06)
$NCSKEW_{t-1}$	0.090***		0.089***	
	(10.03)		(9.94)	
$DUVOL_{t-1}$		0.076***		0.076***
		(7.79)		(7.75)
$DETURN_{t-1}$	-0.061***	-0.051***	-0.058***	-0.050***
	(-4.10)	(-4.22)	(-3.92)	(-4.12)
$SIGMA_{t-1}$	2.275***	1.763***	2.223***	1.745***
	(5.04)	(4.81)	(4.94)	(4.77)
$RETURN_{t-1}$	18.508***	15.844***	18.475***	15.822***
	(15.94)	(14.93)	(15.92)	(14.93)
$SIZE_{t-1}$	0.045***	0.041***	0.044***	0.040***
	(6.29)	(7.02)	(6.15)	(6.93)
MTB_{t-1}	0.017***	0.012***	0.017***	0.012***
	(8.92)	(7.72)	(9.04)	(7.77)
LEV_{t-1}	-0.166***	-0.159***	-0.171***	-0.160***
	(-5.00)	(-5.96)	(-5.16)	(-6.00)
ROA_{t-1}	-0.461***	-0.573***	-0.475***	-0.580***
	(-4.03)	(-6.12)	(-4.16)	(-6.20)
$DACC_{t-1}$	0.135**	0.112**	0.143**	0.116**
	(2.22)	(2.12)	(2.34)	(2.18)
Constant	-1.409***	-1.250***	-1.372***	-1.233***
	(-8.47)	(-9.15)	(-8.21)	(-8.99)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
R^2	0.107	0.153	0.107	0.153
Obs.	21,518	21,518	21,518	21,518
# firms	2,692	2,692	2,692	2,692

Table 4.8: Investment property, non-property financial assets and their effects on crash risk

This table presents the results using random-effects GLS estimator for the effects of financial assets on stock price crash risk. The dependent variables are measured as NCSKEW and DUVOL in year t, respectively. In model 1 and 2 the key independent variable Non-property FA sum of financial assets except investment property scaled by total assets in year t-1. In model 3 and 4, the key independent variable Property is sum of investment property scaled by total assets in year t-1. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1. The t-statistics in parentheses are based on robust standard errors clustered on firms. Detailed variable descriptions are listed in Appendix A. *, **, *** are for significant levels at the 0.10, 0.05, and 0.01, respectively.

Model	(1)	(2)	(3)	(4)
Dep. Var	$NCSKEW_t$	$DUVOL_t$	$NCSKEW_t$	$DUVOL_t$
Non-property FA $_{t-1}$	-0.199*	-0.081		
	(-1.86)	(-0.95)		
Property $_{t-1}$			-0.372***	-0.217**
			(-2.60)	(-1.99)
$NCSKEW_{t-1}$	0.090***		0.089***	
	(10.00)		(9.97)	
$DUVOL_{t-1}$		0.076***		0.076***
		(7.79)		(7.75)
$DETURN_{t-1}$	-0.060***	-0.051***	-0.059***	-0.051***
	(-4.02)	(-4.20)	(-3.99)	(-4.16)
$SIGMA_{t-1}$	2.257***	1.762***	2.235***	1.747***
	(5.00)	(4.81)	(4.97)	(4.78)
$RETURN_{t-1}$	18.508***	15.842***	18.466***	15.808***
	(15.93)	(14.94)	(15.92)	(14.92)
$SIZE_{t-1}$	0.045***	0.041***	0.043***	0.040***
	(6.31)	(7.03)	(6.07)	(6.85)
MTB_{t-1}	0.017***	0.012***	0.017***	0.012***
	(8.92)	(7.69)	(9.10)	(7.83)
LEV_{t-1}	-0.172***	-0.160***	-0.163***	-0.156***
	(-5.16)	(-5.98)	(-4.93)	(-5.86)
ROA_{t-1}	-0.468***	-0.576***	-0.466***	-0.576***
	(-4.10)	(-6.15)	(-4.08)	(-6.15)
$DACC_{t-1}$	0.136**	0.112**	0.144**	0.117**
	(2.24)	(2.12)	(2.35)	(2.20)
Constant	-1.404***	-1.249***	-1.370***	-1.228***
	(-8.42)	(-9.14)	(-8.20)	(-8.96)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
R^2	0.107	0.153	0.107	0.153
Obs.	21,518	21,518	21,518	21,518
# firms	2,692	2,692	2,692	2,692

Table 4.9: State ownership, investment property and crash risk

This table presents the results using random-effects GLS estimator for the effects of financial assets on stock price crash risk. The dependent variables are measured as NCSKEW and DUVOL in year t, respectively. The key independent variable Property is investment property scaled by total assets in year t-1. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1. The t-statistics in parentheses are based on robust standard errors clustered on firms. Detailed variable descriptions are listed in Appendix A. *, **, *** are for significant levels at the 0.10, 0.05, and 0.01, respectively.

	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	All	SOE	Non-SOE	All	SOE	Non-SOE
Dep. Var	$NCSKEW_t$	$NCSKEW_t$	$NCSKEW_t$	$DUVOL_t$	$DUVOL_t$	$DUVOL_{t+1}$
$Property_{t-1}$	-0.317***	-0.489***	-0.157	-0.185**	-0.285**	-0.085
	(-2.87)	(-3.07)	(-0.99)	(-2.03)	(-2.18)	(-0.67)
$NCSKEW_{t-1}$	0.090***	0.125***	0.040***			
	(10.20)	(10.13)	(3.16)			
$DUVOL_{t-1}$				0.078***	0.110***	0.051***
				(7.92)	(7.98)	(3.62)
$DETURN_{t-1}$	-0.049***	-0.066**	-0.041**	-0.047***	-0.090***	-0.026*
	(-3.21)	(-2.24)	(-2.30)	(-3.68)	(-3.72)	(-1.76)
$SIGMA_{t-1}$	2.161***	2.658***	1.763***	1.884***	2.461***	1.526***
	(4.60)	(3.83)	(2.72)	(4.86)	(4.32)	(2.87)
$RETURN_{t-1}$	17.440***	21.999***	11.640***	15.102***	19.262***	10.940***
	(14.37)	(12.12)	(7.02)	(13.58)	(11.61)	(7.19)
$SIZE_{t-1}$	0.049***	0.041***	0.072***	0.043***	0.039***	0.048***
	(6.57)	(4.46)	(5.48)	(7.04)	(5.17)	(4.65)
MTB_{t-1}	0.017***	0.019***	0.016***	0.012***	0.013***	0.012***
	(9.28)	(6.71)	(6.54)	(8.32)	(5.74)	(5.95)
LEV_{t-1}	-0.149***	-0.136***	-0.154***	-0.158***	-0.150***	-0.159***
	(-4.50)	(-2.85)	(-3.22)	(-5.82)	(-3.85)	(-4.15)
ROA_{t-1}	-0.436***	-0.206	-0.624***	-0.547***	-0.347**	-0.672***
	(-3.65)	(-1.17)	(-3.76)	(-5.55)	(-2.40)	(-4.97)
$DACC_{t-1}$	0.138**	0.163*	0.109	0.114**	0.107	0.113*
	(2.33)	(1.76)	(1.42)	(2.34)	(1.41)	(1.78)
SOE_{t-1}	-0.045***			-0.011		
	(-3.46)			(-1.01)		
Constant	-1.469***	-1.373***	-1.979***	-1.306***	-1.263***	-1.407***
	(-8.59)	(-6.24)	(-6.72)	(-9.24)	(-6.97)	(-5.98)
Obs.	19,889	10,211	9,678	19,889	10,211	9,678
# firm	2,526	1,129	1,569	2,526	1,129	1,569

Table 4.10: State ownership, non-property financial assets and crash risk

This table presents the results using random-effects GLS estimator for the effects of financial assets on stock price crash risk. The dependent variables are measured as NCSKEW and DUVOL in year t, respectively. The key independent variable Non-property FA is sum of financial assets except investment property scaled by total assets in year t-1. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1. The t-statistics in parentheses are based on robust standard errors clustered on firms. Detailed variable descriptions are listed in Appendix A. *, **, *** are for significant levels at the 0.10, 0.05, and 0.01, respectively.

	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	All	SOE	Non-SOE	All	SOE	Non-SOE
Dep. Var	$NCSKEW_t$	$NCSKEW_t$	$NCSKEW_t$	$DUVOL_t$	$DUVOL_t$	$DUVOL_t$
Non-property FA_{t-1}	-0.221**	-0.114	-0.378**	-0.087	0.010	-0.242*
	(-2.00)	(-0.90)	(-2.13)	(-1.01)	(0.10)	(-1.68)
$NCSKEW_{t-1}$	0.091***	0.126***	0.040***			
	(9.72)	(9.59)	(3.13)			
$DUVOL_{t-1}$				0.079***	0.111***	0.051***
				(7.80)	(7.86)	(3.53)
$DETURN_{t-1}$	-0.050***	-0.067**	-0.040**	-0.047***	-0.091***	-0.025
	(-3.11)	(-2.08)	(-2.14)	(-3.56)	(-3.44)	(-1.64)
$SIGMA_{t-1}$	2.176***	2.667***	1.731**	1.896***	2.468***	1.504***
	(4.57)	(3.97)	(2.57)	(4.85)	(4.46)	(2.77)
$RETURN_{t-1}$	17.483***	22.051***	11.645***	15.137***	19.299***	10.930***
	(14.63)	(12.45)	(7.11)	(13.74)	(11.57)	(7.33)
$SIZE_{t-1}$	0.050***	0.042***	0.074***	0.044***	0.040***	0.050***
	(6.67)	(4.61)	(5.84)	(7.12)	(5.30)	(4.90)
MTB_{t-1}	0.017***	0.018***	0.016***	0.012***	0.013***	0.012***
	(8.68)	(6.23)	(6.30)	(7.72)	(5.55)	(5.46)
LEV_{t-1}	-0.157***	-0.135***	-0.167***	-0.162***	-0.147***	-0.167***
	(-4.65)	(-2.86)	(-3.38)	(-5.92)	(-3.89)	(-4.24)
ROA_{t-1}	-0.439***	-0.198	-0.643***	-0.547***	-0.340**	-0.685***
	(-3.83)	(-1.21)	(-4.07)	(-5.68)	(-2.58)	(-5.05)
$DACC_{t-1}$	0.131**	0.150	0.105	0.110**	0.099	0.110
	(2.13)	(1.64)	(1.25)	(2.03)	(1.29)	(1.46)
$SOEt_{-1}$	-0.045***			-0.011		
	(-3.36)			(-1.02)		
Constant	-1.496***	-1.402***	-2.014***	-1.324***	-1.286***	-1.432***
	(-8.57)	(-6.32)	(-7.02)	(-9.23)	(-7.04)	(-6.15)
Obs.	19,889	10,211	9,678	19,889	10,211	9,678
# firm	2,526	1,129	1,569	2,526	1,129	1,569

Table 4.11: Financial reporting quality, financial assets investment and stock price crash risk

This table presents the results using random-effects GLS estimator for financial opacity on financial assets and stock price crash risk. The dependent variables are measured as NCSKEW and DUVOL in year t, respectively. The key independent variable FA_INV is financial assets scaled by total assets in year t-1. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1. The t-statistics in parentheses are based on robust standard errors clustered on firms. Detailed variable descriptions are listed in Appendix A. *, **, *** are for significant levels at the 0.10, 0.05, and 0.01, respectively.

Model	(1)	(2)
Dep. Var	$NCSKEW_t$	$DUVOL_t$
FA_INV_{t-1}	-0.319***	-0.195***
	(-3.53)	(-2.83)
$FA\_INV*DACC_{t-1}$	0.519**	0.554***
	(2.53)	(3.26)
$NCSKEW_{t-1}$	0.089***	
	(9.94)	
$DUVOL_{t-1}$		0.076***
		(7.74)
$DETURN_{t-1}$	-0.058***	-0.050***
	(-3.91)	(-4.12)
$SIGMA_{t-1}$	2.222***	1.743***
	(4.94)	(4.77)
$RETURN_{t-1}$	18.470***	15.811***
	(15.91)	(14.92)
$SIZE_{t-1}$	0.044***	0.040***
	(6.17)	(6.94)
MTB_{t-1}	0.017***	0.012***
	(9.06)	(7.80)
LEV_{t-1}	-0.173***	-0.161***
	(-5.20)	(-6.03)
ROA_{t-1}	-0.478***	-0.583***
	(-4.18)	(-6.23)
$DACC_{t-1}$	0.111*	0.082
	(1.68)	(1.45)
Constant	-1.372***	-1.231***
	(-8.21)	(-8.97)
Year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
R^2	0.098	0.02
Obs.	21,518	21,518
# firms	2,692	2,692

Table 4.12: Financial distress, financial assets investment and stock price crash risk

This table presents the results using random-effects GLS estimator for the effects of financial distress on financial assets and stock price crash risk. The dependent variables are measured as NCSKEW and DUVOL in year t, respectively. The key independent variable FA_INV is financial assets scaled by total assets in year t-1. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1. The t-statistics in parentheses are based on robust standard errors clustered on firms. Detailed variable descriptions are listed in Appendix A. *, **, *** are for significant levels at the 0.10, 0.05, and 0.01, respectively.

Model	(1)	(2)	(3)	(4)
	Low Distress Risk	High Distress Risk	Low Distress Risk	High Distress Risk
Dep. Var	$NCSKEW_t$	$NCSKEW_t$	$DUVOL_t$	$DUVOL_t$
FA_INV_{t-1}	-0.092	-0.300**	-0.044	-0.177*
	(-0.81)	(-2.23)	(-0.48)	(-1.68)
$NCSKEW_{t-1}$	0.062***	0.125***		
	(4.36)	(8.86)		
$DUVOL_{t-1}$			0.061***	0.105***
			(3.81)	(6.57)
$DETURN_{t-1}$	-0.027	-0.079**	-0.020	-0.073**
	(-1.30)	(-2.13)	(-1.06)	(-2.52)
$SIGMA_{t-1}$	0.118	5.320***	0.500	4.138***
	(0.16)	(6.82)	(0.81)	(6.47)
$RETURN_{t-1}$	10.891***	21.448***	10.222***	18.626***
	(6.37)	(10.89)	(6.49)	(10.08)
$SIZE_{t-1}$	0.065***	0.025**	0.066***	0.035***
	(5.70)	(2.31)	(7.01)	(3.81)
MTB_{t-1}	0.014***	0.013***	0.010***	0.010***
	(4.05)	(3.84)	(3.53)	(3.50)
LEV_{t-1}	0.020	0.098	-0.023	0.026
	(0.23)	(0.98)	(-0.32)	(0.33)
ROA_{t-1}	-0.092	-0.693***	-0.306**	-0.669***
	(-0.50)	(-3.28)	(-1.99)	(-3.78)
$DACC_{t-1}$	0.103	-0.022	0.088	-0.022
	(1.21)	(-0.22)	(1.16)	(-0.24)
$Z\text{-}Score_{t-1}$	0.000	0.059***	0.001	0.048***
	(0.25)	(3.44)	(0.50)	(3.46)
Constant	-1.848***	-1.417***	-1.842***	-1.448***
	(-6.93)	(-5.31)	(-8.40)	(-6.44)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
R^2	0.164	0.082	0.23	0.121
Obs.	7,768	8,134	7,768	8,134
# firms	1,748	1,467	1,748	1,467

Table 4.13: Firm performance, financial assets investment and stock price crash

This table presents the results using random-effects GLS estimator for the effects of financial distress on financial assets and stock price crash risk. The dependent variables are measured as NCSKEW and DUVOL in year t, respectively. The key independent variable FA_INV is financial assets scaled by total assets in year t-1. To reduce endogeneity concerns, we regress crash risk measures computed for year t on independent variables at the end of year t-1. The t-statistics in parentheses are based on robust standard errors clustered on firms. Detailed variable descriptions are listed in Appendix A. *, **, *** are for significant levels at the 0.10, 0.05, and 0.01, respectively.

Model	(1)	(2)	(3)	(4)
	High_Tobin Q	Low_Tobin Q	High_Tobin Q	Low_Tobin Q
Dep. Var	$NCSKEW_t$	$NCSKEW_t$	$DUVOL_t$	$DUVOL_t$
FA_INV_{t-1}	-0.151	-0.428***	-0.041	-0.271***
	(-1.43)	(-3.23)	(-0.45)	(-2.81)
$NCSKEW_{t-1}$	0.064***	0.091***		
	(5.09)	(6.76)		
$DUVOL_{t-1}$			0.051***	0.090***
			(3.65)	(6.22)
$DETURN_{t-1}$	-0.035*	-0.083***	-0.022	-0.079***
	(-1.71)	(-3.80)	(-1.27)	(-4.55)
$SIGMA_{t-1}$	0.015	3.128***	0.332	2.046***
	(0.02)	(4.28)	(0.66)	(3.47)
$RETURN_{t-1}$	12.257***	24.178***	9.957***	22.319***
	(8.01)	(11.76)	(7.24)	(11.81)
$SIZE_{t-1}$	0.065***	0.051***	0.051***	0.044***
	(6.07)	(5.20)	(5.91)	(5.42)
MTB_{t-1}	0.006**	0.033***	0.004*	0.018**
	(2.43)	(3.93)	(1.95)	(2.48)
LEV_{t-1}	0.026	-0.213***	0.000	-0.183***
	(0.55)	(-3.85)	(0.00)	(-4.19)
ROA_{t-1}	-0.487***	-0.746***	-0.519***	-0.890***
	(-3.48)	(-3.40)	(-4.49)	(-5.18)
$DACC_{t-1}$	0.093	0.129	0.082	0.118
	(1.15)	(1.31)	(1.20)	(1.36)
Tobin Q_{t-1}	0.019***	0.157***	0.014**	0.149***
	(2.97)	(2.92)	(2.55)	(3.52)
Constant	-1.809***	-1.788***	-1.490***	-1.467***
	(-7.19)	(-7.05)	(-7.31)	(-7.05)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
R^2	0.14	0.085	0.203	0.121
Obs.	10,525	10,280	10,525	10,280
# firms	2,163	2,291	2,163	2,291

Appendix 4.A: Description of Variables.

NCSKEW	The negative skewness of firm specific weekly return over the fiscal year.
DUVOL	The down to up volatility. The log of the ratio of standard deviations of down-weeks to standard deviations of up-week firm specific weekly returns.
FA_INV	The value of financial assets scaled by total assets. The financial assets are calculated as sum of trading financial assets, derivatives financial assets, net loans and receivables, available-for-sale financial assets, held-to-maturity investment, net investment property.
CAP_INV	The value of capital investment scaled by total assets.
FA_Dummy	A dummy variable, which equals to 1 if financial assets of a firm above median in a fiscal year, and 0 if not.
DTURN	The average monthly share turnover over the current fiscal year minus the average monthly share turnover over the previous fiscal year. Monthly share turnover is percentage of the monthly trading volume over the total number of shares outstanding during the month.
SIGMA	The standard deviation of firm-specific weekly returns over the fiscal year.
RETURN	The mean of firm-specific weekly returns over the fiscal year.
SIZE	The nature logarithm of the market value of equity.
MTB	The percentage of the market value of equity on the book value of equity.
LEV	The percentage of total liabilities over total assets.
ROA	The percentage of return on assets.
DACC	The absolute value of discretionary accruals estimated by Modified Jones Model (Dechow et al., 1995).
Z-score	The degree of financial distress of the firm as in Altman Z-Score model (1968).
Tobin's Q	The Tobin's Q ration is calculated as market capitalization divided by the value of total assets minus the net intangible assets then minus net goodwill.

Appendix 4.B: The correlations matrix

	NCSKEW	DUVOL	FA_INV	CAP_INV	FAdummy	DTURN	SIGMA	RETURN	SIZE	MTB	LEV	ROA	DACC	Z-score
DUVOL	0.917													
FA_INV	-0.015	-0.008												
CAP_INV	0.020	0.014	-0.164											
FAdummy	-0.016	-0.009	0.456	-0.211										
DTURN	-0.149	-0.171	0.045	-0.106	0.069									
SIGMA	-0.237	-0.296	0.020	-0.049	0.004	0.333								
RETURN	-0.565	-0.695	0.000	0.001	-0.005	0.142	0.383							
SIZE	-0.120	-0.145	-0.013	0.045	0.113	0.108	-0.024	0.086						
MTB	-0.052	-0.102	0.017	-0.059	-0.022	0.101	0.361	0.217	0.025					
LEV	-0.050	-0.050	-0.040	-0.094	0.017	0.096	0.018	-0.011	-0.002	0.061				
ROA	-0.040	-0.064	-0.018	0.150	-0.004	-0.064	-0.071	0.114	0.302	0.008	-0.394			
DACC	-0.003	-0.015	0.031	-0.054	-0.002	-0.007	0.086	0.039	-0.017	0.095	0.055	0.038		
Z-score	-0.014	-0.039	0.008	-0.006	-0.031	-0.025	0.170	0.128	0.065	0.347	-0.627	0.316	0.016	
Tobin's Q	-0.053	-0.102	0.045	-0.079	0.004	0.102	0.313	0.231	0.030	0.677	-0.195	0.064	0.050	0.540

CHAPTER 5

Conclusions

Extensive scholarly work has investigated the role of information quality in equity pricing and stock returns. In this thesis, I continue to focus on the role of information quality in determining stock returns by presenting three related but self-contained empirical studies on stock price crash risk in China which pay particular attentions to firm investments in their suppliers through trade credit as well as financial assets.

First, I examine the impact of customer firms' trade credit provisions to suppliers on stock price crash risk. It is well known that trade credit is an important short-financing resource especially for firms in emerging markets whom are shut out from bank credits. I predict that crash risk is positively related to trade credit provisions through an information channel: managers have more incentive to withhold bad news when firms extend trade credit provision. Using a large sample of Chinese listed firms from 2001-2019 and controlling for a host of previously identified determinants, a battery of tests consistently support this prediction for a positive association between trade credit provision and crash risk. The results are robustness to different measures of stock price crash risk, alternative calculations of trade credit provisions, and various model specifications. In addition, these results support our hypothesis that the link between trade credit provision and crash risk is stronger when information asymmetry between managers and investors is more severe as indicated by financial distress, industrial diversification and internal control quality.

Next, in light of first chapter, I further investigate the influences of debt, as a more general financing resource, on stock price crash risk. Suggested by Jiang et al. (2017), corporate debt in China is primarily short-term. In order to obtain debt refinancing, Chinese firms have stronger incentives to disclose information to creditors. Therefore, creditors serve as an extra monitoring mechanism, in which the extent of managerial "bad new hoarding" can be reduced. Using sample of Chinese firms from 2002-2016, I find that crash risk is negatively and significantly related to debt financing. For robustness, I adopt fixed effects as well as GMM models. I also use two measures of financial leverage, the market value financial leverage ratio and the book value Debt/Assets ratio. I find consistent results. My results support the view that creditors play an important role of monitoring, hence, reducing bad news hoarding by managers of borrowing firms. In further analysis, I find consistent results irrespective of firm ownership type and debt maturity structure. I conclude that the mitigating effects of creditors on borrowing firms' stock price crash risk are homogeneous among SOEs and non-SOEs. Debt maturity structure appears to have insignificant influence on crash risk itself as well as the debt-crash relationship. This result indicates that the negative leverage-crash relation is unlikely to be due to the rollover pressure of short-term debt.

Third, I explore the substitutional relationship between capital assets and financial assets and their impacts on crash risk in China. Prior literature suggests that firm are more likely to substitute more liquid and reversible financial assets for capital assets due to incomplete financial markets while still earning higher returns. It is well-known that capital investment may be associated with agency problems lead to both underinvestment and overinvestment. Compare to capital assets, disclosures on financial assets are more transparent due to requirements of the Chinese accounting standards (CAS, 2006), which has a potential mitigating effect on manager's bad news hoarding behavior. Using a large sample of Chinese firms from 2007-2019, I find that firms investing less in capital assets hold more financial assets. Moreover, I show that stock price crash risk decreases with financial assets investment and increases with capital investment. Further analysis consistently finds that finds the negative effect of financial asset investment on crash risk is stronger among firms with lower financial information quality, higher financial distress risk, poorer performance.

The findings in this thesis contribute to the literature on the sources of firm-specific crash risk and should be of particular interest to scholars interested in the role of information disclosure. Results have important implications for emerging markets with less developed credit environments. Findings should be of great interest to scholars interested in the role of information disclosure in emerging financial markets; as well as to investors and regulators concerned about stock price crash risk.

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