Are financially constrained firms susceptible to a stock price crash?

Guanming He*

Durham University Business School, Durham University

Mill Hill Lane, Durham DH1 3LB

United Kingdom

E-mail: guanming.he@durham.ac.uk

Helen Ren**

University of Liverpool Management School, University of Liverpool

Chatham Street, Liverpool L69 7ZH

United Kingdom

E-mail: helen.ren@liverpool.ac.uk

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Abstract

This study investigates whether and how financial constraints on firms affect the risk of their stock price crashing. We find strong evidence that financial constraints increase future stock price crash risk. This finding is robust to using a dynamic panel generalized method of moments (GMM) estimator and two quasi-natural experiments to control for potential endogeneity. Cross-sectional analyses reveal that the positive relation between financial constraints and future crash risk is more prominent for firms with high abnormal accruals or with weak corporate governance and less pronounced for firms that commit tax avoidance or have a high credit rating. Our study is of interest to investors as well as other stakeholders concerned about firms' creditworthiness and viability.

Keywords

financial constraints, crash risk, bad news hoarding, default risk, accruals, tax avoidance, corporate governance, credit ratings

JEL Classification

G10, G30, M41

1. INTRODUCTION

Corporate scandals such as those involving Enron, Worldcom, and Fannie Mae have triggered increased academic research on the probability of stock price crashes, which are normally observed in the far-left tail of firm-specific return distributions (e.g., Chen et al., 2001; Jin and Myers, 2006; Hutton et al., 2009). The motivation to study the risk of extreme negative residual returns lies in its importance in determining expected stock returns (Conrad et al., 2013), return volatility, and option pricing (Merton, 1976). The objective of our study is to examine whether and how firm financial constraints affect future stock price crash risk. As with Lamont et al. (2001), we define financial constraints as frictions that prevent a firm from funding its desired investments. Previous studies (e.g., Fazzari et al., 1988; Lamont et al., 2001; Livdan et al., 2009; Denis and Sibilkov, 2010) have examined the association of financial constraints with capital investments, firm value, risk, and expected returns, but none has evaluated the stock price crash risk of financially constrained firms. We seek to fill this gap in the literature. Given that stock price crashes have material impacts on investor welfare, our study on financially constrained firms' crash risk should be of interest to investors making portfolio investment decisions, and relevant to creditors, suppliers, customers, and other stakeholders, who are concerned about corporate creditworthiness and viability.

Difficulties in raising external funds induce managers in financially constrained firms to withhold bad news. The accumulated bad news and resultant inflation of stock prices increase the likelihood of future stock price crashes. Moreover, financially constrained firms are subject to a higher probability of corporate failure and are more likely to experience stock price crashes at the point of default. However, if investors can decipher these implications and discount the financially constrained stocks promptly, stock prices will be likely to decline on a timely basis over time without triggering a crash, thereby lowering future stock price crash risk. Therefore, the relation between financial constraints and future stock price crash risk remains ambiguous, which constitutes another motivation for our study.

We posit that bad news hoarding and default risk are two mechanisms that make financially constrained firms susceptible to stock price crashes.[1] First, the literature (e.g., Chen et al. 2001; Jin and Myers, 2006; Hutton et al., 2009; Kim et al., 2011a, b; Andreou et al., 2017) regards withholding bad news as a fundamental cause of stock price crashes. Because bad news might increase the costs of issuing equity and debt, managers in financially troubled firms are particularly prone to hide bad news for an extended period to secure external funds. However, though the amount of bad news that managers are able to hide is limited (Jin and Myers, 2006), managers often cannot *anticipate*, and thus *control*, when such a limit is reached (He, 2015), given constant and unforeseeable changes in the business environments. Once that limit is reached, all the bad news will become uncontainable, resulting in a sudden, dramatic price drop, that is, a stock price crash. In essence, with strong incentives to secure external finance, firms in financial constraints are more likely to withhold bad news and thus have higher future crash risk, compared with unconstrained firms.

Second, financially constrained firms need more cash to fund necessary investments and avoid default. Because external financing is often too expensive for such firms, they have to rely on limited internal funds and hence are more susceptible to default and a stock price crash resulting from corporate failure. Therefore, it follows that financially constrained firms have a high risk of stock price crashes. Furthermore, firms facing financial constraints have an incentive to forego positive net-present-value projects; such underinvestment and debt overhang problem would further exacerbate their potential default risk and associated crash risk.

A counter argument plausibly holds when we take into consideration the investor's ability to decipher the implications of financial constraints for future crash risk. Investors, who do not have access to private information, might not be able to infer the implications of financial constraints for future crash risk, because the amount of hidden bad news and the probability of default can hardly

[1] We refer to default risk as the probability of default, financial distress, economic distress, or bankruptcy, which are often used interchangeably in the literature (Campbell et al., 2008).

be appraised by outsiders (Dye, 1985; Jung and Kwon,1988; Dichev, 1998; Griffin and Lemmon, 2002; Campbell et al., 2008). Therefore, we refute the view that investors tend to promptly discount financially constrained stocks in a way that makes future stock price crash risk lower. We expect the association between financial constraints and future crash risk to be positive.

We also explore cross-sectional variation in financially constrained firms' crash risk in varied circumstances. Earnings management can facilitate bad news hoarding behavior (Hutton et al., 2009; Zhu, 2016). Zhu (2016) argues that managers seeking to withhold bad news are inclined to make aggressive income-increasing accruals estimates; these make it more difficult for outside investors to discern any related hidden bad news, providing managers with stronger incentives to manage accruals upwards to conceal bad news. Hence, we expect that earnings management, as a powerful tool to disguise bad news, strengthens the positive relation between financial constraints and future crash risk.

In the presence of agency conflicts between shareholders and management, managers tend to withhold bad news associated with rent extraction or with adverse firm performance. Strong corporate governance reduces such agency conflicts, curbs opportunistic bad-news-hoarding behavior, and thereby reduces stock price crash risk. Hence, we expect that the positive association between financial constraint and future crash risk is stronger for firms with weak corporate governance.

When firms face financial constraints, equity and debt financing becomes more costly and less accessible (Edward et al., 2016), and consequently, the firms become more reliant on internal funds to meet their investment needs. To make more internal funds available, managers may resort to corporate tax avoidance. The cash savings attributed to tax avoidance help lower the default risk of a financially constrained firm and thereby decrease its future crash risk. Accordingly, we expect that the relationship between financial constraints and future crash risk is weaker for firms that avoid income taxes aggressively. Although some tax avoidance transactions might obfuscate financial reporting and facilitate bad news hoarding (Desai and Dharmapala, 2006, 2009; Kim et al., 2011a), tax avoidance itself is used by a financially constrained firm as a tool primarily to generate cash flows and mitigate default risk, rather than to conceal bad news. Consistent with this notion, Edward et al. (2016) and Law and Mills (2015) predict and find that financial constraints have a positive impact on cash tax savings. Our prediction is in line with Edward et al. (2016) and Law and Mills (2015).

Credit rating measures a firm's default probability. A high credit rating implies a greater distance to default, facilitating external financing for a financially constrained firm. In contrast, a low credit rating limits a financially constrained firm's ability to raise external funds for investments and repayments of debt. As a result, default risk will be heightened, and crash risk will increase. Therefore, we predict that the association between financial constraints and future crash risk is more pronounced for firms that have lower credit ratings.

As with previous studies (e.g., Chen et al., 2001; Jin and Myers, 2006; Hutton et al., 2009), we focus solely on firm-level stock price crashes; crash risk that is attributed to market-wide factors is not within the scope of our study. Following Hutton et al. (2009), we measure crash risk based on the likelihood of extreme negative firm-specific weekly stock returns for a fiscal year. For robustness checks, we use four other proxies for crash risk as well: (i) the number of crash weeks with negative extreme weekly returns, (ii) the negative skewness of firm-specific weekly stock returns, (iii) the "down-to-up" volatility of firm-specific weekly returns, and (iv) the minimum value of firm-specific weekly returns, as per prior research (e.g., Chen et al., 2001; Hutton et al., 2009; Kim et al., 2011a, b; Callen and Fang, 2013, 2015; Andreou et al., 2017; Chang et al., 2017; Lobo et al., 2017). We measure financial constraints by the SA index developed by Hadlock and Pierce (2010), and use dividend payouts as the alternative financial-constraint measure. Using a sample of 28,208 firm-year observations from U.S. listed firms for the period 1995-2016, we find that financial constraints are positively associated with one-year-ahead stock price crash risk. This association is both economically and statistically significant, suggesting that investors may not be capable of appreciating the prospects of financial-constraint firms. In the cross-sectional analyses, we find that this positive relationship is more pronounced for firms with high abnormal accruals or weak corporate governance and is attenuated when firms commit tax avoidance or have high credit ratings.

The past or current crash risk may affect firm financial constraints and thereby influence future crash risk. This engenders a dynamic type of endogeneity. To remediate this concern, we follow Wintoki et al. (2012) to conduct a dynamic panel GMM analysis, in which two lags of crash risk are included in the dynamic model, and all the independent variables lagged three and four years are employed as instruments. Our results of the GMM test suggest that our evidence of the positive association between financial constraints and future crash risk is immune from the dynamic endogeneity bias.

There are two other plausible sources of endogeneity. One is potential measurement error in our financial-constraint proxy, and the other is correlated omitted variable(s), either of which might bias our results and inferences. Such endogeneity is addressed in two quasi-natural experimental settings. First, following Kim (2018), we use the collapse of the junk bond market in 1989 as an exogenous shock to firm financial constraints and conduct a difference-in-differences (DID) regression analysis. The exogenous events in 1989 restricted the supply of credit to speculative-grade firms, thereby considerably tightening up their financial constraints (Lemmon and Roberts, 2010). Accordingly, we define the treatment firms as those that receive a speculative grade from the Standard and Poor's (S&P) credit rating agency, and the control firms as those without an S&P credit rating.[2] Our DID regression results suggest that an increase in crash risk for the treatment firms, which are subject to tightened financial constraints during the post-collapse period, is significantly higher than that for the unrated control firms, of which the financial constraint statuses

[2] In this study, we use the S&P's long-term domestic issuer credit ratings to classify firms into investment-grade firms versus speculative-grade firms.

are much less affected by the junk-bond-market collapse. This result elicits a causal inference that financial constraints lead to higher future crash risk.

The second quasi-experimental setting involves the Internet bubble, which exogenously relaxed financial constraints for non-technology (henceforth, non-tech) firms (Campello and Graham, 2013). With the rapidly increasing use of the Internet for commerce in the 1990s, the technology (hereafters, tech) profession thrived; tech firms soared up, with their stock prices increasingly overvalued by the market. This overvaluation had significant spillover effects on the non-tech stocks, making their prices generally inflated as well (Caballero et al., 2006; Anderson et al., 2010). The market optimism and excess supply of capital in the U.S. stock market gave rise to a stock price bubble, which started in 1995 and persisted until 2000. A firm's financial constraint status hinges critically on the supply of funds to the firm *vis-à-vis* its demand for funds, the latter of which is determined by firms' investment needs. Conditional on the investment needs being unaffected by the bubble, such a bubble would exogenously decrease the financial constraint, if any, of a firm, because the firm can ease the financial constraint by raising more funds from equity issuances in the bubble period. Whereas tech firms had significantly increasing investment opportunities during the bubble, non-tech firms did not (Jorgenson and Stiroh, 1999; Gordon, 2000; Stiroh, 2002) and hence are well suited for use in our natural-experimental setting. Consistent with Campello and Graham (2013), non-tech firms that are (are not) in financial constraints during the pre-bubble period are used as our treatment (control) firms. We implement a coarsened-exact-matching approach, per Iacus et al. (2012), to match the treatment firms with the control firms based on the determinants of financial constraints. Using a difference-in-differences research design, we find that non-tech firms that face financial constraints in the pre-bubble period experience significantly larger decreases in crash risk, as a result of the ease of financial constraints, during the bubble period, compared with the control firms. This again corroborates the causal, positive relationship between financial constraints and future crash risk. In the last test, we examine the association between financial constraints and longer-term future crash risk. Our results show that financial constraints remain positively correlated with future crash risk on the two-year and three-year horizons, respectively.

Our paper makes two major contributions to the literature. First, we contribute to the literature on economic consequences of financial constraints. Prior research focuses on the impact of financial constraints on firm performance (e.g., Lamont et al., 2001; Livdan et al., 2009; Campello and Chen, 2010; Li, 2011), cost of capital (Gomes et al., 2006; Campbell et al., 2012), corporate policies (Denis and Sibilkov, 2010; Hovakimian 2011), and real business activities (Campello et al., 2010). Our study investigates the impact of financial constraints from a different angle by examining the role of financial constraints in information management and focusing on the extreme future returns of financially constrained firms. We employ rigorous identification strategies such as quasi-experimental designs to establish a causal effect of financial constraints on future stock price crash risk. To the best of our knowledge, this study is the first to examine crash risk of financially constrained firms.

Second, there are three key drivers of firm-specific stock price crash risk: (i) managerial bad news hoarding; (ii) firms' fundamental risk profiles, which generate unexpected, egregious bad news impossible for managers to withhold once it occurs; (iii) market frictions that hinder investors' abilities to discern the bad news hoarding or a high risk of the egregious bad news. The vast literature on crash risk (e.g., Kim et al., 2011a, b; He, 2015; Kim et al., 2016; Andreou et al., 2017; Chang et al., 2017; Hong et al., 2017) focuses predominantly on the first driver of crash risk. Our study complements this literature by shedding light on the other two drivers as well. Specifically, we offer insight that financially constrained firms' high crash risk is also attributable to their high risk of corporate failure, and that investors are unlikely to infer the implications of financial constraints for future crash risk.

The remainder of the paper is structured as follows. Section 2 reviews the related literature and develops our hypotheses. Section 3 describes our sample, measurements of key variables, and research design. Section 4 presents our empirical results. Section 5 conducts the further tests, and Section 6 concludes.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 The association between financial constraints and future stock price crash risk

2.1.1 Bad news hoarding

Prior research has proposed a number of explanations for firm-level stock price crashes, among which managerial bad news hoarding is considered as a fundamental cause of stock price crashes (e.g., Jin and Myers, 2006; Bleck and Liu, 2007; Hutton et al., 2009; Benmelech et al., 2010; Kim et al., 2011a, b; Kim and Zhang, 2014, 2016; Chang et al., 2017; Hong et al., 2017). Withholding one piece of bad news entails a low risk of detection by outsiders, because it is difficult for them to discern whether managers are withholding the bad news or unaware of it. However, as withheld bad news accumulates, it would become increasingly hard for insiders to continually hoard it. The occurrence of a stock price crash is attributed to a sudden overrun of a bad-news-hoarding limit, a threshold point at which managers can no longer withhold any unfavorable information. At that point, all the hidden news would come out at once, resulting in a sudden stock price plunge. The maximum amount of bad news that managers can withhold varies unforeseeably and constantly with a firm's changing environments, making it difficult for managers to *anticipate* by themselves when the threshold point will be reached and to prevent a stock price crash from occurring (He, 2015). As such, the incidence of a stock price crash depends on how much bad news managers withhold. The greater the extent to which managers camouflage their firm's unfavorable information, the higher the future crash risk. Given the limited amount of internal funds available for investments, financially constrained firms need more external funds. To facilitate external financing, they are more likely to withhold bad news and have a high risk of future stock price crashes.

2.1.2 Default risk

The potentially high default risk of financially constrained firms provides yet another explanation for their high future crash risk. Default risk (or distress risk) refers to the probability that a firm fails to meet its financial obligations (Vassalou and Xing, 2004; Campbell et al., 2008; Garlappi et al., 2008) and is conceptually different from financial constraints. Kaplan and Zingales (2000, *p*710) argue that financially constrained firms share similar characteristics as financially distressed firms and note that "*financial distress is a form of being financially constrained*". This implies that financial constraint is an important aspect in determining a firm's default risk but not necessarily vice versa.

Fazzari et al. (1988), Almeida et al. (2004), and Acharya et al. (2007) document that the investment spending by financially constrained firms is more sensitive to cash flows than that by unconstrained firms; this is primarily because constrained firms are subject to restrictions in accessing external finance. Whereas cash adequacy helps financially healthy firms avoid default, cash shortages that often beset financial-constraint firms are likely to induce their corporate default (Davydenko, 2012). Thus, a financially constrained firm is more likely to default than an unconstrained firm. Consistent with this notion, the survey research of Campello et al. (2010) suggests that a firm's inability to fund investments, which manifests itself in high financial constraints, would lead to higher distress risk. Because firms with high default risk are more likely to fail and experience crashes at the point of default (Zhu, 2016), it follows that financially constrained firms are more prone to stock price crashes. Furthermore, to avoid, or delay the realization of, a default, financially constrained firms have incentives to bypass some positive net-present-value projects. This gives rise to the debt overhang problem (Smith and Warner, 1979), aggravating future default risk and associated crash risk.

2.1.3 Financial constraints and future stock price crash risk

As discussed in the previous sections, both the bad-news-hoarding and default-risk mechanisms predict that financial constraints are positively associated with future crash risk. This section further considers conditions under which financial constraints might lower future crash risk.

First, managers may opt not to withhold bad news so that stock prices are less likely to be inflated and crash in the future. Managers' decisions to withhold bad news depend on their trade-off between the benefits of securing enough external finance and the costs associated with potential reputational losses and threat of litigation. Prior studies suggest that early revelation of bad news might reduce the likelihood of being sued and the expected costs of litigation (Skinner, 1994; Skinner, 1997; Field et al., 2005; Donelson et al., 2012). If the legal and reputational costs are expected to be high, managers may choose not to hide bad news. However, bad news hoarding is unlikely to detect by outsiders who generally do not have access to private corporate information. Therefore, we posit that managers in financially constrained firms are inclined to withhold bad news since the associated detection risk is low.

Second, if investors are able to discover a financial constraint and infer its implications for bad news hoarding and default probability, financially constrained stocks will be discounted by investors promptly, such that the stock price will not be inflated in a way that likely plunges significantly at a particular point in time. However, it is difficult for outside investors to decipher the implications of financial constraints for associated risk and future payoffs. If investors can perceive a financial constraint and infer its association with heightened risk, they will require a higher risk premium, i.e., a higher return from a financially constrained firm to compensate for the higher risk they bear. In such a case, we should observe a positive association between financial constraints and equity returns. However, empirical evidence (e.g., Lamont et al., 2001; Whited and Wu, 2006; Livdan et al., 2009) shows that financially constrained stocks do not earn significantly higher returns than unconstrained stocks, suggesting that investors might not be able to evaluate the value impact of financial constraints. Furthermore, Lamont et al. (2001) find that financially constrained firms earn even lower average returns than unconstrained firms, which implies the mispricing of financially constrained stocks and the irrationality of market participants. If, as evidenced by Lamont et al. (2001), financially constrained stocks are overpriced for the current period, their future crash risk should be higher.

Even if the market were efficient in pricing constrained stocks based on public information, it might not follow that market participants can decipher the implications of financial constraints for future crash risk because the level of crash risk hinges critically on the amount of bad news hoarded by managers. It is unlikely that, without access to private information, outside investors will be able to appraise the amount of hidden bad news and adjust stock prices for the bad news hoarding (e.g., Dye, 1985; Jung and Kwon, 1988). When the bad news remains withheld and is stockpiled within financially constrained firms, their future crash risk will be higher.

From the perspective of the default risk mechanism, investors are probably able to link financial constraint with higher distress risk, but they are possibly not able to extrapolate future stock price crash risk from current default risk. Prior evidence (Dichev, 1998; Campbell et al., 2008; George and Hwang, 2010) reveals a negative relation between default risk and stock returns, suggesting that investors are not capable of evaluating the potential default probability of a firm and fail to demand a sufficient premium to compensate for their exposure to default risk. Based on the above discussion, we refute the possibility that investors can infer the implications of financial constraints for future crash risk. We posit that financially constrained firms are more likely to encounter future stock price crashes. Therefore, our first hypothesis is as follows:

H1. *Financial constraints and future stock price crash risk are positively associated.*

2.2 Cross-sectional analyses of the association between financial constraints and future crash risk

2.2.1 Earnings management

Under an accrual-accounting system, a firm's performance is based on earnings, which comprise accruals and cash flows. Firm management is responsible for giving shareholders earnings estimates, and the inherent subjectivity of these estimates provides managers with a tool to hide bad news. Prior studies (Hutton et al., 2009; Zhu, 2016) find evidence that earnings management is associated with a larger extent of bad news hoarding and with higher future crash risk, which supports the notion that managers tend to make aggressive accrual estimates to withhold bad news.

One type of accruals that managers can use to disguise bad news is working capital accruals, which involve balance sheet items such as inventory, accounts receivable, accounts payable, and provisions for liabilities. For example, by understating the provision for bad debt, managers can withhold customer-related bad news, which arises from deteriorating financial health of customers or worsening customer relationship. Other bad-news-hoarding strategies include understatements of an obligation to clean up polluted production sites or to provide warranty coverage for low-quality products sold, both of which would lead to a future outflow of cash for a firm. Appendix B shows more examples of managers using accruals to withhold bad news. In essence, aggressive recognition of accruals makes it difficult for outside investors to discern related corporate bad news. Earnings management thereby serves as a device for managers to conceal bad news.

In addition, financial opacity resulting from accruals inflation hampers shareholders from discriminating good projects from bad ones at an early stage. As a result, shareholders cannot abandon bad projects in a timely manner, thereby leading to potentially higher future crash risk (Bleck and Liu, 2007). Based on the above discussion, we expect that earnings management will aggravate the future crash risk of a financially constrained firm. Accordingly, we establish the second hypothesis as follows:

H2. *The positive association between financial constraints and future stock price crash risk is more pronounced for firms that have high abnormal accruals.*

2.2.2 Corporate governance

Bad news is more likely to arise when there is an agency conflict between shareholders and firm management. Such bad news might be attributed to managerial rent extraction or other managers' self-interested behaviors. Concerns about job prospects, personal reputation, the value of option grants, and bonus plans (Graham et al., 2005; Kothari et al., 2009; Jiang et al., 2013; Baginski et al., 2018) give managers an incentive to withhold the bad news. Strong corporate governance puts managers under intense monitoring (Ashbaugh-Skaife et al., 2006) and reduces their ability to hoard bad news (Ajinkya et al., 2005; Karamanou and Vafeas, 2005; Andreou et al., 2016; He et al., 2021), thereby mitigating future crash risk (Kim et al., 2011a, b; Callen and Fang, 2013; Andreou et al., 2016; Chang et al., 2017). On this basis, we expect that managers in a well-governed, financially constrained firm are less likely to withhold bad news, and hence that their firm's future crash risk tends to be lower. This leads to our third hypothesis stated in an alternative form as follows:

H3. *The positive association between financial constraints and future stock price crash risk is weaker for firms with strong corporate governance.*

2.2.3 Corporate tax avoidance

In an imperfect capital market, external finance is not a perfect substitute for internal capital and is particularly costly and difficult for financially constrained firms to access. Firms that face high costs of external financing have to rely more on their own cash holdings (Fazzari et al., 1988; Almeida et al., 2004; Acharya et al., 2007; Denis and Sibilkov, 2010). However, current cash holdings often do not meet financially constrained firms' demand for investments. In such a case, the firms might resort to tax avoidance to generate additional internal funds. Edwards et al. (2016) and Law and Mills (2015) find that an increase in financial constraints incentivizes firms to increase tax avoidance activities to obtain cash tax savings. They argue that reducing tax payments has less adverse impact on firm operations than other cost-cutting strategies that are aimed at building cash reserves.

Some complex tax-avoidance transactions might obfuscate financial reporting, facilitating managers' bad news hoarding and resource diversion (Kim et al., 2011a, b; He et al., 2020). Nonetheless, the main intent of a financially constrained firm avoiding taxes is to obtain additional internal funds and mitigate default risk. When facing financial constraints, firms need to seek alternative funds for investments, since traditional sources of financing (i.e., debt and equity financing) become more costly and less accessible. Edward et al. (2016) and Law and Mills (2015) argue that cash tax savings achieved via tax avoidance is a potential source of financing and that managers can implement various tax planning strategies to reduce tax payments. In this regard, tax avoidance increases internal funds for a financially constrained firm, enhances its ability to fulfill financial obligations and to resist potential default, and thereby reduces its future crash risk. Therefore, we have our fourth hypothesis.

H4. *The positive association between financial constraints and future stock price crash risk is less pronounced for firms that commit tax avoidance.*

2.2.4 Credit rating

A firm's credit rating reflects a credit rating agency's opinion about the firm's creditworthiness and its ability to meet financial obligations (Standard & Poor's, 2009). A low credit rating implies a shorter distance to default. Therefore, financially constrained firms with low credit ratings should be more likely to default and to encounter stock price crashes. Moreover, low-credit-rating firms often find it difficult and costly to access external funds (Kisgen, 2006; Manso, 2013). As a result, they tend to face high risks of default and of stock price crashes. Thus, we have the fifth hypothesis.

H5. *The positive association between financial constraints and future stock price crash risk is stronger for firms with low credit ratings.*

3. DATA AND RESEARCH DESIGN

3.1 Data sources and sample selection

We obtain data primarily from four sources, the Center for Research in Security Prices (CRSP), Compustat, Factset, and Institutional Shareholder Services (ISS). The crash risk variables are constructed using stock returns data from the CRSP database. Firms' financial information is collected from the Compustat database. The institutional ownership data are taken from Factset. Given that our crash risk measure is one-year ahead of the financial-constraint index and control variables in our regressions, the sample period for our crash risk variables (financial constraint variable) ranges from 1996 (1995) to 2016 (2015). We require that firms have necessary data available for constructing the variables of interest for our empirical analyses. In dealing with potential outliers, we winsorize the variables for book-to-market ratios, return on assets, financial opacity, abnormal accruals, and book-tax differences at the top and bottom 1% levels, respectively. Our final sample comprises 28,208 firm-year observations corresponding with 6,533 unique firms. Table 1 shows descriptive statistics of all the key variables used in our main multivariate tests. Our corporate governance variables are constructed using data mainly from the ISS database, where the data are available only for the period 2007-2015. The summary statistics of all the corporate governance measures used in our cross-sectional analysis are shown in Panel A of Table 5. We report in Table 2 the Spearman correlations among the independent variables used in our baseline regression. We also conduct the variance inflation factors (VIF) test. The results, not tabulated for simplicity, reveal that VIF values are less than 10 for all the explanatory variables, indicating that multicollinearity is unlikely to be an issue with our regression analysis.

3.2 Crash risk measures

In line with prior literature (Chen et al., 2001; Hutton et al., 2009; Kim et al., 2011a, b; Callen and Fang, 2013, 2015; Kim and Zhang, 2016; Andreou et al., 2017; Chang et al., 2017; Lobo et al., 2017), we employ five measures of firm-specific stock price crash risk: (i) the likelihood of negative extreme firm-specific weekly returns over a fiscal year (*crashrisk*); (ii) the number of crash weeks with negative extreme firm-specific weekly returns (*ncrash*); (iii) the negative of the third-moment of firm-specific weekly returns (*ncskew*); (iv) the down-to-up volatility of firm-specific weekly returns (*duvol*); and (v) the negative of the minimum weekly return over a fiscal year (*minreturn*). The weekly stock returns are all adjusted for market-wide factors.

As per Hutton et al. (2009) and Kim et al. (2011a, b), a stock price crash is defined as a situation in which a firm experiences a firm-specific weekly return falling 3.2 standard deviations below the mean firm-specific weekly return for a fiscal year.[3] *crashrisk* equals 1 if a firm experiences one or more stock price crashes in a fiscal year and 0 otherwise. *ncrash* is equal to the number of crash weeks, in which a firm experiences a negative extreme weekly return, over a fiscal year. *ncskew* is defined as the third moment of firm-specific weekly returns for a stock and is expressed as follows:

$$ncskew_{it} = -\left(n(n-1)^{\frac{3}{2}} \sum R_{it}^{3} \right) \Big/ \left((n-1)(n-2)\left(\sum R_{it}^{2}\right)^{\frac{3}{2}} \right) \tag{1}$$

duvol is calculated based on the standard deviation of "down"-week firm-specific weekly returns relative to the standard deviation of "up"-week firm-specific weekly returns and is expressed as follows:

$$duvol_{it} = (n_u - 1) \sum_{DOWN} R_{it}^{2} \Big/ \left((n_d - 1) \sum_{UP} R_{it}^{2} \right) \tag{2}$$

where the standard deviation of "down" ("up")-week firm-specific weekly returns is scaled by the number of "down" ("up") weeks ($n_d(n_u)$) minus one. A "down" ("up") week is defined as a week in which firm-specific weekly stock return is below (above) the mean weekly return for a fiscal year. The last crash risk variable, *minreturn*, is computed as -1 times the minimum value of firm-

[3] Our inferences remain qualitatively the same, if we re-define a stock price crash as a firm-specific weekly return falling 3.1, or 3.3, standard deviations below the mean firm-specific weekly return to do our empirical analysis.

specific weekly returns, less the mean firm-specific weekly return, and divided by the standard deviation of firm-specific weekly returns, for a fiscal year.

Our empirical analysis is based mainly on the *crashrisk* variable, which is consistent with Hutton et al. (2009); the other four crash risk variables (i.e., *ncrash*, *ncskew*, *duvol*, *minreturn*) are used for robustness checks.[4] 15.68% of our sample observations (corresponding with 4,424 firm-years) experience one crash (*ncrash*=1), 5.82% (corresponding with 1,641 firm-years) have two crashes (*ncrash*=2), and 1.96% (corresponding with 553 firm-years) undergo more than two crashes. These statistics are close to those reported by Hutton et al. (2009). As reported in Table 1, the mean of *crashrisk* in our sample is 0.2346, indicating that the firm-specific stock price crash risk is, on average, 23.46% for a fiscal year. This is in line with the figures reported in prior research (e.g., Hutton et al., 2009; Kim et al., 2011a, b).

3.3 Financial constraint measures

The SA index constructed by Hadlock and Pierce (2010) is used as our primary measure of financial constraints and is defined as follows:

$$SA = -0.737 \times size + 0.043 \times size^2 - 0.040 \times age \tag{3}$$

where *size* is the natural logarithm of the book value of total assets, and *age* is the number of years for which a firm has been listed. More financially constrained firms have higher SA indices (*SA*). Hadlock and Pierce (2010) manually collect qualitative information that is closely related to firm financial constraints, categorize financial constraint statuses based on the qualitative information,

[4] *ncskew*, *duvol*, and *minreturn* might be less powerful in measuring a stock price crash. Suppose that stock price decreases slowly to a considerably low level in response to a firm's gradual release of bad news and then is maintained continually low for an extended period. In this case, the stock price decline features large negative skewness (*ncskew*), high down-to-up return volatility (*duvol*), and extreme low returns (*minreturn*) but should not be regarded as a stock price crash. The values of *ncrash* do not proportionally reflect the distinction in crash risk across different levels. For instance, the differential in crash risk, as indicated by the difference between *ncrash*=1 and *ncrash*=2, is far smaller than the differential in crash risk, as indicated by the difference between *ncrash*=0 and *ncrash*=1. Moreover, conceptually speaking, the *ncrash* variable measures more of the frequency, rather than the incidence, of stock price crashes, and hence is a relatively weak measure of crash risk.

and estimate the ordered logit regressions of the financial-constraint category on the determinants of two commonly used financial-constraint measures (namely, Kaplan and Zingales' (1997) (KZ) index, Whited and Wu's (2006) (WW) index), respectively. Their ordered logit regression results show that only two out of five determinants of the KZ index and three out of six determinants of the WW index have significant coefficients with predicted signs. This casts doubt on the validity of using the KZ and WW indices as proxies for financial constraints. In developing a more valid measure of financial constraint, Hadlock and Pierce (2010) sort firms by firm characteristics that are arguably associated with financial constraints and test the association between the sorting variables and the foregoing financial-constraint category. They find evidence that only firm size and firm age are powerful in predicting a firm's financial constraint status. They further argue that firm size and firm age are relatively exogenous to a firm's financial choices compared to other firm characteristics and therein use these two variables to construct a new financial-constraint measure, that is, the SA index.

Although the SA index is arguably more advantageous than the KZ index and WW index in measuring financial constraints (e.g., Hadlock and Pierce, 2010), the SA index might still be subject to measurement errors, thereby inducing an endogeneity problem to our multivariate analysis. We address this concern in Section 5 by conducting two natural experiments in which the collapse of the junk bond market in 1989 and the Internet bubble in the late 1990s, respectively, are used as exogenous shocks to firms' financial-constraint statuses. In addition, we use two dividend payout measures as alternative proxies for financial constraints. They are (i) dividend payout ratio (*payout*) calculated as cash dividends paid by a firm, divided by its operating income, for a fiscal year, and (ii) a binary variable (*div*) equal to 1 if a firm pays cash dividends in a fiscal year and 0 otherwise. Lower dividend payout indicates higher financial constraints (e.g., Fazzari et al., 1988; Denis and Sibilkov, 2010).

3.4 Test of the hypothesis H1

We estimate the following pooled logit regression model to test the hypothesis H1:

$$Crashrisk_{i,t+1} = \alpha_0 + \alpha_1 SA_{i,t} + \sum_k \alpha_k Controls_{i,t}^k \\ + Industry\text{-}fixed\text{-}effects + Year\text{-}fixed\text{-}effects + \varepsilon_{i,t} \tag{4}$$

crashrisk and *SA* are defined as previously. If H1 holds, the coefficient on *SA* should be positive and statistically significant at a conventional level. Following prior literature (e.g., Chen et al., 2001; Jin and Myers, 2006; Hutton et al., 2009; Kim et al., 2011a, b; Callen and Fang, 2013), we include a broad set of control variables to ensure that our results are not driven by correlated omitted variable(s). We control for equity value of a firm (*lnequity*) because Chen et al. (2001) and Hutton et al. (2009) show that stock price crashes are more likely to occur among large firms.[5] We control for the book-to-market ratio (*btm*), a proxy for a firm's growth opportunities, since Harvey and Siddique (2000) and Chen et al. (2001) find that growth firms are more prone to future stock price crashes. As per Kim et al. (2011a), we include return on assets (*roa*) to control for the effect of firm performance on crash risk. Previous studies (Chen et al., 2001; Callen and Fang, 2013, 2015) document that analyst coverage might pressure managers into meeting and beating analyst forecasts, thereby exacerbating managerial myopia and increasing stock price crash risk. Hence, we control for analyst coverage (*lanacov*) and expect it to be positively correlated with future crash risk. Callen and Fang (2013) find supportive evidence that high institutional ownership curbs bad news hoarding and reduces future crash risk. Therefore, we also include institutional stock holdings (*insti*) as a control for crash risk.

Hutton et al. (2009) find that firms with high financial opacity are more likely to experience future stock price crashes. Therefore, we control for financial opacity (*opacity*) and predict it to be positively correlated with future crash risk. Chen et al. (2001) find that highly volatile stocks are

[5] The value of variance-inflation factor (VIF) is 5.29 for *lnequity* and 3.27 for *SA*; both are less than 10, suggesting that multicollinearity is not an issue with *lnequity* and *SA*. Our main results remain qualitatively the same if we do not include equity value (*lnequity*) as the control variable in our regressions.

more likely to crash in their stock prices. Hence, we include return volatility (*stdret*) in the regression. We control for abnormal stock returns (*qtrret*), as stocks with high abnormal returns are more likely to crash in their prices in the future (Chen et al., 2001; Kim et al., 2011a). High trading volume is associated with high stock liquidity and hence with a higher likelihood of stock price crashes (Chang et al., 2017). Thus, we control for trading volume (*tradevol*) and predict its positive association with future crash risk. Prior literature (Chen et al., 2001; Jin and Myers, 2006; Kim and Zhang, 2014) finds that firms with high negative skewness in their weekly stock return distributions are more likely to have stock price crashes in future periods. Therefore, we include the negative weekly return skewness (*ncskew*), lagged one-year, as a control in our regressions.[6] All the control variables are defined in detail in Appendix A. Lastly, as with previous research (e.g., Denis and Sibilkov, 2010; Campbell et al., 2012; Callen and Fang, 2015; Chang et al., 2017), we include industry-fixed effects and year-fixed effects in the crash-risk regressions.[7]

3.5 Tests of the hypotheses H2-H5

To ease the interpretation of the results, we undertake subsample analyses to test the hypotheses H2-H5. We construct the moderating variables of abnormal accruals, corporate governance, corporate tax avoidance, and credit ratings, and divide the full sample into two subsamples based on the four moderating variables, respectively.

We employ the balance sheet approach, per Dechow et al. (1995) and Sloan (1996), to estimate abnormal accruals (*da*). The variable definition is presented in Appendix A. We partition our

[6] As a robustness check, we include corporate governance as an additional control in our regression. We obtain qualitatively the same results after controlling for any one of the corporate governance variables which will be covered in Section 3.5. The data used to construct the corporate governance variables are available only for the period 2007-2015 in the Institutional Shareholder Services (ISS) database. Thus, our sample size reduces substantially once a corporate governance variable is included for the regression estimation. For example, 23,170 firm-years are dropped when outside directors' equity ownership is controlled.

[7] We do not include firm-fixed effects in our model not only because they are multicollinear with industry dummies, but also because the inclusion of high-dimensional (firm) fixed effects might exacerbate measurement errors in the independent variables and increase the likelihood of drawing spurious inferences (Jennings et al., 2021).

sample into two groups based on the sample median of abnormal accruals (*da*), and estimate Model (4) separately for the two subsamples. If the coefficient on *SA* is significantly more positive for the high-accruals firms than for the low-accruals firms, the hypothesis H2 holds.

Building on previous studies (e.g., Byrd and Hickman, 1992; Petra, 2005; Callen and Fang, 2013; Andreou et al., 2016), we employ sixteen corporate governance measures for our analysis. These measures are outside directors' stock ownership (*directorownership*) (e.g., Ayers et al., 2011), the proportion of independent directors on board (*indp*) (e.g., Laksmana, 2008; Hoitash et al., 2009; Li and Srinivasan, 2011; Hazarika et al., 2012; Masulis et al., 2012; Morellec et al., 2012; Wintoki et al., 2012), board size (*boardsize*) (e.g., Core et al., 1999; Laksmana, 2008; Hoitash et al., 2009; Li and Srinivasan, 2011; Chen et al., 2012; Hazarika et al., 2012; Hoechle et al., 2012; Masulis et al., 2012; Wintoki et al., 2012; Andreou et al., 2016), the percentage of independent directors who sit on the compensation committee (*indpComp*), nominating committee (*indpNomi*), auditing committee (*indpAudit*), and corporate governance committee (*idpCG*) (e.g., Klein, 2002; Xie et al., 2003; Ashbaugh-Skaife et al., 2006), CEO-chair duality (*CEOduality*) (e.g., Hazarika et al., 2012; Masulis et al., 2012; Andreou et al., 2016), the percentage of busy independent directors (*indpbusy*) (e.g., Laksmana, 2008; Hoitash et al., 2009; Hoechle et al., 2012; Masulis et al., 2012; Andreou et al., 2016), the percentage of directors who age over 64 (*olddirector*) (e.g., Armstrong et al., 2012; Hoechle et al., 2012), the percentage of female independent directors (*indpfemale*) (e.g., Shrader et al., 1997; Carter et al., 2003; Erhardt et al., 2003; Adams and Ferreira, 2009), the independence of the chairman of board (*directorchair*) (e.g., Armstrong et al., 2012), the voting power possessed by independent directors (*indpvotingpower*) (e.g., Ashbaugh-Skaife et al., 2006), the percentage of directors appointed before the current CEO took office (*directorpredate*) (Coles et al., 2014), staggered board (*staggered*) (e.g., Zhao and Chen, 2008), and the percentage of independent directors who have continuously served the board for ten years or more (*longtenuredindp*) (Bonini et al., 2017). Detailed definitions of the corporate governance variables are provided in Appendix A. Low (high) values of *directorownership*, *indp*, *indpComp*, *indpNomi*, *indpAudit, indpCG, indpvotingpower, olddirector, directorchair*, *directorpredate*, *boardsize*, *longtenuredindp*, and *staggered* (*indpbusy*, *indpfemale,* and *CEOduality*) indicate weak corporate governance.

For the corporate governance variables that are non-indicator variables, we use their sample medians as the cut-off point to divide the full sample into two groups. For the corporate governance variables that are binary, we partition our sample based on whether the binary variables are equal to 1 or 0. Based on the hypothesis H3, we expect that the positive relation between financial constraints and future crash risk is statistically more evident for the weak-corporate-governance group than for the strong-corporate-governance group.

We use cash effective tax rate (*cashetr*) (Dyreng et al., 2008; Lisowsky et al., 2013) to proxy for corporate tax avoidance, as it may capture the extent of cash tax savings that mitigate default risk of a financially constrained firm. *cashetr* is calculated as cash taxes paid, divided by pretax book income, over a fiscal year. Firm-year observations with negative pretax book income are excluded from our sample. Following Desai and Dharmapala (2006, 2009), we also use the residual book-tax difference (*ddmpbtd*) to measure corporate tax avoidance. Book-tax differences may result from either upwards accruals management or tax avoidance. Desai and Dharmapala's (2006, 2009) residual book-tax difference measure removes the effect of book-tax differences that are attributed to accruals inflation. A lower (higher) value of *cashetr* (*ddmpbtd*) indicates a larger degree of corporate tax avoidance. We split our sample into high- and low-tax-avoidance subsamples, based on the sample medians of *cashetr* and *ddmpbtd*, respectively. The hypothesis H4 holds if the coefficient on *SA* is less positive for the high-tax-avoidance firms than for the low-tax-avoidance firms.

To test the hypothesis H5, we use credit rating as a measure for default probability and construct two subsamples consisting of investment-grade firms and speculative-grade firms, respectively. We then estimate Model (4) separately for these two subsamples. The investment-grade firms, which are rated with a BBB- grade or above, are believed to have a stronger capacity for meeting financial obligations and be less likely to default, compared with the speculative-grade firms that are rated at BB+ or below. It is predicted that financially constrained firms with higher default risk have higher future crash risk. Therefore, in supporting H5, *SA* should take on a more positive coefficient in the speculative-grade subsample than in the investment-grade subsample. In addition, to see whether the effect of financial constraints on future crash risk is subsumed by the effect of default risk for the speculative-grade firms, we include credit rating as an additional control variable in the subsample analysis.

4. EMPIRICAL RESULTS

Table 3 presents the regression results for the hypothesis H1. Column (1) of Panel A reports the results for Model (4), where $crashrisk_{t+1}$ is the dependent variable. The coefficient for SA_t is positive and statistically significant at the 0.1% level. An increase of one standard deviation in SA_t leads to an increase in the probability of a stock price crash ($crashrisk_{t+1}$) by 2.57 percentage points, which is equivalent to 10.95% of the mean value of $crashrisk_{t+1}$ in our sample and is thus economically significant. This result supports H1, indicating that financial constraint is positively associated with one-year-ahead stock price crash risk, and is consistent with our argument that outside investors are not able to deduce the implications of financial constraints for bad news hoarding and default risk. We use alternative measures of financial constraints (i.e., $payout_t$ and div_t) and of crash risk (i.e., $ncrash_{t+1}$, $ncskew_{t+1}$, $duvol_{t+1}$ and $minreturn_{t+1}$) to check the robustness of our baseline results. In Columns (2) – (3) of Panel A, the coefficients for both financial constraint measures ($payout_t$ and div_t) are statistically significant with the expected negative sign. In Panel B of Table 3 which reports the results for the regressions of the alternative crash-risk measures, the coefficients for SA_t are all positive and statistically significant at the 1% level.

Table 4 reports the regression results for the hypothesis H2. The coefficient for SA_t is positive and statistically significant ($p<0.001$) in the high-abnormal-accruals firms. By contrast, the coefficient for SA_t in the low-abnormal-accruals subsample, albeit positive, is not statistically significant ($p=0.122$). The positive association between financial constraint and future crash risk is evident only in firms with high abnormal accruals. This evidence is consistent with H2, and offers support to our view that earnings management provides managers with a tool to withhold bad news, thereby increasing future crash risk of a financially constrained firm.

The results for the hypothesis H3 are shown in Table 5. Panel A presents descriptive statistics for all the corporate governance variables used in our subsample analyses. Panel B presents the regression results for the subsample test in which *directorownership* is used as a proxy for corporate governance. As expected, the positive relation between financial constraints and future crash risk is statistically significant ($p=0.026$) only in the low-*directorownership* subsample, which features weak corporate governance. Panel C shows the results for the subsample tests, in which fifteen other alternative proxies for corporate governance are used. The intercepts, and the coefficients on the control variables, are not reported for the sake of brevity. The coefficients for the SA index (SA_t) are statistically significant at the 5% level across the weak-corporate-governance groups, except that the coefficient on SA_t is marginally significant for the low-*indpCG* group. By contrast, the coefficients for SA_t are not statistically significant in any of the strong-corporate-governance groups. Together, these results support H3 that the positive link between financial constraints and future crash risk is more pronounced for firms with weak corporate governance.

Table 6 shows the regression results for the hypothesis H4. Column (1) shows that the coefficient on SA_t is only statistically significant ($p<0.001$) in the low-tax-avoidance (high-*cashetr*) subsample but not significant ($p=0.151$) in the high-tax-avoidance (low-*cashetr*) subsample. In Column (2), the coefficient for SA_t is significantly positive at the 5% level in the low-tax-avoidance (low-*ddmpbtd*) subsample but is not significant in the high-tax-avoidance (high-*ddmpbtd*) subsample. These results support the proposition for H4 that tax avoidance helps financially constrained firms generate internal funds from cash tax savings, thereby mitigating their default risk and associated future crash risk. This finding is also in line with Edward et al. (2016) and Law and Mills (2015), suggesting that tax avoidance is used by a financially constrained firm as a device mainly to generate cash flows, not to withhold bad news.

Table 7 reports the regression results for the hypothesis H5. The coefficient for SA_t is positive and significant at the 5% level for the speculative-grade subsample, whereas the coefficient for SA_t is not statistically significant for the investment-grade subsample. This result is consistent with H5 that the positive association between financial constraints and future crash risk is more salient for low-credit-rating firms. In addition, *rating* does not have a statistically significant coefficient for the speculative-grade subsample, suggesting that the association between distress risk and future crash risk is subsumed by the effect of financial constraints.

5. FURTHER TESTS

5.1 A dynamic panel generalized method of moments (GMM) estimator

A potential source of endogeneity is the possibility that the current value of the financial constraint index is a function of current and/or past crash risk. In such a scenario, the crash risk in the past and/or current periods affects current financial constraints and in turn influences crash risk in the future period. To address this dynamic type of endogeneity, we follow Wintoki et al. (2012) and apply the dynamic GMM estimator to Model (4) to re-examine the relation between financial constraints and future crash risk. The dynamic panel GMM model is specified as follows:

$$\begin{aligned} Crashrisk_{i,t+1} = {} & \alpha_0 + \alpha_1 Crashrisk_{i,t} + \alpha_2 Crashrisk_{i,t-1} + \alpha_3 SA_{i,t} + \sum_k \alpha_k Controls_{i,t}^k \\ & + (YearDummies) + (IndustryDummies) + \eta_i + u_{i,t} \end{aligned} \tag{5}$$

where $Controls_{i,t}$ covers the same set of control variables as that included in Model (4), and η_i represents unobserved firm-fixed effects. Two lags of the dependent variable, namely, $Crashrisk_{i,t}$

and $Crashrisk_{i,t-1}$, are included to control for the dynamic aspect of the relationship between crash risk and financial constraints.[8] The estimation procedure consists of two steps that make the dynamic GMM estimator superior to OLS and fixed-effects estimates. First, the first differencing eliminates potential bias that arises from time-invariant unobserved heterogeneity. Second, we follow Wintoki et al. (2012) by including crash risk and all the explanatory variables, lagged three and four years, as instruments for the differenced equations.[9] Because our dependent variable is one-year-ahead crash risk, the dynamic GMM model controls for the influences of current and one-year lagged crash risk on future crash risk. To ensure that we have included proper lags to control for dynamic endogeneity, we employ the Arellano-Bond (1991) (*AR*) tests of first-order and second-order serial correlations. By construction, there should be serial correlations among the residuals in the first differences (*AR*(1)) but not in the second differences (*AR*(2)). Accordingly, we expect to reject the null hypothesis in *AR*(1) but not in *AR*(2). Given that we use multiple lags as instruments, we also conduct a Hansen test of over-identification to check the validity of our instruments.

Table 8 reports the regression results from our dynamic GMM estimation for the hypothesis H1. It is shown that the coefficient for SA_t is positive and statistically significant, supporting H1.[10] Our *AR*(1) (*AR*(2)) test yields a *p*-value of 0.044 (0.883), indicating that we can (cannot) reject the null hypothesis of no serial correlation in the first (second) differences; thus, it is consistent with the assumptions of the GMM specification (Wintoki et al., 2012). The Hansen *J* test yields a *p*-value

[8] We augment Model (4) with $Crashrisk_{i,t-2}$ and $Crashrisk_{i,t-3}$, and run the logistic regression. In results not reported, the coefficients on $Crashrisk_{i,t}$ and $Crashrisk_{i,t-1}$ ($Crashrisk_{i,t-2}$ and $Crashrisk_{i,t-3}$) are (are not) statistically significant. This finding suggests that two lags of crash risk are sufficient to ensure dynamic completeness. Accordingly, crash risk, as well as other explanatory variables, that are lagged beyond two years can be regarded as exogenous and hence as valid instruments for use in our GMM model.

[9] The instruments used in the GMM estimation include $Crashrisk_{i,t-2}$, $Crashrisk_{i,t-3}$, $SA_{i,t-3}$, $SA_{i,t-4}$, $Controls_{i,t-3}$, $Controls_{i,t-4}$, $\Delta YearDummies$, and $\Delta IndustryDummies$ ($\Delta Crashrisk_{i,t-1}$, $\Delta SA_{i,t-2}$ $\Delta Controls_{i,t-2}$, *YearDummies*, and *IndustryDummies*) in the differenced (level) equations. The assumption underlying such a choice of instruments is that all the regressors, except year dummies and industry dummies, are endogenous. The industry dummies used in the GMM specification are based on the Fama-French's twelve industries, rather than the first two digits of Standard Industrial Classification (SIC) codes, because the inclusion of too many industry dummies as instruments might weaken the power of the Hansen test of over-identification.

[10] Similar to our main test, we use alternative crash risk measures to check the robustness of our results. Consistent with H1, $minreturn_{t+1}$ has a positive coefficient (0.3844) statistically significant at the 5% level (*p*-value=0.031).

of 0.159, which implies that we cannot reject the null hypothesis of valid instruments being used in our GMM model. Overall, our results suggest that dynamic endogeneity does not plague our empirical analysis of H1.

5.2 Control for endogeneity – a collapse of the junk bond market and crash risk

As we discussed in Section 2, outside investors, who generally do not have access to private information, are unlikely to appraise the amount of bad news withheld in a firm or extrapolate future crash risk from current default risk. Therefore, it is hard for investors to predict a firm's future stock price crash risk. On this basis, reverse causality is less of a concern in our study. That said, it is possible that either correlated omitted variable(s) or measurement error(s) in the financial-constraint index bias the coefficient estimates in our multivariate tests. To mitigate this concern, we follow Kim (2018) to conduct a quasi-experiment in which the collapse of bond market in 1989 is used as an exogenous shock that increased financial constraints of speculative-grade firms. Lemmon and Roberts (2010) argue that three unexpected events in 1989 led to a substantial decline in the supply of credit to speculative-grade firms. These events include (i) the collapse of Drexel Burnham Lambert, Inc., which caused a substantial reduction in funds available to speculative-grade firms; (ii) the passage of the Financial Institutions Reform, Recovery, and Enforcement Act of 1989 (FIRREA), which resulted in a forced sell-off of all junk bonds by Savings and Loans (S&Ls); and (iii) a change in the National Association of Insurance Companies (NAIC) credit rating guideline, which led to a sharp decrease in the life-insurance companies' commitments to purchase bonds from speculative-grade issuers. As a result of these events, speculative-grade firms, which used to rely heavily on junk bond issuances to secure external funds, became more financially constrained. Therefore, the junk-bond-market collapse offers a nice experimental setting to examine the causal effect of financial constraints on crash risk. If the casual effect is positive as implied by the hypothesis H1, the increase in financial constraints of speculative-grade firms following the junk-bond-market collapse should lead to a more significant increase in crash risk, compared with nonrated firms that do not rely on bond financing.

Using the collapse of the junk bond markets as an exogenous event, we conduct a difference-in-differences (DID) test for the period 1987-1992, in which 1987-1989 (1990-1992) is designated as the pre- (post-) collapse period. The treatment firms are defined as those rated with a speculative grade (i.e., a grade of BB+ or lower) by the S&P credit rating agency in 1989 (i.e., the year prior to the collapse); the control firms are defined as those without an S&P credit rating in 1989.[11] The DID regression is specified below.

$$
\begin{aligned}
Crashrisk_{i,t+1} &= \alpha_0 + \alpha_1 PostCollapse_t + \alpha_2 Junk_i + \alpha_3 PostCollapse_t \times Junk_i \\
&\quad + \sum_k \alpha_k Controls_{i,t}^k + Industry\text{-}fixed\text{-}effects + Year\text{-}fixed\text{-}effects + \varepsilon_{i,t}
\end{aligned} \tag{6}
$$

$PostCollapse_t$ equals 1 if a firm is in the post-collapse period and 0 otherwise. $Junk_i$ equals 1 (0) if a firm pertains to a treatment (control) firm. The interaction term, $PostCollapse_t \times Junk_i$, captures the change in crash risk from the pre-collapse period to the post-collapse period for the treatment firms, relative to the control firms. The control variables included in Model (6) are similar to those in Model (4). The sample size decreases to 1,214 firm-years after clearing missing values for the control variables.[12] Table 9 reports the DID regression results. The coefficient on the interaction term, $PostCollapse_t \times Junk_i$, is positive (1.2775) and statistically significant at the 5% level, indicating that the treatment firms, which suffered from tightened financial constraints after the collapse of the junk bond markets, experienced higher crash risk than the control firms, which were

[11] To reduce potential multivariate imbalance in covariates between the treatment and control groups, we apply coarsened-exact matching (CEM, the same approach used in Section 5.3), a monotonic imbalance bounding approach. Specifically, an automated coarsening *k*-to-*k* match is done between the treatment firms and control firms. We then repeat our DID analysis using the matched data, and obtain qualitatively the same results. However, the number of observations after the matching drops to 191 firm-years, reducing the power of the test. Hence, the results from the test need to be interpreted with caution. Likewise, when we include firm-fixed effects in Model (6), firms that have no time-series variation are removed from the regression estimation, reducing our sample to only 772 firm-years. Due to the lack of power of the test, we do not provide our firm-fixed-effects regression analysis.

[12] To ensure sufficient observations for the test, the *opacity* variable, which has many missing values, is not included in Model (6). *Insti* is not included either, because none of the control firms in the period 1987-1992 have an institutional ownership greater than zero.

not affected by the collapse event.[13] The parallel trends assumption underlying our difference-in-differences analysis requires similar trends of crash risk for both the treatment and control firms during the pre-collapse period. To test the validity of this assumption, we follow Robert and Whited (2013) to rerun our DID regression model by using 1988 and 1989 (as well as 1987 and 1988), respectively, as the pre- and post-"event" periods, respectively. We find no evidence of a substantive change in crash risk for the treatment firms relative to the control firms. This suggests that our DID results reported in Table 9 are not biased by potential violation of the parallel trends assumption.

5.3 Control for endogeneity – the Internet bubble and crash risk

The Internet bubble of the late 1990s, which generated exogenous variation in firms' financial constraints, is employed as our second quasi-experimental setting to examine the causal effect of financial constraint on crash risk. In the late 1990s, due to the prevalent use of computers, investors were keen on investing in tech firms, making technology stocks highly priced and yield over 1,000-percent returns (Ofek and Richardson, 2003). The rise in technology stocks also fueled a run-up in non-tech firms' equity prices, thereby leading to a stock price bubble in the whole equity market. This bubble was argued to be driven by irrational euphoria among retail investors (Shiller, 2000), speculative trading by hedge funds (Brunnermeier and Nagel, 2004; Griffin et al., 2011), and limits of arbitrages (Morck et al., 1990; Shleifer and Vishny, 1997; Ofek and Richardson, 2003). Financially constrained firms could take advantage of the stock price bubble by issuing equities to ease their financial constraints. In this sense, the bubble exogenously decreased firms' financial constraints. Nonetheless, the technological innovations that triggered the Internet bubble also brought a good deal of investment opportunities to tech firms, raising such firms' demand for funds

[13] We also use alternative crash risk measures to run our DID regression. The results show that, when using *ncrash* as the dependent variable, the coefficient on $PostCollapse_t \times Junk_i$ is positive (1.3558) and statistically significant at the 5% (p-value=0.016).

and thereby engendering and/or amplifying their financial constraints; this offset the foregoing, attenuating effect that the bubble *per se* exerted on the tech firms' financial constraints. Therefore, we expect that only financially constrained *non-tech* firms experienced a substantial decrease in financial constraints during the bubble, when external funds became cheaper for the non-tech firms but their investment opportunities and demand for funds remained largely unchanged (Jorgenson and Stiroh, 1999; Gordon, 2000; Stiroh, 2002).

On the above basis and in line with Campello and Graham (2013), our treatment (control) firms are defined as non-tech firms that faced high (low) financial constraints during the pre-bubble period 1990-1994; the bubble period is defined to cover the years 1995-1999.[14] The pre-bubble financial constraint statuses of non-tech firms are measured by the standardized mean of the SA indices over the five-year pre-bubble period.

We implement coarsened exact matching (CEM) to reduce the imbalance in pre-treatment covariates between the treatment and control groups (Blackwell et al., 2009). The idea of CEM is to temporarily coarsen each covariate into meaningful strata, exactly match on these coarsened data, and retain only the un-coarsened values of the matched data. Specifically, we match the treatment firms with the control firms based on the pre-bubble firm characteristics as to equity value (*lnequity*), the book-to-market ratio (*btm*), the leverage ratio (*debt*), return on assets (*roa*), earnings volatility (*stdearnings*), and financial opacity (*opacity*), which are arguably related to firms' financial constraints. Unlike commonly used matching techniques such as propensity score matching (PSM), CEM does not require checking *ex post* the covariate balance, as the coarsening levels are chosen *ex ante* (Iacus et al., 2012; King and Nielsen, 2019). After an automated coarsening *k*-to-*k* match, our matched data contain the same number of treated and control units in all strata.

[14] We obtain qualitatively identical results, when using a bubble period 1996-1999 and a pre-bubble period 1992-1995 for the DID test. We do not include the year 2000 in our bubble period, because the bubble burst, with stock price crashes occurring among a large number of firms, during that year.

The following DID regression model is specified to carry out the experimental test.

$$Crashrisk_{i,t+1} = \alpha_0 + \alpha_1 Bubble_t + \alpha_2 FC_i + \alpha_3 Bubble_t \times FC_i + \sum_k \alpha_k Controls_{i,t}^k + Firm\text{-}fixed\text{-}effects + Year\text{-}fixed\text{-}effects + \varepsilon_{i,t} \tag{7}$$

$Bubble_t$ equals 1 (0) if a firm is in the Internet bubble (pre-bubble) period 1995-1999 (1990-1994). FC_i is equal to 1 (0) if a firm is a treatment (control) firm, defined as having a pre-bubble standardized mean of the SA indices that is higher (lower) than its sample median.[15] The interaction term, $Bubble_t \times FC_i$, captures the DID estimate of crash risk between the treatment and matched control firms across the pre-bubble and bubble periods. We maintain the same control variables as those included in Model (4). It is possible that the Internet bubble also caused exogenous changes in some unobserved firm-specific factors that influence crash risk. Accounting for this possibility, we include firm-fixed effects in the regression. If the causal effect implied by the hypothesis H1 holds, the coefficient on $Bubble_t \times FC_i$ will be negative and statistically significant at conventional levels.

Table 10 reports the DID regression results. As expected, the coefficient on the interaction term, $Bubble_t \times FC_i$, is significantly negative at the 5% level.[16] This indicates that non-tech firms faced with high financial constraints have significantly larger declines in crash risk during the Internet bubble when compared with non-tech firms that are less subject to financial constraints. The general inflation of stock prices during the bubble might imply higher crash risk for our treatment firms, but we still find the significantly lower crash risk of such firms. This reinforces our causal inference that eases in financial constraints lead to lower stock price crash risk. In addition, we

[15] Following previous literature (e.g., Bond and Cummins, 2000; Campello and Graham, 2013), we classify tech firms as those with the first three digits of SIC codes of 355, 357, 366, 367, 369, 381, 382, and 384. These codes correspond to special industry machinery, computer and office equipment, communications equipment, electric components and accessories, electric transmission and distribution equipment, electric industrial apparatus, miscellaneous electrical equipment, search and navigation equipment, measuring and controlling devices, and medical instruments, respectively. The non-tech firms refer to those not in these sectors.

[16] Using the alternative crash risk measures, *ncrash* and *minreturn*, respectively, to repeat our DID test, we obtain similar results: the coefficients on $Bubble \times FC_i$ are negative (-0.4514 and -0.0888) and statistically significant at the 10% level (p-value=0.066 and 0.059).

conduct a multivariate test of the parallel trends assumption for the DID analysis, as per Roberts and Whited (2013). Specifically, we rerun Model (7) by using 1990 and 1991 (as well as 1991 and 1992, 1992 and 1993, 1993 and 1994, or 1994 and 1995), respectively, as the pre-"event" and "event" periods. In the results (not tabulated), none of the DID estimators are statistically significant, which signifies that the parallel trends assumption is tenable. By and large, the results for our second quasi-experiment speak strongly to the positive, causal relationship between financial constraints and future crash risk.

5.4 The association between financial constraints and longer-term future crash risk

Our main test concerns the association between financial constraints and one-year-ahead crash risk. However, if the difficulty in raising external funds induces financially constrained firms to withhold bad news for an extended period (say, two to three years), financial constraints would have an impact on longer-term future crash risk. To test this conjecture, we extend the measurement windows of crash risk to two years and three years ahead of our financial constraint measure (SA_t) and re-estimate Model (4). Specifically, we replace the one-year-ahead crash risk, $crashrisk_{t+1}$, with the two-year and three-year lead measures of crash risk, $crashrisk_{t+2}$ and $crashrisk_{t+3}$, respectively, as the dependent variable for our regression estimations.

Column (1) ((2)) of Table 11 reports the results as to the association between financial constraints and the two-year-ahead (three-year-ahead) crash risk. The coefficients on SA_t are both positive and statistically significant at the 1% level, which suggests that financial constraints can predict crash risk as far as two years and three years ahead, respectively. A one-standard-deviation increase in SA_t leads to an increase in $crashrisk_{t+2}$ ($crashrisk_{t+3}$) by 2.08 (1.60) percentage points, which accounts for 8.46% (6.17%) of its mean value and is thus economically significant. In results not tabulated for brevity, SA_t is also positively associated with the alternative crash risk variables, *ncrash*, *duvol*, and *minreturn*, which are measured on the two-year-ahead and three-year-ahead horizons, respectively. Also, this finding is not only statistically but also economically significant. Overall, our results imply that financial constraints are strongly predictive of future crash risk as far as three years ahead, thereby buttressing the bad-news-hoarding mechanism.

6. CONCLUSION

This study examines whether financial constraints are associated with future stock price crash risk. On the one hand, financially constrained firms have strong incentives to withhold bad news for an extended period to secure external funds. As withheld bad news accumulates, stock prices become increasingly overvalued, leading to a higher risk of future stock price crashes. On the other hand, financially constrained firms are subject to higher default risk and are more likely to undergo a stock price crash when they default. Consistent with these reasonings, we find strong evidence that financial constraints are positively correlated with the one-year-ahead stock price crash risk. This finding is robust to controlling for potential endogeneity in a dynamic panel generalized method of moments (GMM) analysis and in two quasi-experimental settings including the collapse of the junk bond market in 1989 and the Internet bubble in the late 1990s. In the quasi-natural experiments, crash risk was significantly higher (lower) in periods when firms' financial constraints were exogenously exacerbated (eased) by the collapse of the junk bond market (by the Internet bubble). These corroborate our causal inference that financial constraints lead to high future stock price crash risk, suggesting that outside investors are unlikely to extrapolate the implications of financial constraints for future stock price crash risk.

In the cross-sectional analyses, we find that the positive relation between financial constraints and future crash risk is more pronounced for firms with earnings management activities or with weak corporate governance and is less pronounced for firms that commit tax avoidance or have high credit ratings. Additional analysis reveals that financial constraints are associated with future crash risk as far as three years ahead. Together, these findings lend support to the bad-news-hoarding and default-risk mechanisms through which financial constraints lead to higher crash risk. These two mechanisms are not mutually exclusive and could jointly contribute to the positive effect of financial constraints on future crash risk.

Overall, our results shed light on the stock price crash risk of financially constrained firms and should have important implications for not only companies *per se* but also their stakeholders, including investors, creditors, suppliers, and customers concerned about the companies' creditworthiness, viability, and prospects. On the other hand, to mitigate crash risk, it is important for a financially constrained firm to build up strong corporate governance and to increase creditworthiness as well as information transparency to the public.

One limitation of our study is that we do not test the bad-news-hoarding mechanism and the default-risk mechanism directly in our empirical analysis. Managers' bad news hoarding behavior is unlikely to observe by outsiders without access to private information, and hence is hard to empirically measure and test. The default-risk mechanism concerns the default risk unanticipated by investors, which is also difficult to estimate. Therefore, we leave these to future experimental research.

APPENDIX A: SUMMARY OF VARIABLE DEFINITIONS

Variables	Definitions
crashrisk	1 if a firm experiences one or more firm-specific weekly returns falling 3.2 standard deviations below the mean firm-specific weekly return over a fiscal year, and 0 otherwise. The firm-specific weekly returns measure follows Kim et al. (2011a).
ncrash	The number of firm-specific weekly returns that fall 3.2 standard deviations below the mean firm-specific weekly return over a fiscal year.
duvol	The standard deviation of "down"-week firm-specific weekly returns (scaled by the number of "down"-weeks minus one), divided by the standard deviation of "up"-week firm-specific weekly returns (scaled by the number of "up"-weeks minus one) over a fiscal year. The firm-specific weekly returns measure follows Kim et al. (2011a).
minreturn	The minimum value of firm-specific weekly returns over a fiscal year, times -1, less the mean firm-specific weekly return, divided by the standard deviation of firm-specific weekly returns over a fiscal year. The firm-specific weekly returns measure follows Kim et al. (2011a).
ncskew	The negative of the third moment of firm-specific weekly returns. The firm-specific weekly returns measure follows Kim et al. (2011a).
SA	A financial constraint index (*SA*) developed by Hadlock and Pierce (2010). $SA=-0.737\times size+0.043\times size^2-0.040\times age$, where *size* is the natural logarithm of total assets capped at $4.5 billion, and *age* is the number of years for which a firm has been listed. *SA* index is re-scaled by dividing 1,000.
payout	The dividend-payout ratio, which equals cash dividends paid by a firm, divided by its earnings before interests and taxes, for a fiscal year. Observations with negative *payout* are excluded.
div	1 if a firm pays cash dividends in a fiscal year, and 0 otherwise.
lnequity	The natural logarithm of the market value of a firm's equity at the end of a fiscal year.
btm	The book value of firm equity divided by the market value of firm equity at the end of a fiscal year, winsorized at the 1% and 99% levels, respectively.
insti	Institutional investors' stock ownership as a percentage of total outstanding shares of a firm at the end of a fiscal year.
lanacov	The natural logarithm of 1 plus the number of analysts that make at least one annual earnings per share (EPS) forecast for a firm over a fiscal year.
roa	Return on assets at the end of a fiscal year, winsorized at the 1% and 99% levels, respectively.
stdret	The standard deviation of firm-specific weekly returns for a fiscal year. The firm-specific weekly returns measure follows Kim et al. (2011a).
qtrret	Buy-and-hold abnormal stock returns of a firm for a fiscal year.
stdearnings	The standard deviation of income before extraordinary items in the current and previous four fiscal years.
tradevol	The average of monthly trading volume for a firm over a fiscal year, scaled by total shares outstanding of the firm at the end of the year.
opacity	The three-year moving sum of the absolute value of annual discretionary accruals, a measure of financial opacity developed by Hutton et al. (2009). The variable is winsorized at the 1% and 99% levels, respectively.
da	Abnormal accruals of a firm for a fiscal year, which is estimated using industry-specific modified Jones model per Dechow et al. (1995), and that is winsorized at the 1% and 99% levels, respectively.
ddmpbtd	The residual domestic book-tax difference, based on Desai and Dharmapala (2006), which equals the residuals obtained from the following firm-fixed-effects regression model: $MPBTD_{i,t}=\beta_1 TA_{i,t}+u_i+\varepsilon_{i,t}$. *MPBTD* is domestic book-

	tax difference, based on Manzon and Plesko (2002), which is calculated as: (domestic pre-tax income - (current federal income tax expense/statutory tax rate) - state income tax expense - other income tax expense - equity income)/ lagged total assets. *TA* is total accruals measured using the cash flow method of Hribar and Collins (2002). Both *MPBTD* and *TA* are scaled by lagged total assets and are winsorized at the 1% and 99% levels, respectively, for the fixed-effects regression estimation.
cashetr	Cash effective tax rate, calculated as cash taxes paid, divided by pre-tax income net of special items. Observations for *cashetr* are excluded if its denominator is 0 or negative.
PostCollapse	1 if a firm is in the three-year period (i.e., 1990-1992) after the collapse of junk bond market in 1989, and 0 if a firm is in the three-year period (i.e., 1987-1989) as of the 1989 junk bond collapse.
Junk	1 if a firm is rated at BB+ or lower by the S&P credit rating agency, and 0 if a firm does not have an S&P credit rating, in the years (i.e., 1987-1989) prior to the collapse of the junk bond market. Credit ratings used in this study are the Standard & Poor's long-term domestic issuer credit ratings reported by Compustat.
FC	1 (0) if a firm is a financially constrained (unconstrained) non-tech firm that has the standardized mean of the SA indices higher (lower) than its sample median. The standardized mean of the SA indices is calculated based on the pre-bubble period 1990-1994.
Bubble	1 if a firm is in the Internet bubble period 1995-1999, and 0 if a firm is in the pre-bubble period 1990-1994.
rating	Standard & Poor's long-term domestic issuer credit ratings, which range from AAA to D/SD and are transformed into conventional numerical scores ranging from 22 to 0.
directorownership	The outside directors' equity ownership as a percentage of total shares outstanding of a firm at the end of a fiscal year.
indp	The number of the independent outside directors on the board of a firm, divided by the number of all the directors on the board, at the end of a fiscal year.
boardsize	The number of directors on the board of a firm at the end of a fiscal year.
indpComp	The number of the independent outside directors who sit on the compensation committee, divided by the number of all the directors on the board, at the end of a fiscal year.
indpNomi	The number of the independent outside directors who sit on the nominating committee, divided by the number of all the directors on the board, at the end of a fiscal year.
indpAudit	The number of the independent outside directors who sit on the auditing committee, divided by the number of all the directors on the board, at the end of a fiscal year.
indpCG	The number of the independent outside directors who sit on the corporate governance committee, divided by the number of all the directors on the board, at the end of a fiscal year.
CEOduality	1 if the CEO and the chairman of the board are the same person for a firm for a fiscal year and 0 otherwise.
indpbusy	The number of the independent outside directors who hold two or more board directorships, divided by the number of the independent outside directors, for a firm as of the end of a fiscal year.
olddirector	The number of directors who are older than 64, divided by the number of all the directors on the board of a firm, at the end of a fiscal year.
directorchair	1 if the chairman of the board is an independent outside director for a firm for a fiscal year and 0 otherwise.
indpfemale	The number of the female independent outside directors, divided by the number of all the directors on the board of a firm, at the end of a fiscal year.

indpvotingpower	The average percentage of a firm's voting power controlled by an independent outside director at the end of a fiscal year.
directorpredate	The number of directors appointed before the current CEO took office, divided by the number of all the directors on the board, for a firm at the end of a fiscal year.
staggered	1 if a firm's board is a staggered board for a fiscal year and 0 otherwise.
longtenuredindp	The number of the independent outside directors who have continuously served the board for ten years or more, divided by the number of the independent outside directors, for a firm at the end of a fiscal year.

APPENDIX B: EXAMPLES OF USING ACCRUALS TO WITHHOLD BAD NEWS

Strategies	Examples of corporate bad news
Understating impairment loss on inventories	Obsolescence or physical damage of products; Significant decline in some major customers' demand for products due to worsening customer relationship, deteriorating financial health of customers, or changes in customers' tastes, preferences, and needs on products; Emergence and increase in substitute products made by a competitor, which undermine the potential sales outlet and market value of existing products in stock.
Delaying or underestimating write-off of assets	A warehouse fire that impaired assets such as inventories, building, equipment, and machinery; Discontinued operations or disposals of a subsidiary, which reduce the values of currently operated assets; Changes in technologies, markets, or regulations which engendered adverse impacts that reduce the value of brands, goodwill, and other intangible assets.
Understating bad debt provisions	Deteriorating financial health of customers; Uncollectable payments due to bankruptcy or other cash-inadequacy issues of customers.
Understating other provisions or putting the provisions off balance sheet	Obligations to clean up polluted production sites; Obligations to provide warranty coverage for products sold due to malfunction of operating appliances; Obligations to pay expenses incurred from a lawsuit.

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TABLE 1 Descriptive statistics

Variables	No. of firm-years	No. of unique firms	Mean	Std. dev.	25th	Median	75th
$crashrisk_{t+1}$	28,208	6,533	0.2346	0.4238	0	0	0
$ncrash_{t+1}$	28,208	6,533	0.3922	1.6100	0	0	0
$duvol_{t+1}$	27,966	6,477	-0.2064	0.5218	-0.4491	-0.1592	0.0950
$minreturn_{t+1}$	28,158	6,520	2.4197	0.7527	1.9335	2.3130	2.8034
$ncskew_{t+1}$	28,208	6,533	-4.8060	16.6924	-12.1446	-4.4198	3.1580
SA_t	28,208	6,533	-1.0537	1.2120	-1.7529	-0.4397	-0.1078
$payout_t$	27,227	6,423	0.1555	0.3328	0	0	0.1762
div_t	28,208	6,533	0.4433	0.4968	0	0	1
$lnequity_t$	28,208	6,533	6.2918	2.0501	4.9014	6.3427	7.6560
btm_t	28,208	6,533	0.8010	1.9735	0.2836	0.5075	0.8517
$lanacov_t$	28,208	6,533	2.6574	1.6059	1.6094	3.0445	3.8712
$insti_t$	28,208	6,533	0.4699	0.3575	0.1201	0.4897	0.7722
roa_t	28,208	6,533	-0.0244	0.2246	-0.0206	0.0306	0.0691
$stdret_t$	28,208	6,533	0.0675	0.0446	0.0384	0.0563	0.0833
$qtrret_t$	28,208	6,533	0.0337	1.3071	-0.3240	-0.0637	0.2058
$tradevol_t$	28,208	6,533	1.5365	2.5989	0.4872	1.0058	1.9332
$opacity_t$	28,208	6,533	46.6891	216.5818	0.0509	0.1906	1.4063
da_t	21,253	5,771	9.6114	74.6406	-0.0841	0.0009	0.1402
$ddmpbtd_t$	20,379	5,696	0.0111	0.1573	-0.0156	0.0319	0.0762
$cashetr_t$	18,157	4,280	0.3418	5.3409	0.0938	0.2263	0.3397
$rating_t$	9,500	1,992	12.9585	3.3850	10	13	15

Notes: This table presents descriptive statistics for the variables used in the multivariate tests. The sample contains firm-year observations for the period 1995-2016. All the variables are defined in Appendix A.

TABLE 2 Spearman correlations

Variables	SA_t	$lnequity_t$	btm_t	$lanacov_t$	$insti_t$	roa_t	$stdret_t$	$qtrret_t$	$tradevol_t$	$opacity_t$
SA_t	1									
$lnequity_t$	-0.8617***	1								
	(<0.001)									
btm_t	-0.0385***	-0.3472***	1							
	(<0.001)	(<0.001)								
$lanacov_t$	-0.6636***	0.7430***	-0.2347***	1						
	(<0.001)	(<0.001)	(<0.001)							
$insti_t$	-0.3842***	0.4536***	-0.1574***	0.4988***	1					
	(<0.001)	(<0.001)	(<0.001)	(<0.001)						
roa_t	-0.2636***	0.3674***	-0.2001***	0.2084***	0.2282***	1				
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)					
$stdret_t$	0.4951***	-0.4569***	0.0010	-0.1829***	-0.1944***	-0.3842***	1			
	(<0.001)	(<0.001)	(0.865)	(<0.001)	(<0.001)	(<0.001)				
$qtrret_t$	-0.1263***	0.2746***	-0.3310***	0.0704***	0.1634***	0.2747***	-0.1446***	1		
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)			
$tradevol_t$	-0.2166***	0.3524***	-0.2445***	0.5439***	0.4517***	0.0197***	0.2535***	0.0748***	1	
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)		
$opacity_t$	0.1635***	-0.0593***	-0.1319***	-0.0583***	-0.0499***	-0.1212***	0.1689***	0.0011	0.0799***	1
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.850)	(<0.001)	

Notes: This table reports the results for the Spearman correlations among the variables used in Model (4). The sample consists of 28,208 firm-year observations and covers the years 1995-2016. All the variables are defined in Appendix A. The *p*-values in parentheses are based on robust standard errors clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 3 Tests of the hypothesis H1: The association between financial constraints and future stock price crash risk

Panel A:

Variables	Predicted Sign	Dependent Variable = $crashrisk_{t+1}$ (1)	(2)	(3)
Intercept	?	2.7896***		
		(5.678)		
$\boldsymbol{SA_t}$	**+**	**0.1516*** **		
		(6.271)		
$\boldsymbol{payout_t}$	**-**		**-0.0962***	
			(-1.722)	
$\boldsymbol{div_t}$	**-**			**-0.1165*** **
				(-2.889)
$lnequity_t$	+	0.0727***	-0.0047	0.0058
		(3.956)	(-0.330)	(0.424)
btm_t	-	0.0158	-0.0022	-0.0015
		(1.558)	(-0.192)	(-1.120)
$lanacov_t$	+	0.0848***	0.0886***	0.0801***
		(4.942)	(5.009)	(4.662)
$insti_t$	-	-0.0902	-0.0550	-0.0554
		(-1.358)	(-0.896)	(-0.845)
roa_t	-	0.0124	0.0434	0.0089***
		(0.138)	(0.476)	(4.614)
$stdret_t$	+	-0.7799	-0.8794	-1.1106**
		(-1.518)	(-1.452)	(-2.211)
$qtrret_t$	+	0.0005	0.0069	0.0076
		(0.063)	(0.815)	(0.915)
$tradevol_t$	+	0.0079	0.0105*	0.0103*
		(1.448)	(1.695)	(1.765)
$opacity_t$	+	0.0002***	0.0001***	0.0003***
		(3.253)	(2.924)	(3.457)
$ncskew_t$	?	0.0043***	0.0044***	0.0044***
		(4.237)	(4.341)	(4.352)
Industry-fixed effects		included	included	included
Year-fixed effects		included	included	included
No. of observations		28,208	27,227	28,208
Pseudo R-squared		0.1743	0.1741	0.1734

TABLE 3 (Continued)

Panel B: Alternative stock price crash risk measures

Variables	Predicted Sign	(1) $ncrash_{t+1}$	(2) $ncskew_{t+1}$	(3) $duvol_{t+1}$	(4) $minreturn_{t+1}$
		Dependent Variables			
Intercept	?		-8.6952***	-0.5486***	2.0139***
			(-3.451)	(-7.418)	(27.074)
SA_t	+	**0.1401*** **	**0.5518*** **	**0.0139*** **	**0.0415*** **
		(6.160)	**(3.590)**	**(3.293)**	**(6.394)**
$lnequity_t$	+	0.0706***	1.3905***	0.0505***	0.0471***
		(4.038)	(11.681)	(15.094)	(9.512)
btm_t	-	0.0133	-0.0101	0.0033*	0.0035
		(1.333)	(-0.211)	(1.873)	(1.368)
$lanacov_t$	+	0.0809***	0.4776***	0.0067**	0.0085*
		(4.896)	(4.402)	(2.205)	(1.850)
$insti_t$	-	-0.0739	0.2662	-0.0024	-0.0460**
		(-1.195)	(0.708)	(-0.223)	(-2.321)
roa_t	-	0.0118	0.9006**	0.1130***	0.1322***
		(0.134)	(2.330)	(6.096)	(5.366)
$stdret_t$	+	-0.5903	8.8729***	-0.7014***	-1.4542***
		(-1.243)	(3.117)	(-7.269)	(-10.753)
$qtrret_t$	+	0.0003	0.1737	0.0036	0.0033
		(0.042)	(1.004)	(0.853)	(0.715)
$tradevol_t$	+	0.0077	0.0179	0.0021**	0.0036***
		(1.545)	(0.459)	(2.327)	(2.674)
$opacity_t$	+	0.0003***	0.0007	0.0000***	0.0001**
		(4.460)	(1.335)	(3.013)	(2.219)
$ncskew_t$	?	0.0042***	0.0285**	0.0001	0.0015***
		(4.375)	(2.499)	(0.637)	(5.015)
Industry-fixed effects		included	included	included	included
Year-fixed effects		included	included	included	included
No. of observations		28,208	28,208	27,966	28,158
Pseudo R-squared		0.2296			
Adjusted R-squared			0.0632	0.0769	0.0532

Notes: This table presents the regression results for the tests of the association between financial constraints and future crash risk. The sample period covers the years 1995-2016. In Panel A, the dependent variable, $crashrisk_{t+1}$, equals 1 if a firm experiences one or more firm-specific weekly returns falling 3.2 standard deviations below the mean firm-specific weekly return over the fiscal year t+1, and 0 otherwise. The treatment variables are SA_t, $payout_t$, and div_t from Column (1) to Column (3). In Panel B, the dependent variables are $ncrash_{t+1}$, $ncskew_{t+1}$, $duvol_{t+1}$, and $minreturn_{t+1}$ from Column (1) to Column (4), and are the alternative measures of stock price crash risk, while the treatment variable is SA_t for all the columns. All the variables are defined in Appendix A. Industry dummies (constructed based on the first two digits of SIC codes) and year dummies are included in all the regressions but are not reported for simplicity. The t-statistics in parentheses are based on robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.

TABLE 4 Test of the hypothesis H2: The moderating effect of abnormal accruals

Variables	Dependent Variable = $crashrisk_{t+1}$	
	Abnormal accruals (*da*)	
	Low	High
Intercept	2.8555***	2.2132***
	(4.014)	(2.839)
$\boldsymbol{SA_t}$	**0.0604**	**0.1404*** **
	(1.548)	**(3.488)**
$lnequity_t$	0.0716**	0.0520*
	(2.318)	(1.713)
btm_t	0.0221*	0.0261*
	(1.836)	(1.767)
$lanacov_t$	0.0632**	0.0781***
	(2.252)	(2.673)
$insti_t$	0.0005	-0.0915
	(0.005)	(-0.939)
roa_t	0.1925	-0.2560**
	(1.176)	(-1.963)
$stdret_t$	0.8743	-2.1507**
	(0.983)	(-2.410)
$qtrret_t$	0.0150	-0.0140
	(0.493)	(-0.570)
$tradevol_t$	-0.0006	0.0311**
	(-0.084)	(2.003)
$opacity_t$	0.0001	0.0003***
	(0.402)	(2.783)
$ncskew_t$	0.0047***	0.0045***
	(2.886)	(2.730)
Industry-fixed effects	included	included
Year-fixed effects	included	included
No. of observations	10,621	10,626
Pseudo R-squared	0.1816	0.2297

Notes: This table presents the logistic regression results for the test of the hypothesis H2 as to the moderating effect of abnormal accruals (*da*) on the association between financial constraints and future crash risk. The sample period covers the years 1995-2016. The dependent variable, $crashrisk_{t+1}$, equals 1 if a firm experiences one or more firm-specific weekly returns falling 3.2 standard deviations below the mean firm-specific weekly return over the fiscal year t+1, and 0 otherwise. The treatment variable is the SA index (SA_t). Our sample are partitioned, based on the sample median of *da*, into the high-abnormal-accruals subsample and low-abnormal-accruals subsample. All the variables are defined in Appendix A. Industry dummies (constructed based on the first two digits of SIC codes) and year dummies are included in both regressions but are not reported for simplicity. The t-statistics in parentheses are based on robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.

TABLE 5 Tests of the hypothesis H3: The moderating effect of corporate governance

Panel A: Descriptive statistics of corporate governance measures (2007-2015)

CG Variables	Obs.	Mean	Std. dev.	25th	Median	75th
directorownership	5,038	0.0146	0.0509	0.0015	0.0038	0.0086
indp	5,038	0.7972	0.1050	0.7273	0.8284	0.8889
boardsize	5,038	9.0389	2.2540	8	9	10
indpComp	2,473	0.4195	0.1217	0.3333	0.4000	0.5000
indpNomi	2,435	0.4274	0.1454	0.3333	0.4000	0.5000
indpAudit	2,474	0.4274	0.1052	0.3636	0.4286	0.5000
indpCG	2,370	0.4289	0.1465	0.3333	0.4000	0.5000
CEOduality	5,038	0.5123	0.4999	0	1	1
indpbusy	4,089	0.2396	0.1410	0.1250	0.2222	0.3333
olddirector	4,867	0.4356	0.1891	0.2857	0.4286	0.5714
directorchair	5,038	0.0981	0.2974	0	0	0
indpfemale	5,038	0.1151	0.0982	0	0.1111	0.1818
indpvotingpower	1,989	1.4062	4.1106	0	0	1
directorpredate	4,205	0.5785	0.2718	0.3571	0.6000	0.8000
staggered	5,038	0.4460	0.4971	0	0	1
longtenuredindp	4,087	0.3922	0.1878	0.2500	0.3750	0.5000

Panel B: Subsample test using outside directors' equity ownership (*directorownership*) as a measure of corporate governance

Variables	Dependent Variable = $crashrisk_{t+1}$	
	Outside Directors' Equity Ownership (*directorownership*)	
	Low	High
Intercept	2.2597*	3.0120***
	(1.721)	(2.835)
$\boldsymbol{SA_t}$	**0.1888****	**0.1654**
	(2.222)	**(1.639)**
$lnequity_t$	0.0325	0.1001
	(0.405)	(0.929)
btm_t	-0.0945	0.0502
	(-0.557)	(0.286)
$lanacov_t$	0.0995	0.0861
	(0.856)	(0.830)
$insti_t$	-0.4903**	-0.0782
	(-2.040)	(-0.341)
roa_t	0.8470	1.2114*
	(1.120)	(1.842)
$stdret_t$	5.5600	-2.0827
	(1.454)	(-0.571)
$qtrret_t$	-0.1942	0.0367
	(-1.266)	(0.292)
$tradevol_t$	-0.0522	-0.0075
	(-1.229)	(-0.159)
$opacity_t$	0.0001	-0.0001
	(0.196)	(-0.364)
$ncskew_t$	0.0038	0.0029
	(1.293)	(1.016)
Industry-fixed effects	included	included
Year-fixed effects	included	included
No. of observations	2,463	2,513
Pseudo R-squared	0.2536	0.2283

Panel C: Subsample tests using alternative measures for corporate governance

Dependent Variable = *crashrisk*$_{t+1}$										
Corporate governance variables	% of independent directors on board *(indp)*		Board size *(boardsize)*		% of independent directors on compensation committee *(indpComp)*		% of independent directors on nominating committee *(indpNomi)*		% of independent directors on auditing committee *(indpAudit)*	
	Low	High	Small	Large	Low	High	Low	High	Low	High
SA$_t$	**0.1797****	**0.1014**	**0.2989*****	**0.1106**	**0.2536****	**0.2216**	**0.2984****	**0.1402**	**0.3921*****	**0.0844**
	(2.122)	**(1.245)**	**(2.794)**	**(1.462)**	**(1.987)**	**(1.614)**	**(2.143)**	**(1.105)**	**(3.126)**	**(0.637)**
Controls	included	included	included	included	included	included	included	included	included	included
Industry-fixed effects	included	included	included	included	included	included	included	included	included	included
Year-fixed effects	included	included	included	included	included	included	included	included	included	included
No. of observations	2,515	2,511	2,155	2,876	1,252	1,161	1,233	1,131	1,132	1,256
Pseudo R-squared	0.2417	0.2779	0.2112	0.2827	0.0753	0.0565	0.0849	0.0501	0.0646	0.0520

Corporate governance variables	% of independent directors on corporate governance committee *(indpCG)*		CEO serving as chairman of the board *(CEOduality)*		% of busy independent directors *(indpbusy)*		% of directors over age 64 *(olddirector)*		Chairman of board being independent director *(directorchair)*	
	Low	High	No	Yes	Low	High	Low	High	No	Yes
SA$_t$	**0.2400***	**0.1372**	**0.1546**	**0.1729****	**0.0532**	**0.2961*****	**0.2993*****	**-0.0078**	**0.2032*****	**-0.2357**
	(1.740)	**(1.095)**	**(1.644)**	**(2.017)**	**(0.556)**	**(2.882)**	**(3.259)**	**(-0.097)**	**(3.234)**	**(-1.106)**
Controls	included	included	included	included	included	included	included	included	included	included
Industry-fixed effects	included	included	included	included	included	included	included	included	included	included
Year-fixed effects	included	included	included	included	included	included	included	included	included	included
No. of observations	1,062	1,099	2,457	2,538	1,945	2,141	2,299	2,555	4,544	434
Pseudo R-squared	0.0786	0.0510	0.2595	0.2219	0.2998	0.2440	0.2400	0.2806	0.2563	0.0862

Panel C Continued

Corporate governance variables	% of female independent directors *(indpfemale)*		% of voting power by independent directors *(indpvotingpower)*		% of directors appointed before the current CEO took office *(directorpredate)*		Staggered board *(staggered)*		% of independent directors continuously serving the board for 10 years or more *(longtenuredindp)*	
	Low	High	Low	High	Low	High	No	Yes	Low	High
SA_t	**0.0396**	**0.2113****	**0.3396*****	**0.1622**	**0.1902****	**0.0880**	**0.2664*****	**0.0134**	**0.2219****	**0.0538**
	(0.426)	**(2.537)**	**(2.719)**	**(0.700)**	**(2.106)**	**(0.951)**	**(3.334)**	**(0.143)**	**(2.365)**	**(0.616)**
Controls	included	included	included	included	included	included	included	included	included	included
Industry-fixed effects	included	included	included	included	included	included	included	included	included	included
Year-fixed effects	included	included	included	included	included	included	included	included	included	included
No. of observations	2,220	2,767	1,401	537	2,133	2,059	2,788	2,209	1,956	2,113
Pseudo R-squared	0.2156	0.2698	0.2818	0.2491	0.2611	0.2672	0.2719	0.2043	0.2368	0.2739

Notes: Panel A presents descriptive statistics for the corporate governance variables used in the test of the hypothesis H3 as to the moderating effect of corporate governance on the relation between financial constraints and future stock price crash risk. The corporate governance variables are constructed using the data from Institutional Shareholder Services (ISS) database, where the data cover the period starting from 2007. The sample period for the financial constraints (crash risk) variable ranges from 2007 (2008) to 2015 (2016). Panels B and C present the logistic regression results for the tests of H3. The dependent variable is the indicator variable, $crashrisk_{t+1}$. The treatment variable is the SA index (SA_t). The moderator variable used in Panel B is *directorownership*, which is measured by outside directors' equity ownership as a percentage of total shares outstanding of a firm. Our sample is separated into two subsamples based on whether an observation has a value of *directorownership* higher than the sample median of *directorownership*. The high (low) *directorownership* subsample represents strong (weak) corporate governance group. The moderator variables used in Panel C are 15 alternative measures of corporate governance. Our sample is partitioned based on whether an observation has a value of the alternative, non-binary measures of corporate governance higher than their sample medians, respectively. If the corporate governance measures are indicator variables, the sample is split based on the indicators. Observations that have low (high) values of *indp, boardsize, indpComp, indpNomi, indpAudit, indpCG, olddirector, directorchair*, *indpvotingpower*, *directorpredate*, *longtenuredindp*, *staggered* (*indpbusy*, *indpfemale*, *CEOduality*) are classified as having weak corporate governance. All the variables are defined in Appendix A. The control variables included in all the regressions are the same as those included in Model (4), but are not reported for brevity in Panel C. Industry dummies (constructed based on the first two digits of SIC codes) and year dummies are included in all the regressions but are not reported for simplicity. The t-statistics in parentheses are based on robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.

TABLE 6 Test of the hypothesis H4: The moderating effect of corporate tax avoidance

Variables	Dependent Variable = *crashrisk*$_{t+1}$			
	Corporate Tax Avoidance			
	(1) *cashetr*		(2) *ddmpbtd*	
	Low	High	Low	High
Intercept	-2.2063***	3.9977***	1.9429***	-1.1174**
	(-4.490)	(3.578)	(2.988)	(-2.064)
SA$_t$	**0.0548**	**0.2479*** **	**0.0801** **	**0.0488**
	(1.436)	**(5.156)**	**(2.015)**	**(1.246)**
lnequity$_t$	0.0859***	0.1563***	0.0820***	0.0852***
	(2.670)	(4.028)	(2.680)	(2.648)
btm$_t$	-0.0368	0.0750***	0.0245*	0.0258
	(-1.062)	(2.759)	(1.892)	(1.271)
lanacov$_t$	0.0243	0.0622*	0.0450	0.0575**
	(0.864)	(1.661)	(1.600)	(2.056)
insti$_t$	-0.2653***	0.0418	-0.1550	-0.1077
	(-2.836)	(0.458)	(-1.500)	(-1.037)
roa$_t$	-0.7770**	-0.3045	-0.1296	-0.1115
	(-2.033)	(-0.648)	(-1.080)	(-0.288)
stdret$_t$	-4.1633***	-0.5251	-1.5822**	-3.6998***
	(-3.690)	(-0.396)	(-2.036)	(-3.233)
qtrret$_t$	-0.0763**	-0.0048	-0.0032	-0.0369
	(-1.973)	(-0.093)	(-0.324)	(-0.875)
tradevol$_t$	0.0213**	0.0181	0.0154	0.0004
	(2.074)	(0.898)	(1.094)	(0.041)
opacity$_t$	0.0010***	0.0003*	0.0002	0.0011***
	(9.001)	(1.781)	(1.603)	(9.026)
ncskew$_t$	-0.0001	0.0057***	0.0066***	0.0013
	(-0.087)	(3.307)	(3.726)	(0.972)
Industry-fixed effects	included	included	included	included
Year-fixed effects	included	included	included	included
No. of observations	9,073	9,065	10,185	10,190
Pseudo R-squared	0.0471	0.1803	0.2035	0.0771

Notes: This table presents the logistic regression results for the test of H4 as to the moderating effect of corporate tax avoidance on the association between financial constraints and future crash risk. The sample period covers the years 1995-2016. The dependent variable is the indicator variable, *crashrisk*$_{t+1}$. The treatment variable is the SA index (*SA*$_t$). The moderator variable is corporate tax avoidance, which is measured by cash effective tax rate (*cashetr*) and the Desai and Dharmapala's (2006) residual domestic book-tax difference (*ddmpbtd*) in Columns (1) and (2). A lower (higher) value of *cashetr* (*ddmpbtd*) indicates a larger extent of corporate tax avoidance. Our sample is split into the high-tax-avoidance subsample and low-tax-avoidance subsample, based on the sample median of *cashetr* and *ddmpbtd*, respecitvely. All the variables are defined in Appendix A. Industry dummies (constructed based on the first two digits of SIC codes) and year dummies are included in all the regressions but are not reported for simplicity. The t-statistics in parentheses are based on robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.

TABLE 7 Test of the hypothesis H5: The moderating effect of credit ratings

Variables	Dependent Variable = $crashrisk_{t+1}$	
	Speculative-grade	Investment-grade
Intercept	3.1393**	3.0880***
	(2.300)	(3.012)
$\boldsymbol{SA_t}$	**0.1301****	**0.0909**
	(2.267)	**(1.199)**
$lnequity_t$	0.1078*	0.0916
	(1.823)	(1.517)
btm_t	0.0103	0.0376***
	(0.520)	(2.759)
$lanacov_t$	0.0359	-0.0034
	(0.800)	(-0.071)
$insti_t$	-0.2523**	-0.0487
	(-1.969)	(-0.302)
roa_t	0.6294	-0.2919
	(1.143)	(-0.244)
$stdret_t$	2.1198	-2.5059
	(1.128)	(-0.730)
$qtrret_t$	-0.1179*	-0.1671
	(-1.924)	(-1.152)
$tradevol_t$	0.0016	-0.0218
	(0.056)	(-1.451)
$opacity_t$	0.0003	0.0004*
	(0.968)	(1.886)
$ncskew_t$	0.0023	0.0012
	(0.964)	(0.453)
$rating_t$	-0.0036	-0.0675**
	(-0.130)	(-2.173)
Industry-fixed effects	included	included
Year-fixed effects	included	included
No. of observations	5,168	4,296
Pseudo R-squared	0.2199	0.1903

Notes: This table reports the logistic regression results for the test of H5 as to the moderating effect of credit ratings on the association between financial constraints and future crash risk. The sample period covers the years 1995-2016. The dependent variable is the indicator variable, $crashrisk_{t+1}$. The treatment variable is the SA index (SA_t). Our sample is separated into low-credit-rating subsample and high-credit-rating subsample, based on whether a firm receive an investment grade or speculative grade from the S&P's credit rating agency in a year. Investment-grade firms are those rated at BBB- or higher; Speculative-grade firms are rated at BB+ or lower. All the variables are defined in Appendix A. Industry dummies (constructed based on the first two digits of SIC codes) and year dummies are included in both regressions but are not reported for simplicity. The t-statistics in parentheses are based on robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.

TABLE 8 Further analysis: A dynamic panel generalized method of moments (GMM) estimation

Variables	Dependent Variable = $crashrisk_{t+1}$
$\boldsymbol{SA_t}$	**0.0886****
	(2.155)
$lnequity_t$	0.0677*
	(1.713)
btm_t	0.0002
	(0.014)
$lanacov_t$	0.0172
	(0.482)
$insti_t$	0.2871**
	(2.121)
roa_t	0.0014
	(1.027)
$stdret_t$	1.0425
	(0.584)
$qtrret_t$	0.0898
	(0.733)
$tradevol_t$	-0.0218
	(-0.732)
$opacity_t$	-0.0002
	(-1.312)
$ncskew_t$	-0.0098***
	(-2.680)
$crashrisk_t$	-0.0722
	(-0.287)
$crashrisk_{t-1}$	-0.0945
	(-0.275)
No. of observations	13,626
AR(1) test (*p*-value)	0.044
AR(2) test (*p*-value)	0.883
Hansen test of over-identification (*p*-value)	0.159

Notes: This table presents the GMM regression results for the test of the hypothesis H1. The sample period covers the years 1995-2016. The dependent variable is $crashrisk_{t+1}$, as defined previously. The treatment variable is SA_t. All the variables are defined in Appendix A. The instruments used in the GMM estimation include $Crashrisk_{i,t-2}$, $Crashrisk_{i,t-3}$, $SA_{i,t-3}$, $SA_{i,t-4}$, $Controls_{i,t-3}$, $Controls_{i,t-4}$, $\Delta YearDummies$, and $\Delta IndustryDummies$ ($\Delta Crashrisk_{i,t-1}$, $\Delta SA_{i,t-2}$ $\Delta Controls_{i,t-2}$, $YearDummies_{i,t}$, and $IndustryDummies_{i,t}$) in the differenced (level) equations. The industry dummies used in the GMM specification are based on the Fama-French's twelve industries. *AR*(1) and *AR*(2) are the tests for first-order and second-order serial correlation in the first-differenced residuals in the model, under the null hypothesis of no serial correlation. The Hansen test of over-identification has a null hypothesis that all the instruments are valid. The t-statistics in parentheses are based on robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.

TABLE 9 Further analysis: The effect of the junk-bond-market collapse on stock price crash risk

Variables	Dependent Variable = $crashrisk_{t+1}$
Intercept	0.9734
	(1.124)
$PostCollapse_t$	0.4339
	(1.190)
$Junk_i$	-0.5507
	(-1.445)
$PostCollapse_t \times Junk_i$	**1.2775****
	(2.383)
$lnequity_t$	-0.4005***
	(-3.948)
btm_t	0.0109
	(0.430)
$lanacov_t$	0.1828*
	(1.813)
roa_t	1.0976**
	(2.056)
$stdret_t$	-1.0218
	(-0.315)
$qtrret_t$	-0.0349
	(-0.233)
$tradevol_t$	0.1211
	(0.939)
$ncskew_t$	-0.0020
	(-0.387)
Industry-fixed effects	included
Year-fixed effects	included
No. of observations	1,214
Pseudo R-squared	0.0901

Notes: This table reports the logistic regression results of the difference-in-differences test for the effect of the junk-bond-market collapse on stock price crash risk. The dependent variable is $crashrisk_{t+1}$, as defined previously. The indicator variable, $PostCollapse_t$, equals 1 (0) if a sample firm is in the period 1990-1992 (1987-1989). The indicator variable, *Junk*, equals 1 if a sample firm is rated with a speculative grade (BB+ or lower) by the S&P credit rating agency in a year, and 0 if a firm does not receive an S&P credit rating in a year. The interaction term, $PostCollapse_t \times Junk_i$, is the DID estimator. All the variables are defined in Appendix A. Industry dummies (constructed based on the first two digits of SIC codes) and year dummies are included in the regression but are not reported for simplicity. The t-statistics in parentheses are based on robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.

TABLE 10 Further analysis: The effect of the Internet bubble (1995-1999) on stock price crash risk

Variables	Dependent Variable = $crashrisk_{t+1}$
Intercept	-5.2823***
	(-2.798)
$Bubble_t$	1.4153***
	(4.963)
FC_i	2.2824
	(1.332)
$\boldsymbol{Bubble_t \times FC_i}$	**-0.4950****
	(-2.024)
$lnequity_t$	0.5522***
	(3.265)
btm_t	-0.0220
	(-0.096)
$lanacov_t$	-0.1336
	(-1.106)
$insti_t$	-0.3402
	(-0.634)
roa_t	1.8075
	(1.256)
$stdret_t$	-4.4224
	(-1.035)
$qtrret_t$	0.2223*
	(1.657)
$tradevol_t$	0.0488
	(0.246)
$opacity_t$	-0.0000
	(-0.000)
$ncskew_t$	-0.0114***
	(-3.809)
Year-fixed effects	included
Firm-fixed effects	included
No. of observations	2,261
Pseudo R-squared	0.1106

Notes: This table reports the logit regression results of the difference-in-differences tests for the effect of the Internet bubble on stock price crash risk. The sample period for the DID test is 1990-1999. Non-tech firms are those that do not have the first three digits of SICs of 355, 357, 366, 367, 369, 381, 382, or 384. The dependent variable is $crashrisk_{t+1}$, as defined previously. The indicator variable, FC_i, equals 1 (0) if a firm is a financially constrained (unconstrainted) non-tech firm that has the pre-bubble standardized mean of SA indices higher (lower) than its sample median. The indicator variable, $Bubble_t$, equals 1 (0) if a sample firm is in the Internet bubble (pre-bubble) period (1995-1999 (1990-1994)). The interaction term, $Bubble_t \times FC_i$, is the DID estimator. All the variables are defined in Appendix A. Firm-fixed effects, alongside with industry dummies (constructed based on the first two digits of SIC codes) and year dummies, are included in the regression but are not reported for simplicity. The t-statistics in parentheses are based on robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.

TABLE 11 Additional test: The association between financial constraints and two-year- and three-year-ahead stock price crash risk

Variables	(1) Dependent variable = *crashrisk*$_{t+2}$	(2) Dependent variable = *crashrisk*$_{t+3}$
Intercept	2.4753***	2.3925***
	(5.925)	(5.161)
SA$_t$	**0.1184*** **	**0.0871*** **
	(4.411)	**(2.903)**
lnequity$_t$	0.0785***	0.0611***
	(3.792)	(2.596)
btm$_t$	-0.0003	0.0117
	(-0.024)	(0.771)
lanacov$_t$	0.0723***	0.0649***
	(3.852)	(3.007)
insti$_t$	-0.1434**	-0.1128
	(-2.271)	(-1.361)
roa$_t$	0.0015	-0.1927*
	(0.015)	(-1.689)
stdret$_t$	-0.8847	-1.9340***
	(-1.493)	(-2.831)
qtrret$_t$	0.0087	0.0042
	(0.891)	(0.500)
tradevol$_t$	0.0133**	0.0042
	(2.049)	(0.686)
opacity$_t$	0.0004***	-0.0001
	(3.663)	(-0.806)
ncskew$_t$	-0.0001	0.0003
	(-0.045)	(0.246)
Year-fixed effects	included	included
Industry-fixed effects	included	included
No. of observations	23,188	17,620
Pseudo R-squared	0.1848	0.1883

Notes: Column (1) ((2)) of this table reports the logistic regression results for the test of the association between financial constraints and two-year-(three-year-) ahead stock price crash risk. For the results in Column (1) ((2)), the sample period covers the years 1995-2015 (1995-2014), and the dependent variable is *crashrisk*$_{t+2}$ (*crashrisk*$_{t+3}$). The treatment variable is the SA index (*SA*$_t$). All the variables are defined in Appendix A. Industry dummies (constructed based on the first two digits of SIC codes) and year dummies are included in both regressions but are not reported for simplicity. The t-statistics in parentheses are based on robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.