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Does crackdown on corruption reduce stock price crash risk? Evidence from China*

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Abstract

This study examines whether crackdown on political corruption in China affects future stock price crashes. Using data from corruption-related prosecutions, we find that firms under prosecuted official jurisdictions experience a significant decrease in crash risk after the crackdown. Cross-sectional tests show that results are more pronounced for firms with higher political dependence on governments and for firms with worse information environment. Moreover, channel tests provide direct evidence that crackdown decreases crash risk by reducing political risk and bad news hoarding. Overall, our study offers novel evidence on how crackdown on corruption benefits firms.

Keywords: Corruption, crackdown, crash risk, political risk, bad news hoarding

1. Introduction

This paper investigates how China's crackdown on political corruption affects the stock price crash risk of local firms.[1] Political corruption, commonly defined as the use of power by government officials for private gains, is pervasive around the world, especially in emerging economies. Existing literature documents that political corruption is detrimental to economic development as it distorts resource allocation, impairs competition, and hinders productivity growth (Murphy et al., 1993; Shleifer and Vishny, 1993; Mauro, 1995; Fisman and Miguel, 2007; Lin et al., 2016). Political corruption may also adversely affect business environments and influence firm-specific decision making (DeBacker et al., 2015; Smith, 2016; Liu, 2016; Ellis et al., 2016).[2] However, to the best of our knowledge, none of the previous studies provides evidence of the effect of corruption crackdown on future stock price crashes.

Stock price crash risk (hereafter crash risk), namely, extremely negative return outliers, has drawn increased attention in recent literature, especially after the 2008 financial crisis. From a theoretical point of view, stock price crash may be caused by increase in perceived political risk (Pastor and Veronesi, 2012, 2013) and/or by greater ability of mangers to suppress bad news (Jin and Myers, 2006).

As it is uncertain whether government policy under corrupt officials will last, changing of policy increases political uncertainty (i.e., the standard deviation of the political cost) (Pastor and Veronesi, 2012). Rent-seeking activities of corrupt officials therefore increase investors' uncertainty of future economic environment, and result in higher political risk (i.e., higher

[1] A 2017 Financial Times article ("Xi's crackdown on corruption is a boon to corporate China") argues that "the anti-corruption campaign has yielded a short-term benefit to companies' bottom lines that few investors conceived when it was launched". See https://www.ft.com/content/961a8e3c-1824-11e7-9c35-0dd2cb31823a. In this study, we instead focus on the impact of anti-corrupt campaign on firms' future stock price crash risk.

[2] For example, Ellis et al. (2016) find that firms in more corrupt areas are less likely to invest in innovation. In another study, Liu (2016) demonstrates that firms with high corruption culture are more likely to engage in corporate misconduct, such as earnings management, accounting fraud, option backdating, and opportunistic insider trading.

uncertainty about future government policy).This in turn leads to large price decline (i.e., higher crash risk) for firms in corrupted regions (Pastor and Veronesi, 2012, 2013; Huang et al., 2015a, b)[3].

Moreover, with respect to firms located in corrupted regions, their managers often engage in briberies to curry favor with these officials in exchange for preferential treatment and better political protection. Managers are also more likely to engage in high-risk projects, and more importantly, to obfuscate financial information as well as reduce reporting transparency to mask their rent seeking activities (i.e., collusion with corrupt officials).[4] This leads to accumulation and withholding of bad news by managers, which translates into higher crash risk (Jin and Myer, 2006).

After corrupt officials are prosecuted, perceived political risk by investors decreases, and managers are less likely to suppress bad news. Therefore, crackdown on political corruption reduces political risk and bad-news hoarding, and thus decreases the likelihood of firm-level future crash risk.[5]

This study utilizes corruption prosecutions of top municipal-level officials as our focus to examine the impact on crash risk.[6] We manually collect a representative sample of 236 cases.[7]

[3] When investors become more sensitive to the related downside risk, managers are inclined to hoard negative information and support share price. This is because investors may perceive bad news as the realization of political risk (Chan and Wei, 1996; Kim et al., 2011b; Li and Zhang, 2015).
[4] Dass, Nanda and Xiao (2016) find that corrupt firms have lower information transparency, suggesting that corrupt firms may change disclosure behavior to maintain more secrecy.
[5] On the other hand, corruption could be beneficial *economically* because the expected cash flows are positive at least in the short run and/or less reliance on capital market means lower scrutiny. This suggests that the crackdown on corruption could *increase* future crash risk through worse operating performance and/or more bad news hoarding. We will discuss more in the hypothesis development section to note potential tensions in our story.
[6] An advantage of our focus is that crackdowns take place at different times and locations. As mentioned by Gormley et al. (2012), the use of variation in both the timing and location reduces potential confounding effects that might arise from municipality-wide policy changes.
[7] Our paper utilizes Chinese setting for following reasons. First, China is typically viewed as a corrupt country. Surveys show that 35% of Chinese companies report that they have to give officials bribes or gifts to do business (Charney Research, 2015). In 2016, China ranks 79th out of 176 in the world on the Transparency International's Corruption Perception Index (see http://www.transparency.org/news/feature/corruption_perceptions_index_2016). Moreover, the anti-corruption campaign by the central government in recent years results in the downfall of many politicians and provides a unique setting to examine the impact of reduced political corruption. As reported by the

Using the 10,464 firm-year observations from 2001 to 2014, we empirically test the impact of anti-corruption on firm-level crash risk using a difference-in-difference model after controlling for firm fixed effect. Our main variable of interest is a dummy variable, *Post*, which equals one if a firm-year observation is in and after the event year, and zero otherwise. Following prior literature (Hutton et al., 2009; Kim et al., 2011a, b), we use two proxies for firm-specific crash risk: (1) the negative conditional skewness of firm-specific weekly returns (*Ncskew*), and (2) the down-to-up volatility of crash likelihood (*Duvol*). Our empirical results show that the *Post* indicator is significantly and negatively related with either measure of crash risk, suggesting that when top government officials are prosecuted, firms under their jurisdiction experience a significant decrease in stock price crash risk. Our inferences stay the same after controlling for firm-specific determinants of crash risk, such as firm size, market-to-book ratio and leverage, as well as including firm fixed effects and year fixed effects.

Next, we conduct several cross-sectional tests to examine how corruption crackdown reduces crash risk. We find that the impact of crackdowns on crash risk is more pronounced for firms with political dependency on their local governments. In particular, the results are stronger for municipal-level state-owned enterprises (SOEs hereafter), and for firms receiving government subsidy. Moreover, we show that the results are also more pronounced for firms with higher information asymmetry, such as firms with higher analyst forecast dispersion, greater intangible asset ratio, and higher earnings volatility.

Then, we provide some evidence on the potential channels through which corruption crackdown reduces crash risk. Specifically, we test whether anti-corruption decreases political risk and curbs bad news hoarding, which in turn reduces future crash risk. Following the research

Chinese government in 2016, one million Chinese officials were punished for corruption since the anti-corruption campaign began (see www.ccdi.gov.cn/).

design in Kim et al. (2016), we first document that anti-corruption results in a reduction of political risk (as measured by political connectivity and government subsidy following Kim et al. (2012) and Piotroski et al. (2015)) , and decreased political risk is associated with lower level of crash risk. Similarly, we find that crackdown on corruption constrains bad news hoarding (as measured by financial reporting opacity following Hutton et al. (2009)), and reduced hoarding leads to lower future stock price crash risk. These findings serve as direct evidence that crackdown on corruption reduces future crash risk through decreasing political risk and constraining managerial bad news hoarding.

We also perform several robustness tests. First, we rerun our main regression using a matched sample to alleviate the concern that our results are driven by some unobservable firm characteristics that may influence crash risk, and our inferences stay the same. Second, we perform a placebo test to exclude the effects of time-varying factors, and we fail to find any results during the pseudo-shock periods.

In addition, we conduct a couple of additional tests. First, we investigate the short-window market reactions around the anti-corruption event and our results show that investors react negatively around the announcement of the corruption scandal. This is consistent with the notion that anti-corruption leads to bad news being quickly released in a short period. Second, we use the corruption event of a former Nanjing mayor to examine the monthly crash risk change in the six months before and after the crackdown. The results also show that crash risk temporarily increases immediately after the crackdown (i.e., suppressed bad news is released to the public in about one month to three months right after the crackdown), but it decreases months later in the longer period. Taken together, these findings provide a thorough picture of the impact of corruption crackdown on crash risk. After the crackdown on corrupted officials, stock price crashes immediately, and although crash risk increases temporarily right after the crackdown, in the long run it is lower as political risk is lower and bad news hoarding behavior is less likely to take place.

Our study makes the following contributions to the literature. First, it contributes to the emerging research on the economic consequence of corruption (or anti-corruption). Existing studies primarily focus on the impact of corruption in the context of macroeconomics.[8] By taking advantage of municipal-level corruption conviction data in China, to our best knowledge, our study is the first to find that while political corruption increases political risk and facilitates bad news hoarding activities by firm managers (both of which increases the likelihood of future stock price crashes), corruption crackdown reduces both and leads to lower crash risk. Second, this study adds to a growing literature investigating anti-corruption in China in recent years.[9] Different from these studies, our paper focuses on the municipal-level anti-corruption cases and provides evidence that corruption crackdowns contribute to the stability of the stock market by reducing future stock price crashes. Finally, our paper contributes to the literature on determinants of stock price crashes.[10] Our findings provide further empirical support to the political risk explanation and bad news hoarding theory of stock price crashes (Pastor and Veronesi, 2012; Jin and Myers, 2006; Bleck and Liu, 2007), and suggest that corrupt officials, as well as their political protections for local firms, are determinants of a firm's stock price crashes.

[8] Mironov (2015) creates a measure of corruption using traffic violations and examine how firms with corrupt managers perform. Using US Department of Justice data on local political corruption, Smith (2016) finds that firms in more corrupted areas hold less cash and have greater leverage than firms in less corrupted areas.
[9] Ke et al. (2016) find that Chinese President Xi Jinping's anti-corruption campaign reduces the probability of firms that sell luxury goods and services. In a similar vein, Lin et al. (2016) investigate the market reaction to the announcement of Xi Jinping' Eight-Point Regulation, and Liu et al. (2017) examine the impact of Bo Xilai scandal on asset prices.
[10] Crash risk has received increasing attention from both academic researchers and the investment community (An and Zhang, 2013; Xu et al., 2014; An et al., 2015; Yuan et al., 2016; Chen et al., 2017; Chen et al., 2018). Recent empirical evidence suggests that extreme outcomes in the stock market significantly impact investor welfare, and that investors are greatly concerned about the probability of extreme risk (Pan, 2002; Yan, 2011).

The remainder of the paper proceeds as follows. Section 2 introduces the institutional background of the Chinese anti-corruption campaign and develops the main hypothesis. Section 3 describes our sample and research design. We present our main empirical results and additional test results in Section 4 and Section 5, respectively. Section 6 concludes.

2. Institutional Background and Hypothesis Development

As argued in Gold et al. (2002), dense networks of *guanxi* ("connections") have historically and culturally been a deep-rooted part of business in China.[11] When such interpersonal obligations become excessive, they can turn into official corruption. In China, corruption has been an increasing concern, especially recently (Wedeman, 2012). Accordingly, China's anti-corruption campaign has experienced many stages with the focus on anti-corruption dramatically increasing in recent years. In 1987, the concepts of "corruption" and "anti-corruption" were introduced. Two years later, China set up anti-corruption and anti-bribery bureaus all over China. In September 2007, the National Agency for Corruption Prevention was founded, which suggested that China has started taking an important step in building an anti-corruption system and institution.

Most recently, Xi Jinping administration took office, and he himself formally took the leadership role of the Communist Party of China (CPC hereafter) during the 18th National Congress (November 8th to 12th, 2012). Shortly after assuming power, Xi Jinping's Politburo announced a series of new ideas and strategies on anti-corruption. The "Eight-Point Regulation" is one of the most famous provisions that created clear guidelines and regulations for all the government officials to follow to eliminate corruption, and marks the beginning of the anti-corruption campaign (Lin et al., 2016). For example, government officials and SOE executives are banned

[11] The traditional concept of "*guanxi*" in China suggests that it is a common rule to build relationships based on gift, banqueting, or small favors when doing business.

from consuming luxury goods and services. Since then, four national leaders, many high-ranking government officials, and military officers were investigated and prosecuted.[12]

Using China as their setting, Liu et al. (2017) find that firms whose directors have ties with Chongqing's government and were potentially involved in corruption experienced greater stock price decline after the arrest of the former Chongqing's leader and member of the Political Bureau of the CPC Central Committee, Bo Xilai. In a similar case, a couple of firms with connections to the arrested local official in Nanjing suffered from a plunge in stock price after its mayor Ji Jianye was arrested for corruption reasons.[13] Evidence presented above shows that after the crackdown of corrupt officials, stock prices of related firms crashed immediately, consistent with the release of bad news in the short run.[14] However, it is unclear what the long-term effect of anti-corruption on crash risk is. Thus, we explore how the crackdown of corrupt officials affects future crash risk of local firms.[15]

We argue that corruption increases crash risk through higher political risk and more bad news hoarding, while crackdown decreases future crash risk by reducing both.

Political corruption increases political risk in the region, which may also result in a greater likelihood of stock price crashes for local firms (Pastor and Veronesi, 2012)[16]. Corruption is inefficient to the economy since it can lead to distorted investments and misallocated resources (Shleifer and Vishny, 1993; Murphy et al., 1991, 1993). These rent-seeking actions by governments and potential political forces imply a higher uncertainty about government policies

[12] For details, please refer to http://www.ccdi.gov.cn/.
[13] For details, please refer to http://finance.ifeng.com/stock/special/wzztx/.
[14] The government's crackdown on corruption means the arrest or prosecution of corrupt officials. In this paper, we use *crackdown*, *arrest*, and *prosecution* interchangeably.
[15] In this study, we empirically proxy future stock price crash risk by measuring it in year *t+1*, with year *t* being the year when the crackdown of the corrupted official takes place.
[16] Media also regards political risk as one of the main determinants of stock price crash (e.g., See "Six Things that Could Cause a Stock Market Crash" from *The Motley Fool* by Matthew Frankel, Feb 17, 2018).

and the impact of the potential policies on future business environment (Huang et al., 2015a). Uncertainty is the key channel through which political risk affect the financial market (Huang et al., 2015b). Anticipating an increase in perceived political risk, investors will increase their assessment of firm's risk (discount rate) (Chan and Wei, 1996; Leuz and Oberholzer-Gee, 2006; Kim et al., 2012; Pastor and Veronesi, 2012, 2013; Liu et al., 2017), leading to a contemporaneous drop in stock price (i.e., a price crash).[17] However, such political risk would be lower after crackdown of corrupt officials as the main source of political risk is exposed and the future business environment would be more stable (i.e., it is less likely to be another crackdown soon). Investors' perception of a lower uncertainty of government policies and smaller impact of uncertainty on business environment in turn leads to lower future crash risk. Therefore, after the crackdown takes place, lower political risk (i.e., more certain government policies and economic environment) will decrease future crash risk.

Managers can be motivated by a variety of incentives, such as compensation contracts, career concerns, tax avoidance, and political incentives, to delay the disclosure of negative information (Kothari et al., 2009; Kim et al., 2001a, b; Xu et al., 2014; Piotroski et al., 2015; Callen and Fang, 2015; Chang et al., 2017).[18] From a theoretical point of view (Jin and Myer, 2006), the better managers are at suppressing bad news, the higher the crash risk. Specifically, lack of information transparency enables managers to capture a portion of cash flows about firm performance in ways not perceived by outside investors; therefore, managers are willing to personally absorb limited downside risk by hiding firm-specific bad news for an extended period. Nevertheless, when

[17] Pastor and Veronesi (2012) show analytically that change of political policy increases discount rate as its impact on profitability is more uncertain, and this effect is stronger than the cash flow effect (which could be positive). Therefore, stock prices fall when policy changes.

[18] Using Chinese setting, Piotroski et al. (2015) find that firms temporarily suppress bad news in response to political incentives such as National Congress meetings and provincial political promotions.

managers cannot withhold bad news any longer, accumulated negative information is released to the public all at once, resulting in a sudden and dramatic decline in stock price (i.e., a stock price crash) (Jin and Myers, 2006; Hutton et al., 2009; Kim and Zhang, 2016).[19]

Drawing on prior studies (Fan et al., 2014; Huang et al., 2015a, b; Piotroski et al., 2015; Jin et al., 2016), we predict that managers of firms located in corrupted regions are more likely to hide bad news. Political corruption increases managerial incentives and abilities to withhold bad news, thus leading to higher future firm-level crash risk. In the Chinese political system, local leaders enjoy great political power in their jurisdictions and have strong influence on the decision making of various functional departments (Piotroski et al., 2015). Therefore, these government officials can intervene in the operation of local firms with policy formation and implementation. In such an environment, firms have the incentive to curry favor with the local corrupt officials as market-based resource allocation is largely absent.[20] Bribing activity itself is detrimental as investors usually respond negatively to corruption scandals (Ke et al., 2016; Liu et al., 2017). As a result, managers prefer to keep these interactions secret, resulting in a stockpile of bad news.[21]

Second, in a corrupted environment, it is much easier for firms to build up direct or indirect connections (*guanxi*) with local government officials for political protection. As corrupt officials provide protection for connected firms, the detection risk and punishment cost for these firms is lower, which leads to a lower expected cost of risk-taking activities and withholding such activities. Cautious managers are less likely to engage in high-risk projects that directly increase the crash

[19] Moreover, managerial bad news hoarding behaviors prevent board of directors and outside investors from taking action to liquidate negative net present value (NPV) projects in a timely manner. As a result, bad performance of negative NPV projects accumulate and eventually materialize, leading to an asset price crash (Bleck and Liu, 2007).
[20] A number of studies provide supporting evidence that firms often give public officials bribes to obtain favorable loan terms or preferential government contracts (e.g., Fisman, 2001; Faccio et al., 2006; Duchin and Sosyura, 2012; Tahoun, 2014).
[21] When investing in influencing government officials crowds out investments in conventional forms of capital spending, economic growth will also be impaired (Murphy et al., 1991, 1993; Shleifer and Vishny, 1993; Svensson, 2005).

risk of the firm (Chen et al., 2018), while politically connected and protected managers are exactly the opposite. Namely, they are more inclined to pursue risky projects and withhold such negative information.

Lastly, to pursue political goals such as promotion, government officials may collude with local firms for political rent-diversion. They can use threats of regulation and targeted taxation to solicit bribes and extort firm performance (Mcchesney, 1987). As a result, managers may respond by participating in such activities as earnings manipulation and corporate misconduct. More importantly, corporate insiders might be encouraged to make opportunistic decisions to gain private benefits at the expense of shareholders (Debacker et al., 2015). The collusive rent-seeking motivations associated with a culture of corruption will also induce managers to obfuscate financial disclosures to mask expropriation and self-dealing (Leuz et al., 2003). Therefore, a corrupted environment helps managers to conceal bad news/negative information including bribery, risky projects and rent-diversion activities, and facilitates bad news hoarding activities for an extended period, leading to a greater likelihood of crash risk. When the crackdown of corrupt officials takes place, firms would experience a contemporaneous price drop (i.e., a release of crash risk). In addition, their future crash risk will be lower because the improved business environment will constrain managers' incentives and abilities to withhold bad news.

However, we need to note potential tensions in this hypothesis. Frist, corruption can be beneficial especially in less developed areas (Wei, 2001; McMillan and Woodruff, 2002; Li et al., 2008), and bribery can be value-enhancing to shareholders if the expected net cash flows from bribery is positive, at least in the short run. Managers bribe government officials with the expectation of gaining corporate benefits, such as regulatory favors, subsidies, and tax breaks. In such cases, the crackdown of local officials may disrupt a firm's political connections and resource allocation. This will then impede firm-level economic development. In addition, the revelation of firm's bribery will hurt firm's reputation, give rise to negative market reaction and decreases firm value. As a result, there may be a greater future crash risk after the crackdown.

Second, in corrupted areas, a firm's business transactions tend to be relation-based rather than market-based (Fan et al., 2014). Consequently, there is no need to withhold bad news in order to obtain resources from the capital market. However, once the crackdown takes place, and relation-based transactions are not available, local firms have to rely more on capital market resources. As a result, withholding bad news becomes necessary to avoid market scrutiny, which in turn increases future crash risk.[22]

Finally, crackdown may not significantly reduce political risk and/or bad news hoarding if (1) the Chinese legal system is not trust-worthy and the prosecuted officials are just innocent underdogs in political fights, (2) the newly appointed officials are also corrupt, or (3) all other officials in other non-corrupted cities, who have not been targeted, are corrupt. In any of these cases, we would not observe any effect of anti-corruption on firm-level crash risk.[23]

To summarize, the above arguments suggest that it is unclear what the impact of a crackdown on future firm-level crash risk is. Accordingly, we present our main hypothesis in null form:

H1: *There is no association between the crackdown of local corrupted officials and a firm's future stock price crash risk.*

3. Research Design

3.1 Data and Sample

[22] In a corrupted environment, if managers do not care about capital market reaction, they will not withhold bad news in many aspects, such as tax avoidance and negative NPV projects. Besides bribery-related bad news, we are referring to bad news hoarding activities in general here.

[23] We would like to thank the anonymous referee for pointing this out.

To examine whether a firm's stock price crash risk decreases after the crackdown on the corruption of local officials, we compile a list of corruption cases related to top municipal-level officials in China from 2001 to 2014, and then identify all publicly listed firms located where these officials were in office.

We identify 236 corruption cases concerning top officials at the municipal level by employing the following procedures. First, we manually collect all municipal-level corruption cases from the China Procuratorial Yearbook, and the official website of the Commission for Discipline Inspection of the Central Committee of the CPC (CCDI hereafter). Then for detailed information, we search through Google and Baidu using key words including the name of the corrupt official, the municipality where the crackdown took place, "*Shuanggui*", "Bribery", and "Arrest".[24] After identifying the corruption scandal, we define the event day of corruption crackdown as the day when the official's wrongdoings firstly became public. Such disclosures can be *Shuanggui*, removal from their current position, investigation by the CCDI, disciplinary treatment from the CCDI (such as expulsion from the CPC), or arrest.[25] Table 1 presents a summary of corruption cases by province. We find that most corruption cases are taken place in Guangdong, Henan, Anhui and Sichuan.[26]

[24] *Shuanggui* is an internal disciplinary process conducted by the Central Commission for Discipline Inspection of the CPC–and its lower-level affiliates–on members of the Party who are suspected of "violations of discipline". It is a detention measure that orders the member to confess at a specific time in a specific location, which is usually related to corruption.

[25] For example, on October 17th, 2013, the official website of CCDI announced that the mayor of city Nanjing, Ji Jianye, was suspected of serious discipline violations and was under investigation by the CCDI. Two months later, on January 30th, 2014, CCDI ascertained the truth about the wrongdoings of Ji Jianye and decided to expel him from the CPC as punishment for his disciplinary violations and transfer him to judicial organizations. In this case, we use October 17th, 2013, the first day when Ji Jianye's wrongdoings become public, as the event day (and 2013 as our event year).

[26] We focus on municipal-level cities, so we delete observations from Beijing, Chongqing, Shanghai and Tianjin, as the four cities are province level directly under the central government.

Our initial sample are all listed (A-shares) in the Shenzhen and Shanghai Stock Exchanges. We obtain all financial data from the China Stock Market and Accounting Research Database (CSMAR), and impose the following requirements: (1) excluding firms with missing data; (2) excluding firms whose annual trading weeks are less than thirty in order to calculate crash risk; and (3) excluding firms in financial and banking industries. We end up with 10,464 firm-year observations between 2001 and 2014.

3.2 Measurement of Crash Risk

Following prior literature Chen et al. (2001), and Kim et al. (2011a, b), we construct two measures of crash risk:

We first use the regression model Eq. (1) to estimate firm-specific weekly returns, in which we denote $W_{i,t}$, as the natural log of one plus the residual return from Eq. (1) estimated for each firm and year:

$$R_{i,t} = \alpha_i + \beta_1 R_{m,t-2} + \beta_2 R_{m,t-1} + \beta_3 R_{m,t} + \beta_4 R_{m,t+1} + \beta_5 R_{m,t+2} + \varepsilon_{i,t} \quad (1)$$

where $R_{i,t}$ is the return on stock *i* in week *t* and $R_{m,t}$ is the market value-weighted stock return on week *t*. We also include lag and lead terms to adjust the effect of non-synchronous trade (Dimson, 1979). The firm-specific weekly returns for firm *i* in week *t* are measured by $W_{i,t} = Ln(1 + \varepsilon_{i,t})$, where $\varepsilon_{i,t}$ is the residual in Eq. (1).

We then construct two measures of crash risk based on $W_{i,t}$. The first measure is the negative coefficient of skewness which we denote *Ncskew*, calculated by taking the negative of the third moment of firm-specific weekly returns for each sample year and dividing it by the standard deviation of firm-specific weekly returns raised to the third power. Thus, for each stock *i* in year *t*, we have

$$\text{Ncskew}_{i,t} = -\left[n(n-1)^{3/2}\sum W_{i,t}^{3}\right] / \left[(n-1)(n-2)(\sum W_{i,t}^{2})^{3/2}\right] \tag{2}$$

The second measure we use is the down-to-up volatility (*Duvol*) of crash likelihood, which is calculated as follows:

$$\text{Duvol}_{i,t} = log\left[(n_u - 1)\sum_{Down} W_{i,t}^{2}\right] / \left[(n_d - 1)\sum_{Up} W_{i,t}^{2}\right]\} \tag{3}$$

where $n_u(n_d)$ is the number of up (down) weeks during which the firm-specific weekly returns are above (below) its annual mean. *Duvol* is the log of the ratio of the standard deviation on down weeks to the standard deviation on up weeks.

3.3 Model Specification

To examine the impact of corruption scandals on the future stock price crash risk of local firms, we use a difference-in-difference model after controlling for firm fixed effects (Bertrand and Schoar, 2003):

$$\text{CrashRisk}_{i,t+1} = \beta_0 + \beta_1\text{Post}_{i,t} + \beta_2\text{Controls}_{i,t} + Firm\ Fixed\ Effects + Year\ Fixed\ Effects + \mu_{i,t} \tag{4}$$

In Eq. (4), *CrashRisk* is our proxy for stock price crash risk, measured by *Ncskew* or *Duvol*. Our main variable of interest is an indicator variable, *Post*, which equals one if the firm-year observation is in or after the prosecution event year, and zero otherwise. Following previous literature (Chen et al., 2001; Kim et al., 2001a, b), the dependent variable, *CrashRisk*, is measured in year *t+1* and the independent variables are measured in year *t*.

We include a set of control variables that have been identified to be potential determinants of crash risk by prior research studies (Jin and Myers, 2006; Hutton et al., 2009; Piotroski et al., 2015; Kim and Zhang, 2016). These controls include $Ncskew_t$, $Size_t$, Roa_t, Mb_t, Lev_t, $Sigma_t$, Ret_t, $Dturn_t$, $Fshr_t$, $Accm_t$, Gdp_t, $Politic_t$ and Soe_t. $Ncskew_t$ is the negative coefficient of skewness for firm-specific daily returns in year *t*. $Size_t$ is measured as the natural log of a firm's total assets. Roa_t is measured as the income before extraordinary items divided by total assets. Mb_t is measured as the ratio of the firm's market value to the book value. Lev_t is measured as the total liability scaled by total assets; $Sigma_t$ is the standard deviation firm-specific weekly return over the fiscal year. Ret_t is the average firm-specific weekly return over the fiscal year. $Dturn_t$ is the detrended stock trading volume, calculated as the average monthly share turnover for the current fiscal year minus the average monthly share turnover for the previous fiscal year, where monthly share turnover is the monthly trading volume divided by the number of shares outstanding over the month. $Fshr_t$ is the percentage of outstanding shares owned by the firm's first big shareholder. $Accm_t$ is measured as the past three-year moving sum of absolute abnormal accruals where the accruals are estimated from the modified Jones model (Dechow et al.,1995). Gdp_t is measured as the natural log of the GDP of the municipal city where the firm is located. $Politic_t$ is an indicator variable that is equal to one if the CEO or the Chairman of the firm has political ties (e.g., the CEO has past or concurrent work experience in the government or political appointment). Soe_t is an indicator variable equal to one if the firm is state-controlled. Finally, we add year fixed effects to account for a potential time trend effect or any other significant economic events that may confound our findings. Firm fixed effects are also included to control for unobservable firm characteristics that may remain constant over time. We provide detailed definitions for all variables in the Appendix A.

Based on our null hypothesis, we do not have any specific prediction on β_1. If β_1 is negative, it will show that there is a negative association between the crackdown of corrupted officials and a local firm's future stock price crash risk. If β_1 is positively significant, a positive relation between anti-corruption and crash risk will be supported.

4. Empirical Results

4.1 Descriptive Statistics

Table 2 presents the descriptive statistics for our sample firms. All continuous variables are winsorized at the 1st and 99th percentiles.[27] In Panel A of Table 2, the mean (median) value of $Ncskew_{t+1}$ is -0.246 (-0.210), with a standard deviation of 0.612, and the mean (median) value of $Duvol_{t+1}$ is -0.169 (-0.167), with a standard deviation of 0.345. The wide range in values for both measures indicates that there are large variations of crash risk among the sample. Descriptive statistics for other control variables are comparable to those from prior studies (e.g., Kim and Zhang, 2016).

Panel B presents the Pearson correlation coefficients among our main variables. We find that our main variable of interest, $Post_t$, is negatively correlated with both measures of stock price crash risk ($Ncskew_{t+1}$ and $Duvol_{t+1}$) at -0.067 and -0.066. In addition, the results show that our two measures of crash risk are highly correlated at 0.962, and crash risk measures are positively correlated with the bad news hoarding proxy ($Accm_t$). The correlations of other variables are also largely consistent with prior literature (e.g., Kim and Zhang, 2016).

4.2 Main Results

In Table 3, we report the results of the regression on the impact of corruption crackdown on future crash risk based on Eq. (4). Columns (1) and (2) present the results of $Ncskew_{t+1}$ as the dependent variable. Columns (3) and (4) present the results of $Duvol_{t+1}$ as the dependent variable. As shown in columns (1) and (3), where all control variables are excluded, we find that the coefficients on the key variables of interest, $Post_t$, are negatively and highly significant (-0.234 with t-value = -9.43 and -0.132 with t-value = -9.42). In columns (2) and (4), when control

[27] To be in the sample, we require a firm to have available data for at least one year before the event year period and at least one year after the event year period.

variables are included, we continue to find that the coefficients on $Post_t$ are negatively and highly significant (-0.058 with t-value = -2.26 and -0.036 with t-value = -2.46).

Taken together, the empirical results represented in Table 3 suggest that the crackdown on corruption reduces crash risk in the years after the crackdown event, and support the negative association between anti-corruption and future crash risk.

4.3 Cross-Sectional Tests: the Impact of Political Dependence on Governments

Since the corruption cases are at the municipal level, we further consider whether the impact of corruption crackdown on future crash risk differs between firms with and without political dependency on local governments. As firms depending more on local governments have higher exposure to political risk and greater incentive to withhold bad news (Leuz and Oberholzer-Gee, 2006; Kim et al., 2012; Piotroski et al., 2015), the impact of crackdown on future crash risk should be stronger for this group of firms.

We use two ways to measure the degree of firm's closeness to the local government. As shown in Panel A of Table 4, we divide our sample into three groups based on the ultimate property control. The first group refers to the private firms (columns (1) and (4)); the second group consists of the firms controlled by central or provincial government (columns (2) and (5)); and the third group consists of the firms controlled by municipal government (columns (3) and (6)). Since municipal-level officials enjoy greater power in their jurisdictions, firms located in those areas should have the greatest dependence on the local government. If so, the impact of crackdown on crash risk should be the strongest for firms controlled by the municipal government. Consistent with our prediction, the results in Panel A of Table 4 show that the coefficients of $Post_t$ in columns (3) and (6) are negatively significant (-0.035 with t-value = -4.51 and -0.058 with t-value = -3.34) at 1% level, while the coefficients in columns (1), (2) and (5) are significant at 10% level and the coefficient in column (4) is not significant. Together with the difference tests of coefficients, our findings suggest that, municipal SOEs experience a greater reduction in crash risk after the corruption crackdown than Non-SOEs and Central SOEs.

Moreover, we measure the degree of a firm's dependency on government by considering whether a firm can acquire government subsidy (Piotroski et al., 2015; Wong et al., 2017). In Panel B of Table 4, the first group (*D_sub*=1) represents firms that get government subsidy in year *t-1*, while the other group (*D_sub*=0) includes firms that do not receive government subsidy in year *t-1*. We predict that firms that enjoying subsidy have closer relationship with government. As demonstrated in Panel B of Table 4, when crash risk is measured by $Ncskew_{t+1}$, for firms with subsidy (column (1)), the coefficient of $Post_t$ is negatively and highly significant (-0.052 with t-value = -2.38), while the coefficient of $Post_t$ for firms without subsidy (column (2)) is not significant (-0.027 with t-value = -0.74). When crash risk is measured by $Duvol_{t+1}$, for firms with subsidy (column (3)), the coefficient of $Post_t$ is negatively and highly significant (-0.038 with t-value = -2.92), while the coefficient of $Post_t$ for firms without subsidy (column (4)) is not significant (-0.102 with t-value = -0.42). These results suggest that the influence of corruption crackdown on local firms' crash risk is stronger for firms that enjoy government subsidy.

Taken together, the findings in Table 4 indicate that the crackdown on corruption leads to a greater reduction of crash risk for firms with higher dependence on government.

4.4 Cross-Sectional Tests: the Impact of Information Environment

As firms with greater information asymmetry have higher exposure to political risk and are subject to fewer constraints preventing them from withholding bad news (Hutton et al., 2009), we expect that these firms will experience a more significant decrease in crash risk due to an improved information environment after corruption scandals.

We use three measures to proxy for the information environment. First, we consider the analyst forecast dispersion.[28] Extant studies show that if the forecast dispersion is lower for a certain firm, then the firm's information environment is more transparent (Hope, 2003). We divide our sample based on the median analyst forecast dispersion value in year *t-1*. If the forecast dispersion exceeds the median, we define the group (*High*) as firms with a worse *ex-ante* information environment, while the other group (*Low*) as firms with a better information environment. Results in Panel A of Table 5 suggest that, when crash risk is measured by $Ncskew_{t+1}$, the coefficient of $Post_t$ for firms with a higher forecast dispersion (column (1)) is negatively and highly significant (-0.082 with t-value = -3.31), while the coefficient of $Post_t$ for firms with a lower forecast dispersion (column (2)) is not significant (-0.059 with t-value = -1.03). When crash risk is measured by $Duvol_{t+1}$, the coefficient of $Post_t$ for firms with a higher forecast dispersion (column (3)) is negatively and highly significant (-0.049 with t-value = -2.37), while the coefficient of $Post_t$ for firms with a lower forecast dispersion (column (4)) is not significant (-0.017 with t-value= -0.52).

Our second proxy is the ratio of intangible assets to total assets because the higher the proportion of intangible assets, the lower the information transparency (Abooy and Lev, 2010). We first calculate the intangible asset ratio in year *t-1* and then divide our sample based on the median value. We classify the group (*High*) above the median as firms with more opaque information, while the remaining group (*Low*) as firms with less opaque information. Panel B of Table 5 shows that for $Post_t$, the coefficients for firms with a higher intangible asset ratio (columns (1) and (3)) are both negatively and highly significant (-0.071 with t-value = -2.86 for $Ncskew_{t+1}$, and -0.040 with t-value = -2.95 for $Duvol_{t+1}$). In contrast, the coefficients for firms with a lower

[28] We also consider the number of analyst followings and define firms with more analyst followings as the group with better information environment. Our inferences stay the same.

intangible asset ratio (columns (2) and (4)) are not significant (-0.023 with t-value = -0.51 for $Ncskew_{t+1}$, and -0.006 with t-value = -0.24 for $Duvol_{t+1}$).

Lastly, we use earnings volatility as a proxy for information environment (Callen and Fang, 2015). We divide our sample based on the median value of earnings volatility in year *t-1*. If earnings volatility exceeds the median, we define the group (*High*) as firms that are more opaque, while the remaining group (*Low*) as firms that are less opaque. Panel C of Table 5 demonstrates that the coefficients of $Post_t$ for firms with a higher earnings volatility (columns (1) and (3)) are negatively and highly significant (-0.115 with t-value = -2.90 and -0.065 with t-value = -2.84). In comparison, the coefficients of firms with a lower earnings volatility (columns (2) and (4)) are not significant (-0.009 with t-value = -0.25 and -0.012 with t-value = -0.44) for the two crash risk measures ($Ncskew_{t+1}$ and $Duvol_{t+1}$).

Overall, we find that the impact of anti-corruption on crash risk is more pronounced for firms with a larger analyst forecast dispersion, higher intangible asset ratio, and more volatile earnings.

4.5 Channel Test: Reduced Political Risk

We identify whether corruption crackdown reduces crash risk through reducing political risk using the following channel test. Specifically, we utilize the two-step regression approach following Kim et al. (2016). In the first step, we examine the relation between anti-corruption and political risk. In the second step, we examine the association between political risk and future crash likelihood. If anti-corruption decreases future crashes by reducing political risk, we expect a negative relation in the first step regression and a positive relation in the second step regression.

Kim et al. (2012) argue that firms' proximity to political power reflects firms' exposure to political risk, so following prior studies (Kim et al., 2012; Piotroski et al., 2015), we use two measures to proxy for political risk, political connectivity (*Politic*) and government subsidy (*Sub*).

The first measure, *Politic*, is an indicator variable equal to one if the CEO or the Chairman of the firm has political ties (e.g., the CEO has past or concurrent work experience in the government or political appointment), zero otherwise. The second measure, *Sub*, is the natural log of one plus a firm's acquired government subsidy. The results are presented in Table 6. Panel A shows the first step regression results. The coefficients of $Post_t$ on both political connection measures, $Politic_t$ and Sub_t, are significantly negative (-0.002 with t-value = -2.66 and -0.017 with t-value = -2.35), indicating that crackdown on corruption disrupts firm's political connections and thus reduces political risk as a whole. Panel B reports the regression results of the second step model. As shown from columns (1) to (4), the coefficients on $Politic_t$ and Sub_t are significantly positive with both crash risk measures ($Ncskew_{t+1}$ and $Duvol_{t+1}$), suggesting a positive relation between political risk and future crash risk likelihood.

Taken together, Table 6 demonstrates that the crackdown on corruption decreases political risk and reduced political risk results in lower level of future crash risk. Therefore, the above findings support our expectation that corruption crackdown reduces future crash risk through decreasing political risk.

4.6 Channel Test: Constrained Bad News Hoarding

Similar to section 4.5, to determine whether bad news hoarding is another channel through which corruption crackdown reduces future crash risk, we perform the following channel test using a two-step regression approach following Kim et al. (2016). In the first step, we examine the association between anti-corruption and bad news hoarding. In the second step, we examine the association between bad news hoarding and future crash risk. If the crackdown on corruption reduces future crash risk through curtailing bad news hoarding, we expect that anti-corruption is negatively associated with bad news hoarding in the first step regression while bad news hoarding is positively associated with future crash risk in the second step regression.

Since opaque financial reporting facilitates bad news hoarding behaviors (Jin and Myers, 2006; Hutton et al., 2009), we use financial reporting opacity ($Accm_t$) as our measure of bad news hoarding.[29] $Accm_t$ is defined as the past three-year's moving sum of absolute accruals, similar to Hutton et al. (2009). We test the relationship between corruption crackdown and bad news hoarding in the first step, and the relationship between bad news hoarding and crash risk in the second step. Table 7 presents our findings. Panel A reports the regression results of the first step model. The coefficient of $Post_t$ is significantly negative (-0.005 with t-value = -2.06), suggesting that the crackdown on corruption reduces bad news hoarding or reduces financial reporting opacity. Panel B shows the regression results of the second step model. The coefficients on $Accm_t$ are significantly positive (0.037 with t-value = 2.49 and 0.021 with t-value = 2.91) for both crash risk measures ($Ncskew_{t+1}$ and $Duvol_{t+1}$). These results confirm the findings in Hutton et al. (2009) that bad news hoarding is the culprit of future crash risk.

To summarize, Panel A and B of Table 7 show that the crackdown on corruption reduces bad news hoarding and less bad news hoarding, in turn, leads to lower future stock price crashes. These findings provide direct evidence that corruption crackdown reduces future crash risk through constraining bad news hoarding.

5. Additional Tests

5.1 Matched Sample Test

To address the concern that other unobservable characteristics may confound our findings, we utilize a matched sample to rerun the main regression. Specifically, we label sample firms in

[29] Unreported results suggest when using the market-based measure, KV index (Kim and Verrecchia, 2001), to proxy for bad news hoarding, our inferences stay the same.

corrupted regions as the treatment group. Then we select one control firm to match with each treatment firm. Our criteria for control firms include (1) in the same province with the treatment firm; (2) in a different city where there are no corruption scandals; (3) in the same industry with the treatment firm; and (4) the closest one in terms of firm size as compared with the treatment firm.[30]

Table 8 reports the main results. $Corrupt_t$ is an indicator variable equal to one for treatment firm, zero otherwise. $Post_t$ is a time period dummy variable. $Post1_t$ is equal to one if the firm-year observation is in the event year or the subsequent two years after the event, and zero if the firm-year observation is in the two years before the event. $Post2_t$ is equal to one if the observation is within the event year or one year after the event, and zero if the firm-year observation is within one year before the event. As shown in columns (1) and (2), where $Ncskew_{t+1}$ is the dependent variable, we find that the coefficients on the key variables of interest, $Corrupt_t*Post1_t$ and $Corrupt_t*Post2_t$, are negatively and highly significant (-0.137 with t-value = -3.64 and -0.167 with t-value = -3.54). Columns (3) to (4) report results of using $Duvol_{t+1}$ as the dependent variable. We find that the coefficients on the key variables of interest, $Corrupt_t*Post1_t$ and $Corrupt_t*Post2_t$, are still negatively significant (-0.082 with t-value = -3.91 and -0.093 with t-value = -3.46). Therefore, our inferences stay the same.

5.2 Placebo Test

To exclude the effects of time-varying factors, we perform a placebo test. We shift the event-year by three years before or after the actual event-year. *Post_Pseudo1* is an indicator variable that is equal to one for years after the pseudo-event-year, where pseudo-event-year is three years after the actual event-year, and zero for years before the pseudo-event-year. *Post_Pseudo2* is an

[30] If the same province requirement does not yield a valid match, we relax the same province requirement.

indicator variable that is equal to one for years after the pseudo-event-year, where pseudo-event-year is three years before the actual event-year, zero for years before the pseudo-event-year. All other variables are the same with those used in the main regression. Table 9 shows that the coefficients on *Post_Pseudo1* and *Post_Pseudo2* are insignificant, suggesting that there is no relation between anti-corruption and crash risk during pseudo-shock periods.

5.3 Market Reaction of the Corruption Cases

In this section, we investigate whether the market reacts when the corruption cases are first made public. We only keep observations when the exact corruption exposure date can be identified, and then calculate the cumulative abnormal return (CAR) in different windows around the exposure date using the market-adjusted model, where abnormal return is the firm's stock return minus the value-weighted market return. Table 10 presents our results, and we find that the CAR is significantly negative within different event windows. The findings indicate that market investors react negatively to the exposure of corruption cases and the negative reaction is possibly attributable to the sudden release of previously suppressed bad news (i.e., temporary increase in crash risk).

5.4 Release of Bad News around the Corruption Event

Using an annual crash risk measure, our paper demonstrates that the crackdown of corrupt officials reduces firm-level crash risk in the post-event years. To provide further understanding about the impact of crackdown on political corruption, here we focus on monthly crash risk change in the six months before and after the corruption event. Specifically, we choose the corruption event of Ji Jianye, the former mayor in Nanjing, from the full sample, and then calculate the median values of monthly crash risk.[31] Figure 1 presents our findings with *t*=0 being the month when the

[31] For calculating monthly crash risk, we use daily return to proxy $R_{i,t}$ and $R_{m,t}$ in model (1).

crackdown of corruption is publicly disclosed. We find that there is a *temporary* increase of crash risk in the first one to three months after the event, and then the crash risk decreases sharply. These findings suggest that, in the short run, the suppressed bad news within the firm is being released to the public; while in the long run, political risk reduces and bad news are less likely to be accumulated, leading to a lower likelihood of crash risk.[32]

Our results presented in Section 5.3 and 5.4 collectively show that corruption crackdown release previously suppressed bad news, and increases stock price crash risk temporarily for a short window of time (up to two months in our sample), and eventually decreases the crash risk and contributes to a more stable stock market in the future.

6. Conclusion

This study investigates the impact of corruption crackdown on firm-specific crash risk. Using data of corruption prosecution cases of municipal-level officials in China, we find that firms located in corrupted regions experience a significant decrease in crash risk in the years after the crackdown. Our empirical results suggest that the crackdown on corrupt government officials disrupts political connections and protections, and reduces political risk as well as impairs the ability and incentive of managers to suppress bad news. Consequently, crash risk in the future becomes smaller.

Further analyses show that our results are stronger for firms with closer political dependency on local governments and for firms with worse information environment. Finally, using channel tests, we provide direct evidence that crackdown reduces future crash risk by lowering political

[32] Our results are consistent with the empirical findings in Piotroski et al. (2015) as well as the following anecdotal evidence: when Ji Jianye, the former Mayor in Nanjing, was arrested, several listed firms under his jurisdiction were also involved. One of them is Jin Tanglang (listed code: 002081), whose Chairman, Zhu Xingliang, was arrested because of Ji's corruption. After the arrest of Zhu Xingliang was announced, the stock price of Jin Tanglang decreased sharply by about 20.6% in five days.

risk and curbing bad news hoarding. Our empirical results are also robust to a battery of sensitivity checks.

To sum up, our evidence suggests that crackdown on political corruption reduces future stock price crash risk and contributes to the stability of the stock market.

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Appendix A

Variable Definitions

Ncskew	The negative coefficient of skewness, calculated by taking the negative of the third moment of firm-specific weekly returns for each sample year and dividing it by the standard deviation of firm-specific weekly returns raised to the third power. See Eq. (2) for details.
Duvol	The down-to-up volatility. For any stock *i* in year *t*, we separate all the weeks with firm specific weekly returns below the annual mean (down weeks) from those with firm-specific weekly returns above the annual mean (up weeks) and compute the standard deviation for each of these subsamples separately. We then take the log of the ratio of the standard deviation of the down weeks to the standard deviation of the up weeks. See Eq. (3) for details.
Post	An indicator variable, equals one if the firm-year observation is in or after the prosecution event year, and zero otherwise.
Size	The natural log of a firm's total assets.
Roa	Income before extraordinary items divided by total assets.
Lev	Total liability scaled by total assets.
Mb	The ratio of the firm's market value to the book value.
Ret	The average firm-specific weekly return over the fiscal year.
Sigma	The standard deviation of the firm-specific weekly return over the fiscal year.
Soe	An indicator variable equal to one if the firm is state-controlled, and zero otherwise.
Dturn	The detrended stock trading volume, calculated as the average monthly share turnover for the current fiscal year minus the average monthly share turnover for the previous fiscal year, where monthly share turnover is the monthly trading volume divided by the number of shares outstanding.
Fshr	The percentage of outstanding shares owned by the firm's largest shareholder.
Accm	The past three-year moving sum of absolute abnormal accruals where the accruals are estimated from the modified Jones model (Dechow et al.,1995).
Politic	An indicator variable equal to one if the CEO or the Chairman of the firm has political ties, and zero otherwise.
Gdp	The natural log of the GDP of the municipal city where the firm is located.
D_sub	A dummy variable that equals one if firms can acquire subsidies from government, and zero otherwise.
Dispersion	Analysts forecast dispersion calculated as the standard deviation of forecast scaled by the actual price.
Intan_ratio	Intangible assets ratio calculated as intangible assets divided by total assets.
Earn_vol	Standard deviation of earning over the previous 5 years.

Table 1

Summary of Corruption Cases by Province

Province	N	Province	N
Anhui	18	*Jilin*	9
Fujian	14	*Jiangsu*	15
Gansu	4	*Jiangxi*	14
Guangdong	16	*Liaoning*	11
Guangxi	2	*Neimonggol*	9
Guizhou	2	*Shandong*	10
Hebei	3	*Shanxi*	6
Henan	26	*Shaanxi*	4
Heilongjiang	5	*Sichuan*	23
Hubei	15	*Yunnan*	6
Hunan	14	*Zhejiang*	10

Table 2

Descriptive Statistics and Correlation Matrix

Panel A: Basic Statistics

Variables	N	Mean	Std. Dev.	P25	P50	P75
$Ncskew_{t+1}$	10464	-0.246	0.612	-0.625	-0.210	0.172
$Duvol_{t+1}$	10464	-0.169	0.345	-0.391	-0.167	0.058
$Post_t$	10464	0.207	0.406	0.000	0.000	0.000
$Ncskew_t$	10464	-0.222	0.621	-0.593	-0.183	0.199
$Sigma_t$	10464	0.049	0.019	0.035	0.046	0.059
Ret_t	10464	-0.002	0.007	-0.006	-0.002	0.002
$Dturn_t$	10464	0.003	0.287	-0.132	0.006	0.138
$Size_t$	10464	21.686	1.199	20.876	21.589	22.356
Roa_t	10464	0.021	0.078	0.007	0.025	0.052
Lev_t	10464	0.537	0.247	0.377	0.529	0.665
Mb_t	10464	3.404	3.974	1.515	2.368	3.945
$Fshr_t$	10464	0.359	0.157	0.235	0.333	0.470
Soe_t	10464	0.631	0.483	0.000	1.000	1.000
$Politic_t$	10464	0.199	0.399	0.000	0.000	0.000
Gdp_t	10464	28.171	1.026	27.455	28.211	28.962
$Accm_t$	10464	0.197	0.136	0.100	0.162	0.255

Panel B: Pearson Correlation

	$Ncskew_{t+1}$	$Duvol_{t+1}$	$Post_t$	$Ncskew_t$	$Sigma_t$	Ret_t	$Dturn_t$	$Size_t$	Roa_t	Lev_t	Mb_t	$Fshr_t$	Soe_t	$Politic_t$	Gdp_t	$Accm_t$
$Ncskew_{t+1}$	1															
$Duvol_{t+1}$	0.962***	1														
$Post_t$	-0.067***	-0.066***	1													
$Ncskew_t$	0.221***	0.207***	-0.063***	1												
$Sigma_t$	0.034***	0.006	0.024**	-0.058***	1											
Ret_t	0.023**	0.016	-0.012	-0.193***	0.222***	1										
$Dturn_t$	0.092***	0.085***	-0.014	-0.126***	0.294***	0.098***	1									
$Size_t$	-0.170***	-0.166***	0.090***	-0.159***	-0.189***	-0.056***	-0.022**	1								
Roa_t	-0.037***	-0.043***	0.013	-0.057***	-0.068***	0.189***	-0.006	0.230***	1							
Lev_t	0.023**	0.020**	0.059***	0.024**	0.163***	-0.077***	0.006	0.054***	-0.458***	1						
Mb_t	0.092***	0.088***	0.014	-0.002	0.287***	0.193***	0.078***	-0.255***	0.019*	0.015	1					
$Fshr_t$	-0.016	-0.015	-0.048***	-0.006	-0.104***	0.014	-0.021**	0.242***	0.108***	-0.051***	-0.071***	1				
Soe_t	-0.022**	-0.018*	-0.077***	-0.011	-0.076***	-0.011	-0.002	0.172***	-0.004	-0.002	-0.088***	0.255***	1			
$Politic_t$	0.021**	0.018*	-0.039***	0.016	-0.050***	0.006	0.027***	0.063***	0.031***	-0.004	-0.030***	-0.01	-0.036***	1		
Gdp_t	-0.131***	-0.124***	0.199***	-0.125***	-0.023**	-0.020**	-0.045***	0.238***	0.106***	-0.024**	-0.017*	-0.052***	-0.076***	-0.070***	1	
$Accm_t$	0.017*	0.013	0.021**	0.021**	0.075***	-0.01	-0.051***	-0.043***	-0.014	0.186***	0.100***	0.012	-0.126***	0.016	0.007	1

Table 2 presents descriptive statistics for the sample. Panel A reports summary statistics on crash risk and other control variables. Panel B presents the Pearson correlation results. The superscripts ***, **, and * indicates statistical significance at 1%, 5% and 10% levels (two-tailed), respectively.

Table 3

Main Results: Impact of Corruption Crackdown on Stock Price Crash Risk

Variables	$Ncskew_{t+1}$		$Duvol_{t+1}$	
	（1）	（2）	（3）	（4）
$Post_t$	-0.234***	-0.058**	-0.132***	-0.036**
	(-9.43)	(-2.26)	(-9.42)	(-2.46)
$Ncskew_t$		0.055***		0.026***
		(5.52)		(4.67)
Mb_t		0.012***		0.007***
		(7.12)		(7.64)
$Size_t$		0.007**		0.008*
		(2.28)		(1.83)
Lev_t		0.159***		0.081***
		(3.97)		(3.56)
Roa_t		0.106		0.016
		(1.11)		(0.30)
$Dturn_t$		0.167***		0.096***
		(8.16)		(8.27)
$Fshr_t$		-0.079		-0.059
		(-1.03)		(-1.38)
$Sigma_t$		0.025		0.533***
		(0.07)		(2.66)
Ret_t		2.159**		1.314***
		(2.43)		(2.62)
Gdp_t		-0.223***		-0.125***
		(-14.52)		(-14.31)
$Accm_t$		0.034**		0.020**
		(2.35)		(2.52)
$Politic_t$		0.037*		0.016**
		(1.76)		(2.36)
Soe_t		-0.007		0.005
		(-0.26)		(0.33)
Constant	-0.183***	5.839***	-0.133***	3.175***
	(-21.36)	(16.26)	(-27.62)	(15.63)
Firm fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Observations	10,464	10,464	10,464	10,464
R^2_adj	0.049	0.064	0.042	0.060

Table 3 presents the impact of corruption crackdown on firm-specific stock price crash risk. All variables are defined in Appendix A. The superscripts ***, **, and * indicates statistical significance at 1%, 5% and 10% levels (two-tailed), respectively.

Table 4

Cross-Sectional Tests: the Impact of Political Dependence on Governments

Panel A: SOEs versus Non-SOEs

Variables	*$Ncskew_{t+1}$*			*$Duvol_{t+1}$*		
	(1)	(2)	(3)	(4)	(5)	(6)
	Non-SOE	*Provincial/Central SOE*	*Municipal SOE*	*Non-SOE*	*Provincial/Central SOE*	*Municipal SOE*
$Post_t$	-0.018*	-0.011*	-0.035***	-0.026	-0.020*	-0.058***
	(-1.65)	(-1.76)	(-4.51)	(-1.49)	(-1.74)	(-3.34)
Controls	YES	YES	YES	YES	YES	YES
Firm fixed effect	YES	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES	YES
Observations	3,862	4,218	2,384	3,862	4,218	2,384
R^2_adj	0.044	0.077	0.063	0.040	0.071	0.061
*Difference-Test for the coefficients of **Post:***						
Diff-Test [(3)=(2)]		Chi^2=2.90*			*Diff-Test [(6)=(5)]*	Chi^2=3.11*
Diff-Test [(3=(1)]		Chi^2=3.47*			*Diff-Test [(6)=(4)]*	Chi^2=3.65*

Panel B: Firms with Government Subsidies versus Firms without Government Subsidies

Variables	*$Ncskew_{t+1}$*		*$Duvol_{t+1}$*	
	(1)	(2)	(3)	(4)
	D_sub=1	*D_sub*=0	*D_sub*=1	*D_sub*=0
$Post_t$	-0.052**	-0.027	-0.038***	-0.012
	(-2.38)	(-0.74)	(-2.92)	(-0.42)
Controls	YES	YES	YES	YES
Firm fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Observations	6,414	3,727	6,414	3,727
R^2_adj	0.097	0.110	0.094	0.113
*Difference-Test for the coefficients of **Post:***				
	Chi^2=3.29*		Chi^2=3.70*	

Table 4 presents the impact of politician's downfalls on firm-specific stock price crash risk considering the firms' closeness to government. Panel A presents the results considering whether the firm is stated owned or not. Non-SOE refers to the group in which firms are privately held; Provincial/Central SOE refers to the group in which firms are controlled by central or provincial government; and Municipal SOE refers to the group in which firms are controlled by municipal government. Panel B shows the results considering whether firms can acquire government subsidies. D_*sub*=1 means that firms have subsidies from government in the year *t-1* and D_*sub*=0 means that firms don't get subsidies from government in the year *t-1*. All variables are defined in Appendix A. The superscripts ***, **, and * indicates statistical significance at 1%, 5% and 10% levels (two-tailed), respectively.

Table 5

Cross-Sectional Tests: Impact of Information Environment

Panel A: High versus Low Analysts Forecast Dispersion

Variables	*Ncskew*$_{t+1}$		*Duvol*$_{t+1}$	
	(1)	(2)	(3)	(4)
	High	*Low*	*High*	*Low*
Post$_t$	-0.082***	-0.059	-0.049**	-0.017
	(-3.31)	(-1.03)	(-2.37)	(-0.52)
Controls	YES	YES	YES	YES
Firm fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Observations	2,912	2,918	2,912	2,918
R^2_adj	0.084	0.057	0.067	0.047
*Difference-Test for the coefficients of **Post:***				
	Chi^2=3.15*		Chi^2=2.87*	

Panel B: High versus Low Intangible Asset Ratio

Variables	*Ncskew*$_{t+1}$		*Duvol*$_{t+1}$	
	(1)	(2)	(3)	(4)
	High	*Low*	*High*	*Low*
Post$_t$	-0.071***	-0.023	-0.040***	-0.006
	(-2.86)	(-0.51)	(-2.95)	(-0.24)
Controls	YES	YES	YES	YES
Firm fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Observations	5,004	5,012	5,004	5,012
R^2_adj	0.062	0.050	0.055	0.048
*Difference-Test for the coefficients of **Post:***				
	Chi^2=3.61*		Chi^2=4.26**	

Panel C: High versus Low Earnings Volatility

Variables	*Ncskew*$_{t+1}$		*Duvol*$_{t+1}$	
	(1)	(2)	(3)	(4)
	High	*Low*	*High*	*Low*
Post$_t$	-0.115***	-0.009	-0.065***	-0.012
	(-2.90)	(-0.25)	(-2.84)	(-0.44)
Controls	YES	YES	YES	YES
Firm fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Observations	5,230	5,234	5,230	5,234
R^2_adj	0.070	0.050	0.064	0.049
*Difference-Test for the coefficients of **Post:***				
	Chi^2=5.71**		Chi^2=4.56**	

Table 5 presents the impact of corruption crackdown on firm-specific stock price crash risk considering the impact of information environment. We use analysts forecast dispersion, intangible asset ratio, earnings volatility as proxies for firm-level information environment. Panel A presents results for samples stratified on the median of analysts forecast dispersion (*Dispersion*) of year *t-1*. Panel B presents results for samples stratified on the median of intangible assets ratio (*Intan_ratio*) of year *t-1*. Panel C presents the results for samples stratified on the median of earnings volatility (*Earn_vol*) of year *t-1*. Detailed variable definitions are presented in Appendix A. The superscripts ***, **, and * indicates statistical significance at 1%, 5% and 10% levels (two-tailed), respectively.

Table 6

Channel Test: Reduced Political Risk

Panel A: Regression of Political Risk on *Post*			**Panel B: Regression of Crash Measures on *Political Risk***				
Variables	Sub_t	$Politic_t$	Variables	$Ncskew_{t+1}$	$Duvol_{t+1}$	$Ncskew_{t+1}$	$Duvol_{t+1}$
	(1)	**(2)**		**(1)**	**(2)**	**(3)**	**(4)**
$Post_t$	-0.002***	-0.017**	Sub_t	0.150**	0.068**		
	(-2.66)	(-2.35)		(2.29)	(2.48)		
$Size_t$	0.002***	0.018***	$Politic_t$			0.022**	0.007**
	(2.79)	(2.89)				(2.03)	(1.98)
Roa_t	0.033***	0.052	$Ncskew_t$	0.056***	0.025***	0.056***	0.026***
	(7.44)	(1.03)		(5.34)	(4.23)	(5.43)	(4.43)
Lev_t	0.020***	0.016	Mb_t	0.008***	0.004***	0.007***	0.004***
	(10.82)	(0.77)		(4.01)	(4.19)	(3.91)	(4.02)
$Fshr_t$	-0.008*	0.144***	$Size_t$	0.032**	0.017**	0.030**	0.017**
	(-1.81)	(2.89)		(2.42)	(2.27)	(2.35)	(2.36)
Ch_sales_t	-0.002***	-0.003	Lev_t	0.145***	0.076***	0.156***	0.085***
	(-4.34)	(-0.58)		(3.26)	(3.02)	(3.70)	(3.57)
Ind_board_t	-0.004	0.090	Roa_t	0.005	-0.016	-0.025	-0.035
	(-0.63)	(1.32)		(0.05)	(-0.27)	(-0.24)	(-0.61)
Dr_t	-0.000	0.057***	$Dturn_t$	0.014	0.006	0.014	0.006
	(-0.10)	(4.63)		(0.47)	(0.34)	(0.50)	(0.35)
Age_t	0.007**	-0.095**	$Fshr_t$	-0.164**	-0.115**	-0.146*	-0.103**
	(2.13)	(-2.41)		(-2.05)	(-2.53)	(-1.84)	(-2.30)
$Mshr_t$	0.001	0.098	$Sigma_t$	0.307	0.091	0.230	0.059
	(0.12)	(0.72)		(0.61)	(0.32)	(0.46)	(0.21)
$Boardsize_t$	0.002	-0.020	Ret_t	2.760***	1.246**	3.065***	1.427***
	(0.72)	(-0.74)		(2.81)	(2.24)	(3.19)	(2.62)
			Gdp_t	0.102**	0.062**	0.069*	0.035
				(2.20)	(2.37)	(1.75)	(1.55)
			$Accm_t$	0.023**	0.014**	0.038*	0.021*
				(2.41)	(2.44)	(1.68)	(1.66)
			Soe_t	-0.033	-0.010	-0.019	-0.001
				(-1.10)	(-0.57)	(-0.67)	(-0.09)
Constant	0.023*	-0.045	$Constant_t$	-3.523***	-2.101***	-2.623**	-1.380**
	(1.82)	(-0.31)		(-2.74)	(-2.89)	(-2.35)	(-2.19)
Firm fixed effect	YES	YES	Firm fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	Year fixed effect	YES	YES	YES	YES
Observations	9,613	9,911	Observations	9,613	9,613	9,911	9,911
R^2_adj	0.030	0.031	R^2_adj	0.093	0.091	0.091	0.089

Table 6 presents the impact of politician's downfalls on firm-specific stock price crash risk through decreasing political risk. Panel A is the result of regression of political risk on *Post*, and Panel B is the result of regression of crash measures on *political risk.* The superscripts ***, **, and * indicates statistical significance at 1%, 5% and 10% levels (two-tailed), respectively.

Table 7

Channel Test: Constrained Bad News Hoarding

Panel A: Regression of *Accm* on *Post*		**Panel B: Regression of Crash Measures on *Accm***		
Variables	*Accm* $_t$	Variables	$Ncskew_{t+1}$	$Duvol_{t+1}$
	(1)		**(1)**	**(2)**
$Post_t$	-0.005**	$Accm_t$	0.037**	0.021***
	(-2.06)		(2.49)	(2.91)
$Size_t$	0.012***	$Ncskew_t$	0.055***	0.026***
	(6.55)		(5.58)	(4.73)
Roa_t	0.215***	Mb_t	0.012***	0.007***
	(11.98)		(7.10)	(7.63)
Lev_t	0.078***	$Size_t$	0.004*	0.006*
	(10.39)		(1.75)	(1.88)
$Fshr_t$	0.049***	Lev_t	0.157***	0.079***
	(3.65)		(3.93)	(3.52)
$Dual_t$	0.006	Roa_t	0.108	0.017
	(1.38)		(1.13)	(0.32)
Soe_t	-0.023***	$Dturn_t$	0.168***	0.096***
	(-4.35)		(8.18)	(8.29)
		$Fshr_t$	-0.075	-0.057
			(-0.99)	(-1.33)
		$Sigma_t$	0.015	0.539***
			(0.04)	(2.69)
		Ret_t	2.156**	1.312***
			(2.43)	(2.61)
		Gdp_t	-0.230***	-0.128***
			(-15.19)	(-15.02)
		$Politic_t$	0.038*	0.017
			(1.80)	(1.41)
		Soe_t	-0.005	0.006
			(-0.19)	(0.41)
Constant	-0.106***	Constant	6.060***	3.311***
	(-2.70)		(17.54)	(16.94)
Firm fixed effect	YES	Firm fixed effect	YES	YES
Year fixed effect	YES	Year fixed effect	YES	YES
Observations	10,214	Observations	10,214	10,214
R^2_adj	0.129	R^2_adj	0.063	0.059

Table 7 presents the impact of politician's downfalls on firm-specific stock price crash risk through constraining bad news hoarding. Panel A is the result of regression of *Accm* on *Post*, and Panel B is the result of regression of crash measures on *Accm*. The superscripts ***, **, and * indicates statistical significance at 1%, 5% and 10% levels (two-tailed), respectively.

Table 8

Matched-Sample Test

Variables	*Ncskew*$_{t+1}$		*Duvol*$_{t+1}$	
	(1)	(2)	(3)	(4)
Corrupt$_t$**Post1*$_t$	-0.137***		-0.082***	
	(-3.64)		(-3.91)	
Post1$_t$	-0.064		-0.036	
	(-0.84)		(-0.86)	
Corrupt$_t$**Post2*$_t$		-0.167***		-0.093***
		(-3.54)		(-3.46)
Post2$_t$		-0.053		-0.026
		(-1.26)		(-1.11)
Controls	YES	YES	YES	YES
Firm fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Observations	3,079	1,942	3,079	1,942
R^2_adj	0.099	0.149	0.105	0.151

Table 8 reports results using matched sample. *Corrupt*$_t$ is an indicator variable which is equal to one if the firm is located in the city where the top municipal government officials are exposed with corruption, zero for the control firms. *Post1*$_t$ is an indicator variable, equal to one if the firm-year of treatment and control samples is the event (exposure) year or the following two years after the event (exposure) year, and zero if the firm-year observation is in the two years before the event year. *Post2*$_t$ is an indicator variable, equal to one if the firm-year of treatment and control samples is the event (exposure) year or following one year after the event (exposure) year, and zero if the firm-year observation is in the one year before the event year. The superscripts ***, **, and * indicates statistical significance at 1%, 5% and 10% levels (two-tailed), respectively.

Table 9

Placebo Test

Variables	*Ncskew$_{t+1}$*	*Duvol$_{t+1}$*	*Ncskew$_{t+1}$*	*Duvol$_{t+1}$*
	（1）	（2）	（3）	（4）
Post_Pseudo1$_t$	-0.031	-0.016		
	(-1.25)	(-1.13)		
Post_Pseudo2$_t$			-0.028	-0.024
			(-0.91)	(-1.37)
Controls	YES	YES	YES	YES
Firm fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Observations	10,464	10,464	10,278	10,278
R^2_adj	0.035	0.058	0.029	0.062

Table 9 reports results for placebo test. We assume the event-year are there years before or after the actual event-year. *Post_Pseudo1$_t$* is an indicator variable that is equal to one for years after the pseudo-event-year, where pseudo-event-year is three years after the actual event-year, and zero for years before the pseudo-event-year. *Post_Pseudo2$_t$* is an indicator variable that is equal to one for years after the pseudo-event-year, where pseudo-event-year is three years before the actual event-year, zero for years before the pseudo-event-year. All other variables are the same as main results. The superscripts ***, **, and * indicates statistical significance at 1%, 5% and 10% levels (two-tailed), respectively.

Table 10

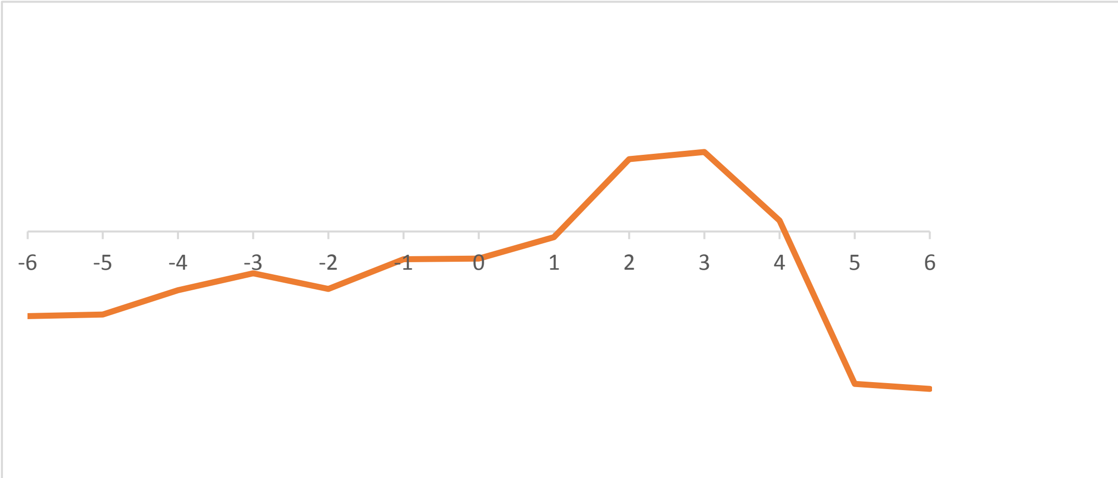
Market Reaction of the Corruption Cases

Event widows	[-1,+1]	[-2,+2]	[-3,+3]	[-4,+4]
CAR	-0.0228***	-0.0246***	-0.0254***	-0.0293***
t-stat	(-2.69)	(-3.44)	(-5.22)	(-10.65)

Table 10 shows the market reaction when the top municipal government officials are exposed with corruption for samples which we can identify the specific date of the exposure. We estimate abnormal return using market-adjusted model and calculate CAR for different windows.

Figure 1

Median Value of Monthly Crash Risk Changes for Samples in Nanjing, Jiangsu Province



We use the corruption event of former mayor of Nanjing, Ji Jianye as an example to illustrate the monthly crash risk changes. Specifically, we calculate the median values of monthly crash risk for firms involved in this event. Month 0 is the event month (on October 17th, 2013, the official website of the CCDI announced that the mayor of city Nanjing, Ji Jianye, was suspected of serious discipline violations and was under investigation by the CCDI, therefore October, 2013 is the event month). We employ model (1) to estimate firm-specific daily return first, then we use firm-specific daily return to calculate monthly crash risk (i.e., the monthly negative coefficient of skewness).

Highlights

•We examine the relation between crackdown on corruption and a firm's future crash risk.
•We define the event day of corruption crackdown as the day when the wrongdoings of top officials at the municipal level firstly became public.
•A firm, on average, has lower future stock price crash risk after crackdown.
•It is consistent with reduced political risk and bad news hoarding stories.
•Our results are robust.